A LANDSCAPE-SCALE PERSPECTIVE TO GRASSLAND BIRD CONSERVATION IN AGROECOSYSTEMS

by

JOHN M. YEISER

(Under the Direction of James A. Martin)

ABSTRACT

Conserving biodiversity in agricultural ecosystems is a global imperative. The Conservation Reserve Program (CRP) is the primary tool for conserving agroecosystems in the United States. There have been positive local effects of programs like CRP, but there is uncertainty about whether local effects scale up to population-level benefits. We used a landscape-scale approach to understand the effects of a grassland conservation program, the Conservation Reserve Enhancement Program (CREP), on Northern Bobwhite (*Colinus virginianus*) and other grassland bird populations. We demonstrated that Northern Bobwhite populations were positively influenced by the CREP. However, there can be opportunity costs for other species when landscapes are managed for Northern Bobwhite through these programs. Similarities between landscape-scale resource requirements likely dictate opportunity costs. We provide a decision support tool with which practitioners can establish an adaptive management strategy for private lands.

INDEX WORDS: Private land conservation, Northern Bobwhite, *Colinus virginianus*, grassland birds, state-space models, agroecosystem, farmland, conservation

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by

John M. Yeiser

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JOHN M. YEISER

Major Professor:	James A. Martin
Committee:	Danna L. Baxley Richard B. Chandler Jeffrey Hepinstall-Cymerman

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
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CHAPTER 1

CONTEXT AND PURPOSE

> *All the old Swedes and Englishmen born in America, whom I ever questioned, asserted that there were not nearly so many birds fit for eating at present as there used to be when they were children, and that their decrease was visible*
>
> Naturalist Peter Kalm, 1753

1.1 Introduction

Conserving biodiversity on farmlands despite the increasing demands of human populations is a global imperative (Altieri, 1999; Tscharntke et al., 2012a; Laurance et al., 2014). Government policy can establish guidelines or goals for wildlife conservation, but on-the-ground implementation over broad spatial scales is complicated by the different priorities of landowners and varying opportunities for conservation delivery (Paloniemi and Tikka, 2008; Morgan et al., 2012). Balancing effective policies and agricultural land use is a formidable challenge for conservation around the world (Tscharntke et al., 2012a), especially in areas where the majority of land is privately owned. For example, the commonwealth of Kentucky is 96.5% privately owned and approximately half of that is agricultural land.

Government-funded conservation initiatives are primary channels for wildlife management in agroecosystems (Donald and Evans, 2006; Baker et al., 2012; Evans et al., 2014). Landowners are compensated by government agencies for either turning production land into natural vegatation or abiding by strict land use regulations. The largest farmland conservation initiative in the U.S. is the Conservation Reserve Program (CRP). As of September 2017, 9.48 million ha were enrolled and the budget outlay for fiscal year 2016 equaled $1.8 billion (USDA FSA, 2017). From 2007–2013 the European Union spent nearly €20 billion on agri-environmental schemes (AES). The 2014 Common Agricultural Policy reform predicts that approximately €85 billion will be spent on Rural Development from 2014–2020. Thirty percent of those funds are mandated to be reserved "for voluntary measures that are beneficial for the environment and climate change" (European Commission, 2013).

Farmland conservation generally benefits biodiversity, but impacts have been mixed (e.g., Halloum et al., 2000; Kleijn et al., 2006; Perkins et al., 2011; Evans et al., 2014), likely because of differing landscape contexts, varying quality of resources added by conservation programs (i.e., the degree of contrast between conservation practices and existing land cover), or because evaluation techniques are disparate from policy objectives (Kleijn et al., 2011). Kleijn et al. (2011) suggested that farmland conservation be informed by investigations into how local processes scale up to larger biodiversity trends. A landscape-scale approach (Kohler et al., 2008; Baker et al., 2012) can facilitate spatial targeting of landowner enrollment, which may optimize conservation outcomes (e.g., Ekroos et al., 2014).

Informing conservation planning with research findings can require the distillation of complex mechanisms into elements that are usable to policy-makers and practitioners. One example is the use of umbrella species, or "a species whose conservation confers protection to a large number of naturally co-occurring species" (Roberge and Angelstam, 2004). The usefulness of umbrella species and its multi-species analogue, the focal-species approach, have been debated thoroughly (Lambeck, 1997; Simberloff, 1998; Caro and O'Doherty, 1999; Andelman and Fagan, 2000; Roberge and Angelstam, 2004; Branton and Richardson, 2011). The effectiveness of these schemes (e.g., surrogate approaches) is determined by the selection criteria used to choose representative species and the availability of data to inform decisions (Poiani et al., 2001; Lindenmayer et al., 2002; Seddon and Leech, 2008). Rare species can be effective umbrellas (Launer and Murphy, 1994; Warman et al., 2004), but funding for their management is not always accessible to land managers (Fleishman et al., 2000). Crosby et al. (2015) suggests using socially and economically valueable game animals as umbrellas. There are funding avenues for the management and conservation of game species that are available to practitioners (e.g., Pittman-Robertson, license sales), and government agencies monitor populations either actively (e.g., systematic sampling) or passively (e.g., hunting logs) to inform hunting regulations.

1.2 Objectives

1. Estimate landscape-scale effects of agroecosystem conservation on Northern Bobwhite populations
2. Test whether Northern Bobwhite are suitable surrogate species for grassland conservation
3. Investigate patterns of management within fields enrolled in a grassland conservation program.

1.3 Study area

We studied the influence of a grassland conservation program, the Conservation Reserve Enhancement Program, on Northern Bobwhites (*Colinus virginianus*; hereafter bobwhite), Dickcissels (*Spiza americana*), Eastern Kingbirds (*Tyrannus tyrannus*), Eastern Meadowlarks (*Sturnella magna*), Field Sparrows (*Spizella pusilla*), and Grasshopper Sparrows (*Ammodramus savannarum*) in the Green River Basin in south central Kentucky during 2010–2015.

The Green River Basin (Figure 1.1) is characterized by karst topography with elevation ranging from 91 to 365 m above sea level. Annual high temperatures average 20.5°C, with average highs in November–February, March–May, June–August, and September–October of 10.3°C, 20.7°C, 31.1°C, and 24.7°C, respectively. Average annual precipitation is 126.2 cm.

The major goals of the Kentucky CREP were to improve water quality and wildlife habitat. A total of 40469 ha were enrolled in the program and it was estimated that the KY CREP will pay approximately $260 million to farmers over the life of the program (Kentucky Division of Conservation, 2012). The KY CREP consisted of several conservation practices (Table 1.1), although the majority were CP29 (Marginal Pastureland Wildlife Buffer, 71%) and CP22 (Riparian Buffer, 16%). Conservation Practice 29 is described as a buffer, but

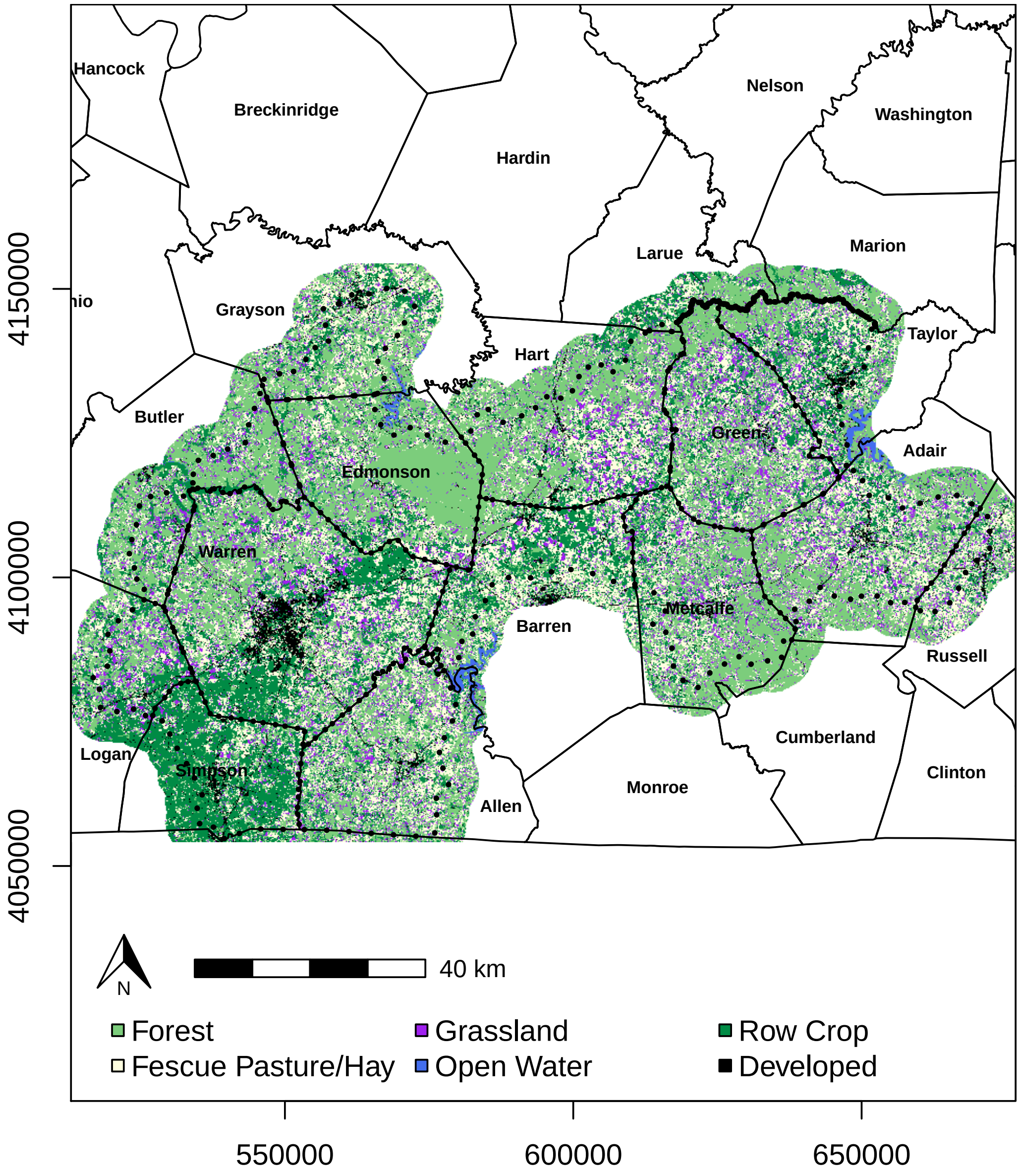

Figure 1.1: Land cover within the Green River Basin in south central Kentucky. We classified the area using a random forest algorithm (more detail in Chapter 3). The boundary of our study area included a 5000 m buffer around the original CREP area (dashed lines) in order to minimize edge effects of covariates.

this practice was implemented in pastures where sinkholes were present, and sink holes were buffered to an extent that encompassed the entire field. Conservation Practice 29

Table 1.1: Type and proporation of conservation practices in the Kentucky CREP.

Practice	**Description**	**Proportion of total acreage**
CP1	introduced grasses, forbs and legumes	0.0025
CP2	native grass plantings	0.0464
CP3	general tree planting	0.0004
CP3A	hardwood tree planting	0.0015
CP8A	grass waterway	0.0001
CP11	trees already established	0.0006
CP21	filter strips	0.0005
CP22	riparian buffer	0.1595
CP25	restoration of rare and declining habitat	0.0790
CP29	marginal pastureland wildlife buffer	0.7095

consisted of mostly short-grass prairie mixes. Fields enrolled in CP22 were primarily a row of planted hardwoods with extended buffers seeded in tallgrass prairie mixes. The majority of contracts were initiated in 2008, thus our initial year of sampling (2010) was at least one growing season after fields had been planted. We did not have contract-level initiation dates.

1.4 Bird data collection methods

Bird data were collected by Kentucky Department of Fish and Wildlife Resources biologists from 2010–2015 using 5-minute road-side point counts during the month of June. Observers were mostly constant at points over time. Some points were not surveyed correctly in our initial year of sampling (2010), so we removed those sampling events from the analysis (i.e., those points for that year are ’NA’). We truncated detection distances to appropriate distances (e.g., 450 m for bobwhite) and aggregated detections by distance bands based on the recommendations of Buckland (2001).

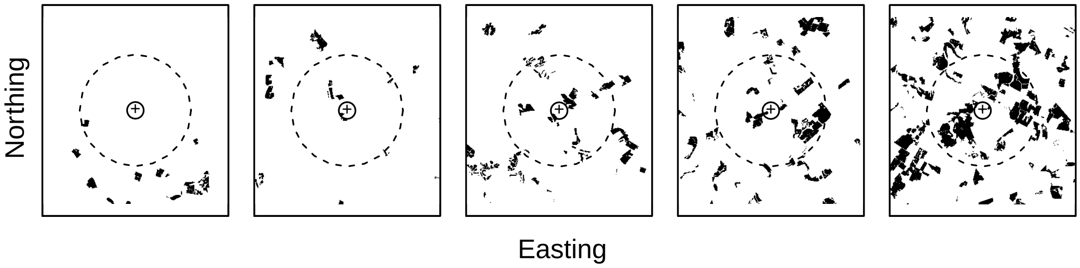

Figure 1.2: Example landscapes demonstrating our study design. From left to right, the amount of Conservation Reserve Enhancement Program (solid shapes) in the sampling areas (solid circles) remains relatively static while the amount of CREP in surrounding landscapes (dashed circles) increases. Note that we only delineated landscapes in this matter to guide site selection.

Point locations were determined using a stratified random sampling design (Figure 1.2), where the strata of interest was landscape-scale CREP density. We assumed that a 3000 m radius circle was an appropriate landscape scale to inform study design (Twedt et al., 2007); however, our statistical methods directly test this assumption. We randomly selected sampling points within each of 5 CREP density strata (Table 1.2), and point selection was informed by a power analysis (Evans and Burger, *unpub. data*). Points that were in forested areas or surrounded by forest were excluded from consideration because of the interest in grassland bird species only.

Table 1.2: Target and actual CREP proportions for each strata used in sampling design to estimate the influence of the Conservation Reserve Enhancement Program on Northern Bobwhite (*Colinus virginianus*) in the Green River Basin in south-central Kentucky.

	Target		Actual Mean and Range	
Strata	Local	Landscape	Local	Landscape
A	$<$0.015	$<$0.015	0.0 (0.0–0.0)	0.007 (0.0–0.015)
B	0.035–0.095	$<$0.015	0.060 (0.036–0.091)	0.01 (0.004–0.015)
C	0.035–0.095	$0.05 < x < 0.10$	0.059 (0.036–0.092)	0.069 (0.050–0.098)
D	0.035–0.095	$0.10 < x < 0.15$	0.066 (0.036–0.093)	0.117 (0.100–0.141)
E	0.035–0.095	$>$0.15	0.059 (0.037–0.093)	0.171 (0.150–0.222)

CHAPTER 2

PRIVATE LAND CONSERVATION HAS LANDSCAPE-SCALE BENEFITS FOR WILDLIFE IN AGROECOSYSTEMS[1]

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[1] Yeiser, J.M., J.J. Morgan, D.L. Baxley, R.B. Chandler, and J.A. Martin. 2018. *Journal of Applied Ecology*. 55:1930–1939, Reprinted here with permission of the publisher.

2.1 Abstract

Private lands contain much of the world's biodiversity. Conservation of private land, especially agricultural land, is urgent yet challenging because of the diverse priorities of landowners. Local effects of farmland conservation programmes have been evaluated thoroughly, but population-level response to these programmes may depend on effects that extend beyond targeted land parcels. We investigated the landscape-scale effects of a grassland conservation initiative, the Conservation Reserve Enhancement Program (CREP), on a socially and economically important gamebird, the Northern Bobwhite *Colinus virginianus*. Barriers to assessing population-level response to conservation include determining the spatial scale at which a species responds to environmental change (the scale of effect) and untangling density-dependent processes. We performed point counts over 6 years at 247 sites with similar local CREP density but varying landscape-scale CREP density. We used an open-population distance sampling model to evaluate population response to landscape-level CREP density and to forecast population densities under differing re-enrollment scenarios. Our model included kernel smoothing techniques to estimate scale of effect and an estimator of the strength of density dependence. Density dependence moderated the effectiveness of the CREP, but overall populations responded positively to increasing landscape-scale CREP density. We estimated that at least 5% of the landscape needs to be in CREP to meet population density goals of 0.25 bobwhite/ha. Conservatively, we recommend 10% of the landscape to be in CREP. Our percent cover recommendations are based on a distance-weighted average of CREP around focal sites. Landscape-scale effects diminished with distance. For example, assuming all else is equal, a CREP field 3000 m away had 88% less of an effect on local abundance than a field 1000 m away. Fields farther than 5000 m away had no effect on local abundance. Our study underscores the importance of a landscape-scale approach to farmland conservation. Benefits of these programmes to wildlife can extend beyond the local scale,

but their importance to local populations diminishes with distance. Estimating this relationship and incorporating it into a decision framework could help practitioners target land enrollment to meet broad-scale population objectives.

2.2 Introduction

Private land conservation programs such as agri-environmental schemes (AES) and the Conservation Reserve Program (CRP) are used throughout Europe and United States, respectively, to offset farmland bird population declines. The CRP is a U.S. Department of Agriculture program administered by the Farm Service Agency that incentivizes landowners to temporarily remove agricultural land from production in lieu of an approved conservation practice. Similar to set-aside programs within AES, CRP can be viewed as a form of land sparing (Fischer et al., 2008). Fields enrolled in grassland CRP practices are typically higher quality habitat for grassland birds than active agriculture (Johnson and Schwartz, 1993; Best et al., 1998). Although localized positive effects of CRP and similar conservation programs are well documented (e.g., Buckingham et al. 1999; Halloum et al. 2000), the effectiveness of private land conservation in reversing grassland bird declines is tied to landscape-scale effects (Kleijn et al., 2011), i.e., the geographic extent of conservation benefits beyond targeted land parcels. Landscape-scale studies directly modeling the impacts of conservation on population growth are less common (but see Veech 2006; Riffell et al. 2008; Baker et al. 2012). Conservation in agricultural landscapes should be designed to benefit multiple populations (or sub-populations or communities) simultaneously, yet there is little congruence in what constitutes a landscape for grassland birds (Osborne and Sparling 2013; Pabian et al. 2013; Riffell et al. 2015).

The mechanisms driving the spatial scale at which a species is most responsive to environmental change (the scale of effect, e.g,. Jackson and Fahrig 2012) include a species' traits (e.g., mobility), demography (e.g., reproductive rate), and landscape characteristics (e.g., matrix quality), and these mechanisms may vary regionally (Miguet et al., 2016). Thus, determining the scale of effect of a conservation program on wildlife is a necessary step to understanding population-level response (Wiens 1989; Smith et al. 2011). One way to determine scale of effect is to use the focal patch approach, in which independent variables within several nested landscapes are related to dependent variables measured at local sites (Brennan et al., 2002). This method reduces uncertainty about appropriate spatial scales but can produce spurious scale selection (Jackson and Fahrig, 2015), implicitly ignores theories of how populations and individuals interact with landscapes such as optimal foraging theory (Charnov, 1976) and metapopulation dynamics (Hanski and Gilpin, 1991), and ignores uncertainty about chosen scale of effect. An alternative approach is to estimate the scale of effect using smoothing kernels to acknowledge that the importance of a landscape feature should decline with distance to the focal site (Chandler and Hepinstall-Cymerman, 2016). Understanding the relationship between the importance of a resource patch and distance to a local population is critical to effective private land conservation over broad scales (Whittingham, 2007), and this relationship can directly inform conservation planning by defining species-specific landscapes (Figure 2.1).

Just as population response to conservation varies across space, population performance in response to conservation measures will vary with time as intrinsic factors such as density dependence manifest. Modeling population dynamics usually requires information on marked individuals (e.g., Pradel, 1996); however, spatially and temporally replicated counts can be sufficient to estimate population growth rates (Royle, 2004; Dail and Madsen, 2011). Modeling growth allows us to use classical population models that do not assume resources are unlimited (Hostetler and Chandler, 2015; Nadeem et al., 2016). Realistic growth models facilitate population forecasting and allow us to compare the ramifications of alternative management scenarios. Understanding potential population response to alternative conservation strategies is especially relevant to the CRP because

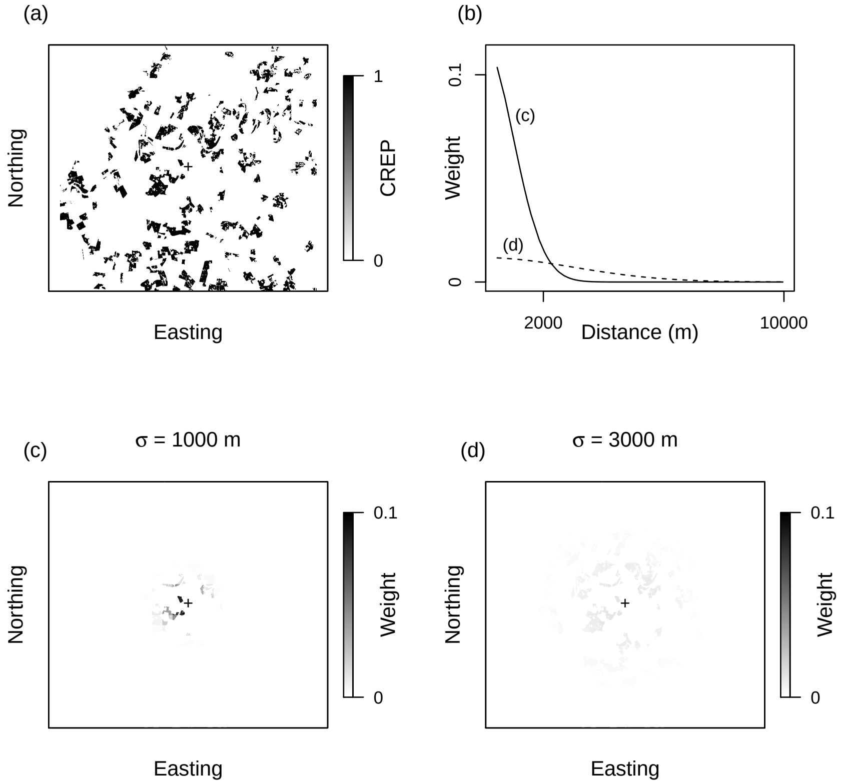

Figure 2.1: An example of using kernel smoothing to estimate the scale at which a species responds to environmental change. Part (a) shows an example landscape with Conservation Reserve Enhancement Program (CREP) fields represented. The “+" represents the location of a hypothetical point count. Part (b) describes two alternate relationships: (c) a relatively fine scale of effect where the parameter dictating the shape of the relationship, σ, is 1000 m, and (d) a relatively course scale of effect where $\sigma = 3000$m.

landowner contracts are temporary and resource management agencies have finite political, monetary, and logistical capital to dedicate to re-enrollment efforts. Thus, we need biologically realistic models to understand the uncertainty surrounding the response of populations to differing re-enrollment strategies.

In agricultural landscapes, grassland bird populations are driven by resource availability (Butler et al., 2010), specifically food and nesting resources (Benton et al. 2002, Butler et al. 2007). Assuming that increased amount of nesting habitat would result in increased net reproductive output (Sutherland, 1996), we would expect individual fitness and population growth to increase in response to a grassland conservation program (Matthiopoulos et al., 2015). Particularly, we would expect the population response to outweigh the conservation footprint (i.e., a 10% increase in high quality nesting habitat would result in more than a 10% population increase; Taylor 1934), especially if additional nesting habitat complements existing resources (Dunning et al. 1992). However, if nesting resources are not complementary to other resources, we may expect to see a non-linear trend in abundance in our first year of sampling across the gradient of conservation land density as other resources become limiting. Alternatively, if nesting resources are not the main factor limiting a grassland-associated species (e.g., Janke and Gates, 2013), implementing a grassland conservation program would merely supplement existing resources (Dunning et al., 1992) and would initiate a response proportional to conservation footprint. Under any of these scenarios, density-dependent processes may manifest over time as population density increases (Roseberry and Klimstra, 1984).

Our goal was to investigate the population-level effects of implementing a grassland conservation program. We used the Kentucky Conservation Reserve Enhancement Program (CREP) as a model conservation program and Northern Bobwhite (*Colinus virginianus*, hereafter: bobwhite) as a model species. We chose bobwhite because the adoption of high efficiency “clean farming" has contributed to their exacerbated declines (reviewed in Hernández et al., 2013) and they are a socially and economically valueable gamebird. The CREP is an offshoot of the CRP that allows eligible states to define specific conservation priorities. Practices implemented for the CREP are based on CRP practices, but landowner eligibility requirements are often more stringent. Our objectives were to (i) estimate the spatial scale at which bobwhite respond to private land conservation, (ii) model the response of bobwhite population density and growth to increasing landscape-scale

CREP density, while holding local CREP density constant, and (iii) project populations under varying levels of CREP re-enrollment, concurrent with contract expiration dates, up to 25 years beyond the starting point of our study.

We had three competing hypotheses about how bobwhite populations would respond to the CREP soon after program implementation, and these hypotheses were based on the assumption that CREP was primarily providing nesting resources. We hypothesized that bobwhite would display (i) a positive response that outweighs conservation footprint and does not diminish along the CREP density gradient (resource complementation hypothesis), or (ii) a positive response that outweighs conservation footprint yet diminishes as conservation land density reaches high densities (nesting resources only hypothesis), or (iii) a positive response directly proportional to conservation footprint (nesting resource supplementation hypothesis). We also hypothesized population growth would display negative density dependence because bobwhite are thought to be regulated via reduction in survival or recruitment (Errington, 1945; Roseberry and Klimstra, 1984).

2.3 Materials and methods

We fit an open-population distance sampling model to our data (Royle et al. 2004; Sollmann et al. 2015). These models have three main components: (i) a model for initial abundance, (ii) a model for abundance in subsequent years $t = 2...T$, and (iii) detection conditional on abundance. We modeled initial abundance at each site $\mathbf{x}_i$ using a negative binomial distribution, where expected abundance $\lambda(\mathbf{x}_i)$ varied with linear and quadratic landscape-scale CREP density. We allowed initial abundance to vary with local CREP density, although our study design rendered relatively low variation in local CREP density:

$$\log(\lambda(\mathbf{x}_i)) = \alpha_0 + \alpha_1 \text{CREP}(\mathbf{x}_i) + \alpha_2 s(\text{CREP}(\mathbf{x}_i), \sigma_{\text{CREP}}) + \alpha_3 s(\text{CREP}(\mathbf{x}_i), \sigma_{\text{CREP}})^2 \tag{2.1}$$

$$\mathrm{N}(\mathbf{x}_{i,1}) \sim \mathrm{NegBin}(\lambda(\mathbf{x}_i), r) \tag{2.2}$$

where α_0 is the intercept, α_1 is the effect of local CREP density, α_2 is the linear effect of landscape-scale smoothed CREP density, α_3 is the quadratic effect of landscape-scale smoothed CREP density, and r is an estimate of overdispersion in counts. We modeled abundance in subsequent years using a Poisson distribution, with expected density a product of abundance in the previous year and a population growth rate. We chose a Poisson distribution based on preliminary assessments of Bayesian *p*-values. Our model combines elements of the Dail-Madsen model (Dail and Madsen, 2011) into one growth rate, γ. Because $\mathrm{N}(\mathbf{x}_{i,t})$ is tied to $\mathrm{N}(\mathbf{x}_{i,t-1})$, estimating γ alone does not account for immigration following local extinction, which can superficially deflate detection probabilities and overestimate abundance. Thus, we modeled an immigration rate I separate from γ. Therefore γ represents the results of survival, recruitment, and emigration and I represents immigration, and together they represent overall population growth at site $\mathbf{x}_i$ from year $t-1$ to year t. We assumed γ and I to be constant among years, yet overall growth rate could vary based on density-dependent processes:

$$\gamma(\mathbf{x}_{i,t}) = \mathrm{N}(\mathbf{x}_{i,t-1})\exp(\theta_0 + \theta_1\mathrm{N}(\mathbf{x}_{i,t-1}) + \theta_2\mathrm{CREP}(\mathbf{x}_i) + \theta_3 s(\mathrm{CREP}(\mathbf{x}_i), \sigma_{\mathrm{CREP}})) \tag{2.3}$$

$$I(\mathbf{x}_{i,t}) = \exp(\iota_0 + \iota_1 s(\mathrm{CREP}(\mathbf{x}_i), \sigma_{\mathrm{CREP}}) \tag{2.4}$$

$$\mathrm{N}(\mathbf{x}_{i,t}) \sim \mathrm{Poisson}(\gamma(\mathbf{x}_{i,t}) + I(\mathbf{x}_{i,t})) \tag{2.5}$$

where θ_0 is intrinsic γ, θ_1 is the strength of density dependence on γ, θ_2 is the influence of site-level CREP density on γ, θ_3 is the influence of landscape-scale smoothed CREP density on γ, ι_0 is the intercept of immigration rate, and ι_1 is the effect of landscape-scale smoothed CREP on immigration rate. For each year in our model, we used a half-normal key function to estimate the probability of detecting a singing individual in each of our distance bands $ydet$, and observations y were modeled using a multinomial distribution:

$$\begin{aligned}
p_{k,t} &= \frac{\left(\frac{\sigma_t^2(1-exp(-db[k+1]^2}{(2\sigma_t^2))}\right)-\left(\frac{\sigma_t^2(1-exp(-db[k]^2}{(2\sigma_t^2))}\right)*2\pi}{pa*pix[k]} \\
pi_{k,t} &= p_{k,t}*pix[k] \\
P_t &= \sum_1^K pi_t \\
y(\mathbf{x}_{i,t}) &\sim \text{Binomial}(P_t, N(\mathbf{x}_{i,t})) \\
ydet(\mathbf{x}_{i,k,t}) &\sim \text{Mulitnomial}(pi_{1\ldots K,t}, y(\mathbf{x}_{i,t}))
\end{aligned} \tag{2.6}$$

where σ is the scaling parameter adjusting the shape of the detection curve, db is the radius of each distance band, pi is the detection probability for each distance band, P is the overall detection probability in the sampling point, pa is the total area of the sampling point, and pix is the proportion of the sampling point encompassed by each distance band.

We smoothed landscape-scale CREP by aggregating (via means) our input raster to cell sizes approximately equal to our sampling units (63 ha) and produced a distance-weighted average of CREP density at each cell using the spatial smoother examined in Chandler and Hepinstall-Cymerman (2016):

$$s(\text{CREP}(\mathbf{x}_i), \sigma_{\text{CREP}}) = \sum_{(\mathbf{x}_j \neq \mathbf{x}_i) \in S} \text{CREP}(\mathbf{x}_j) w(\mathbf{x}_i, \mathbf{x}_j, \sigma_{\text{CREP}}) \tag{2.7}$$

where weights $w(.)$ are determined by a Gaussian kernel:

$$w(\mathbf{x}_i, \mathbf{x}_j, \sigma_{\text{CREP}}) = \frac{\exp\big(-||\mathbf{x}_i - \mathbf{x}_j||^2)/(2\sigma^2_{\text{CREP}})\big)}{\sum_{(\mathbf{x}_j \neq \mathbf{x}_i) \in S} \exp\big(-||\mathbf{x}_i - \mathbf{x}_j||^2)/(2\sigma^2_{\text{CREP}})\big)} \tag{2.8}$$

where $|\mathbf{x}_i - \mathbf{x}_j|$ is the Euclidean distance between coordinates of pixel i and pixel j, and σ_{CREP} is the estimated scale parameter that dictates the shape of the Gaussian kernel.

The summation does not include the pixel of interest “i” because we are interested in the effect of the surrounding landscape on local abundance. We restricted the search area of the Gaussian kernel to a 10 km radius circle to reduce computational effort. We assumed a 10 km radius circle would easily encompass the maximum scale of effect for bobwhite.

We modeled data from 2010–2015 and forecasted populations for 20 additional years under six different scenarios: 100%, 80%, 60%, 40%, 20%, and 0% CREP re-enrollment. For each scenario each year, we randomly selected a percentage of contracts set to expire and "re-enrolled" them. We assumed detection in years 2016–2035 was a random draw from a Normal distribution with mean and standard deviation informed by estimates from years with data (2010–2015). To quantify the probability that one scenario would result in higher densities than another, we calculated the intergral of overlap between any two posterior distributions of estimated densities in 2035.

We ran each model scenario in a Bayesian framework using the Markov Chain Monte Carlo algorithm in JAGS (Plummer, 2003) with the R package rjags (Plummer, 2016). We discarded the adaptive phase and appropriate number of iterations for each scenario to remove the influence of starting values. We ensured model convergence using Gelman-Rubin diagnostics and visual inspection of trace plots.

2.4 Results

We sampled 231 points in 2010 and 247 points from 2011–2015. We detected 159, 182, 180, 195, 227, and 180 male singing bobwhite in 2010–2015, respectively. We estimated detection probabilities for years 2010–2015 to be 0.35 (0.28–0.43, 95% BCI), 0.33 (0.29–0.39), 0.33 (0.29–0.37), 0.31 (0.27–0.35), 0.33 (0.29–0.38), 0.30 (0.25–0.34), respectively.

Bobwhite landscapes were delineated at approximately 5000 m radius circles. The importance of CREP density to a local bobwhite population decreased with increasing

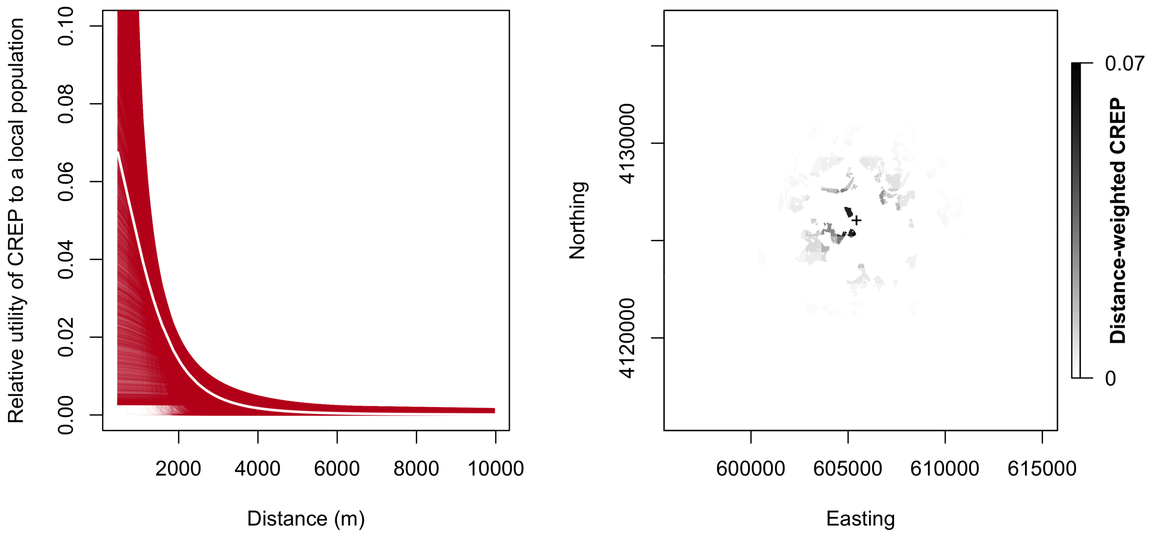

Figure 2.2: Left: the relationship between distance and the relative utility of Conservation Reserve Enhancement Program (CREP) density to a local Northern Bobwhite (*Colinus virginianus*) population in south-central Kentucky (the scale of effect). The y-axis represents Gaussian kernel weights of a given pixel (i.e., a 63 ha area) relative to all pixels in a 10 km radius search area (31416 ha). Higher values reflect distances at which increases in CREP density are more likely to influence the local population. Each red line represents one of 10000 randomly chosen model iterations. The solid white line represents the median estimate. Right: a visual representation of how Northern Bobwhite utilize CREP at landscape-scales in south-central Kentucky. The “+" symbol represents a local population, and the black polygons represent CREP fields. The degree to which each field is shaded represents the relationship between increasing distance and relative utility of a that field to the local population abundance and growth rate.

distance (Figure 2.2). For example, the median weight of a pixel (i.e., a cell in the covariate raster) 3000 m away from a local population was 88% lower than a pixel 1000 m away.

There was a 99.3% probability of a positive effect of landscape-scale CREP density on initial bobwhite density (Figure 2.3). Bobwhite densities in the initial year of sampling ranged from 0.016 (0.009–0.025 95% BCI) to 0.056 males/ha (0.006–0.162 95% BCI)

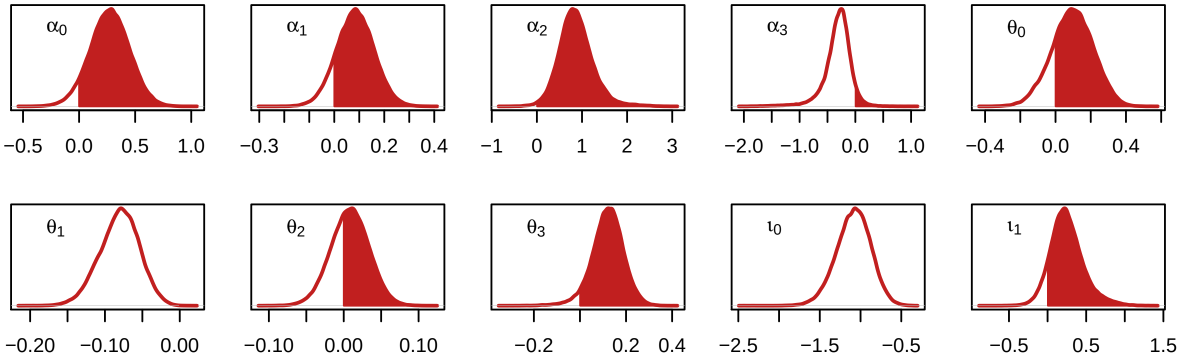

Figure 2.3: Posterior densities of parameters describing the response of Northern Bobwhite (*Colinus virginianus*) to Conservation Reserve Enhancement Program (CREP) density. Shaded areas represent the proportion of posterior mass greater than zero for: (α_0) the intercept of abundance in our first year of sampling (initial abundance); (α_1) local effect of CREP density on initial abundance; (α_2) landscape-scale linear effect of CREP density on initial abundance; (α_3) landscape-scale quadratic effect of CREP density on initial abundance; (θ_0) the intercept of γ (the combined rates of survival, recruitment, and emigration); (θ_1) effect of local population abundance on γ; (θ_2) local effects of CREP density on γ; (θ_3) landscape-scale effects of CREP density on γ, (ι_0) intercept of immigration, and (ι_1) landscape-scale effects of CREP density on immigration.

across the landscape-scale CREP density gradient. The response of initial bobwhite density to the CREP was consistent with our “nesting habitat only" hypothesis. An increase from 0.0 to 0.1 landscape-scale CREP density resulted in a 182% increase in bobwhite density. However, an increase from 0.1 to 0.2 landscape-scale CREP density resulted in only a 21% increase in bobwhite density (Figure 2.4).

There was a 95.2% probability that γ (the result of survival, recruitment, and emigration) was positively influenced by landscape-scale CREP density (Figure 2.3). There was a 89.6% probability that *I* (immigration) was positively influenced by landscape-scale CREP density (Figure 2.3). We estimated that negative density dependence on γ was approximately 8% of the previous year’s abundance. Overall population growth mirrored conservation footprint at low amounts of landscape-scale CREP but outweighed conservation

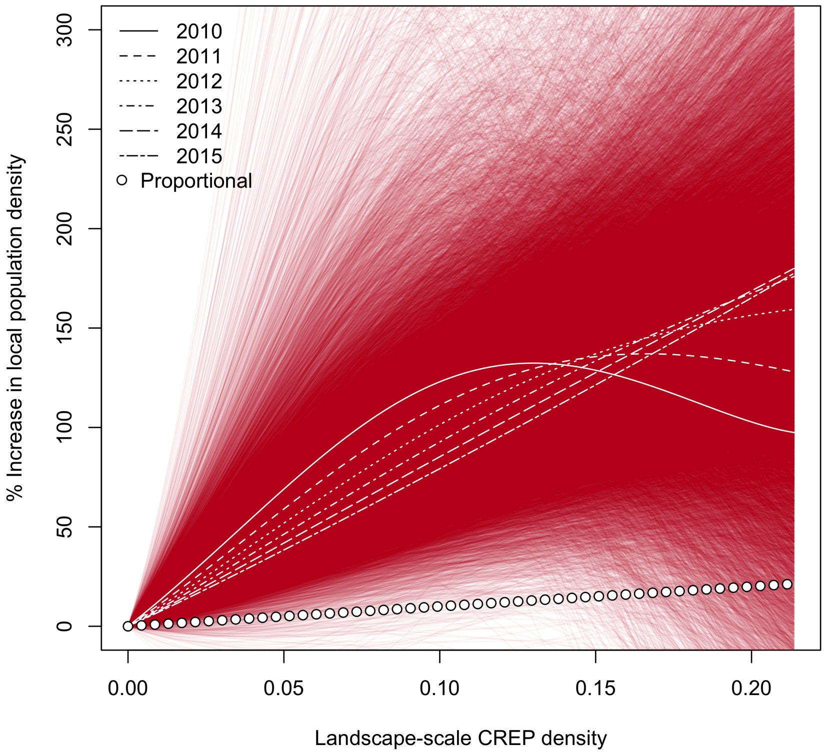

Figure 2.4: Magnitude of response of Northern Bobwhite (*Colinus virginianus*) density to increasing landscape-scale Conservation Reserve Enhancement Program (CREP) density in years 2010–2015. Each red line is one iteration in the MCMC algorithm and white lines represent means for each year. The circles reference a proportional response to a one unit increase in landscape-scale CREP density.

footprint at high amounts of landscape-scale CREP (Figure 2.5). Densities in our final year of sampling (2015) ranged from 0.034 (0.024–0.046 95% BCI) to 0.105 males/ha (0.063–0.159 95% BCI).

We predicted that re-enrolling 80%, 60%, 40%, 20%, and 0% would result in mean densities 10%, 19%, 26%, 33%, and 39% lower than if 100% of contracts were re-enrolled, respectively (Figure 2.6). Our forecasts indicated a 32%, 57%, 71%, 81%, and 87% probability

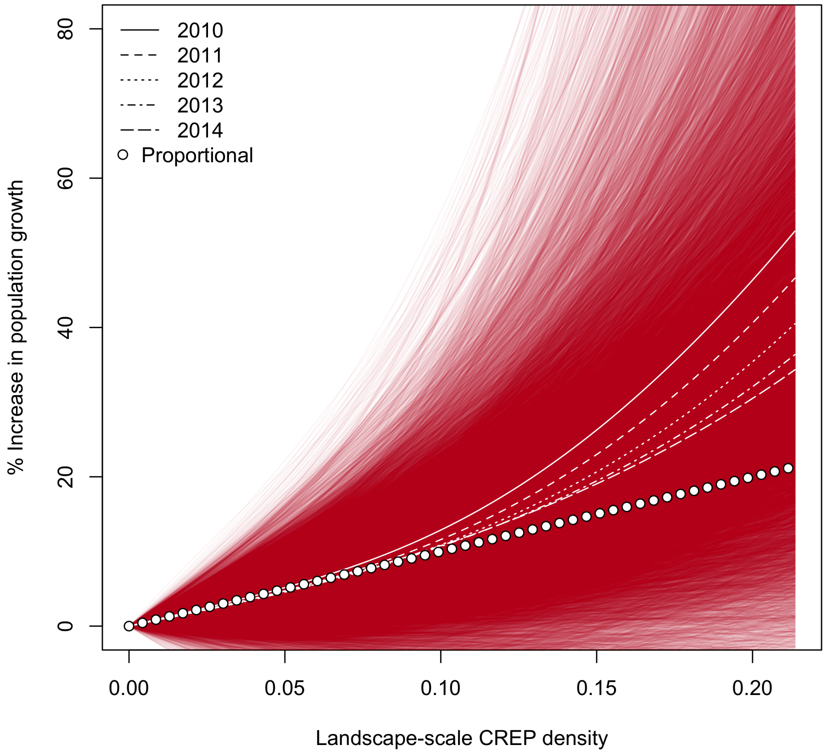

Figure 2.5: Magnitude of response of Northern Bobwhite (*Colinus virginianus*) population growth to increasing landscape-scale Conservation Reserve Enhancement Program (CREP) density in years 2010–2015. Each red line is one iteration in the MCMC algorithm and white lines represent means for each year. The circles reference a proportional response to a one unit increase in landscape-scale CREP density.

that re-enrolling 100% of CREP contracts would lead to higher densities in year 2035 than 80%, 60%, 40%, 20%, and 0% re-enrollment, respectively.

2.5 Discussion

Agricultural landscapes—and thus resources added by farmland conservation programs—are inherently patchy. Understanding whether benefits of conservation extend beyond local scales is paramount to assessing the population-level success of farmland conserva-

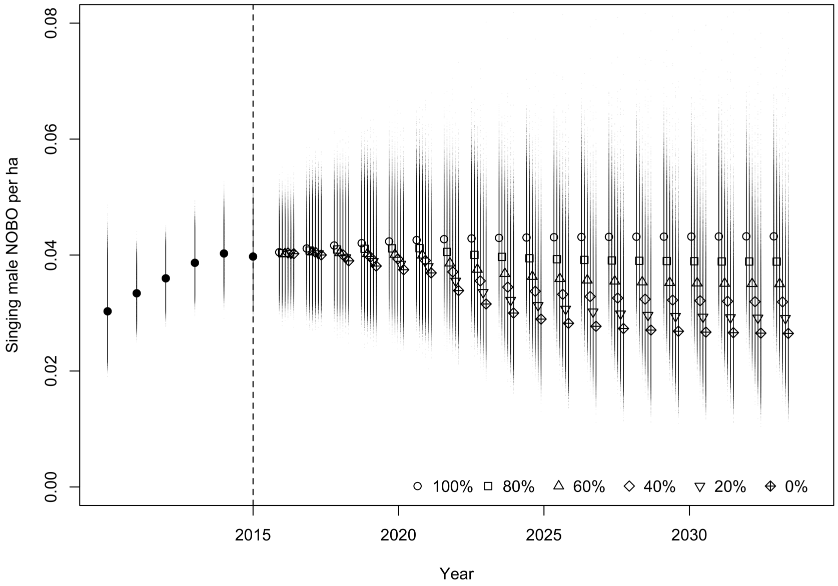

Figure 2.6: Projected mean densities of Northern Bobwhite (*Colinus virginianus*) populations under different re-enrollment scenarios for the Conservation Reserve Enhancement Program. Error bars are composed of estimates from each model iteration.

tion programs (Kleijn et al., 2011). We found evidence that (i) farmland conservation benefits population growth via landscape-scale effects, (ii) landscape-scale effects decrease with increasing distance to a local population, (iii) density dependent growth moderates population response, and (iv) long-term success will be tied to re-enrollment effort.

Translating local effects of farmland conservation programs to scales meaningful to populations is a challenge to successful regional-scale conservation. Donald and Evans (2006) noted that benefits of farmland conservation programs could extend beyond local scales via metapopulation dynamics and mechanisms of island biogeography theory; however, evidence for landscape-scale benefits to bird populations is sparse. Baker et al. (2012) demonstrated how AES can have landscape-scale positive effects on birds in England, but regional-scale assessments of the CRP have not explicitly considered the effects of increasing conservation land density in the surrounding landscape on population growth (Veech, 2006; Riffell et al., 2008). The evidence that population response to CREP density was disproportionately positive supports the assertion that farmland conservation has potential to connect populations over large scales (Donald and Evans, 2006) and underscores the importance of the landscape-scale approach to farmland conservation (e.g., Merckx et al., 2009).

The non-linear relationship between bobwhite density and landscape-scale CREP density in 2010 could reflect an ecological threshold. Increased amount of landscape-scale CREP likely resulted in increased landscape complexity (Fahrig, 2003). Benefits of landscape complexity include increased dispersal capabilities as a result of high connectivity and increased complementation of resources as a result of land cover configuration (Concepción et al., 2012). We would expect that in landscapes with high CREP density (complex landscapes), CREP fields would be closer to existing brood rearing cover, thermal cover, and escape cover relative to landscapes with low CREP density, which would have complementary benefits to bobwhite populations (Dunning et al., 1992; Guthery, 1997). Tscharntke et al. (2012b) reviews evidence for an upper threshold after which increased landscape complexity no longer benefits biodiversity (20% habitat amount). The inflection point in the non-linear relationship we observed occurred before 20% CREP density, which suggests that the resources provided to bobwhite by CREP fields do not reflect total habitat amount.

Alternatively, the non-linear response of bobwhite abundance to increasing landscape-scale CREP density in 2010 could reflect the composition, not configuration, of resources in landscapes. A major resource limiting bird populations in farm landscapes is nesting cover (Benton et al. 2002, Butler et al. 2007). Fields planted in warm season grasses and forbs (e.g., CREP fields) provide ample nesting sites for bobwhite (Washburn et al., 2000), but unless frequently and appropriately disturbed, openness at ground level and quality of brood rearing cover diminishes (e.g., Yeiser et al., 2015). Additionally, it was unlikely that the CREP provided thermal or escape cover in 2010 because landowners planted woody cover infrequently. If we assume that bobwhite populations are indeed limited by resources that they require but are not readily available (Taylor, 1934), the non-linear trend in 2010 could reflect other resources limiting populations after nesting resources are sufficiently dense. Thresholds are typically discussed in terms of total habitat amount (e.g., Swift and Hannon, 2010), but management of wildlife populations may benefit from estimating inflection points in the profile of resources that are limiting population growth.

The regulation of population growth by population density in bobwhite during our study was consistent with the idea that density dependence is an elemental feature of population dynamics (Brook and Bradshaw, 2006). Carrying capacity is influenced by the availability of resources and the use of those resources by individuals within the population, intra- and interspecific competition, and predators (del Monte-Luna et al., 2004). Similar to Baker et al. (2012), we demonstrated that by increasing a limiting resource (nesting cover), we can increase the carrying capacity of landscapes. Our results also suggest that increasing carrying capacity further may require conservation programs to provide a variety of resources to the species or taxa of interest, which underscores the importance of a functional approach to private land conservation. Inventory of existing resources via remote sensing, evaluation of freely available land cover data (e.g., National Land Cover Database), and expert opinion could facilitate an understanding of the functional quality of landscapes (Fahrig et al., 2011a) and inform future private land conservation priorities.

Recent literature advocates for goal-oriented, spatially targeted farmland conservation (e.g., Whittingham, 2007; Batáry et al., 2015; Díaz and Concepción, 2016). Spatially-targeted conservation intented to optimize biodiversity, species abundance, or species occurrence requires an understanding of landscape context because landscape factors influence population structure and dynamics (Tscharntke et al., 2012b). An implicit assumption of spatial targeting, then, is that we know the appropriate landscape scale. Landscapes are species-specific concepts (Jackson and Fahrig, 2012), and the likelihood that a population will utilize resources added by farmland conservation will be moderated by its distance to those resources (Whittingham, 2007), with the assumption being that resources closer to the focal population are more likely to be utilized (Charnov, 1976; Hanski and Gilpin, 1991). Consequently, understanding species-specific forms of the relationship between increasing distance and the utility of resources would facilitate spatially targeted conservation. The kernel smoother we used is tractable and can be implemented in many modeling scenarios (Chandler and Hepinstall-Cymerman, 2016), thus when empirical data is available it is a powerful framework for spatial optimization. However, if empirical data are unavailable during conservation planning, we recommend using potential mechanisms of species-specific scales of effect (e.g., Miguet et al., 2016) to hypothesize appropriate landscape boundaries and to predict the shape of the relationship between resource utility and increasing distance (e.g., half-normal or negative exponential). Subsequent monitoring and modeling similar to what we present herein could be used to establish an adaptive management framework that continually informs planning decisions.

The enrollment strategy of the CREP simply was to implement 40,468 ha of conservation land. There was no consideration of landscape structure or ecological connectivity. Is this opportunistic approach a viable private land conservation strategy? The National Bobwhite Conservation Initiative (NBCI) established density goals for Kentucky of 0.25 bobwhite/ha in the non-breeding season in pasture-dominated landscapes (National Bobwhite Technical Committee., 2011). If we use our last year of data (2015), assume all singing males paired with a female, singing males represented the entire breeding male population, and use a conservative estimate of overwinter survival (0.40), non-breeding season densities in 2014 ranged from 0.17 (0.12–0.24 95%BCI) to 0.48 (0.34–0.67 95%

BCI) across the landscape-scale CREP gradient. The landscape would need to have at least 5% (1–10%) CREP cover to produce 0.25 bobwhite/ha. Conservatively, we recommend practitioners aim for 10% grassland land cover in the landscape surrounding focal sites to reach this goal. These percent cover recommendations are weighted by distance. Evaluating the amount of grassland landcover in any given landscape will require accounting for its configuration, specifically distances between grassland fields and the focal site.

Our forecasts indicate that the ultimate factor dictating long-term success of the CREP in Kentucky will be re-enrollment effort. By presenting forecasted outcomes of alternative management scenarios, we have provided resource management agencies with information that could aid prioritization of re-enrollment of CREP in Kentucky. First, prioritization should be rooted in conservation outcomes, for example, meeting or maintaining NBCI density goals for bobwhite. Managing landscapes for bobwhite may be the most practical way to conserve grassland bird biodiversity in the eastern U.S., as bobwhite can be an umbrella species for other grassland and shrubland birds (Crosby et al., 2015) and their importance to sportsmen and women often drive farmland conservation policy (e.g., Conservation Practice 33). Second, agencies could use our forecasts to understand opportunity costs of different management decisions. For example, is the increased cost of re-enrolling 100% of contracts versus 80% of contracts worth the potential gain in bobwhite density, given that there is only a 32% probability of obtaining greater densities? Finally, spatial prioritization could be guided by the estimated relationship between increasing distance and utility of CREP fields to local populations. Simulations quantifying the potential differences in carrying capacities resulting from random, opportunistic, and spatially targeted re-enrollment at some percentage (e.g., 80%) are necessary to fully inform these decisions, and we believe our modeling framework is a first step in that process. The development of user-friendly, data-driven decision support tools that allow spatially explicit value inputs such as population goals, monetary and logistical resources, and landowner interest would facilitate the transfer of research findings and policy objectives to on-the-ground conservation.

Our study is an example of how outcome-based monitoring contributes to strategic habitat conservation, and provides guidance on the practical considerations of employing a landscape-scale approach to farmland conservation. Specifically, we expect our findings to have implications for planning and implementation of CRP and CREP in the U.S. and similar voluntary set-aside practices across Europe. We believe the advancement of knowledge on (i) how and why landscape scales vary among and within species, (ii) functional relationships between population growth and land cover composition and landscape context, and (iii) repercussions of spatially targeted land enrollment versus random or opportunistic enrollment would improve the efficiency of farmland conservation.

CHAPTER 3

SPECIES-SPECIFIC LANDSCAPES AND THE OPPORTUNITY COSTS OF THE FLAGSHIP APPROACH[2]

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[2] Yeiser, J.M., J.J. Morgan, D.L. Baxley, R.B. Chandler, and J.A. Martin. To be submitted to *Biological Conservation*

3.1 Abstract

Conserving biodiversity on farmlands despite the increasing demands of human populations is a global imperative. The Conservation Reserve Program has been a major avenue for managing wildlife on farmlands, especially game birds like Northern Bobwhite (Colinus virginianus). Northern Bobwhites are considered a âĂIJflagshipâĂİ species for grassland conservation because they are of great recreational and cultural value, have relatively abundant revenue sources, and have similar habitat needs to other grassland birds of conservation concern. However, agricultural landscapes are complex networks of production, natural, and semi-natural land cover. The functional value of a patch type to two similar species may vary because of differing life history requirements. Furthermore, the spatial scale at which land management influences populations (the scale of effect) differs among species. Given these potential conflicting factors, we sought to investigate the opportunity costs of managing landscapes for Northern Bobwhite on a suite of similar species. We used an open-population distance-sampling model with an embedded predictor of scale of effect to estimate the relationship between population growth and landscape structure. We used a novel decision support tool to predict spatially explicit densities under competing management scenarios. We found that several species had similar responses to landscape structure as Northern Bobwhite, but the scale of effect of landscape structure on population growth varied. For example, the area surrounding sites that mattered to local Northern Bobwhite population growth was a 12 km radius circle, while for Dickcissels it was a 20 km radius circle. We predicted that managing landscapes for Northern Bobwhite would incur opportunity costs of -76.4% for Dickcissels, 0.5% for Eastern Meadowlarks, and -5.7% for Field Sparrows. Although the flagship approach is assumed to benefit a suite of species, we provide evidence that there are opportunity costs that need to be considered when planning and implementing farmland conservation.

3.2 Introduction

The spatial extent at which landscape features influence a local population is species-specific. This spatial scale (the scale of effect) may be influenced by body size, migratory status, reproductive rate, or several other factors (reviewed in Miguet et al., 2016). For instance, a simulation study (Jackson and Fahrig, 2012) suggested that dispersal capabilities determine scale of effect. A practical conceptualization of the scale of effect for farmland conservation is the likelihood that any conservation action will influence a target population unit (Whittingham, 2007). This is affected by distance between the action and the target unit (e.g., population), assuming that as distance decreases the likelihood of the conservation action influencing the population increases. This assumption is supported by theories on how animals utilize resources (Charnov, 1976) and how population units interact (Hanski and Gilpin, 1991). Using this conceptualization of scale of effect, spatial targeting of enrollment centers on the rate at which benefits of conservation decrease with distance to a local population. The shape of that curve, as discussed above, is likely influenced by many factors (Figure 3.1).

Agricultural landscapes are often complex groupings of production, natural, and semi-natural land cover patches. Certain patch types offer resources that meet life-history requirements of species, for instance, patches of prairie offer nesting resources for many grassland-associated birds, including Northern Bobwhite (*Colinus virginianus*, hereafter bobwhite; Washburn et al. 2000), Dickcissels (*Spiza americana*,Gross 1921), and Eastern Meadowlarks (*Sturnella magna*, Roseberry and Klimstra 1970). Often because of differing life history requirements, the functional value of a patch type to two similar species may be entirely different. For example, neither Dickcissels or Eastern Meadowlarks typically nest in row crop agriculture, yet Eastern Meadowlarks forage on waste grains in the non-breeding season (Bent, 1965), while Dickcissels migrate south. In addition to species-specific relationships to patch type, the arrangement of patches may influence

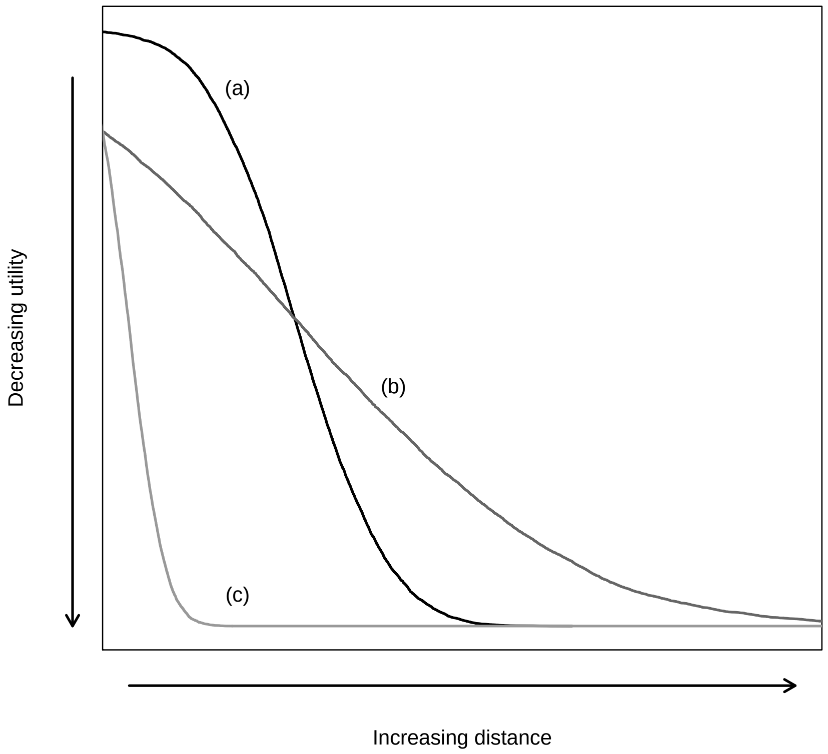

Figure 3.1: An example of how species traits may influence the relationship between increasing distance and the utility of conservation fields to a local population (scale of effect). Species **a** and **b** are resident species, but species **a** has a smaller scale of effect because it has lesser dispersal capabilities than species **b**. Species **c** has a very small scale of effect because it is a migratory species whose activity within the study landscape is restricted to its breeding territory.

two species differently. Grasshopper Sparrows (GRSP, *Ammodramus savannarum*) generally avoid nesting near wooded edges (Johnson and Temple, 1990), yet wooded edges provide thermal and escape cover for bobwhite (Roseberry and Klimstra, 1984). Understanding how the composition and configuration of land cover types translate to the functional value of landscapes for different species may elucidate the mechanisms behind biodiversity responses to agroecosystem conservation (sensu Fahrig et al., 2011b). Specifically for programs like CRP and AES, information on the functional value of landscapes to different species would help practitioners avoid implementing spatially and temporally concurrent practices that have antagonistic effects.

The implementation of broad-scale agroecosystem conservation is shaped by landowner values. For farmland conservation, particularly voluntary incentive-based programs, the relevance of ecologically sound criteria used to select umbrella species may be eclipsed by public support for the management or conservation of a single species. Flagship species, unlike umbrella or focal species, are not bound by ecological criteria (Caro and O'Doherty, 1999), which means that management for a flagship species may not always benefit other similar species of conservation concern (Carlisle et al., 2018). However, the flagship approach to private land conservation is common in the U.S. (e.g., greater sage-grouse *Centrocercus urophansianus*, Carlisle et al. 2018). For grassland restoration on private lands, conservation organizations aiming to benefit populations of gamebirds such as the National Bobwhite Conservation Initiative (NBCI) drive regional- and national-scale conservation planning (Morgan et al. 2016; e.g., CP33 – Habitat Buffers for Upland Birds). Bobwhite can be considered both flagships and umbrellas for grassland conservation in the eastern U.S. because it is presumed that other grassland-associated species benefit from landscape management for bobwhite.

Given the species-specific nature of landscapes, the potential for antagonistic effects of different practices within the same conservation program, and the need for a landscape-scale approach to farmland conservation, our objective was to evaluate the flagship approach for conserving grassland bird populations in agroecosystems. First, we determined landscape-scale effects of land features on population growth of a flagship species (bobwhite) and other grassland-associated bird species of conservation concern (Dickcissel, DICK; Eastern Kingbird, *Tyrannus tyrannus*, EAKI; Eastern Meadowlark, EAME; Field Sparrow; FISP, and Grasshopper Sparrow, GRSP; hereafter background species), while estimating species-specific landscape scales. Second, we investigated how prevalent conservation practices contributed to population growth for each species. We then used a novel decision support tool to quantify the opportunity cost of managing landscapes for one species.

We had three general predictions about how each species would respond to land features at landsape scales: (i) populations would respond to the functional composition of landscapes, (ii) the functional configuration of landscapes, or (iii) general landscape complexity metrics. We used existing literature or expert opinion to determine how each land cover type contributed to four general life-history requirements for each species: (i) breeding cover, (ii) forage (iii) brood-rearing cover, and (iv) escape cover (Table 3.1). If a species was a year-round resident, we also considered potential contributions of each land cover type to (i) winter forage and (ii) thermal cover, if applicable. Similarly, we predicted how edges between relevant land cover types would either enhance or diminish the contribution of a land cover to a species' life history requirements (Table 3.1).

In our study region Dickcissels, Eastern Kingbirds, and Grasshopper Sparrows are migratory and Eastern Meadowlarks, Field Sparrows, and bobwhite are residents. Migratory species may have relatively small scale of effects (i.e., equal to or less than the sampling area) because their activity is restricted to establishing and maintaining breeding territories (migratory status hypothesis). Conversely, migratory species may be selecting breeding habitat based on the suitability of landscapes to harbor nesting resources and mates. This selection process would operate at scales larger than that of breeding territories, and thus we would expect scale of effect to be relatively large. Resident species must search for resources beyond breeding season territories or home ranges to meet all life history requirements, so we would expect their scale of effects to be relatively large. Alternatively, scale of effect may be influenced by natal dispersal capabilities (dispersal capabilities hypothesis), in which case we would expect scale of effect to reflect 4–9 times the me-

Table 3.1: Predicted relationships between each grassland-associated bird species and land cover types mapped in south-central Kentucky. "+" indicates a positive relationship, "-" indicates a negative relationship, zeroes indicate a neutral relationship, "nl" represent non-linear relationships, and vertical lines represent competing predictions. Adjacency measures are the total distance of two adjacent land cover types. FOR = forest, FPH = fescue pasture or hayfield, GRA = grassland cover, WAT = open water, RC = row crop, DEV = developed, MPAg = mean patch area of grassland cover, G-F = grassland adjacent to forest, RC-G = row crop adjacent to grassland, F-FPH = forest adjacent to fescue pasture or hayfield, F-RC = forest adjacent to row crop, MPAa = mean patch area of all land cover types, ShDI = Shannon's diversity index of land cover types

Species	%FOR	%FPH	%GRA	%WAT	%RC	%DEV	MPAg	G-F	RC-G	F-FPH	F-RC	MPAa	ShDI
Dickcissel[a]	−	−	+	−	−	−	+|0	−	0	0	0	0	nl$^{+,-}$
Eastern Kingbird[b]	−	0	+	−	0	−	0	+	0	+	+	−	+
Eastern Meadowlark[c]	−	0	+	−	+|0	−	+	−	+	0	0	0	nl$^{+,-}$
Field Sparrow[d]	−	−	+	−	+|0	−	0	+	+	0	+	−	+
Grasshopper Sparrow[e]	−	−	+	−	−	−	+	−	0	0	0	0	nl$^{+,-}$
Northern Bobwhite[f]	−	−	+	−	+|0	−	0	+	+	0	+	−	nl$^{+,-}$

a b c d e f

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[a] Gross 1921; Zimmerman 1984; Herkert 1994; Johnson and Igl 1995; Patterson and Best 1996; Helzer and Jelinski 1999; Hughes et al. 1999; Winter et al. 2000; Temple 2002

[b] Davis 1941; Hespenheide 1971; Johnston 1971; Murphy 1983, 1987; Rosa and Murphy 1994; Best et al. 1997; Klute et al. 1997; Murphy et al. 1997; Murphy 2001; Puckett et al. 2009

[c] Roseberry and Klimstra 1970; Bent 1965; Herkert 1994; Patten et al. 2006; Riffell et al. 2008

[d] Verna R. Johnston 1947; Allaire and Fisher 1975; Best 1977, 1978; Pearson 1991; Herkert 1994; Beck and Watts 1997

[e] Johnston and Odum 1956; Wiens 1969, 1973; Kaspari and O'Leary 1988; Johnson and Temple 1990; **?**; Vickery et al. 1994

[f] Stoddard 1931; Klimstra and Roseberry 1975; Roseberry and Klimstra 1984; Barnes et al. 1995; Taylor et al. 1999; Washburn et al. 2000; McCoy et al. 2001; Staller et al. 2005; Lusk et al. 2006

Table 3.2: Hypotheses and predictions for how species traits will influence scale of effect of the Conservation Reserve Enhancement Program on grassland birds. We have two competing predictions for the Migratory Status Hypothesis: **A** that migratory species movements are contained to breeding territories, and thus scale of effect is relatively small (i.e., smaller than the sampling area) and **B** migratory species are choosing breeding sites at larger scales upon arrival and thus their scale of effect is relatively large. Predictions for each species under the Dispersal Capabilities Hypothesis were calculated according to Jackson and Fahrig 2012 and informed by the citations listed.

	Migratory Status Hypothesis		Dispersal Capabilities Hypothesis
Species	Prediction A	Prediction B	Prediction
Dickcissel*[a]	Small	Large	0.09–0.5 km
Eastern Kingbird*[b]	Small	Large	0.6–1.0 km
Eastern Meadowlark[c]	Large	Large	1.5–2.5 km
Field Sparrow	Large	Large	-
Grasshopper Sparrow*[d]	Small	Large	0.04–0.5 km
Northern Bobwhite[e]	Large	Large	3.0-6.75 km

a b c d e

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[a] Berkeley et al. 2007; Wells et al. 2008; Small et al. 2012a
[b] Murphy 1996
[c] Kershner et al. 2004; Wells et al. 2008
[d] Gordon 2000; Hovick et al. 2011; Small et al. 2015
[e] Fies et al. 2002; Townsend et al. 2003; Liberati 2013

dian dispersal distance or 0.3–0.5 times the maximum dispersal distance of a species (Jackson and Fahrig 2012; Table 3.2).

Although the above hypotheses may elucidate some mechanisms behind potential differences in response of similar species to a farmland conservation program, they are not exhaustive (Miguet et al., 2016), and not necessarily mutually exclusive. To understand the potential tradeoffs of using a flagship approach, the opportunity costs need to be quantified, and ideally they should be predictable. In this context, for any background species, the opportunity cost equates to the difference in population density between the flagship approach and a species-specific approach to landscape management. We hypothesized that for any one background species, the difference in density under our competing landscape management scenarios would be proportional to (i) the difference in how the two species respond to functional composition of landscapes, (ii) the differences in how the two species respond to functional configuration of landscapes, or (iii) differences in scale of effect.

3.3 Material and methods

We estimated land cover composition using 400 trees in a random forest classifier in Google Earth Engine (Appendix A.2). We used Landsat-8 and Landsat-5 TM images for classification. We searched for images over the time period of our study (2010–2015) and separated images into 3 general categories: winter (Nov. 15–Mar. 1), early-mid summer (May 1–July 31), and late summer (Aug. 15–Sept. 31). For each time period, we calculated Enhanced Vegetation Index (EVI), New Burn Ratio 1 (NBR1), New Burn Ratio 2 (NBR2) and the standard deviation of each metric using a 3x3 roving window (i.e., texture). We then calculated the difference among time periods (early-mid summer $-$ winter; early-mid summer $-$ late summer) for each metric. In total, there were 30 bands used in the classifier. Our land cover classes of interest were: Forest, Fescue Pasture/Hayfield, Grassland, Open Water, Row Crop, and Developed. Training areas for the classifier were informed by DigitalGlobe, SPOT-6, SPOT-7, and NAIP imagery from 2010–2015. We assessed accuracy of the final classified image by selecting 611 random points and using high resolution imagery (see above) and Google Earth to determine reference classes. We stratified point selection according to prevalance of land cover type estimated from an early version of a classified map and set a minimum of 50 points per class. Validation points consisted of 42.4% Forest, 23.6% Fescue Pasture/Hayfield, 6.2% Grassland, 9.5% Open Water, 13.6% Row Crop, and 4.7% Developed. Class-level accuracy was 89.0% for Forest, 77.2% for Fescue Pasture/Hayfield, 69.2% for Grassland, 92.0% for Open Water, 88.6% for Row Crop, and 69.8% for Urban, with an overall classified map accuracy was 75.3%.

We calculated landscape metrics using user-defined functions (Table 3.1, Appendix A.3). We aggregated input rasters to match sampling areas for each species, resulting in different values for each species because of how we censured distance-sampling observations (Buckland, 2001). Multicollinearity was assessed for each metric for each species. When covariates were highly correlated ($r > 0.7$), we removed appropriate parameters in a way that maximized information gained through the analysis. For example, if Forest and Grassland were highly correlated for Dickcissels, and every other species' model included Grassland but not Forest, then we removed Forest. Parameters were also removed if initial modeling efforts demonstrated that they were not estimable.

We used an open-population distance sampling framework to model data (Royle et al. 2004; Sollmann et al. 2015). Our model had three main components: (i) a model for initial abundance, (ii) a model for abundance in years $t = 2...T$, and (iii) a model for detection conditional on abundance. Let $\mathbf{x}$ denote the coordinates of a site, or a pixel containing a site within the descretized version of our study area (i.e., a raster), and j denote species. In order to account for potential skew in our count data, we estimated a species-specific zero-inflation parameter, ψ_j, which we modeled as a random process drawn from a Unif$(0, 1)$. We modeled whether each site was "suitable" as a Bernoulli trial: $S(\mathbf{x}_{i,j}) \sim$ Bern(ψ_j). We modeled initial abundance as random negative binomial outcome

$\mathrm{N}(\mathbf{x}_{i,1,j}) \sim \mathrm{NegBin}(\exp(\beta_0(\mathbf{x}_{i,j}))S(\mathbf{x}_{i,j}), r)$. We modeled N in subsequent years as a random Poisson outcome, where the expected abundance $\lambda(\mathbf{x}_{i,t,j})$ was a result of a population growth that varied with site-level N in the previous year and smoothed landscape-scale covariates V:

$$\begin{aligned}\log(\lambda(\mathbf{x}_{i,t,j})) = N(\mathbf{x}_{i,t-1,j})\exp(\theta_{0,j} + \theta_{1,j}N(\mathbf{x}_{i,t-1,j}) + \theta_{2,j}s(\mathrm{V}_1(\mathbf{x}_i), \sigma_j)...\\ +\theta_{n,j}s(\mathrm{V}_n(\mathbf{x}_i), \sigma_j))\end{aligned} \tag{3.1}$$

or if N in the previous year was zero, a colonization rate $C(\mathbf{x}_{i,t,j})$ that varied with the distance-weighted sum of the previous year's N at sites within landscapes surrounding the focal site:

$$\log(\lambda(\mathbf{x}_{i,t,j})) = \exp(\iota_{0,j} + \iota_{1,j}s(N(\mathbf{x}_{j...J,t-1,j}), \sigma_j)) \tag{3.2}$$

$$N(\mathbf{x}_{i,t-1,j}) \sim \mathrm{Pois}(\lambda(\mathbf{x}_{i,t,j})S(\mathbf{x}_{i,j}) \tag{3.3}$$

We assumed that immigration could also happen when $N > 0$ and was encompassed within λ. We estimated species-specific landscape scales using a Gaussian smoother embedded in the linear model (Chandler and Hepinstall-Cymerman, 2016). We aggregated covariate rasters to pixel sizes approximately equal to the sampling unit associated with each species and provided them as data. The model then smoothes these input rasters to produce distance-weighted values, e.g., $s(\mathrm{V}_1(\mathbf{x}_i))$. The species-specific shapes of the Gaussian smoother, σ_j, is estimated.

Counts of unmarked animals at one site over time often have intermittent zeroes, for example $y = \{1, 0, 0, 1, 0, 1\}$. In open-population distance sampling models these zeroes would be identified as false negatives, even if it is biologically plausible for sites to exhibit dynamic occupancy over time. Our model specification allows us to estimate the rate at which sites are colonized after local extinctions. For each year in our model for each species, we used a half-normal key function to estimate the probability of detecting a singing individual in each species-specific distance band, and observations were modeled using a multinomial distribution:

$$
\begin{aligned}
p_{k,t} = \frac{\left(\frac{\sigma_t^2(1-exp(-db[k+1]^2}{(2\sigma_t^2))}\right) - \left(\frac{\sigma_t^2(1-exp(-db[k]^2}{(2\sigma_t^2))}\right) * 2\pi}{pa * pix[k]} \\
pi_{k,t} = p_{k,t} * pix[k] \\
P_t = \sum_{1}^{K} pi_t \\
y(\mathbf{x}_{i,t}) \sim \text{Binomial}(P_t, N(\mathbf{x}_{i,t})) \\
ydet(\mathbf{x}_{i,k,t}) \sim \text{Mulitnomial}(pi_{1\ldots K,t}, y(\mathbf{x}_{i,t}))
\end{aligned}
\tag{3.4}
$$

where σ is the scaling parameter adjusting the shape of the detection curve, db is the radius of each distance band, pi is the detection probability for each distance band, P is the overall detection probability in the sampling point, pa is the total area of the sampling point, and pix is the proportion of the sampling point encompassed by each distance band.

We prioritized land management for each species using a novel decision support tool. We discretized the landscape into pixels equal to the mean farm size in Kentucky (approximately 69 ha), resulting in 23,400 management blocks. For each management block, we simulated converting all Fescue Pasture/Hayfield to Grassland land cover. We used mean parameter estimates from our model to predict birds/ha throughout the landscape surrounding the management block after land conversion, and compared this density to predictions made before simulating land conversion. When considering each management block for each species, we incorporated landscapes sufficiently large to encompass distance-weighted effects of surrounding land features. The final product of the decision support tool was a raster prioritizing land management for each species across our study area, represented in potential birds/ha added for each of the 23,400 management blocks.

We simulated a private land initiative similar to Conservation Practice 29 (see Chapter 1 for description) to quantify the opportunity costs of landscape management for each species. The simulated initiative had three conditions: the only "approved practice" was converting Fescue Hay/Pasture to Grassland land cover, all Fescue Pasture/Hay areas were eligible, and 10,000 ha were available to be enrolled. For each species, we targeted the 10,000 ha using the outcome of the decision support tool, where cell values were used as the only ranking criteria. We did not consider cells that had values outside of the 95% CI to lessen the influence of outliers on opportunity costs. To determine the opportunity costs of managing landscapes for bobwhite, we converted the Fescue Pasture/Hayfield pixels in targeted areas to Grassland pixels ("managed for bobwhite scenario"). We used mean parameter estimates to predict the number of birds/ha added across our study area for each species under the managed for bobwhite scenario. We repeated this process for each background species in addition to running the analysis with a random 10,000 ha chosen. We calculated opportunity costs as the percent change in total densities between competing management scenarios.

3.4 Results

Dickcissel and Eastern Meadowlark populations declined while bobwhite and Field Sparrow populations increased from 2010–2016 (Table 3.3, Figure 3.2). Most sites were occupied by each species (DICK: 0.91, 0.73–1.0 95% BCI; EAME: 0.96, 0.91–1.0 95% BCI; FISP: 0.97, 0.92–1.0 95% BCI; NOBO: 0.91, 0.86–0.97 95% BCI). We could not fit Eastern Kingbird data to a model because of their excessively large scale of effect (see below).

The direction of Dickcissel, Field Sparrow, and bobwhite response to several landscape features was similar (Figure 3.3 and Table 3.4), but density dependence and the magni-

Table 3.3: Trends in observations of each species from 2010 to 2015. Estimates of detection for EAKI and GRSP are from most recent versions of their respective models. However, EAKI estimates are not included further because of their excessive scale of effect, and GRSP estimates are not included further because of problems with estimating scale of effect (i.e., excessive computational effort).

Species	Year	Counts	Detection (95% BCI)	Species	Year	Counts	Detection (95% BCI)
DICK	2010	43	0.10 (0.07–0.13)	EAME	2010	249	0.18 (0.16–0.21)
	2011	93	0.20 (0.16–0.25)		2011	306	0.19 (0.17–0.21)
	2012	67	0.17 (0.14–0.21)		2012	292	0.20 (0.18–0.22)
	2013	69	0.16 (0.13–0.20)		2013	308	0.20 (0.18–0.22)
	2014	67	0.18 (0.14–0.23)		2014	251	0.19 (0.17–0.21)
	2015	62	0.15 (0.11–0.19)		2015	256	0.19 (0.17–0.22)
FISP	2010	136	0.22 (0.18–0.27)	NOBO	2010	153	0.36 (0.29–0.45)
	2011	143	0.23 (0.20–0.27)		2011	172	0.34 (0.29–0.39)
	2012	177	0.26 (0.23–0.30)		2012	178	0.34 (0.29–0.38)
	2013	174	0.23 (0.20–0.26)		2013	189	0.31 (0.27–0.36)
	2014	197	0.25 (0.22–0.29)		2014	221	0.34 (0.29–0.39)
	2015	180	0.24 (0.21–0.28)		2015	174	0.30 (0.26–0.35)
EAKI*	2010	38	0.10 (0.07–0.14)	GRSP*	2010	27	0.10 (0.07–0.15)
	2011	41	0.08 (0.06–0.10)		2011	54	0.23 (0.17–0.30)
	2012	44	0.07 (0.05–0.09)		2012	32	0.17 (0.12–0.22)
	2013	51	0.08 (0.06–0.10)		2013	36	0.17 (0.12–0.23)
	2014	57	0.11 (0.08–0.14)		2014	35	0.21 (0.16–0.29)
	2015	69	0.11 (0.09–0.14)		2015	20	0.10 (0.07–0.15)

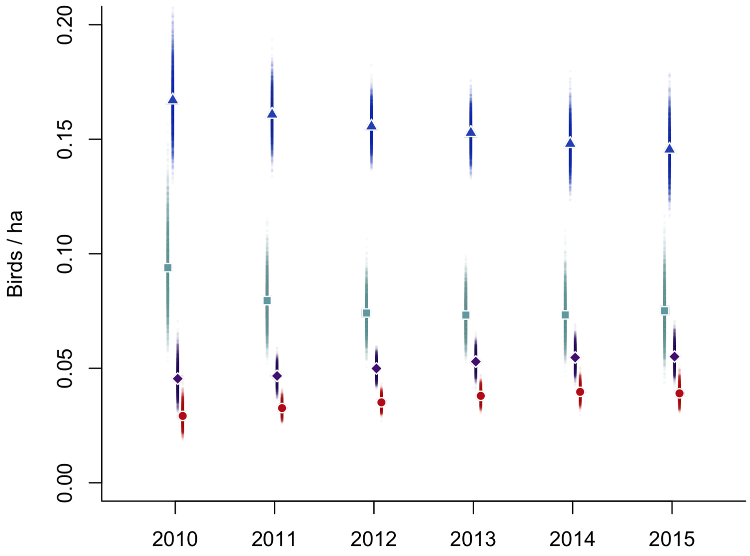


Figure 3.2: Realized densities of Eastern Meadowlarks (blue, triangle), Dickcissels (cyan, square), Field Sparrows (purple, diamond), and bobwhite (red, circle) across our sampling points from 2010–2015. Error bars consist of estimates from 5000 randomly chosen model iterations.

tude of parameter estimates moderated how population growth varied along covariate gradients (Figure 3.4). For example, Dickcissel displayed thresholds in distance-weighted Forest-Row Crop adjacency ($<$100 m), Grassland-Forest adjacency ($>$300 m), and % Grassland ($<$10%) after which population growth was negative, regardless of density-dependent processes. We did not find any similar thresholds for Field Sparrow, and only one similar threshold for bobwhite (approx. $<$5% distance-weighted Grassland) (Figure 3.4). Only one landscape feature (distance-weighted Grassland-Forest adjacency) had a greater than 90% probability of influencing Eastern Meadowlark population growth.

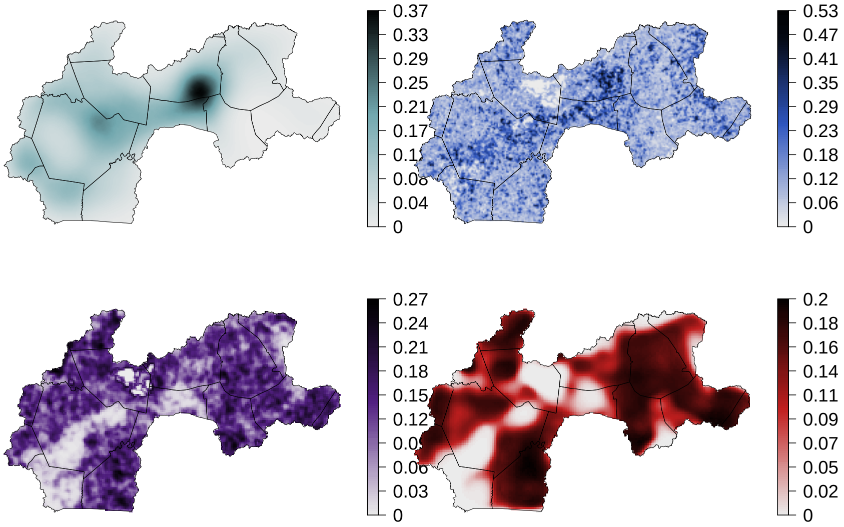
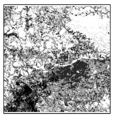
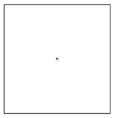
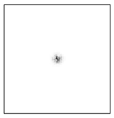
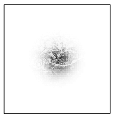
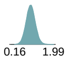
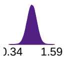
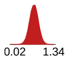
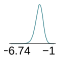
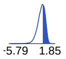
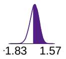
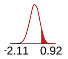
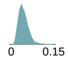
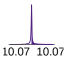
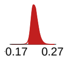
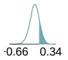
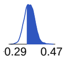
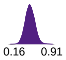
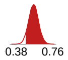
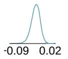
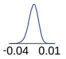
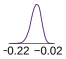
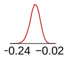
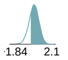
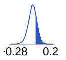
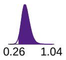
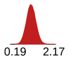
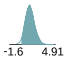
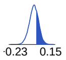
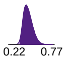
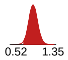
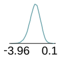
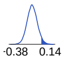
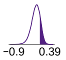
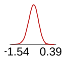
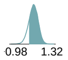
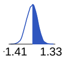
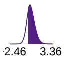
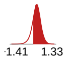
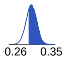
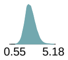
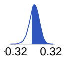
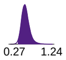
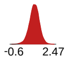
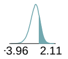
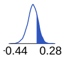
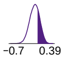
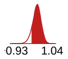
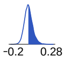
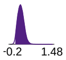
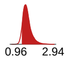
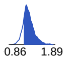
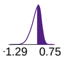
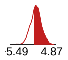
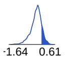
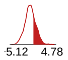


Figure 3.3: Expected density surfaces for each species (birds/ha) in year 2015. Cyan = Dickcissels, Blue = Eastern Meadowlarks, Purple = Field Sparrows, Red = bobwhite.

The area of surrounding landscape that mattered to each species varied substantially (Table 3.4, row 1). Dickcissel landscape boundaries (i.e., radii) were approximately 20 km ($\sigma_{\text{DICK}} = 8.68$ km, 4.92–16.53 km, 95% BCI), Eastern Meadowlark landscape boundaries were approximately 1 km ($\sigma_{\text{EAME}} = 0.31$ km, 0.17–0.48 km 95% BCI), Field Sparrow landscape boundaries were approximately 3 km ($\sigma_{\text{FISP}} = 0.97$ km, 0.41–1.91 km 95% BCI), bobwhite landscape boundaries were approximately 12 km ($\sigma_{\text{NOBO}} = 3.60$ km, 2.33–6.87 km 95% BCI), and Eastern Kingbird boundaries were greater than 40 km ($\sigma_{\text{EAKI}} = 30.21$ km (17.82–39.48 km, 95% BCI). A substantial amount of posterior mass of the σ estimate for Eastern Kingbird was at the boundary of the 40 km search window we used for their model, so the actual landscape boundary for Eastern Kingbird's is likely to be much larger than 40 km. Essentially, one Eastern Kingbird landscape was likely to encompass the majority of our study area and thus further model results for Eastern Kingbird are ommitted. Alternatively, the flat shape of the kernel may indicate that there were no covariate effects on

Table 3.4: Row 1: Visual representations of landscape scales for each species. The far left landscape is 1587 km^2 area with differing land covers indicated by grayscale. Subsequent images represent the boundaries (circles) of landscapes for each species and the degree to which utility of land featrues decrease with distance (transparancy). Rows 2–16: Posterior density of model estimates for each species (see text and Table 3.1 for meaning of Greek letters and acronyms)

	DICK	EAME	FISP	NOBO
				
β_0				
κ_0				
κ_1				
θ_0				
θ_1				
F-FPH				
F-RC				
G-F				
MPAa				
%FPH				
%G				
%RC				
RC-G				
SHDI				
SHDI^2				

Eastern Kingbird population growth. The size of species-specific landscapes determined whether colonization parameters were estimable. For example, Eastern Meadowlark landscape boundaries were shorter than the minimum distance between our sampling sites,

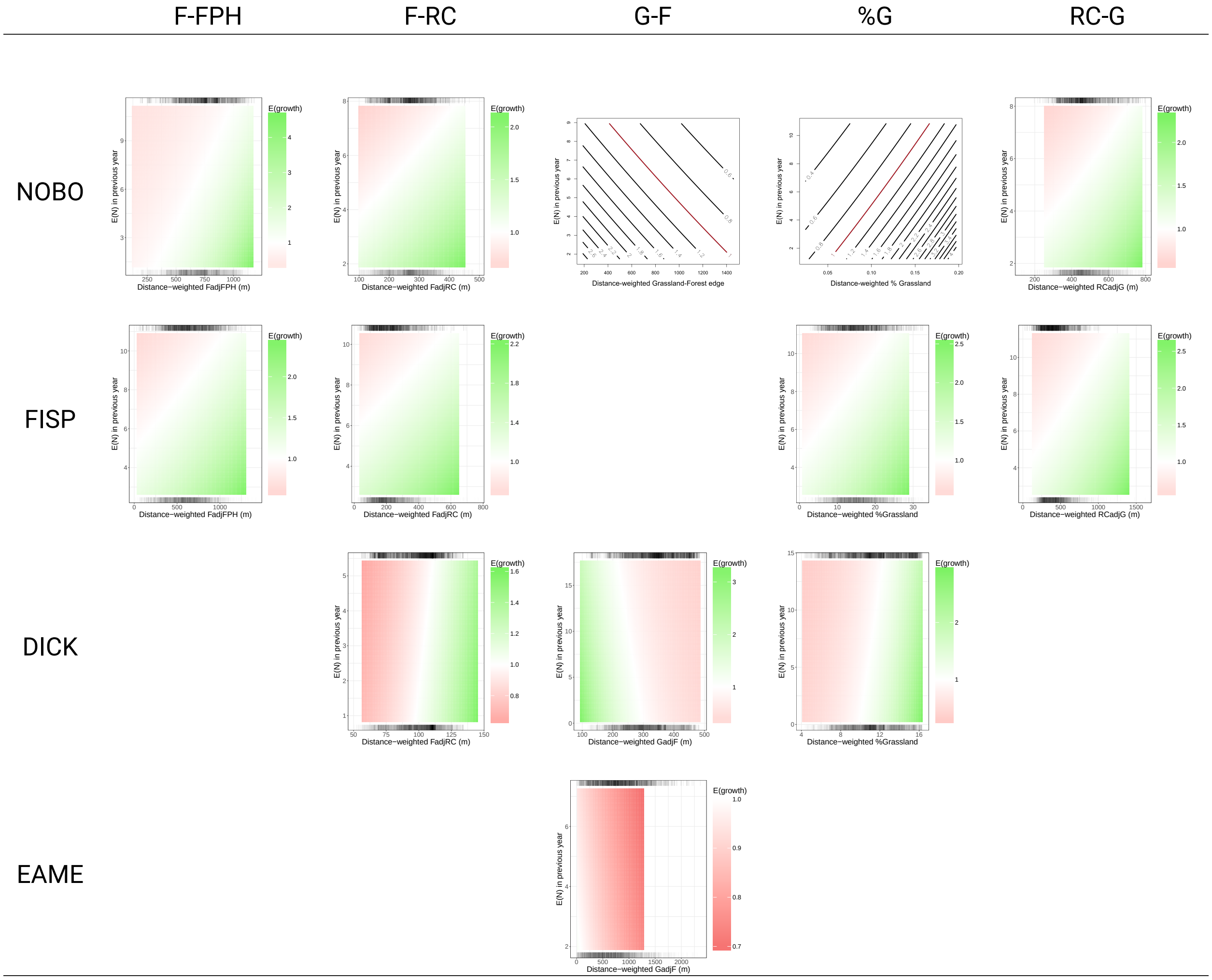


Figure 3.4: Moderation of significant (>90% chance of being non-zero) covariate effects by density-dependence. Thick white stripes within figures can be interpreted as carrying capacties along the covariate gradient. Black bars on top of figures indicate the density of a covariate within landscapes that surround CP22 contracts. Black bars on the bottom of figures indicate the density of a covariate within landscapes that surround CP29 contracts.

so no information was available on how density in the surrounding landscape influenced colonization rate. For Dickcissel and bobwhite populations, landscapes were large enough to estimate that increased density in surrounding landscapes has a positive influence on colonization rate after local sites go extinct (Table 3.4, row 4).

Landscapes that encompassed CP29 and CP22 contracts often had similar features (Table 3.4). CP29 and CP22 landscapes provided structure that may have had conflicting effects on bobwhite populations. Grassland-Forest adjacency was relatively high in CP29 and CP22 landscapes, which had a negative affect on population growth; however, %Grassland was relatively high in these landscapes, which had a positive affect on population growth (Table 3.4, row 1). For Field Sparrows, CP29 and CP22 landscapes provided relatively high %Grassland, which had a positive affect on population growth, but they provided Forest-Row Crop and Row Crop-Grassland adjacencies associated with relatively lower rates of population growth (Table 3.4, row 2). For Dickcissels, CP22 landscapes had slightly higher concentrations of Grassland-Forest adjancies than CP29 landscapes, which had a negative affect on population growth. CP29 and CP22 landscapes often did not harbour enough %Grassland to ensure population growth. We estimated that mean population growth was negative below approximately 10-12% distance-weighted (i.e., landscape scale) Grassland land cover in Dickcissel landscapes. For Eastern Meadowlarks, CP29 and CP22 landscapes did not harbour increasing populations.

Landscape management for the flagship species, bobwhite, would incur mean opportunity costs of -76.4% for Dickcissels, 0.5% for Eastern Meadowlarks, and -5.7% for Field Sparrows (Figure 3.5). Landscape management for Dickcissels would incur mean opportunity costs of -0.2% for Eastern Meadowlarks, -30.8% for Field Sparrows, and -23.4% for bobwhites. Landscape management for Eastern Meadowlarks would incur mean opportunity costs of -69.1% for Dickcissels, -27.0% for Field Sparrows, and -22.3% for bobwhites. Landscape management for Field Sparrows would incur mean opportunity costs of -84.8% for Dickcissels, 0.3% for Eastern Meadowlarks, and -6.9% for bobwhites. The random management scenario caused mean opportunity costs of -89.7% for Dickcissels, -6.2% for Eastern Meadowlarks, -60.2% for Field Sparrows, and -72.7% for bobwhites.

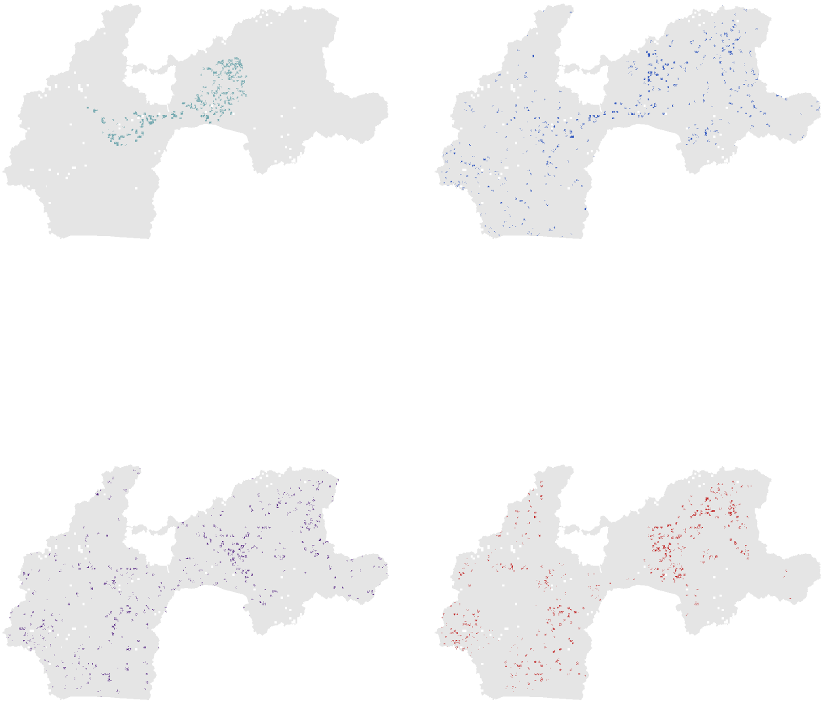


Figure 3.5: 10,000 targeted management ha for each species based on a decision support tool that incorporates model estimates to predict mean increases in population density if Fescue Pasture/Hay was converted to Grassland land cover. Land conversions were simulated in 23,400 management blocks that were approximately 69 ha each. Cyan = Dickcissels, Blue = Eastern Meadowlarks, Purple = Field Sparrows, Red = bobwhite.

3.5 Discussion

It is difficult to predict how managing a landscape for one species will influence the dynamics of other species with similar taxonomy, biology, or geographic distribution (Roberge and Angelstam, 2004; Franco et al.; Wesner and Belk, 2012; Minin et al., 2013; Banks et al., 2014). In order to have realistic expectations of how a surrogate approach will affect a suite of background species, we need to be able to quantify the ramifications of alternative management scenarios. We used an open-population distance sampling framework and a novel decision support tool to predict the opportunity costs of the flagship approach in agroecosysems. Our results indicate that even when there are similarities in how land features influence species, there are opportunity costs associated with single-species management. These opportunity costs likely are driven by the availability of landscapes that can harbour growing populations of both background species and the surrogate species.

We did not find support for dispersal capabilities predicting scale of effect. The central tendency of natal dispersal of Dickcissels is restricted to less than 1 km (Berkeley et al., 2007; Wells et al., 2008; Small et al., 2012b), yet we estimated their landscape boundaries near 20 km. We found similar mismatches between natal dispersal and landscape boundaries for Eastern Kingbird, Eastern Meadowlark, Field Sparrows, and bobwhites. We found some support for migratory status predicting scale of effect, as both Dickcissel and Eastern Kingbird displayed relatively larger scale of effect than resident species. This suggests that migratory birds select resources based on their availability at scales that far exceed territory size. Even within our small sample of species, however, scales of effect among resident or migratory species varied substantially, so migratory status alone is not sufficient to predict scale of effect with a high degree of certainty. A multi-region assessment of a large suite of species with varying life-history requirements, migratory behavior, and dispersal capabilities is needed to improve our understanding of the mechansisms of scale of effect in grassland birds.

The relationships we observed between landscape structure and population growth of Dickcissels, Field Sparrows, and bobwhites are best understood from a functional landscape perspective. The composition and configuration of resources– depending on the seasonality of their use– influenced population growth. Increasing amounts of land cover that provided nesting resources (i.e., % grassland; Gross 1921; Klimstra and Roseberry

1975; Best 1978) was generally beneficial to population growth. Increasing amounts of land cover that provided forage during the non-breeding season (i.e., % row crop; Allaire and Fisher 1975; Roseberry and Klimstra 1984) did less to limit population growth. Forest edges, which we assume provided either escape or thermal cover (hereafter, woody cover) in the absence of true scrub/shrub vegetation, varied in their effect depending on the composition of adjacent land. We observed negative trends in the response of population growth to grassland-forest edge. This suggests that recruitment is lower near wooded edges or that birds avoided nesting near wooded edges (Hughes et al., 1999; Winter et al., 2000; Patten et al., 2006). Woody cover adjacent to winter forage (forest-row crop edge) and marginal nesting cover (forest-fescue pasture/hayfield edge) benefited Dickcissel, Field Sparrow, and bobwhite population growth. We suspect that the positive effect of forest-fescue pasture/hayfield edge is reflective of these areas providing thermal or escape cover during non-breeding season, although Dickcissels rarely overwinter in breeding grounds (Root, 1988). Positive effects of edges between woody cover and winter forage indicate that individuals benefit from nearby escape cover when foraging in open areas.

When acreage available for a private land initiative is limited, as it is for programs like CRP and was for our simulation study, there is a trade-off between the spatial aggregation and extent of land management. For ubiquitous species, spatial targeting is not important, as any arrangement of the alotted acreage will have similar effects. For species restricted by specific landscape requirements, benefits of the program will depend almost entirely on the spatial arrangement of conservation action.

Eastern Meadowlarks were influenced strongly by only one of the ten landscape structure parameters considered, had relatively small scale of effect, and were generally ubiquitous across our study area. Consequently, the spatial arrangement of grassland conservation in our simulated private land initiative did not influence their predicted population response, as any management scenario caused similar opportunity costs for Eastern

Meadowlarks. Even the completely non-targeted management scenario caused relatively minor opportunity costs for Eastern Meadowlarks. Species like this, whose population dynamics were largely independent of conservation action, are not likely to be negatively influenced by programs like the CRP and should not be considered a species with which to guide management planning.

Growing Dickcissel populations were restricted to landscapes with greater than 10% Grassland, greater than 100 m of Forest-Row Crop adjacency, and less than 300 m of Forest-Grassland adjacency. Also, Dickcissels had a relatively large scale of effect. A consequence of the large scale of effect was that there were relatively few landscapes, and thus few areas where landscape-scale resource requirements of Dickcissels could be fulfilled. As a result, both Dickcissel density and targeted management areas were highly aggregated and any land management not targeting Dickcissels caused high opportunity costs. Additionally, land management targeted for Dickcissels caused substantial opportunity costs for both Field Sparrows and bobwhite. This result is inconsistent with one proposed requirement of umbrella species: large area requirements (Noss et al., 1996). Scale of effect is an analogue to species area requirements because it describes both the boundary of area that matters to local populations and the degree to which the importance of land features to local populations declines with distance. Dickcissels also have specialized resource needs (i.e., they are an obligate grassland species in their breeding range, Gross 1921), which is another proposed requirement of umbrella species (e.g., Suter et al., 2002; Franco et al.). However, although bobwhites and Field Sparrows also utilize grasslands (Best 1978; Klimstra and Roseberry 1975, Table 3.4), they did not respond positively to Dickcissel landscape management. Traditional criteria for choosing surrogate species may not transfer to agroecosystem conservation effectively.

The opportunity costs of managing landscapes for bobwhite on Field Sparrows and vice versa were relatively small. We cannot attribute this to similarity of scale of effect, as the magnitude of difference between bobwhites and Field Sparrows was larger than that of bobwhites and Dickcissels. The way landscape structure interacted with density dependence to produce increasing populations, however, were notably similar (Table 3.4). There were few situations where landscapes harbouring growing bobwhite populations would not also harbour growing Field Sparrow populations. This is consistent with traditional criteria for good surrogate species: that the surrogate and background species should share resource requirements. An additional implication is that the landscape-scale perspective is necessary to understand whether management for a surrogate species will benefit a background species.

Overall, less than half of our predictions were supported by estimates (16/33) and only one third (11/33) were strongly supported (e.g., a predicted positive response had a >90% estimated probability of positive effect). This underscores the uncertainties and complexities of managing wildlife with private land initiatives that use multiple practices, such as the CREP. Ideally, future research would harness data from marked individuals to understand the selection of resources within different conservation practices, consider multiple similar species, and cover a large geographic area for an extended period of time. However, the logistical challenges of such a study are likely insurmountable, especially in agroecosystems where land ownership, and thus landowner willingness to allow access, varies. An integrated study design with spatially and temporally restricted data collection on marked individuals paired with spatially and temporally broad sampling of unmarked individuals would reduce uncertainty around the relationship between landscape structure and population dynamics of grassland birds in agroecosystems.

We provided evidence that a surrogate species chosen because of its large area requirements or specialized resource needs is not necessarily gonig to be effective at promoting density of like species in agricultural landscapes. Landscape management for bobwhites, often used as flagship species for grassland conservation in the eastern U.S., can be expected to benefit some species but cost other species. Opportunity costs will correlate to the availability of landscapes that harbour growing populations of both bobwhite and the background species of interest. We provided an analytical framework, including a spatially explicit decision support tool, that could help practitioners predict how managing for a surrogate species will influence a suite of background species. Quantifying the availability of these landscapes a priori will require reduction in uncertainty surrounding our knowledge of (i) the mechanisms of species-specific scale of effect and (ii) the functional role of landscape structure.

CHAPTER 4

SPATIAL VARIABILITY IN MANAGEMENT OF FIELDS ENROLLED IN THE CONSERVATION RESERVE ENHANCEMENT PROGRAM[3]

> *The mower's work too is beautiful,*
> *granting rest and health to his mind.*
>
> Wendell Berry
> *Leavings: Poems*

> *Books or no books, it is a fact, patent both to my dog and myself, that at daybreak I am the sole owner of all the acres I can walk over.*
>
> Aldo Leopold, *A Sand Couny Almanac: And Sketches Here and There*

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[3] Yeiser, J.M., J.J. Morgan, D.L. Baxley, and J.A. Martin. To be submitted to *The Journal of Wildlife Management*

4.1 Abstract

Private land initiatives such as the Conservation Reserve Program (CRP) are primary channels for wildlife conservation in agricultural ecosystems. In the United States, billions of dollars are budgeted to the CRP annually, so ensuring cost-effeciency is a high priority. The way landowners manage land enrolled in CRP can moderate how effective the program is at meeting goals, especially wildife population goals; therefore, it is important to accurately monitor and predict landowner compliance to contract specifications. We investigated landowner compliance to wildlife-friendly recommendations in the Kentucky Conservation Reserve Enhancement Program. Specifically, we estimated whether greater than 50% of any given field had been mowed in 2016. We used two methods to estimate conformance to wildlife-friendly mowing recommendations and woody encroachment: helicopter sampling and remote sensing. We used a double observer binomial model to estimate impacts of landscape features (i.e., distance to road) on the percentage of fields mowed and the amount of woody cover. We used unsupervised classification on SPOT-6 and SPOT-7 images to classify mowed, unmowed, and woody vegetation. We surveyed 318 fields in February 2016 via helicopter and classified images from November 2015. Spatially explicit agreement between remote sensing and helicopter flights was low at fine scales, however, overall estimates were consistant between methods. Approximately 70% of contracts were non-conformant to wildlife-friendly recommendations. Most variation in the percent mowed and percent woody cover among fields was random, thus landscape features alone are not likely to be sufficient predictors of landowner behavior. We found that if the goal is to understand coarse rates of conformance to a set of criteria, statistical modeling of data collected via helicopter flights or remote sensing paired with estimates of vegetative status as a reference are sufficient. Our study warrants a discussion among resource management agencies to determine if the conformance rates we observed are acceptable, and if not, what changes need to be made to meet conformance goals.

4.2 Introduction

Targeting enrollment to optimize environmental benefits is a staple of private land conservation in the U.S. (Baylis et al., 2008) and is gaining momentum in the E.U. (Merckx et al., 2009). The Conservation Reserve Program, a U.S. Department of Agriculture program administered by the Farm Service Agency (FSA) with support from the Natural Resources Conservation Service (NRCS), optimizes cost-benefits by ranking participants with an Environmental Benefits Index (EBI) (reviewed in Claassen et al., 2008). Using the EBI to guide program participation has improved effectiveness of the CRP in providing outdoor recreation (Feather et al., 1999; Ribaudo et al., 2001). Private land conservation has also benefited wildlife populations directly (e.g., Batáry et al., 2015), although it is not always effective (e.g., Pabian et al., 2013). Targeted enrollment is important, but one factor that can potentially modify cost-effectiveness of private land conservation is the way participants manage land.

The management of conservation land can influence the magnitude of response from wildlife populations (Osborne et al., 2011). Management of grassland conservation initiatives, such as the Kentucky Conservation Reserve Enhancement Program (CREP) (see Chapter 1 for description of the KY CREP), is especially important because of the influence of plant succession on the habitat quality, and thus potential environmental benefits, of fields. In order to benefit targeted wildlife species such as grassland gamebirds and songbirds, fields need to be intermittently disturbed to mimic early successional ecosystems. Prescribed fire is an effective way to suppress succession (e.g., Miller et al., 2017); however, landowners often have a negative perception of prescribed fire (e.g., Harr et al., 2014) or lack the experience or logistical support to conduct prescribed fire. In lieu of fire, many landowners enrolled in the CREP mow their fields annually in an effort to counter succession. However, timing of mowing can influence breeding success of grassland birds (e.g., Perkins et al., 2013) and mowing can accumulate thatch, suppress forb establishment, and contribute to grasslands becoming "rank", or overvegetated and unsuitable for grassland-associated wildlife (McCoy et al., 2001).

Administration of CRP field management occurs at the local level. Contracts are landowner- or parcel-specific and contain specific conservation plans to which landowners are required to adhere. The NRCS is responsible for conducting annual compliance reviews. If landowners are non-compliant, local NRCS officials begin a collaborative process with the landowner to remediate outstanding problems (NRCS Title 440 Part 512.55). The Kentucky Department of Fish and Wildlife Resources (KDFWR) provided the following wildlife-friendly recommendations regarding the mowing of fields to reduce woody succession: (i) do not mow more than 50% of any field in a given year (strip mowing is preferred) (ii) do not mow the same acreage in back to back years, (iii) do not mow between May 15 and August 1, (iv) do not mow at a height of less than 8 in (20 cm), and (v) mowing is used to control woody growth and other undesirable species (mowing for cosmetic purposes is prohibited).

Monitoring the status of individual fields is a logistical challenge. Plot sampling captures fine-scale variability in vegetation structure but is restricted in its sampling extent, and there are well documented issues with scaling up these measurements across heterogeneous space (Wiens, 1989). Conversely, entire landscapes can be assessed using freely available Landsat imagery (e.g., Rao et al., 2007) but this method may not encapsulate variation in wildlife value if land management practices are heterogeneous at fine scales (e.g., strip mowing). Surveying land parcels from helicopters or fixed wing aircraft is an alternate way to sample field status and can easily cover large extents, but aerial surveys can be cost-prohibitive and they produce relatively coarse estimates compared to plot sampling. High resolution images from satellites such as SPOT (*Satellite Pour l'Observation de la Terre*) or WorldView can capture fine-scale heterogeneity in vegetation across entire landscapes, but obtaining adequate spatio-temporal coverage requires substantial financial committment. Regardless of the method used to monitor fields, there will be trade-offs between costs and the spatial, spectral, and temporal resolution of data aquired. Understanding the information gap between extensive sampling (aerial flights) and remote sensing (high resolution satellite images) could inform best practices for monitoring land management patterns over large areas.

Our objective was to estimate mowing and woody encroachment in fields enrolled in the CREP via two methods: sampling field status via helicopter flights and monitoring field status via remote sensing. We also aimed to identify the factors influencing conformance to KDFWR recommendations, specifically whether less than 50% of a field was mowed. We had two general hypotheses on why fields may be inconsistent with wildlife-friendly recommendations: (i) county-level differences in how the NRCS and FSA administered wildlife-friendly recommendations or (ii) variation in landowner intent or ability to manage fields.

We predicted that although KDFWR recommendations were intended for all counties participating in the CREP, county offices would operate independently and there would be variation in how effectively each county transferred KDFWR recommendations to on-the-ground management. We predicted that landowner conformance with KDFWR mowing recommendations would manifest in several ways: conformity would decrease with (i) increasing field size because of the added cost of mowing greater areas, and (ii) decreased distance to roads because of a desire for maintaining aesthetics near areas where fields are visual to the public. We predicted that woody encroachment would (i) increase with decreasing field size because smaller fields have relatively greater perimeter-to-area ratio, thus making them more prone to woody encroachment, and (ii) increase with increasing nearest distance to road, for reasons mentioned above. Additionally, we predicted that there would be spatial structure in woody encroachment and mowing patterns because of the effect influential land owners can have on the management actions of other nearby landowners (i.e., the "Bell Cow" effect).

4.3 Material and methods

In 2012, 342 fields were surveyed as a pilot study estimating differences in mowing patterns among counties. We used a simulation approach to estimate the number of fields per county we would need to sample in order to observe similar effects to the pilot study. We estimated that 9 fields per county was sufficient, but because our study design also included other covariates, we considered 9 fields a conservative estimate (Appendix A.6).

We used a stratified random sampling approach to select sites. We had two main strata: county and CREP density. We included CREP density as a strata to test the assumption of Chapter 2 that field management did not covary with landscape-scale CREP density in a meaningful way. In each county, one field within each of 5 CREP density strata (Table 1.2) was randomly chosen as a "focal field". We centered a Fibonacci spiral pattern (a pattern condusive to understanding spatial autocorrelation) on each focal field. We determined the appropriate size of the Fibonnaci pattern by dividing the study area by the number of focal fields. For each focal field, we randomly selected 6 points in the pattern. We sampled the closest fields to each of the 6 points. We selected 318 fields in total. Twelve of these contracts were set to expire before our sampling date. We sampled expired fields but excluded them from analysis. The study design resulted in a representative gradient of distance to road, field size, and landscape-scale CREP density within each county (Figures 4.1, 4.2, 4.3, 4.4).

We surveyed fields on February 22 and 23, 2016. The flight team included two observers and a pilot. Both observers independently estimated percent cover of woody vegetation and percentage of the field that was mowed. The pilot would make an initial pass of the field then circle the field continuously until both observers were confident in their es-

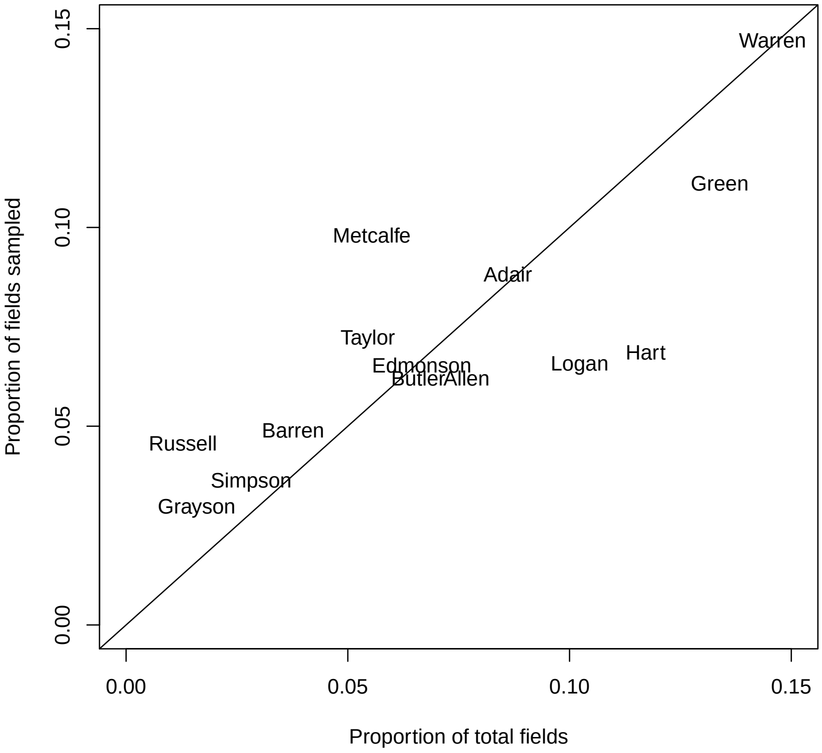


Figure 4.1: Proportion of fields sampled via helicopter surveys compared to proportion of total CREP fields within each county.

timates. We measured spatial autocorrelation of mowing and woody coverage estimated from both observers using a semivariogram.

We modeled the percentage of woody cover and mowed area estimated from each observer as random variables drawn from a binomial distribution with 100 trials (i.e., potential percentage points) (Kéry and Schaub, 2012). Data from each observer j were assumed to be independent (Riddle et al., 2010):

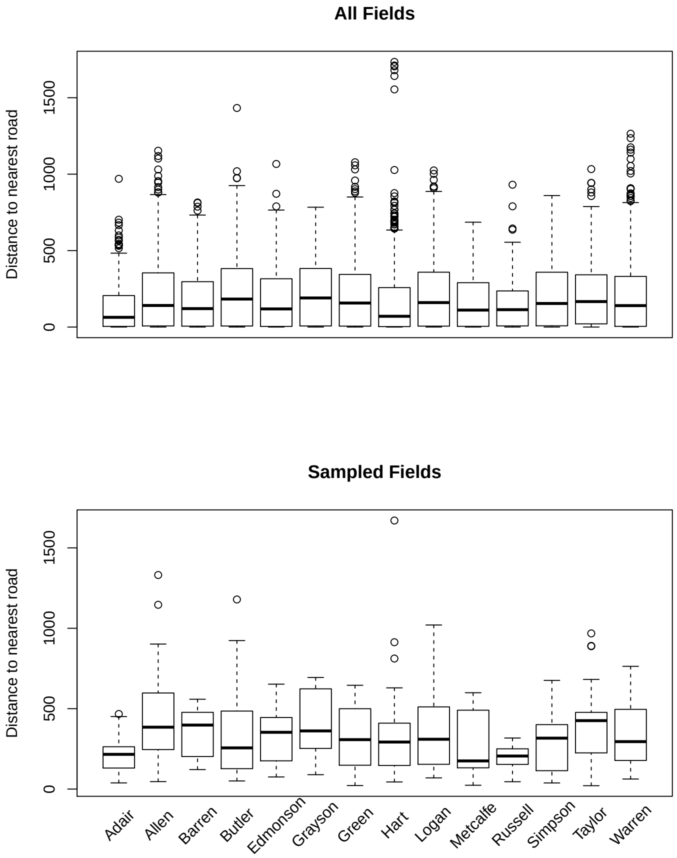


Figure 4.2: A comparison of distance-to-nearest-road (m) in fields sampled via helicopter surveys and all fields enrolled in the CREP.

$$\begin{aligned} \text{mow}_{i,j} &\sim \text{Bin}(100, \psi_i) \\ \text{wood}_{i,j} &\sim \text{Bin}(100, \theta_i) \end{aligned} \tag{4.1}$$

where ψ_i and θ_i were the expected percentages at each site *i*, which varied by county, field size, distance to nearest road, CREP density within a 3000 m radius circle, and a site-level random effect drawn from N(0,σ^2), where σ was drawn from a Unif(0,10):

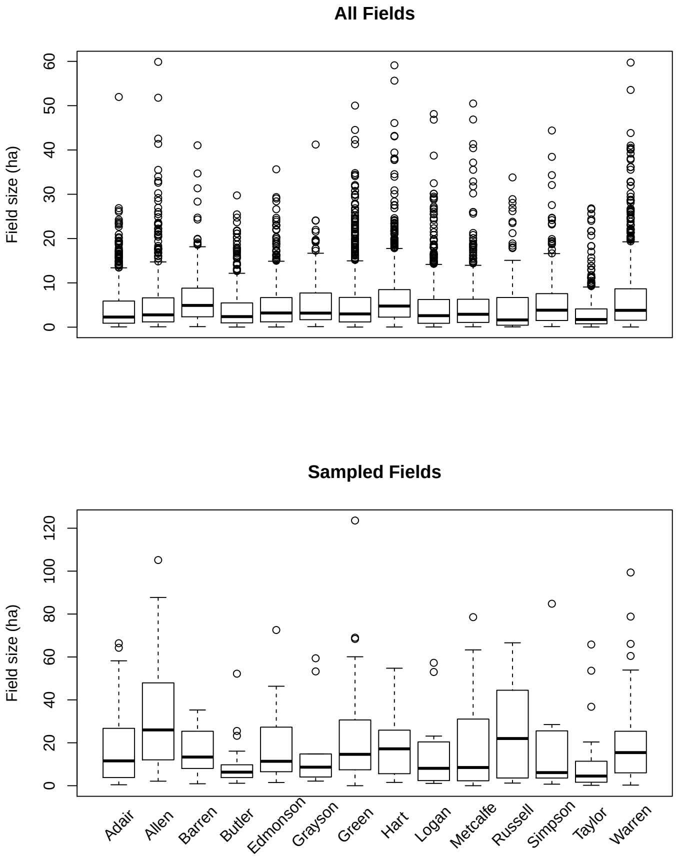
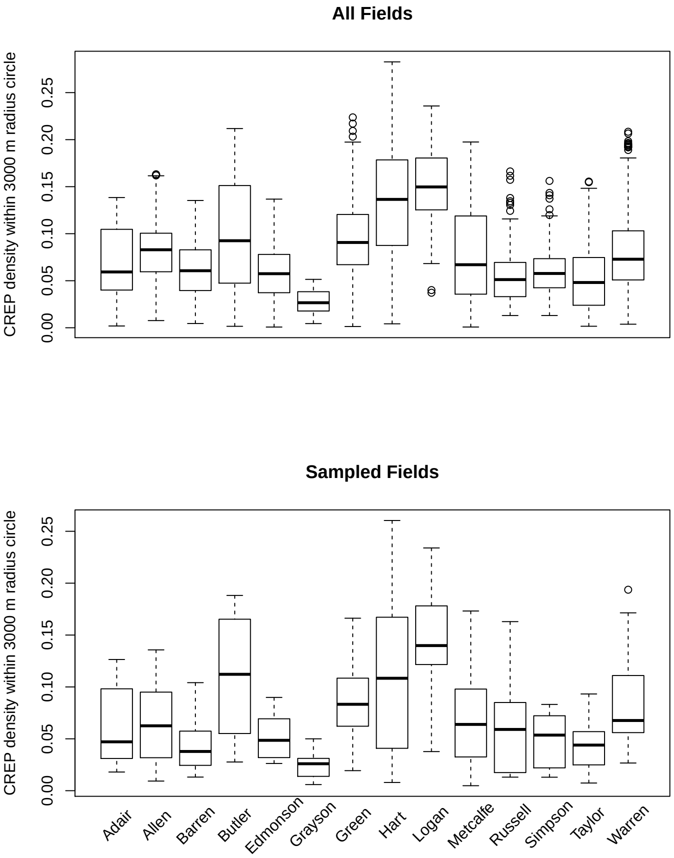


Figure 4.3: A comparison of size (ha) of fields sampled via helicopter surveys and all fields enrolled in the CREP.

$$\begin{aligned}\psi_i &= \alpha_{0,c} + \alpha_1 \text{RdDist}_i + \alpha_2 \text{Size}_i + \alpha_3 \text{CREPd}_i + \epsilon_i \\ \theta_i &= \beta_{0,c} + \beta_1 \text{RdDist}_i + \beta_2 \text{Size}_i + \beta_3 \text{CREPd}_i + \epsilon_i\end{aligned} \tag{4.2}$$

We determined the partioning of variance between random and fixed effects using methods similar to Nakagawa and Holger (2012). We had two versions of the model: one with only the intercept and random site effects and one model fully parameterized. We calculated marginal and conditional R^2 as:



All Fields

Sampled Fields

Figure 4.4: A comparison of CREP density surrounding fields sampled via helicopter surveys and all fields enrolled in the CREP.

$$\begin{aligned} R_m^2 &= \mathrm{V}\theta_f/(\mathrm{V}\theta_f + \mathrm{V}\theta_r + \mathrm{V}\theta_d) \\ R_c^2 &= (\mathrm{V}\theta_f + \mathrm{V}\theta_r)/(\mathrm{V}\theta_f + \mathrm{V}\theta_r + \mathrm{V}\theta_d) \end{aligned} \tag{4.3}$$

where $\mathrm{V}\theta_f$ describes a vector of variance estimates from the posterior distribution of predicted fixed effects, $\mathrm{V}\theta_r$ describes a vector of variance estimates from the posterior of random effects, and $\mathrm{V}\theta_d$ describes distribution variance (Nakagawa and Holger, 2012).

We used 5.5 m resolution images from SPOT-6 and SPOT-7 satellites to classify CREP fields. We targeted images taken during our flights, however none were available, so we purchased images from the non-growing season concurrent with our sampling dates (November 8th to 15th). We assumed that all landowners had mowed their fields before this time period in preperation for next years growing season. We also assumed that woody vegetation would not change between the time the images were taken and when we sampled fields. We targeted images with no cloud cover. We orthorectified images using NAIP before data analysis. We used k-means clustering (where k = 50) of red, blue, green, and near-infrared bands to categorize pixels within CREP fields into four classes: grassland, mowed, woody, and other. We used helicopter flight data as baseline reference information, and compared field-level estimates from both observers to proportions of classes from classified satellite images to determine accuracy.

4.4 Results

We sampled at least 9 fields in each county (Table 4.1). Mean field size was 7.8 ha (0–50 ha), mean distance-to-nearest road was 845 m (21–1670 m), and mean CREP density within a 3000 m radius circle was 13.3% (0.5–26%). Both observers estimated similar conformance to KDFWR mowing recommendations (i.e., no more than 50% of the field was mowed; Observer 1 = 67.6%, Observer 2 = 68.6%). Remote sensing indicated 67.6% of sampled fields and 72.1% of fields covered by purchased satellite images were conformant. When fitting data to a double-observer model, we estimated that 71.9% (63.7–78.1%, 95% BCI) of sampled fields were conformant. Marginal R^2, i.e., the proportion of variance explained by fixed effects, was 0.11 (0.07–0.16, 95% BCI) for the mowing model and 0.14 (0.09–0.18%, 95% BCI) for the woody cover model. Conditional R^2, i.e., the proportion of variance explained by fixed and random effects, was 0.67 (0.63–0.71, 95% BCI) for the mowing model and 0.53 (0.48–0.57, 95% BCI) for the woody cover model.

Table 4.1: Raw estimates of proportions of Conservation Reserve Enhancement Program fields in each county that were less than 50% mowed (i.e., conformant with the Kentucky Department of Fish and Wildlife Resources recommendation)

		Proportion conformant		
County	Fields sampled	Observer 1	Observer 2	Remote sensing
Warren	45	0.62	0.64	0.63
Taylor	22	0.73	0.73	0.58
Simpson	11	0.64	0.64	0.60
Russell	14	0.71	0.86	0.84
Metcalfe	30	0.70	0.67	0.80
Logan	20	0.55	0.70	0.56
Hart	21	0.81	0.67	0.76
Green	34	0.62	0.62	0.71
Grayson	9	0.33	0.33	0.40
Edmonson	20	0.90	0.90	0.70
Butler	19	0.68	0.79	0.50
Barren	15	0.87	0.73	0.55
Allen	19	0.47	0.53	1.0
Adair	27	0.74	0.74	0.62

Mowing and woody encroachment varied at the county level (Figures 4.5 and 4.6). Mowing did not vary with increasing distance from nearest road or field size ($\alpha_1 =$ -0.05, -0.22–0.13 95% BCI; α_2 = -0.10, -0.28–0.08 95% BCI). The influence of landscape-scale CREP on mowing was mostly positive (α_3=0.17, -0.03–0.36) but varied substantially (Figure 4.7). Woody cover decreased with increasing distance to the nearest road ($\beta_1 =$ -0.24, -0.42–-0.06 95% BCI; Figure 4.8) and increasing field size ($\beta_2 =$ -0.49, -0.67–-0.31 95% BCI; Figure 4.9). CREP density within 3000 m radius circles had a negative effect on woody cover ($\beta_3 =$ -0.23, -0.44–-0.04 95% BCI; Figure 4.10). Site-level variation not captured by our covariates was high ($\sigma =$ 1.47, 1.35–1.61 95% BCI). We did not find evidence of spatial autocorrelation in mowing or woody cover (Appendix A.5).

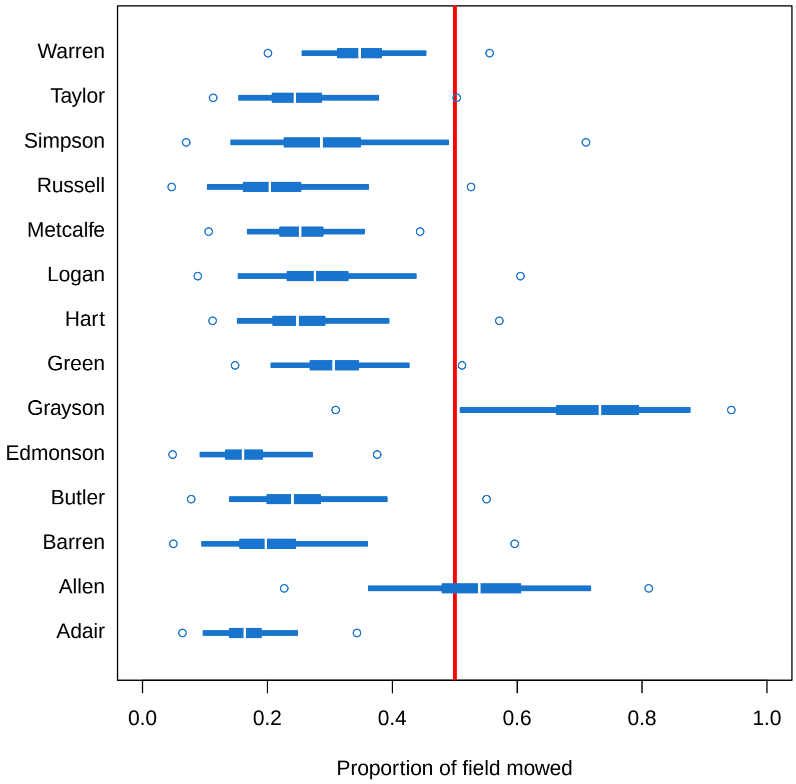


Figure 4.5: County estimates of mowing within Conservation Reserve Enhancement Program fields in south central Kentucky. Within blue bars, thicker parts represent 50% of the posterior, thinner bars represent 95% of the posterior, dots indicate minimum and maximum values, and white lines represent the median. The red vertical line indicates the threshold for conformance with Kentucky Department of Fish and Wildlife Resources recommendations.

The mean difference between observer 1 and observer 2 estimates of mowing and woody cover were 10.1% ± 20.8% SD and 7.5% ± 11.1% SD, respectively. There was low agreement between field-level estimates from helicopter data and remote sensing. The mean difference between remote sensing and observer 1 estimates of mowing and woody cover were 30.0% ± 25.9% SD and 13.4% ± 15.7% SD, respectively. The mean difference between remote sensing and observer 2 estimates of mowing and woody cover were 29.1%

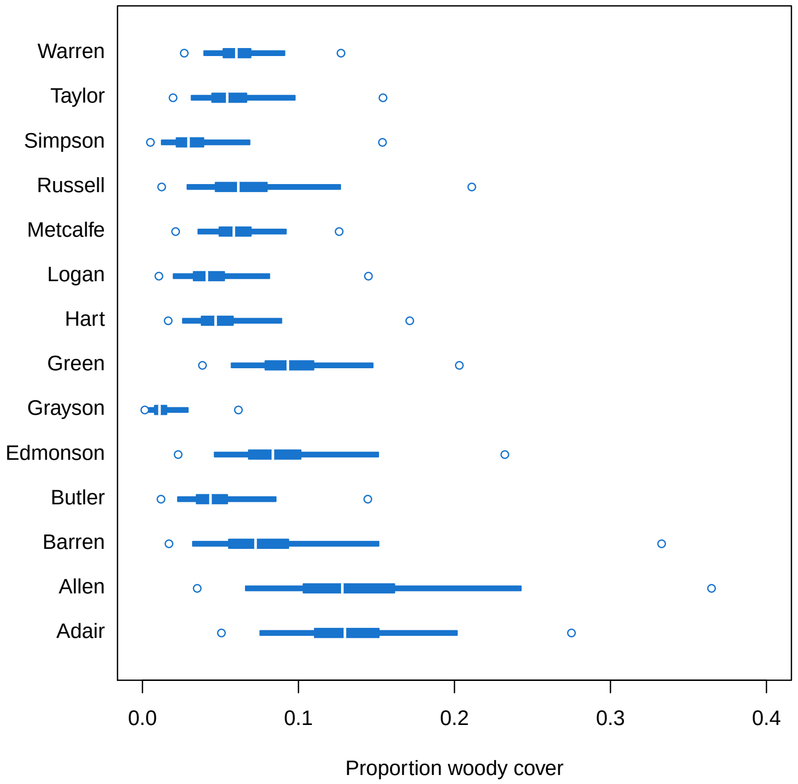


Figure 4.6: County estimates of woody cover within Conservation Reserve Enhancement Program fields in south central Kentucky. Within blue bars, thicker parts represent 50% of the posterior, thinner bars represent 95% of the posterior, dots indicate minimum and maximum values, and white lines represent the median.

± 26.6% SD and 14.6% ± 18.2% SD, respectively. The spatial arrangement of land management as described by remote sensing was largely random (Figures 4.11 and 4.12).

4.5 Discussion

Broad-scale habitat restoration is an important component of grassland wildlife recovery efforts. Private land initiatives like CRP are unique. They are well-funded, far reaching, and coordinated landscape management efforts. Continued government support for these

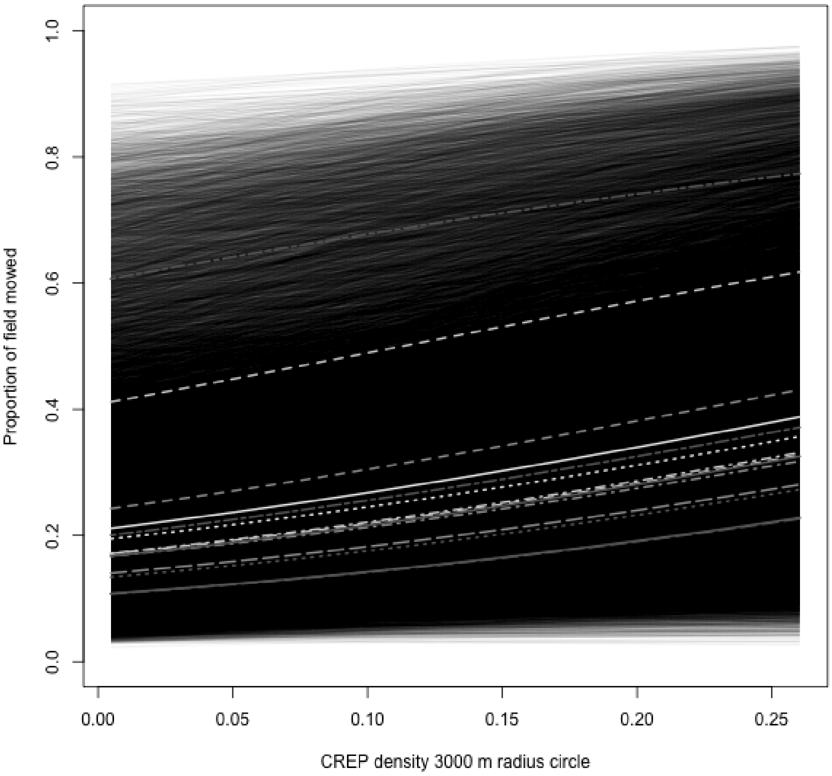


Figure 4.7: Influence of Conservation Reserve Enhancement Program (CREP) field density within a 3000 m radius circle on mowing intensity within CREP fields. Each white or gray line is a different county mean and each dark line is one of 5000 random model iterations per county.

programs will be contingent on sustained environmental benefits. Variation in land management could potentially undermine cost-effectiveness. We estimated that the majority of landowners enrolled in the CREP followed a key KDFWR mowing recommendation: to mow less than 50% of a field. Furthermore, we estimated that most variation in land management was random, indicating that landowners are acting independent of covariates and other landowners.

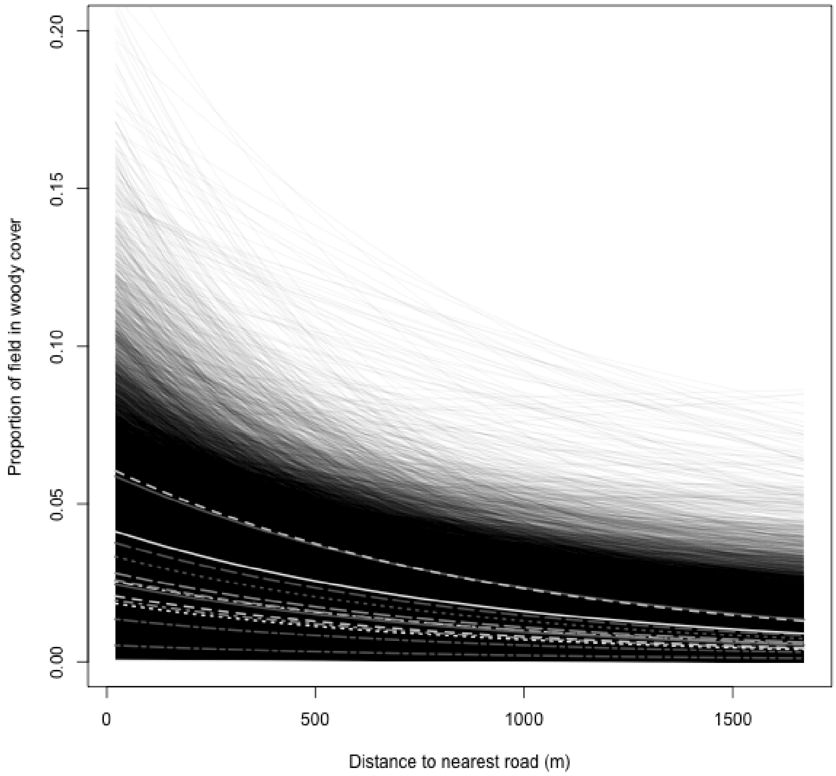


Figure 4.8: Expected woody cover within Conservation Reserve Enhancement Program fields along a gradient of distance-to-nearest-road in south central Kentucky. Each white or gray line is a different county mean and each dark line is one of 5000 random model iterations per county.

Although we found several non-zero effects of covariates on field management, the actual implications are likely insignificant. Fixed effects had considerable uncertainty and explained little variation. Most variation in land management was random and there was no evidence of spatial autocorrelation. It is unrealistic to use our models to predict land management patterns beyond our sampled fields, to predict how land management of CREP fields may vary in the future, or to predict how land management may vary in similar conservation programs. An important implication of our study is that landowners manage

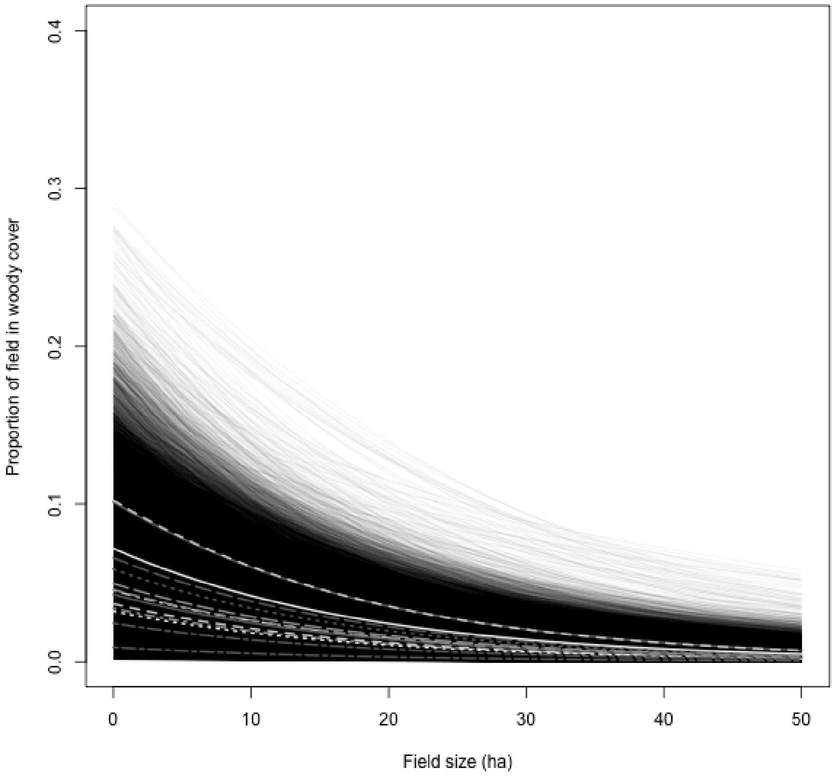


Figure 4.9: Expected woody cover within Conservation Reserve Enhancement Program fields along a gradient of field size in south central Kentucky. Each white or gray line is a different county mean and each dark line is one of 5000 random model iterations per county.

land randomly and it was ineffective to predict land management over space using political boundaries and landscape covariates. Including parameters that capture the demographics, motivations, and values of landowners may enhance predictability of conservation field management (e.g., Dayer et al., 2016; Nielsen et al., 2017).

Wildlife management agencies can recommend management that would best promote quality grassland habitat, but it is within the purview of the FSA and NRCS to ensure that those recommendations are included in conservation plans. Regardless of the methodol-

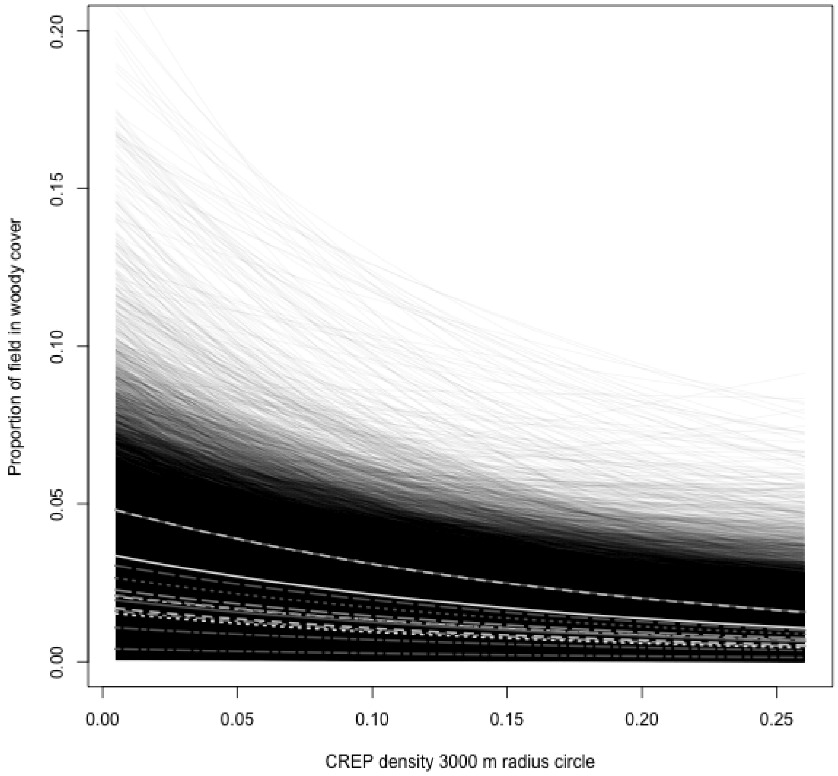


Figure 4.10: Influence of Conservation Reserve Enhancement Program field density within a 3000 m radius circle on woody cover. Each white or gray line is a different county mean and each dark line is one of 5000 random model iterations per county.

ogy we used, we estimated that at least 67% of landowners were following KDFWR recommendations. Most of the variation we explained with fixed effects was caused by county-level factors. A potential mechanisms of county-level effects is differences in local administrative norms such as a willingness to break from KDFWR recommendations. Local policies or common practices that are counterproductive to broad-scale goals could undercut effective delivery of biodiversity gains. Communication (e.g., annual workshops) between wildlife management agencies and local NRCS and FSA personnel wherein com-

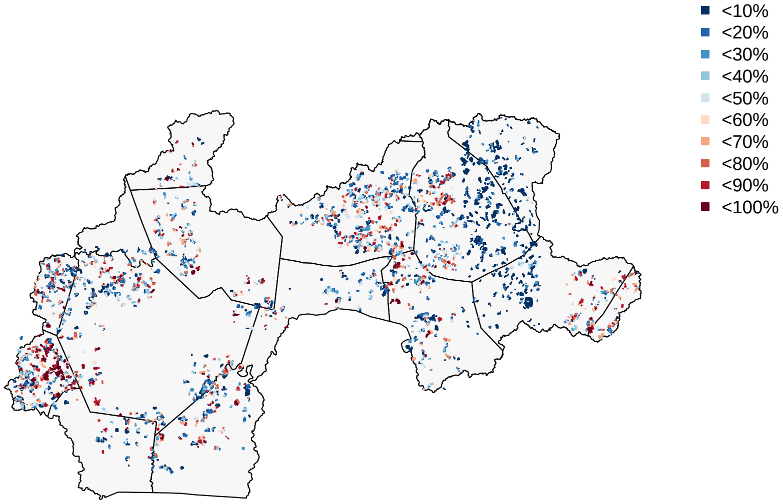


Figure 4.11: Mowing intensity within Conservation Reserve Enhancement Program fields as estimated by classification of SPOT-6 and SPOT-7 satellite images.

mon problems are discussed may help provide local offices with a framework for addressing specific issues in context of broader biodiversity goals.

The relationship we estimated between distance-to-road and field management was inconsistent with the idea that landowners have explicit intent to disregard KDFWR recommendations. Fields near roads are more likely to be noticed by the public. If the intent of landowners were to either maintain aesthetics or avoid detection of practices nonconformant with KDFWR recommendations, we would expect woody cover and mowing to decrease with decreasing distance to roads. Mowing did not differ with distance-to-road and in contrast to our predictions, woody cover decreased with increasing distance to roads.

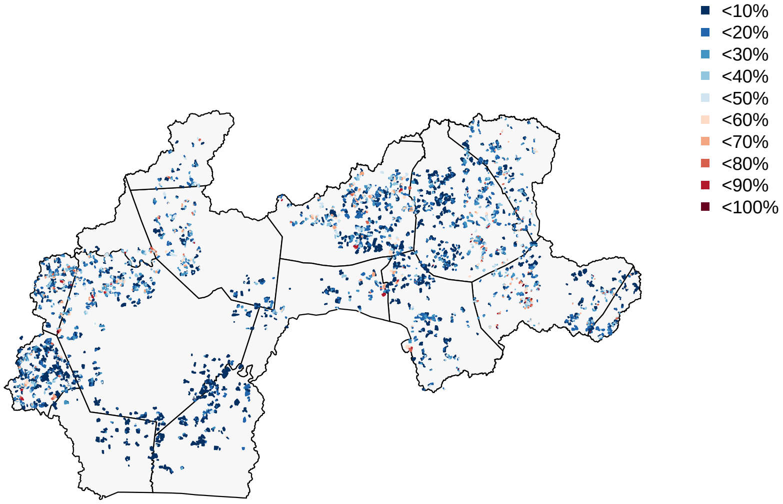


Figure 4.12: Woody cover within Conservation Reserve Enhancement Program fields as estimated by classification of SPOT-6 and SPOT-7 satellite images.

Smaller fields have greater perimeter-to-area ratios than larger fields of the same shape. Therefore, increased woody encroachment in smaller fields is likely a byproduct of simple geometry. Any given point within a smaller field is relatively closer to the edge than any given point in a larger field. Distance to forest edge, depending on the dispersal mechansims of surrounding tree species (e.g., Ratajczak et al., 2011), will likely drive forest regeneration. Smaller fields, especially those in close proximity to forests, are relatively more susceptible to greater percentages of woody encroachment. Considering field size or surrounding landscape context in the prioritization process may reduce the number of fields enrolled into conservation programs such as CREP that are susceptible to woody encroachment. Alternatively, inclusion of comprehensive woody control measures in conservation plans may help reduce succession in smaller fields.

Field-level estimates of woody cover and mowing intensity differed between helicopter survey data and classified satellite images. This could be because the resolution of satellite data was too coarse, uncertainty in the true state of sampled fields, or mismatched dates among data collection methods. Field characteristics such as blackberry (Rubus sp.) cover and strip mowing were evident from the helicopter but less distinguishable from SPOT images. Conversely, SPOT images captured tree shadow, which could have resulted in overestimates of woody cover in many fields, especially along field edges. However, using helicopter flight data as validation implies that observers were perfect at detecting field status, which we know is not true because estimates differed between observers. The patterns of mowing intensity and woody cover estimated from remote sensing were consistent with the concept that landowners were acting randomly. If the goal is to simply describe spatial variation in land management, remote sensing may be more appropriate than using aerial surveys with human observers. The use of satellite imagery paired with on the groudn quantitative measurements of vegetative reflectance (e.g., Ishida et al., 2018) may be an effective way to quantify fine-scale vegetative heterogeneity over large scales.

Overall estimates of conformance to KDFWR mowing recommendations were consistent among our methodologies, which indicates that if the goal is to understand basic rates of conformance to a set of criteria, statistical modeling of data collected via helicopter sampling or remote sensing paired with coarse estimates of cover as a reference are sufficient. We believe our study warrants a discussion among the KDFWR, FSA, and NRCS about whether a 67-71% conformance rate is acceptable and whether the rates of woody encroachment we found were acceptable, and if not, what changes need to be made to conservation plans or enforcement policies in order to achieve conformance goals. Our results could inform these changes to some degree, but further analysis that includes demographic parameters of landowners will likely be more informative to policy changes and targeted enforcement efforts.

CHAPTER 5

A NEW PERSPECTIVE FOR FARMLAND CONSERVATION

In Brief: The Conservation Reserve Program benefits wildlife at field-scales, but do these local effects add up? A new approach to understanding the extent of conservation effects can guide land management in farm landscapes.

Farms Have Replaced Grasslands Across the U.S. As the American population grew and settled ever westward, the demand for food and land quickly outweighed our value for prairies. Noss et al. (1995) estimates that all eastern and midwestern states have lost at least 90% of their original prairie acreage. Corn fields, beans, hay fields, and pastures simply provide a different set of vegetative characteristics than prairies. Not suprisingly, population numbers of birds that historically relied on prairie vegetation for habitat have declined substantially over the last century.

The Conservation Reserve Program is an Avenue for Managing Grassland Birds The Conservation Reserve Program (CRP) is a federally-funded private land initiative that pays producers to convert agriculture into natural vegatation. The CRP is one of the main ways practitioners implement grassland conservation in agricultural landscapes. Research has shown that converting active agriculture to CRP land is beneficial for grassland birds, but we do not know whether these local effects scale up to population-level benefits. Does converting a pasture to prairie vegetation help birds that live 100 m away? 200 m? 1000 m? The Kentucky Department of Fish and Wildlife Resources (KDFWR) and partners like the University of Georgia sought to answer this question by studying the landscape-scale

Figure 5.1: A native prairie planting in Kentucky.

effects of a CRP program, the Conservation Reserve Enhancement Program (CREP) on grassland bird populations in Kentucky.

Studying Landscape-scale Effects in a New Way From 2010–2015, biologists from KDFWR sampled 247 points along a gradient of landscape-scale CREP density. The density at local scales (i.e., within the sampling point) was kept relatively similar among points. Researchers at the Warnell School of Forestry and Natural Resources at the University of Georgia used novel modeling techniques to estimate not only the effects of CREP on grassland bird populations, but the extent of the landscape that matters to local populations and the rate at which benefits of conservation decay with distance. The CREP had landscape-scale benefits to Northern Bobwhite populations, but benefits decayed rapidly with distance. For instance, all else being equal, a CREP field 3000 m away from a local population was 88% less important than a field 1000 m away. Population forecasts in-

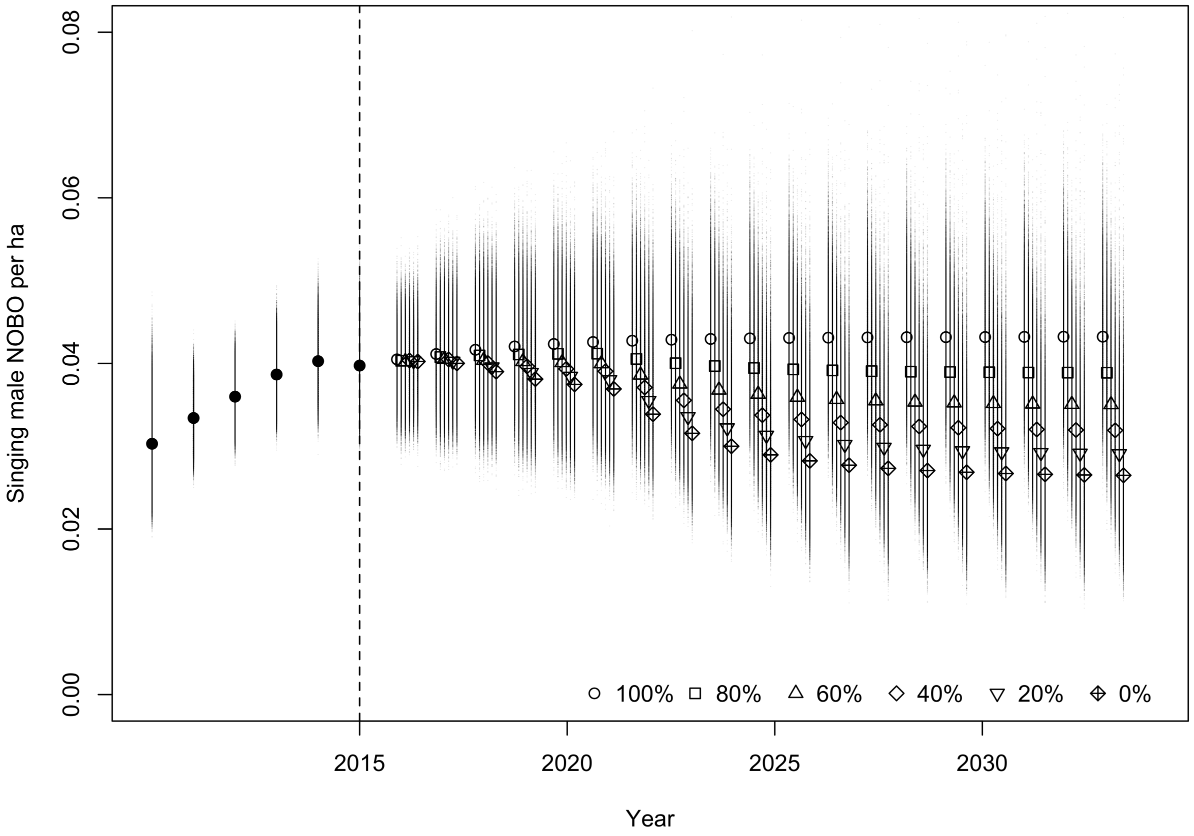
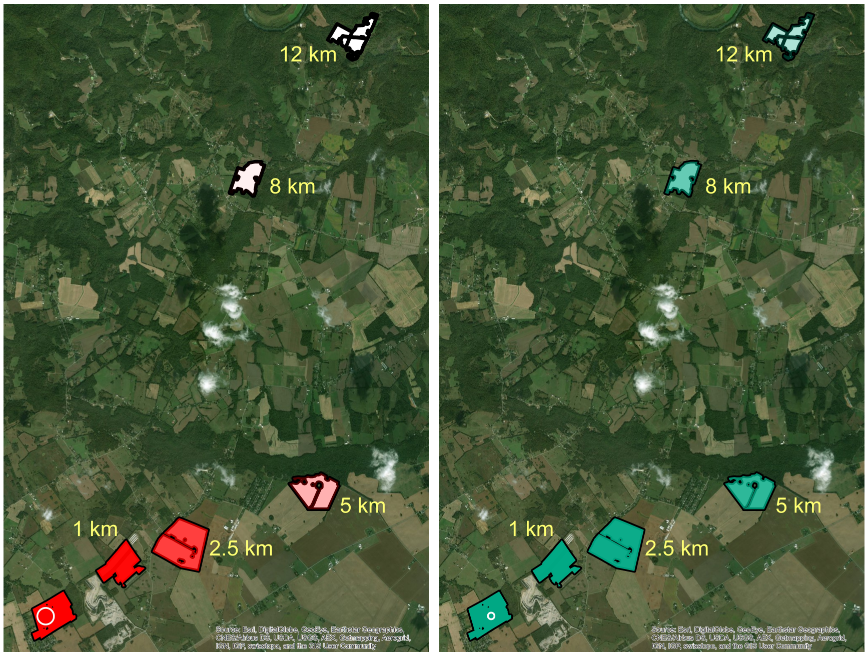


Figure 5.2: The importance of re-enrolling the CREP for Northern Bobwhite

dicated that re-enrollment of the CREP will drive Northern Bobwhite density in the future (Figure 5.2).

The effect of landscape composition (i.e., prevelance of different land cover types) and configuration (i.e., how different land cover types are arranged) influenced species differently. Additionally, the spatial scale at which land features influenced local populations differed among species (Figure 5.3). This study supports the idea that habitat and landscapes are species-specific concepts, which has implications for how private land conservation should be planned. Much grassland conservation in the eastern U.S. is driven



Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Figure 5.3: An example of the difference in what a "landscape" means to Northern Bobwhites (left) and Dickcissels (right). The darker the colored shading, the more important that resource patch is to the individual within the home range (for bobwhites) or territory (for Dickcissels). White circles represent hypothetical home ranges or territories. Compared to Northern Bobwhites, Dickcissels are impacted by fields that are farther away, which has implications for landscape management.

by interest in game birds, particularly Northern Bobwhite. Bobwhites act as a surrogate for other grassland birds. We assume that because other grassland birds utilize similar resources, then they too will respond positively to landscape management for bobwhites. This study designed a decision support tool to calculate the opportunity costs of using the surrogate approach to conserving farmlands.

A Surrogate for Some The decision support tool mimicked a private land conservation initiative similar to Conservation Practice 29, *Marginal Pastureland Wildlife Buffers*. Using this program to manage landscapes in a way that would maximize bobwhite abundance caused steep opportunity costs for the Dickcissel, but not for the Field Sparrow or the East-

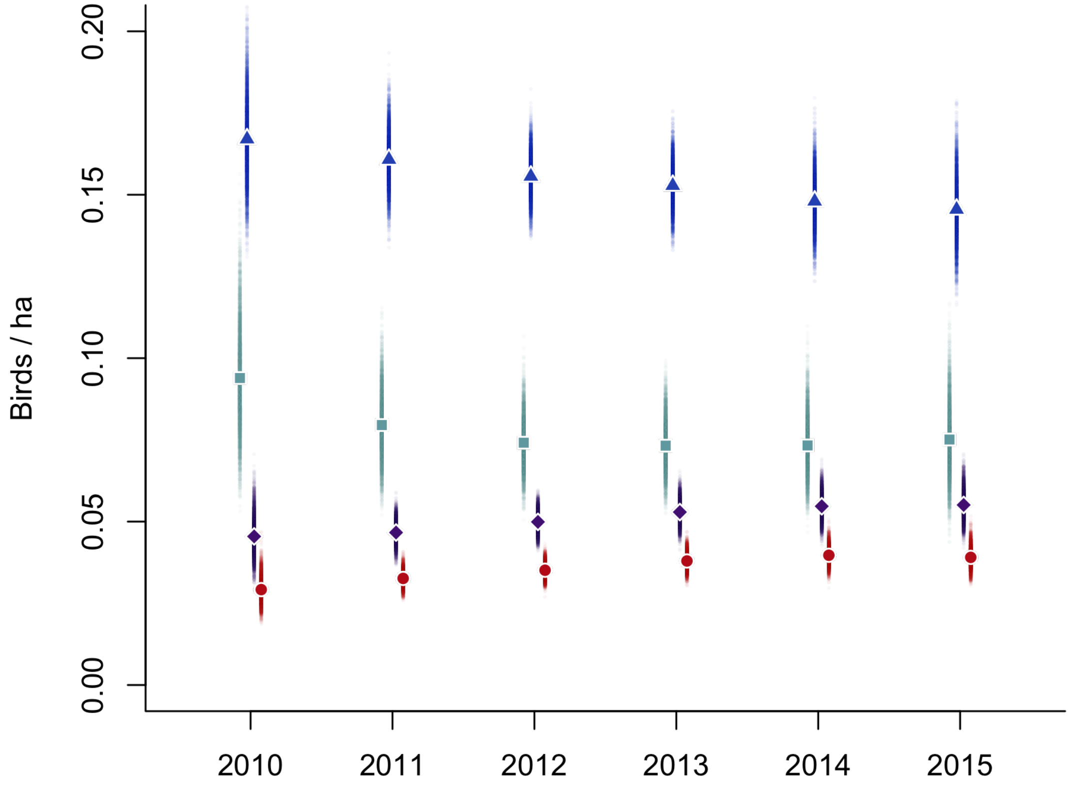


Figure 5.4: Trends in density for different species in the CREP area. Blue triangles = Eastern Meadowlarks; cyan squares = Dickcissels, purple diamonds = Field Sparrows, and red circles = Northern Bobwhite.

ern Meadowlark. Dickcissels had more restrictive landscape requirements than bobwhite, and their landscape scale exceeded the bobwhite's. Understanding how resource require-

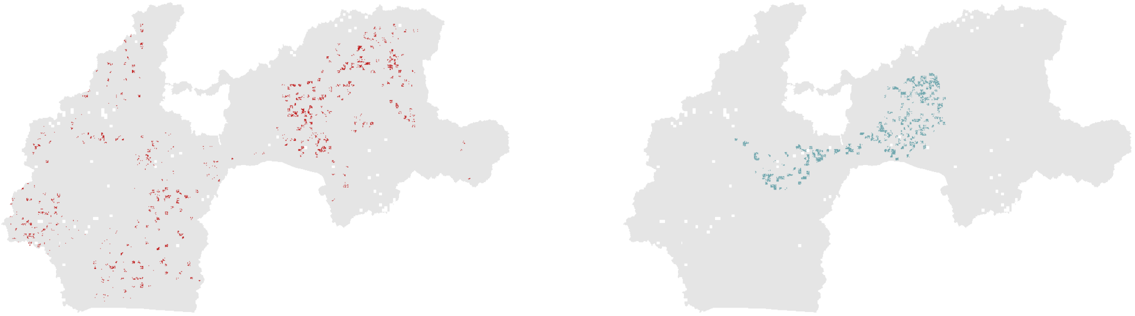


Figure 5.5: Areas chosen by the decision support tool to convert to native grasslands for optimizing Northern Bobwhite (left) and Dickcissels (right).

ments at landscape scales vary within and among species is key to efficient targeting of conservation efforts.

Going Forward with Farmland Conservation Private land initiatives benefit Northern Bobwhite populations (Chapter 2). Although there are many grassland birds who have similar resource requirements to bobwhites, species have unique landscape-scale requirements that may lead to opportunity costs when using a surrogate approach to conservation (Chapter 3). The development of a decision support tool has opened the door for an adaptive approach to broad-scale conservation planning. Practitioners can use the decision support tool to predict bird populations under different management scenarios. Acceptable management alternatives could be informed by a structured decision making process. Implementing planned landscape management through programs like CRP, then using targeted population monitoring to assess conservation success would form the feedback loop needed to start the next iteration of the adaptive learning process.

Bibliography

Allaire, P. N. and Fisher, C. D. (1975). Feeding ecology of three resident sympatric sparrows in eastern texas. *The Auk*, (2):260–269.

Altieri, M. A. (1999). The ecological role of biodiversity in agroecosystems. *Agriculture, Ecosystems & Environment*, 74(1):19–31.

Andelman, S. J. and Fagan, W. F. (2000). Umbrellas and flagships: efficient conservation surrogates or expensive mistakes? *Proceedings of the National Academy of Sciences*, 97(11):5954–5959.

Baker, D. J., Freeman, S. N., Grice, P. V., and Siriwardena, G. M. (2012). Landscape-scale responses of birds to agri-environment management: a test of the english environmental stewardship scheme. *Journal of Applied Ecology*, 49(4):871–882.

Banks, J. E., Stark, J. D., Vargas, R. I., and Ackleh, A. S. (2014). Deconstructing the surrogate species concept: a life history approach to the protection of ecosystem services. *Ecological Applications*, 24(4):770–778.

Barnes, T. G., Madison, L. A., Sole, J. D., and Lacki, M. J. (1995). An assessment of habitat quality for northern bobwhite in tall fescue-dominated fields. *Wildlife Society Bulletin*, 23(2):231–237.

Batáry, P., Dicks, L. V., Kleijn, D., and Sutherland, W. J. (2015). The role of agri-environment schemes in conservation and environmental management. *Conservation Biology*, 29(4):1006–1016.

Baylis, K., Peplow, S., Rausser, G., and Simon, L. (2008). Agri-environmental policies in the eu and united states: A comparison. *Ecological Economics*, 65(4):753 – 764. Payments for Environmental Services in Developing and Developed Countries.

Beck, C. W. and Watts, B. D. (1997). The effect of cover and food on space use by wintering song sparrows and field sparrows. *Canadian Journal of Zoology*, 75(10):1636–1641.

Bent, A. C. (1965). *"Dickcissels" in Life histories of North American blackbirds, orioles, tanagers, and allies*. New York, Dover Publications, 1965.

Benton, T. G., Bryant, D. M., Cole, L., and Crick, H. Q. P. (2002). Linking agricultural practice to insect and bird populations: a historical study over three decades. *Journal of Applied Ecology*, 39(4):673–687.

Berkeley, L. I., McCarty, J. P., Wolfenbarger, L. L., and Bollinger, E. K. (2007). Postfledging survival and movement in dickcissels (*Spiza americana*): implications for habitat management and conservation. *The Auk*, (2):396–409.

Best, L. B. (1977). Nestling biology of the field sparrow. *The Auk*, 94(2):308–319.

Best, L. B. (1978). Field sparrow reproductive success and nesting ecology. *The Auk*, 95(1):9–22.

Best, L. B., Campa, H., Kemp, K. E., Robel, R. J., Ryan, M. R., Savidge, J. A., Weeks, H. P., and Winterstein, S. R. (1997). Bird abundance and nesting in crp fields and cropland in the midwest: a regional approach. *Wildlife Society Bulletin (1973-2006)*, 25(4):864–877.

Best, L. B., Campa III, H., Kemp, K. E., Robel, R. J., Ryan, M. R., Savidge, J. A., Weeks Jr, H. P., and Winterstein, S. R. (1998). Avian abundance in crp and crop fields during winter in the midwest. *The American Midland Naturalist*, 139(2):311–324.

Branton, M. and Richardson, J. S. (2011). Assessing the value of the umbrella-species concept for conservation planning with meta-analysis. *Conservation Biology*, 25(1):9–20.

Brennan, J. M., Bender, D. J., Contreras, T. A., and Fahrig, L. (2002). Focal patch landscape studies for wildlife management: optimizing sampling effort across scales. In Liu, J. and Taylor, W. W., editors, *Integrating landscape ecology into natural resource management*, pages 68–91. Cambridge University Press, Cambridge.

Brook, B. W. and Bradshaw, C. J. A. (2006). Strength of evidence for density denpendence in abundance time series of 1198 species. *Ecology*, 87(6):1445–1451.

Buckingham, D., Evans, A., Morris, A., Orsman, C., and Yaxley, R. (1999). Use of set-aside land in winter by declining farmland bird species in the uk. *Bird Study*, 46(2):157–169.

Buckland, S. T. (2001). *Introduction to distance sampling : estimating abundance of biological populations*. Oxford University Press, New York, USA.

Butler, S., Boccaccio, L., Gregory, R., Vorisek, P., and Norris, K. (2010). Quantifying the impact of land-use change to european farmland bird populations. *Agriculture, Ecosystems & Environment*, 137(34):348–357.

Butler, S. J., Vickery, J. A., and Norris, K. (2007). Farmland biodiversity and the footprint of agriculture. *Science*, 315(5810):381–384.

Carlisle, J. D., Keinath, D. A., Albeke, S. E., and Chalfoun, A. D. (2018). Identifying holes in the greater sage-grouse conservation umbrella. *The Journal of Wildlife Management*, x(x):x–x.

Caro, T. M. and O'Doherty, G. (1999). On the use of surrogate species in conservation biology. *Conservation Biology*, 13(4):805–814.

Chandler, R. B. and Hepinstall-Cymerman, J. (2016). Estimating the spatial scales of landscape effects on abundance. *Landscape Ecology*, 31:1–12.

Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, 9(2):129–136.

Claassen, R., Cattaneo, A., and Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: U.s. experience in theory and practice. *Ecological Economics*, 65(4):737–752. Payments for Environmental Services in Developing and Developed Countries.

Concepción, E. D., Dáaz, M., Kleijn, D., Báldi, A., Batáry, P., Clough, Y., Gabriel, D., Herzog, F., Holzschuh, A., Knop, E., Marshall, E. J. P., Tscharntke, T., and Verhulst, J. (2012). Interactive effects of landscape context constrain the effectiveness of local agri-environmental management. *Journal of Applied Ecology*, 49(3):695–705.

Crosby, A. D., Elmore, R. D., Leslie Jr., D. M., and Will, R. E. (2015). Looking beyond rare species as umbrella species: Northern bobwhites (*Colinus virginianus*) and conservation of grassland and shrubland birds. *Biological Conservation*, 186:233–240.

Dail, D. and Madsen, L. (2011). Models for estimating abundance from repeated counts of an open metapopulation. *Biometrics*, 67(2):577–587.

Davis, D. E. (1941). The belligerency of the kingbird. *The Wilson Bulletin*, (3):157–168.

Dayer, A. A., Stedman, R. C., Allred, S. B., Rosenberg, K. V., and Fuller, A. K. (2016). Understanding landowner intentions to create early successional forest habitat in the northeastern united states. *Wildlife Society Bulletin*, 40(1):59–68.

del Monte-Luna, P., Brook, B. W., Zetina-RejÃşn, M. J., and Cruz-Escalona, V. H. (2004). The carrying capacity of ecosystems. *Global Ecology and Biogeography*, 13(6):485–495.

Díaz, M. and Concepción, E. D. (2016). Enhancing the effectiveness of cap greening as a conservation tool: a plea for regional targeting considering landscape constraints. *Current Landscape Ecology Reports*, 1(4):168–177.

Donald, P. F. and Evans, A. D. (2006). Habitat connectivity and matrix restoration: the wider implications of agri-environment schemes. *Journal of Applied Ecology*, 43(2):209–218.

Dunning, J. B., Danielson, B. J., and Pulliam, H. R. (1992). Ecological processes that affect populations in complex landscapes. *Oikos*, 65(1):169–175.

Ekroos, J., Olsson, O., RundlÃűf, M., WÃďtzold, F., and Smith, H. G. (2014). Optimizing agri-environment schemes for biodiversity, ecosystem services or both? *Biological Conservation*, 172(Supplement C):65 – 71.

Errington, P. L. (1945). Some contributions of a fifteen-year local study of the northern bobwhite to a knowledge of population phenomena. *Ecological Monographs*, 15(1):2–34.

European Commission (2013). Agricultural policy perspectives brief no. 5, december 2013. overview of cap reform 2014–2020.

Evans, K. O., Burger, L. W., Riffell, S., and Smith, M. D. (2014). Assessing multiregion avian benefits from strategically targeted agricultural buffers. *Conservation Biology*, 28(4):892–901.

Evans and Burger, *unpub. data*. Ky green river crep sample size estimation study.

Fahrig, L. (2003). Effects of habitat fragmentation on biodiversity. *Annual Review of Ecology, Evolution, and Systematics*, 34(1):487–515.

Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M., and Martin, J. (2011a). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, 14(2):101–112.

Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M., and Martin, J.-L. (2011b). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, 14(2):101–112.

Feather, P., Hellerstein, D., and Hansen, L. (1999). Economic valuation of environmental, benefits and the targeting of conservation programs: the case of the crp. agricultural economic report, vol. 778. u.s. department of agriculture, economic research service, washington, dc. 56 pp.

Fies, M. L., Puckett, K. M., and Largson-Brogdon, B. (2002). Breeding season movements and dispersal of northern bobwhites in fragmented habitats of virginia. In DeMaso, S. J., Kuvlesky, W. P., Hernández, F., and Berger, M. E., editors, *Quail V: Proceedings of the Fifth National Quail Symposium*, pages 173–179. Texas Parks and Wildlife Department, Austin, TX.

Fischer, J., Brosi, B., Daily, G. C., Ehrlich, P. R., Goldman, R., Goldstein, J., Lindenmayer, D. B., Manning, A. D., Mooney, H. A., Pejchar, L., Ranganathan, J., and Tallis, H. (2008). Should agricultural policies encourage land sparing or wildlife-friendly farming? *Frontiers in Ecology and the Environment*, 6(7):380–385.

Fleishman, E., Murphy, D. D., and Brussard, P. F. (2000). A new method for selection of umbrella species for conservation planning. *Ecological Applications*, 10(2):569–579.

Franco, A. M. A., Anderson, B. J., Roy, D. B., Gillings, S., Fox, R., Moilanen, A., and Thomas, C. D. Surrogacy and persistence in reserve selection: landscape prioritization for multiple taxa in britain. *Journal of Applied Ecology*, 46(1):82–91.

Gordon, C. E. (2000). Movement patterns of wintering grassland sparrows in arizona. *The Auk*, (3):748–759.

Gross, A. O. (1921). The dickcissel (*spiza americana*) of the illinois prairies. *The Auk*, (38):1–26.

Guthery, F. S. (1997). A philosophy of habitat management for northern bobwhites. *Journal of Wildlife Management*, 61:291–301.

Halloum, D. J., Leo, W., and Heard, L. (2000). A comprehensive review of farm bill contributions to wildlife conservation, 1985–2000. usda, nrcs, wildlife habitat management institute. Technical report.

Hanski, I. and Gilpin, M. (1991). Metapopulation dynamics: brief history and conceptual domain. *Biological Journal of the Linnean Society*, 42(1-2):3–16.

Harr, R. N., Morton, L. W., Rusk, S. R., Engle, D. M., Miller, J. R., and Debinski, D. (2014). Landowners' perceptions of risk in grassland management: woody plant encroachment and prescribed fire. *Ecology and Society*, 19(2):41.

Helzer, C. J. and Jelinski, D. E. (1999). The relative importance of patch area and perimater-area ratio to grassland breeding birds. *Ecological Applications*, 9(4):1448–1458.

Herkert, J. R. (1994). The effects of habitat fragmentation on midwestern grassland bird communities. *Ecological Applications*, (3):461–471.

Hernández, F., Brennan, L. A., DeMaso, S. J., Sands, J. P., and Wester, D. B. (2013). On reversing the northern bobwhite population decline: 20 years later. *Wildlife Society Bulletin*, 37(1):177–188.

Hespenheide, H. A. (1971). Flycatcher habitat selection in the eastern deciduous forest. *The Auk*, 88(1):61–74.

Hostetler, J. A. and Chandler, R. B. (2015). Improved state-space models for inference about spatial and temporal variation in abundance from count data. *Ecology*, 96(6):1713–1723.

Hovick, T. J., Miller, J. R., Koford, R. R., Engle, D. M., and Debinski, D. M. (2011). Postfledging survival of grasshopper sparrows in grasslands managed with fire and grazing. *Condor*, 113(2):429–437.

Hughes, J. P., Robel, R. J., Kemp, K. E., and Zimmerman, J. L. (1999). Effects of habitat on dickcissel abundance and nest success in conservation reserve program fields in kansas. *The Journal of Wildlife Management*, 63(2):523–529.

Ishida, T., Kurihara, J., Viray, F. A., Namuco, S. B., Paringit, E. C., Perez, G. J., Takahashi, Y., and Marciano, J. J. (2018). A novel approach for vegetation classification using uav-based hyperspectral imaging. *Computers and Electronics in Agriculture*, 144:80–85.

Jackson, H. B. and Fahrig, L. (2012). What size is a biologically relevant landscape? *Landscape Ecology*, 27(7):929–941.

Jackson, H. B. and Fahrig, L. (2015). Are ecologists conducting research at the optimal scale? *Global Ecology & Biogeography*, 24(1):52–63.

Janke, A. K. and Gates, R. J. (2013). Home range and habitat selection of northern bobwhite coveys in an agricultural landscape. *Journal of Wildlife Management*, 77(2):405–413.

Johnson, D. H. and Igl, L. D. (1995). Contributions of the conservation reserve program to populations of breeding birds in north dakota. *The Wilson Bulletin*, 107(4):709–718.

Johnson, D. H. and Schwartz, M. D. (1993). The conservation reserve program and grassland birds. *Conservation Biology*, 7(4):934–937.

Johnson, R. G. and Temple, S. A. (1990). Nest predation and brood parasitism of tallgrass prairie birds. *Journal of Wildlife Management*, 54(1):106–111.

Johnston, D. W. (1971). Niche relationships among some deciduous forest flycatchers. *The Auk*, 88(4):796–804.

Johnston, D. W. and Odum, E. P. (1956). Breeding bird populations in relation to plant succession on the piedmont of georgia. *Ecology*, 37(1):50–62.

Kaspari, M. and O'Leary, H. (1988). Nonparental attendants in a north-temperate migrant. *The Auk*, (4):792.

Kentucky Division of Conservation (2012). Kentucky green river conservation reserve enhancement program. Annual Program Accomplishment Report CEP-68R, Kentucky Energy and Environment Cabinet.

Kershner, E. L., Walk, J. W., and Warner, R. E. (2004). Postfledging movements and survival of juvenile eastern meadowlarks (*sturnella magna*) in illinois. *The Auk*, (4):1146–1154.

Kéry, M. and Schaub, M. (2012). *Bayesian population analysis using WinBUGS: a hierarchical perspective*. Boston : Academic Press, 2012.

Kleijn, D., Baquero, R. A., Clough, Y., DÃŋaz, M., De Esteban, J., FernÃąndez, F., Gabriel, D., Herzog, F., Holzschuh, A., JÃűhl, R., Knop, E., Kruess, A., Marshall, E. J. P., Steffan-Dewenter, I., Tscharntke, T., Verhulst, J., West, T. M., and Yela, J. L. (2006). Mixed biodiversity benefits of agri-environment schemes in five european countries. *Ecology Letters*, 9(3):243–254.

Kleijn, D., RundlÃűf, M., Scheper, J., Smith, H. G., and Tscharntke, T. (2011). Does conservation on farmland contribute to halting the biodiversity decline? *Trends in Ecology & Evolution*, 26(9):474 – 481.

Klimstra, W. D. and Roseberry, J. L. (1975). Nesting ecology of the bobwhite in southern illinois. *Wildlife Monographs*, 41:3–37.

Klute, D. S., Robel, R. J., and Kemp, K. E. (1997). Will conversion of conservation reserve program (crp) lands to pasture be detrimental for grassland birds in kansas? *The American Midland Naturalist*, 137(2):206–212.

Kohler, F., Verhulst, J., Van Klink, R., and Kleijn, D. (2008). At what spatial scale do high-quality habitats enhance the diversity of forbs and pollinators in intensively farmed landscapes? *Journal of Applied Ecology*, 45(3):753–762.

Lambeck, R. J. (1997). Focal species: a multi-species umbrella for nature conservation. *Conservation Biology*, 11(4):849–856.

Launer, A. E. and Murphy, D. D. (1994). Umbrella species and the conservation of habitat fragments: A case of a threatened butterfly and a vanishing grassland ecosystem. *Biological Conservation*, 69(2):145 – 153.

Laurance, W. F., Sayer, J., and Cassman, K. G. (2014). Agricultural expansion and its impacts on tropical nature. *Trends in Ecology & Evolution*, 29(2):107–116.

Liberati, M. R. (2013). *Spring dispersal and breeding ecology of northern bobwhite in southwest Ohio*. PhD thesis, Ohio State University, Ohio, USA.

Lillesand, T. M., Kiefer, R. W., and Chipman, J. W. (2015). *Remote sensing and image interpretation. 7th Edition*. Wiley, New York, New York, USA 2015.

Lindenmayer, D. B., Manning, A. D., Smith, P. L., Possingham, H. P., Fischer, J., Oliver, I., and McCarthy, M. A. (2002). The focal-species approach and landscape restoration: a critique. *Conservation Biology*, 16(2):338–345.

Lusk, J. J., Smith, S. G., Fuhlendorf, S. D., and Guthery, F. S. (2006). Factors influencing northern bobwhite nest-site selection and fate. *Journal of Wildlife Management*, (2):564–571.

Matthiopoulos, J., Fieberg, J., Aarts, G., Beyer, H. L., Morales, J. M., and Haydon, D. T. (2015). Establishing the link between habitat selection and animal population dynamics. *Ecological Monographs*, 85(3):413–436.

McCoy, T. D., Kurzejeski, E. W., Burger, L. W., and Ryan, M. R. (2001). Effects of conservation practice, mowing, and temporal changes on vegetation structure on crp fields in northern missouri. *Wildlife Society Bulletin*, 29(3):979–987.

Merckx, T., Feber, R. E., Riordan, P., Townsend, M. C., Bourn, N. A., Parsons, M. S., and Macdonald, D. W. (2009). Optimizing the biodiversity gain from agri-environment schemes. *Agriculture, Ecosystems & Environment*, 130(3):177 – 182.

Miguet, P., Jackson, H. B., Jackson, N. D., Martin, A. E., and Fahrig, L. (2016). What determines the spatial extent of landscape effects on species? *Landscape Ecology*, 31(6):1177–1194.

Miller, J. E. D., Damschen, E. I., Ratajczak, Z., and Özdoğan, M. (2017). Holding the line: three decades of prescribed fires halt but do not reverse woody encroachment in grasslands. *Landscape Ecology*, 32(12):2297–2310.

Minin, E. D., Moilanen, A., and Minderman, J. (2013). Improving the surrogacy effectiveness of charismatic megafauna with well-surveyed taxonomic groups and habitat types. *Journal of Applied Ecology*, 51(2):281–288.

Morgan, J. J., Duren, K., and Dailey, T. V. (2016). Nbci coordinated implementation program v1.1. addendum, the national bobwhite conservation initiative: A range-wide plan for recovering bobwhites. *National Bobwhite Technical Committee Technical Publication, ver. 2.0. Knoxville, TN*.

Morgan, J. J., Sprandel, G., Robinson, B. A., and Wethington, K. (2012). A county-based northern bobwhite habitat prioritization model for kentucky. In Braun, C. E. and Daily, T. V., editors, *Quail VII: Proceedings of the Seventh National Quail Symposium*, pages 281–287. The University of Tennessee, National Bobwhite Conservation Initiative, Knoxville, Tennessee.

Murphy, M. T. (1983). Nest success and nesting habits of eastern kingbirds and other flycatchers. *The Condor*, 85(2):208–219.

Murphy, M. T. (1987). The impact of weather on kingbird foraging behavior. *Condor*, 89(4):721–730.

Murphy, M. T. (1996). Survivorship, breeding dispersal and mate fidelity in eastern kingbirds. *The Condor*, (1):82–92.

Murphy, M. T. (2001). Habitat-specific demography of a long-distance, neotropical migrant bird, the eastern kingbird. *Ecology*, 82(5):1304–1318.

Murphy, M. T., Cummings, C. L., and Palmer, M. S. (1997). Comparative analysis of habitat selection, nest site and nest success by cedar waxwings (*bombycilla cedrorum*) and eastern kingbirds (*tyrannus tyrannus*). *The American Midland Naturalist*, 138(2):344–356.

Nadeem, K., Moore, J. E., Zhang, Y., and Chipman, H. (2016). Integrating population dynamics models and distance sampling data: a spatial hierarchical state-space approach. *Ecology*, 97(7):1735–1745.

Nakagawa, S. and Holger, S. (2012). A general and simple method for obtaining R^2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, 4(2):133–142.

National Bobwhite Technical Committee. (2011). The national bobwhite conservation initiative: a range-wide plan for recovering bobwhites. w. e. palmer, t. m. terhune, and d. f. mckenzie, editors. national bobwhite technical committee technical publication, version 2.0. knoxville, tennessee, usa.

Nielsen, A. S. E., Strange, N., Bruun, H. H., and Jacobsen, J. B. (2017). Effects of preference heterogeneity among landowners on spatial conservation prioritization. 31(3):675 – 685.

Noss, R. F., LaRoe, E. T., and Scott, J. M. (1995). *Endangered ecosystems of the United States [microform] : a preliminary assessment of loss and degradation*. Biological report: 28. Washington, D.C. : U.S. Dept. of the Interior, National Biological Service, 1995.

Noss, R. F., Quigley, H. B., Hornocker, M. G., Merrill, T., and Paquet, P. C. (1996). Conservation biology and carnivore conservation in the rocky mountains. *Conservation Biology*, 10(4):949–963.

Osborne, D. C. and Sparling, D. W. (2013). Multi-scale associations of grassland birds in response to cost-share management of conservation reserve program fields in illinois. *Journal of Wildlife Management*, 77(5):920–930.

Osborne, D. C., Sparling, D. W., and Hopkins, R. L. (2011). Influence of conservation reserve program mid-contract management and landscape composition on northern bobwhite in tall fescue monocultures. *The Journal of Wildlife Management*, 76(3):566–574.

Pabian, S. E., Wilson, A. M., and Brittingham, M. C. (2013). Mixed responses of farmland birds to the conservation reserve enhancement program in pennsylvania. *Journal of Wildlife Management*, 77(3):616–625.

Paloniemi, R. and Tikka, P. M. (2008). Ecological and social aspects of biodiversity conservation on private lands. *Environmental Science & Policy*, 11(4):336–346.

Patten, M. A., Shochat, E., Reinking, D. L., Wolfe, D. H., and Sherrod, S. K. (2006). Habitat edge, land management, and rates of brood parasitism in tallgrass prairie. *Ecological Applications*, 16(2):687–695.

Patterson, M. P. and Best, L. B. (1996). Bird abundance and nesting success in iowa crp fields: the importance of vegetation structure and composition. *The American Midland Naturalist*, 135(1):153–167.

Pearson, S. M. (1991). Food patches and the spacing of individual foragers. *Auk (American Ornithologists Union)*, 108(2):355–362.

Perkins, A. J., Maggs, H. E., Watson, A., and Wilson, J. D. (2011). Adaptive management and targeting of agri-environment schemes does benefit biodiversity: a case study of the corn bunting emberiza calandra. *Journal of Applied Ecology*, 48(3):514–522.

Perkins, A. J., Maggs, H. E., Wilson, J. D., and Watson, A. (2013). Delayed mowing increases corn bunting emberiza calandra nest success in an agri-environment scheme trial. *Agriculture, Ecosystems & Environment*, 181:80–89.

Plummer, M. (2003). Jags: A program for analysis of bayesian graphical models using gibbs sampling.

Plummer, M. (2016). *rjags: Bayesian Graphical Models using MCMC*. R package version 4-6.

Poiani, K. A., Merrill, M. D., and Chapman, K. A. (2001). Identifying conservation-priority areas in a fragmented minnesota landscape based on the umbrella species concept and selection of large patches of natural vegetation. *Conservation Biology*, 15(2):513–522.

Pradel, R. (1996). Utilization of capture-mark-recapture for the study of recruitment and population growth rate. *Biometrics*, 52:703–709.

Puckett, H. L., Brandle, J. R., Johnson, R. J., and Blankenship, E. E. (2009). Avian foraging patterns in crop field edges adjacent to woody habitat. *Agriculture, Ecosystems & Environment*, 131(1):9–15. Temperate agroforestry: When trees and crops get together.

Rao, M., Fan, G., Thomas, J., Cherian, G., Chudiwale, V., and Awawdeh, M. (2007). A web-based gis decision support system for managing and planning usda's conservation reserve program (crp). *Environmental Modelling & Software*, 22(9):1270 – 1280.

Ratajczak, Z., Nippert, J. B., Hartman, J. C., and Ocheltree, T. W. (2011). Positive feedbacks amplify rates of woody encroachment in mesic tallgrass prairie. *Ecosphere*, 2(11):1–14.

Ribaudo, M. O., Hoag, D. L., Smith, M. E., and Heimlich, R. (2001). Environmental indices and the politics of the conservation reserve program. *Ecological Indicators*, 1(1):11 – 20.

Riddle, J. D., Pollock, K. H., and Simons, T. R. (2010). An unreconciled double-observer method for estimating detection probability and abundance. *The Auk: A Quarterly Journal of Ornithology*, (4):841–849.

Riffell, S., Scognamillo, D., and Burger, L. W. (2008). Effects of the conservation reserve program on northern bobwhite and grassland birds. *Environmental Monitoring and Assessment*, 146(1):309–323.

Riffell, S. K., Monroe, A. P., Martin, J. A., Evans, K. O., Burger, L. W., and Smith, M. D. (2015). Response of non-grassland avian guilds to adjacent herbaceous field buffers: testing the configuration of targeted conservation practices in agricultural landscapes. *Journal of Applied Ecology*, 52(2):300–309.

Roberge, J.-M. and Angelstam, P. (2004). Usefulness of the umbrella species concept as a conservation tool. *Conservation Biology*, 18(1):76–85.

Root, T. L. (1988). *Atlas of wintering North American birds : an analysis of Christmas bird count data*. Chicago : University of Chicago Press, 1988.

Rosa, S. M. and Murphy, M. T. (1994). Trade-offs and constraints on eastern kingbird parental care. *The Wilson Bulletin*, 106(4):668–678.

Roseberry, J. L. and Klimstra, W. D. (1970). The nesting ecology and reproductive performance of the eastern meadowlark. *The Wilson bulletin.*, 82:243–267.

Roseberry, J. L. and Klimstra, W. D. (1984). *Population ecology of the bobwhite*. Southern Illinois University Press, Carbondale, IL, USA.

Royle, J. A. (2004). N-mixture models for estimating population size from spatially replicated counts. *Biometrics*, 60(1):108–115.

Royle, J. A., Dawson, D. K., and Bates, S. (2004). Modeling abundance effects in distance sampling. *Ecology*, 85(6):1591–1597.

Seddon, P. J. and Leech, T. (2008). Conservation short cut, or long and winding road? a critique of umbrella species criteria. *Oryx*, 42(2):240âĂŞ–245.

Simberloff, D. (1998). Flagships, umbrellas, and keystones: Is single-species management passÃľ in the landscape era? *Biological Conservation*, 83(3):247 – 257. Conservation Biology and Biodiversity Strategies.

Small, D. M., Blank, P. J., and Lohr, B. (2015). Habitat use and movement patterns by dependent and independent juvenile grasshopper sparrows during the post-fledging period. *Journal of Field Ornithology*, 86(1):17–26.

Small, D. M., Gimpel, M. E., and Gill, D. E. (2012a). Site fidelity and natal philopatry in dickcissels. *Northeastern Naturalist*, 19(1):123–129.

Small, D. M., Gimpel, M. E., and Gill, D. E. (2012b). Site fidelity and natal philopatry in dickcissels. *Northeastern Naturalist*, 19(1):123–129.

Smith, A. C., Fahrig, L., and Francis, C. M. (2011). Landscape size affects the relative importance of habitat amount, habitat fragmentation, and matrix quality on forest birds. *Ecography*, 34(1):103–113.

Sollmann, R., Gardner, B., Chandler, R. B., Royle, J. A., and Sillett, T. S. (2015). An open-population hierarchical distance sampling model. *Ecology*, 96(2):325–331.

Staller, E. L., Palmer, W. E., Carroll, J. P., Thornton, R. P., and Sisson, D. C. (2005). Identifying predators at northern bobwhite nests. *Journal of Wildlife Management*, 69(1):124–132.

Stoddard, H. L. (1931). *The bobwhite quail; its habits, preservation and increase.* New York, C. Scribner, 1931.

Suter, W., Graf, R. F., and Hess, R. (2002). Capercaillie (*Tetrao urogallus*) and avian biodiversity: testing the umbrella-species concept. *Conservation Biology*, 16(3):778–788.

Sutherland, W. J. (1996). Predicting the consequences of habitat loss for migratory populations. *Proceedings: Biological Sciences*, 263(1375):1325–1327.

Swift, T. L. and Hannon, S. J. (2010). Critical thresholds associated with habitat loss: a review of the concepts, evidence, and applications. *Biological Reviews*, 85(1):35–53.

Taylor, J. S., Church, K. E., and Rusch, D. H. (1999). Microhabitat selection by nesting and brood-rearing northern bobwhite in kansas. *Journal of Wildlife Management*, 63(2):686–694.

Taylor, W. P. (1934). Significance of extreme or intermittent conditions in distribution of species and management of natural resources, with a restatement of liebig's law of minimum. *Ecology*, 15:374.

Temple, S. A. (2002). Dickcissel (*spiza americana*), version 2.0. In Rodewald, P. G., editor, *The Birds of North America*. Cornell Lab of Ornithology, Ithaca, New York, USA.

Townsend, D. E., Leslie, D. M., Lochmiller, R. L., DeMaso, S. J., Cox, S. A., and Peoples, A. D. (2003). Fitness costs and benefits associated with dispersal in northern bobwhites (*colinus virginianus*). *The American Midland Naturalist*, 150(1):73–82.

Tscharntke, T., Clough, Y., Wanger, T. C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., and Whitbread, A. (2012a). Global food security, biodiversity conservation and the future of agricultural intensification. *Biological Conservation*, 151(1):53–59.

Tscharntke, T., Tylianakis, J. M., Rand, T. A., Didham, R. K., Fahrig, L., BatÃąry, P., Bengtsson, J., Clough, Y., Crist, T. O., Dormann, C. F., Ewers, R. M., FrÃijnd, J., Holt, R. D., Holzschuh, A., Klein, A. M., Kleijn, D., Kremen, C., Landis, D. A., Laurance, W., Lindenmayer, D., Scherber, C., Sodhi, N., Steffan-Dewenter, I., Thies, C., van der Putten, W. H., and Westphal, C. (2012b). Landscape moderation of biodiversity patterns and processes - eight hypotheses. *Biological Reviews*, 87(3):661–685.

Twedt, D. J., Wilson, R. R., and Amy S., K. (2007). Spatial models of northern bobwhite populations for conservation planning. *Journal of Wildlife Management*, 71(6):1808–1818.

USDA FSA (2017). Conservation reserve program status - end of september 2017.

Veech, J. A. (2006). A comparison of landscapes occupied by increasing and decreasing populations of grassland birds. *Conservation Biology*, 20(5):1422–1432.

Verna R. Johnston, a. (1947). Breeding birds of the forest edge in illinois. *The Condor*, (2):45–53.

Vickery, P. D., Hunter, Jr., M. L., and Melvin, S. M. (1994). Effects of habitat area on the distribution of grassland birds in maine. *Conservation Biology*, (4):1087–1097.

Warman, L. D., Forsyth, D. M., Sinclair, A. R. E., Freemark, K., Moore, H. D., Barrett, T. W., Pressey, R. L., and White, D. (2004). Species distributions, surrogacy, and important conservation regions in canada. *Ecology Letters*, 7(5):374–379.

Washburn, B. E., Barnes, T. G., and Sole, J. D. (2000). Improving northern bobwhite habitat by converting tall fescue fields to native warm-season grasses. *Wildlife Society Bulletin*, 28:97–104.

Wells, K. M. S., Millspaugh, J. J., Ryan, M. R., and Hubbard, M. W. (2008). Factors affecting home range size and movements of post-fledging grassland birds. *The Wilson Journal of Ornithology*, (1):120–130.

Wesner, J. S. and Belk, M. C. (2012). Habitat relationships among biodiversity indicators and co-occurring species in a freshwater fish community. *Animal Conservation*, 15(5):445–456.

Whittingham, M. J. (2007). Will agri-environment schemes deliver substantial biodiversity gain, and if not why not? *Journal of Applied Ecology*, 44(1):1–5.

Wiens, J. A. (1969). An approach to the study of ecological relationships among grassland birds. *Ornithological Monographs*, (8):1–93.

Wiens, J. A. (1973). Pattern and process in grassland bird communities. *Ecological Monographs*, 43(2):237–270.

Wiens, J. A. (1989). Spatial scaling in ecology. *Functional Ecology*, 3(4):385–397.

Winter, M., Johnson, D. H., and Faaborg, J. (2000). Evidence for edge effects on multiple levels in tallgrass prairie. *The Condor*, 102(2):256–266.

Yeiser, J. M., Baxley, D. L., Robinson, B. A., and Morgan, J. J. (2015). Using prescribed fire and herbicide to manage rank native warm season grass for northern bobwhite. *Journal of Wildlife Management*, 79(1):69–76.

Zimmerman, J. L. (1984). Nest predation and its relationship to habitat and nest density in dickcissels. *The Condor*, 86(1):68–72.

APPENDICES

A.1 JAGS Model Code for Chapter 2

```
model{

#1 Priors
alpha0 ~ dnorm(0,0.01)
alpha1 ~ dnorm(0,0.01)
alpha2 ~ dnorm(0,0.01)
for(t in 1:T){ beta0[t] ~ dnorm(0,0.01) }
theta0 ~ dnorm(0,0.01)
theta2 ~ dnorm(0,0.01)
theta3 ~ dnorm(0,0.01)
iota ~ dnorm(0,0.01)
iota1 ~ dnorm(0,0.01)
iota2 ~ dnorm(0,0.01)
sigma_x ~ dunif(0,10000)
theta1 ~ dnorm(0, 0.01)
alpha3 ~ dnorm(0, 0.01)
r ~ dunif(0,5)
rout <- log(r)


#2 Linear constraints

#2.2 Initial abundance
for(i in 1:nsites){
log(lambda[i,1]) <- alpha0 + alpha1*crep0[i,1] + alpha2*crep.w[i
   ,1]  +
alpha3*(crep.w[i,1]*crep.w[i,1])
} #i

# 3. Likelihoods
for(i in 1:nsites){
```

```
#3.1 Abundance
prob[i,1] <- r/(r + lambda[i,1])
N[i,1] ~ dnegbin(prob[i,1], r)
y[i,1] ~ dbin(pCirc[1], N[i,1])
ydet[i,,1] ~ dmulti(pi[1:nBins,1], y[i,1])

# Pearson's residuals for model fit metric
Pres[i,1] <- (N[i,1]-lambda[i,1])/sqrt(lambda[i,1])
N.new[i,1] ~ dnegbin(prob[i,1],r)
Pres.new[i,1] <- (N.new[i,1]-lambda[i,1])/sqrt(lambda[i,1])
Pres2[i,1] <- pow(Pres[i,1], 2)
Pres.new2[i,1] <- pow(Pres.new[i,1], 2)

#3.2 Scale of effect of CREP on growth rate
for(u in 1:U[i]){
w0[i,u] <- exp(-D[i,u]^2 / (2*sigma_x^2))
}
which.min[i,1:U[i]] <- ifelse(D[i,1:U[i]] == min(D[i,1:U[i]]),
   0,1)
w0new[i,1:U[i]] <- w0[i,1:U[i]]*which.min[i,1:U[i]]
w[i,1:U[i]] <- w0new[i,1:U[i]]/sum(w0new[i,1:U[i]])

for(t in 1:T){
crep.w[i,t] <- sum(w[i,1:U[i]]*crepall[i,1:U[i],t] )
}

for(t in 2:T){
#3.2 Trend model
lam[i,t] <- N[i,t-1]*exp(theta0 + theta1*N[i,t-1] +
theta2*crep0[i,t] + theta3*crep.w[i,t]) + exp(iota + iota1*crep.w
   [i,t])
N[i,t] ~ dpois(lam[i,t])
y[i,t] ~ dbin(pCirc[t], N[i,t])
ydet[i,,t] ~ dmulti(pi[1:nBins,t], y[i,t])

# 3.2.1 Pearson's residuals for model fit metric
Pres[i,t] <- (N[i,t]-lam[i,t])/sqrt(lam[i,t])
N.new[i,t] ~ dpois(lam[i,t])
Pres.new[i,t] <- (N.new[i,t]-lam[i,t])/sqrt(lam[i,t])
Pres2[i,t] <- pow(Pres[i,t], 2)
Pres.new2[i,t] <- pow(Pres.new[i,t], 2)
} #t
```

```
} #i

#3.3 Detection probability
for(t in 1:T){
# Detection varies each year, but not among sites
log(sigma[t]) <- beta0[t]

for(k in 1:nBins){
p[k,t] <- (sigma[t]^2*(1-exp(-db[k+1]^2/(2*sigma[t]^2)))-sigma[t
   ]^2*
(1-exp(-db[k]^2/(2*sigma[t]^2))))*2*3.1416/(point.area*pix[k])
pi[k,t] <- p[k,t] *pix[k]

} #k

# Overall detection in sampling area (constant among sites)
pCirc[t] <- sum(pi[1:nBins,t])

} # t


#4. Derived parameters
# Total individuals each year, each species
for(t in 1:T){ N.tot.year[t] <- sum(N[,t])}

# Discrepancy measures
for(t in 1:T){
fit[t] <- sum(Pres2[,t])
fit.new[t] <- sum(Pres.new2[,t])
b_pvalue[t] <- step(fit.new[t] - fit[t])
}

##### Do this when running forecast models ####
#3.3 Detection probability
#for(t in 1:6){
# Detection varies each year, but not among sites
#log(sigma[t]) <- beta0[t]
#}

# Detection for years beyond our data is a random draw from
#normal distribution with a mean and sd
#of beta0 estimates from years with data
#m.beta0 <- mean(beta0[1:6])
```

```
#prec.beta0 <— 1/(sd(beta0[1:6])∗sd(beta0[1:6]))

#for(t in 7:T){
#beta0[t] ~ dnorm(m.beta0, prec.beta0)
#log(sigma[t]) <— beta0[t]
#}

#for(t in 1:T){
# Detection varies each year, but not among sites
#   for(k in 1:nBins){
#      p[k,t] <— (sigma[t]^2∗(1—exp(—db[k+1]^2/(2∗sigma[t]^2)))—
#          sigma[t]^2∗(1—exp(—db[k]^2/(2∗sigma[t]^2))))∗2∗3.1416/
#         (point.area∗pix[k])
#      pi[k,t] <— p[k,t] ∗pix[k]

#   } #k
#   pCirc[t] <— sum(pi[1:nBins,t])

#} # t
##### ////Do this for the forecasts ####

}
```

A.2 Using Google Earth Engine to Classify Land Cover

We used a supervised classification scheme to classify land cover in our study area. Generally, we followed the guidelines of (Lillesand et al., 2015). First, we trained each class by outlining areas on the Landsat images that were relatively homogeneous. We used SPOT-6, SPOT-7, and DigitalGlobe data to supplement the selection of training areas. We then used a random forest algorithm in Google Earth Engine (trained with pixels included in training areas) to classify the entire image. We tested the accuracy of the image as described in above in text. If accuracy was unsatisfactory, we started again with training areas and repeated the process as necessary.

```
//—————————— Extract Landsat Vegetation Indices
var year = 2012
```

```
var bound = ee.FeatureCollection("users/yeisjohn/
   StudyArea_Buffer5000m");
var crep = ee.FeatureCollection("users/yeisjohn/
   CRPCREPmerged5000m")
var imperv = ee.Image("users/yeisjohn/
   impervareas_tnroads_mosaic2_recode")
var compliance = ee.FeatureCollection("users/yeisjohn/
   ComplianceFields2016_WGS84")


// Load the Landsat ImageCollections
var L5collect = ee.ImageCollection(’LANDSAT/LT05/C01/T1_SR’);
//var L7collect = ee.ImageCollection(’LANDSAT/LE07/C01/T1_SR’);
var L8collect = ee.ImageCollection(’LANDSAT/LC08/C01/T1_SR’);


//−−−−−−−−−−−Make masked collections from periods of interest
// date is julian day, midpoint of 305 and 75 for example

var L5_filt_07 = filt_coll(L5collect,year,319,60).map(L5cldmask);
//var L7_filt_05 = filt_coll_nongrow(L7collect,year,305,75).map(
   L5cldmask);
var L8_filt_07 = filt_coll(L8collect,year,319,60).map(L8cldmask);

var L5_filt_166 = filt_coll(L5collect,year,121,212).map(L5cldmask
   );
var L8_filt_166 = filt_coll(L8collect,year,121,212).map(L8cldmask
   );

var L5_filt_250 = filt_coll(L5collect,year,227,273).map(L5cldmask
   );
var L8_filt_250 = filt_coll(L8collect,year,227,273).map(L8cldmask
   );

//−−−−−−−−−−−EVI bands
var L5_evi_07 = L5_filt_07.map(L5evi)
var L8_evi_07 = L8_filt_07.map(L8evi)

var evi_07_m1 = ee.ImageCollection(L5_evi_07)//.merge(L7_evi_05))
var evi_07 = ee.ImageCollection(evi_07_m1.merge(L8_evi_07)).mean
   ().float().clip(bound).set(’bname’,’evi_07’).rename(’evi_07’);
//Map.addLayer(evi_07, {min: −.1, max: 1, palette: [’blue’, ’
   green’, ’red’] }, ’evi_07’);
```

```
//print('evi_07', evi_07)

var L5_evi_166 = L5_filt_166.map(L5evi)
var L8_evi_166 = L8_filt_166.map(L8evi)

var evi_166_m1 = ee.ImageCollection(L5_evi_166)//.merge(L7_evi_05
   ))
var evi_166 = ee.ImageCollection(evi_166_m1.merge(L8_evi_166)).
   mean().float().clip(bound).set('bname','evi_166').rename('
   evi_166');
//Map.addLayer(evi_166, {min: −.1, max: 1, palette: ['blue', '
   green', 'red'] }, 'evi_166');


var L5_evi_250 = L5_filt_250.map(L5evi)
var L8_evi_250 = L8_filt_250.map(L8evi)

var evi_250_m1 = ee.ImageCollection(L5_evi_250)//.merge(L7_evi_05
   ))
var evi_250 = ee.ImageCollection(evi_250_m1.merge(L8_evi_250)).
   mean().float().clip(bound).set('bname','evi_250').rename('
   evi_250');
//Map.addLayer(evi_250, {min: −.1, max: 1, palette: ['blue', '
   green', 'red'] }, 'evi_250');

// Texture (sd) of evi
var evi_07_tex_sd = texture_sd(evi_07).rename('evi_07_tex_sd')
//Map.addLayer(evi_07_tex_sd,{min: 0, max: 0.1, palette: ['0000CC
   ', 'CC0000']},'evi_07_tex_sd');

var evi_166_tex_sd = texture_sd(evi_166).rename('evi_166_tex_sd')
//Map.addLayer(evi_166_tex_sd,{min: 0, max: 0.1, palette: ['0000
   CC', 'CC0000']},'evi_166_tex_sd');

var evi_250_tex_sd = texture_sd(evi_250).rename('evi_250_tex_sd')
//Map.addLayer(evi_250_tex_sd,{min: 0, max: 0.1, palette: ['0000
   CC', 'CC0000']},'evi_250_tex_sd');

//———————————NBR bands
var L5_nbr_07 = L5_filt_07.map(L5nbr)
//var L7_nbr_05 = L7_filt_05.map(L5nbr)
var L8_nbr_07 = L8_filt_07.map(L8nbr)
```

```
var nbr_07_m1 = ee.ImageCollection(L5_nbr_07)//.merge(L7_nbr_05))
var nbr_07 = ee.ImageCollection(nbr_07_m1.merge(L8_nbr_07)).mean
   ().float().clip(bound).set('bname','nbr_07').rename('nbr_07');
//Map.addLayer(nbr_07, {min: -.1, max: 1, palette: ['gray', '
   purple', 'brown'] }, 'nbr_07');

var L5_nbr_166 = L5_filt_166.map(L5nbr)
var L8_nbr_166 = L8_filt_166.map(L8nbr)

var nbr_166_m1 = ee.ImageCollection(L5_nbr_166)//.merge(L7_nbr_05
   ))
var nbr_166 = ee.ImageCollection(nbr_166_m1.merge(L8_nbr_166)).
   mean().float().clip(bound).set('bname','nbr_166').rename('
   nbr_166');
//Map.addLayer(nbr_166, {min: -.1, max: 1, palette: ['gray', '
   purple', 'brown'] }, 'nbr_166');

var L5_nbr_250 = L5_filt_250.map(L5nbr)
var L8_nbr_250 = L8_filt_250.map(L8nbr)

var nbr_250_m1 = ee.ImageCollection(L5_nbr_250)//.merge(L7_nbr_05
   ))
var nbr_250 = ee.ImageCollection(nbr_250_m1.merge(L8_nbr_250)).
   mean().float().clip(bound).set('bname','nbr_250').rename('
   nbr_250');
//Map.addLayer(nbr_250, {min: -.1, max: 1, palette: ['gray', '
   purple', 'brown'] }, 'nbr_250');

// Texture (sd) of nbr
var nbr_07_tex_sd = texture_sd(nbr_07).rename('nbr_07_tex_sd')
//Map.addLayer(nbr_07_tex_sd,{min: 0, max: 0.1, palette: ['0000CC
   ', 'CC0000']},'nbr_07_tex_sd');

var nbr_166_tex_sd = texture_sd(nbr_166).rename('nbr_166_tex_sd')
//Map.addLayer(nbr_166_tex_sd,{min: 0, max: 0.1, palette: ['0000
   CC', 'CC0000']},'nbr_166_tex_sd');

var nbr_250_tex_sd = texture_sd(nbr_250).rename('nbr_250_tex_sd')
//Map.addLayer(nbr_250_tex_sd,{min: 0, max: 0.1, palette: ['0000
   CC', 'CC0000']},'nbr_250_tex_sd');

//------------NBR2 bands
var L5_nbr2_07 = L5_filt_07.map(L5nbr2)
```

```
//var L7_nbr2_05 = L7_filt_05.map(L5nbr2)
var L8_nbr2_07 = L8_filt_07.map(L8nbr2)

var nbr2_07_m1 = ee.ImageCollection(L5_nbr2_07)//.merge(
   L7_nbr2_05))
var nbr2_07 = ee.ImageCollection(nbr2_07_m1.merge(L8_nbr2_07)).
   mean().float().clip(bound).set(’bname’,’nbr2_07’).rename(’
   nbr2_07’);
//Map.addLayer(nbr2_07, {min: −.1, max: 1, palette: [’blue’, ’
   yellow’, ’pink’] }, ’nbr2_07’);

var L5_nbr2_166 = L5_filt_166.map(L5nbr2)
var L8_nbr2_166 = L8_filt_166.map(L8nbr2)

var nbr2_166_m1 = ee.ImageCollection(L5_nbr2_166)//.merge(
   L7_nbr2_05))
var nbr2_166 = ee.ImageCollection(nbr2_166_m1.merge(L8_nbr2_166))
   .mean().float().clip(bound).set(’bname’,’nbr2_166’).rename(’
   nbr2_166’);
//Map.addLayer(nbr2_166, {min: −.1, max: 1, palette: [’blue’, ’
   yellow’, ’pink’] }, ’nbr2_166’);

var L5_nbr2_250 = L5_filt_250.map(L5nbr2)
var L8_nbr2_250 = L8_filt_250.map(L8nbr2)

var nbr2_250_m1 = ee.ImageCollection(L5_nbr2_250)//.merge(
   L7_nbr2_05))
var nbr2_250 = ee.ImageCollection(nbr2_250_m1.merge(L8_nbr2_250))
   .mean().float().clip(bound).set(’bname’,’nbr2_250’).rename(’
   nbr2_250’);
//Map.addLayer(nbr2_250, {min: −.1, max: 1, palette: [’blue’, ’
   yellow’, ’pink’] }, ’nbr2_250’);


// Texture (sd) of nbr2
var nbr2_07_tex_sd = texture_sd(nbr2_07).rename(’nbr2_07_tex_sd’)
//Map.addLayer(nbr2_07_tex_sd,{min: 0, max: 0.1, palette: [’0000
   CC’, ’CC0000’]},’nbr2_07_tex_sd’);

var nbr2_166_tex_sd = texture_sd(nbr_166).rename(’nbr2_166_tex_sd
   ’)
//Map.addLayer(nbr_166_tex_sd,{min: 0, max: 0.1, palette: [’0000
   CC’, ’CC0000’]},’nbr2_166_tex_sd’);
```

```
var nbr2_250_tex_sd = texture_sd(nbr_250).rename(’nbr2_250_tex_sd
   ’)
//Map.addLayer(nbr_250_tex_sd,{min: 0, max: 0.1, palette: [’0000
   CC’, ’CC0000’]},’nbr2_250_tex_sd’);

//------------Compute the seasonal differences
var evi_diff_166_07 = evi_166.subtract(evi_07).float().rename(’
   evi_diff_166_07’);
var evi_diff_166_250 = evi_166.subtract(evi_250).float().rename(’
   evi_diff_166_250’);
var evi_diff_tex_sd_166_07 = evi_166_tex_sd.subtract(
   evi_07_tex_sd).float().rename(’evi_diff_tex_sd_166_07’);
var evi_diff_tex_sd_166_250 = evi_166_tex_sd.subtract(
   evi_250_tex_sd).float().rename(’evi_diff_tex_sd_166_250’);



var nbr_diff_166_07 = nbr_166.subtract(nbr_07).float().rename(’
   nbr_diff_166_07’);
var nbr_diff_166_250 = nbr_166.subtract(nbr_250).float().rename(’
   nbr_diff_166_250’);
var nbr_diff_tex_sd_166_07 = nbr_166_tex_sd.subtract(
   nbr_07_tex_sd).float().rename(’nbr_diff_tex_sd_166_07’);
var nbr_diff_tex_sd_166_250 = nbr_166_tex_sd.subtract(
   nbr_250_tex_sd).float().rename(’nbr_diff_tex_sd_166_250’);
//Map.addLayer(nbr_diff_166_07,{min: −0.5, max: 1, palette:
   [’0000CC’, ’CC0000’]},’nbr_diff_166_07’);

var nbr2_diff_166_07 = nbr2_166.subtract(nbr2_07).float().rename
   (’nbr2_diff_166_07’);
var nbr2_diff_166_250 = nbr2_166.subtract(nbr2_250).float().
   rename(’nbr2_diff_166_250’);
var nbr2_diff_tex_sd_166_07 = nbr2_166_tex_sd.subtract(
   nbr2_07_tex_sd).float().rename(’nbr2_diff_tex_sd_166_07’);
var nbr2_diff_tex_sd_166_250 = nbr2_166_tex_sd.subtract(
   nbr2_250_tex_sd).float().rename(’nbr2_diff_tex_sd_166_250’);

//------------Image classification

//Stupid functions to add classes to all features of
   featurecollection
var addClass_dec = function(feature) {
```

```
return feature.set('class', 1);
};
var addClass_eve = function(feature) {
return feature.set('class', 2);
};
var addClass_fhp = function(feature) {
return feature.set('class', 3);
};
var addClass_gra = function(feature) {
return feature.set('class', 4);
};
var addClass_wat = function(feature) {
return feature.set('class', 5);
};
var addClass_row = function(feature) {
return feature.set('class', 6);
};
var addClass_urb = function(feature) {
return feature.set('class', 7);
};
var addClass_urbline = function(feature) {
return feature.set('class', 7);
};
// Load training areas
var dec = ee.FeatureCollection("users/yeisjohn/deciduous_training
   ");
var dec = dec.map(addClass_dec)
var eve = ee.FeatureCollection("users/yeisjohn/evergreen_training
   ");
var eve = eve.map(addClass_eve);
var fhp = ee.FeatureCollection("users/yeisjohn/
   fescuehaypasture_training2");
var fhp = fhp.map(addClass_fhp);
var gra = ee.FeatureCollection("users/yeisjohn/
   grassland_training3");
var gra = gra.map(addClass_gra);
var wat = ee.FeatureCollection("users/yeisjohn/openwater_training
   ");
var wat = wat.map(addClass_wat);
var row = ee.FeatureCollection("users/yeisjohn/rowcrop_training2
   ");
var row = row.map(addClass_row);
var urb = ee.FeatureCollection("users/yeisjohn/urban_training2");
```

```
var urb = urb.map(addClass_urb);
var urbline = ee.FeatureCollection("users/yeisjohn/
   urban_training2_lines");
var urbline = urb.map(addClass_urbline);


var urb_2 = ee.FeatureCollection(urb2)
var urb_2 = urb_2.map(addClass_urb);
print(urb_2, ’urb_2:’)

// Merge polygons together
var allTraining = dec.merge(eve).merge(fhp).merge(gra).merge(wat)
   .merge(row).merge(urb).merge(urbline).merge(urb_2);
//print(allTraining, ’allTraining: ’)

// Select the bands to be used in training
var bands = [’evi_07’,’evi_07_tex_sd’,
’evi_166’,’evi_166_tex_sd’, ’evi_250’, ’evi_250_tex_sd’,
’evi_diff_166_07’, ’evi_diff_166_250’ ,’evi_diff_tex_sd_166_07’ ,
’evi_diff_tex_sd_166_250’,’nbr2_07’,’nbr2_07_tex_sd’,’nbr2_166’,
’nbr2_166_tex_sd’,’nbr2_250’,’nbr2_250_tex_sd’,’nbr2_diff_166_07
   ’,
’nbr2_diff_166_250’,’nbr2_diff_tex_sd_166_07’,
’nbr2_diff_tex_sd_166_250’,’nbr_07’,’nbr_07_tex_sd’,’nbr_166’,
’nbr_166_tex_sd’,’nbr_250’,’nbr_250_tex_sd’,’nbr_diff_166_07’,
’nbr_diff_166_250’,’nbr_diff_tex_sd_166_07’,’
   nbr_diff_tex_sd_166_250’];

// Image to be classified
var finalImage = ee.Image.cat([evi_07,evi_07_tex_sd,
evi_166,evi_166_tex_sd,evi_250,evi_250_tex_sd,
evi_diff_166_07,evi_diff_166_250,evi_diff_tex_sd_166_07,
evi_diff_tex_sd_166_250,nbr2_07,nbr2_07_tex_sd,nbr2_166,
nbr2_166_tex_sd,nbr2_250,nbr2_250_tex_sd,nbr2_diff_166_07,
nbr2_diff_166_250,nbr2_diff_tex_sd_166_07,
nbr2_diff_tex_sd_166_250,nbr_07,nbr_07_tex_sd,nbr_166,
nbr_166_tex_sd,nbr_250,nbr_250_tex_sd,nbr_diff_166_07,
nbr_diff_166_250,nbr_diff_tex_sd_166_07,nbr_diff_tex_sd_166_250])
   ;
//print("finalImage: ", finalImage)

var train = finalImage.sampleRegions({
collection: allTraining,
```

```
properties: ['class'],
scale: 30  // should reflect the scale of your imagery
});
//print('train: ', train.limit(5))

// Make a classifier and train it.
// for analysis: 128 trees
var classifier = ee.Classifier.randomForest(400).train({
classProperty: 'class',
features: train,
inputProperties: bands
});


// Classify the input imagery.
var classified = finalImage.classify(classifier);
//print("classified", classified)

// Define a palette for the Land Use classification.
var palette = [
'75F311', // deciduous
'0AA940', // evergreen
'F7F8E4', //  fescue/hay/pasture
'B45F48', //  grassland
'29ACE9', //  open water
'E4DA0D', //  rowcrop
'2F2E2E', //  urban

];

print(compliance, 'compliance')
var class_comp = classified.sampleRegions({
collection: compliance,
//  properties: ['class'],
scale: 30  // should reflect the scale of your imagery
});

var class_crep = classified.sampleRegions({
collection: crep,
//  properties: ['class'],
scale: 30  // should reflect the scale of your imagery
})
```

```
//Decided not to go with road burn, overall accuracy was lower
var classified_rb = roadburn(imperv, classified)




//—————————— Export classified image to google drive

ExGdrive(classified,"ClassifiedImage_RanFor400_20180123");

//Simplified export function
function ExGdrive(im,name){
Export.image.toDrive({
image: im,
description: name,
scale: 10,
region: bound,
maxPixels: 20000000000,
folder: "GEE",
});
}

//function to filter a collection by year and doy range, for non—
   growing season
function filt_coll(coll,year,sdoy,edoy){
var filt = coll
.filterBounds(bound)
.filterDate(String(year—2)+'—01—01',String(year+3)+'—12—31')
.filter(ee.Filter.dayOfYear(sdoy,edoy))
.filter(ee.Filter.lt('CLOUD_COVER_LAND',50));
return filt
}

// L5 cloudMask function
function L5cldmask(im) {
var tmask1 = ee.Image(0).where(im.select('pixel_qa').eq(66), 1);
var tmask2 = ee.Image(0).where(im.select('pixel_qa').eq(130), 1);
var twat1 = ee.Image(0).where(im.select('pixel_qa').eq(68), 1);
var twat2 = ee.Image(0).where(im.select('pixel_qa').eq(132), 1);
var tmask3 = ee.Image(0).where(im.select('radsat_qa').eq(0), 1);
var mask = tmask1.add(tmask2).add(twat1).add(twat2).multiply(
   tmask3);
return im.updateMask(mask);
```

```
}


// L8 cloudMask function
function L8cldmask(im) {
var tmask1 = ee.Image(0).where(im.select('pixel_qa').eq(322), 1);
var tmask2 = ee.Image(0).where(im.select('pixel_qa').eq(386), 1);
var twat1 = ee.Image(0).where(im.select('pixel_qa').eq(324), 1);
var twat2 = ee.Image(0).where(im.select('pixel_qa').eq(388), 1);
var tmask3 = ee.Image(0).where(im.select('radsat_qa').eq(0), 1);
var mask = tmask1.add(tmask2).add(twat1).add(twat2).multiply(
   tmask3);
return im.updateMask(mask);
}


// Function to compute EVI for landsat5
function L5evi(im) {
var tevi = ee.Image(
im.expression('2.5 *(B4 - B3) / (B4 + 6.0*B3 - 7.5*B1 + 1.0)', {
'B4': im.select('B4').divide(10000),
'B3': im.select('B3').divide(10000),
'B1': im.select('B1').divide(10000)
})).set('system:time_start', im.get('system:time_start')).rename
   ('EVI');

var tmask1 = ee.Image(0).where(tevi.gte(-1.0), 1);
var tmask2 = ee.Image(0).where(tevi.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tevi.updateMask(mask);
}


// Function to compute EVI for landsat8
function L8evi(im) {
var tevi = ee.Image(
im.expression('2.5 * ((NIR - RED) / (NIR + 6 * RED - 7.5 * BLUE +
    1))', {
'NIR': im.select('B5').divide(10000),
'RED': im.select('B4').divide(10000),
'BLUE': im.select('B2').divide(10000)
})).set('system:time_start', im.get('system:time_start')).rename
   ('EVI');
```

```
var tmask1 = ee.Image(0).where(tevi.gte(−1.0), 1);
var tmask2 = ee.Image(0).where(tevi.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tevi.updateMask(mask);
}


// Function to compute NBR for landsat5
function L5nbr(im) {
var tnbr = ee.Image(
im.expression('(B4 − B7) / (B4 + B7)', {
'B4': im.select('B4').divide(10000),
'B7': im.select('B7').divide(10000),
})).set('system:time_start', im.get('system:time_start')).rename
   ('NBR');

var tmask1 = ee.Image(0).where(tnbr.gte(−1.0), 1);
var tmask2 = ee.Image(0).where(tnbr.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tnbr.updateMask(mask);
}

// Function to compute NBR for landsat8
function L8nbr(im) {
var tnbr = ee.Image(
im.expression('(B5 − B7) / (B5 + B7)', {
'B5': im.select('B5').divide(10000),
'B7': im.select('B7').divide(10000),
})).set('system:time_start', im.get('system:time_start')).rename
   ('NBR');

var tmask1 = ee.Image(0).where(tnbr.gte(−1.0), 1);
var tmask2 = ee.Image(0).where(tnbr.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tnbr.updateMask(mask);
}


// Function to compute NBR2 for landsat5
function L5nbr2(im) {
var tnbr2 = ee.Image(
im.expression('(B5 − B7) / (B5 + B7)', {
```

```
’B5’: im.select(’B5’).divide(10000),
’B7’: im.select(’B7’).divide(10000),
})).set(’system:time_start’, im.get(’system:time_start’)).rename
   (’NBR2’);

var tmask1 = ee.Image(0).where(tnbr2.gte(−1.0), 1);
var tmask2 = ee.Image(0).where(tnbr2.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tnbr2.updateMask(mask);
}


// Function to compute NBR2 for landsat8
function L8nbr2(im) {
var tnbr2 = ee.Image(
im.expression(’(B6 − B7) / (B6 + B7)’, {
’B6’: im.select(’B6’).divide(10000),
’B7’: im.select(’B7’).divide(10000),
})).set(’system:time_start’, im.get(’system:time_start’)).rename
   (’NBR2’);

var tmask1 = ee.Image(0).where(tnbr2.gte(−1.0), 1);
var tmask2 = ee.Image(0).where(tnbr2.lte(1.0), 1);
var mask = tmask1.multiply(tmask2);
return tnbr2.updateMask(mask);
}

// Function to compute texture (sd)
// Compute standard deviation (SD) as texture of the NDVI.
function texture_sd(im) {
var tsd = im.reduceNeighborhood({
reducer: ee.Reducer.stdDev(),
kernel: ee.Kernel.square(3),
});
return tsd
}


// function to burn in roads
function roadburn(im, im2) {
var tmask1 = im2.where(im.select(’b1’).eq(1), 7);
return tmask1;
}
```

A.3 User-defined Functions to Calculate Landscape Metrics

Functions that calculate mean patch area or adjacency are based on functions from the SDMTools package in R, which is based on functions used in FRAGSTATS.
Function to calculate all landscape metrics for a given species:

```
fun.LandscapeMetrics <- function(x, fac, cellside, spcode) {

require(raster)
require(vegan)
require(caret)
require(Hmisc)
require(SDMTools)
require(rgdal)
prop1 <- aggregate(x ==1 | x==2, fac=fac, fun=mean)
prop3 <- aggregate(x ==3,fac=fac, fun=mean)
prop4 <- aggregate(x ==4,fac=fac, fun=mean)
prop5 <- aggregate(x ==5,fac=fac, fun=mean)
prop6 <- aggregate(x ==6,fac=fac, fun=mean)
prop7 <- aggregate(x ==7,fac=fac, fun=mean)

mpa4 <- aggregate(x ==4,fac=fac, fun=function(x,...){
        fun.MeanArea(x, cellside, na.rm=na.rm))
}

gadjf <- aggregate(x,fac=fac, fun=function(x,...) fun.GrassForAdj
   (x, cellside) )
rcadjg <- aggregate(x,fac=fac, fun=function(x,...) fun.RCAdjGrass
   (x, cellside) )
fadjfph <- aggregate(x,fac=fac, fun=function(x,...) fun.ForFPHAdj
   (x, cellside) )
fadjrc <- aggregate(x,fac=fac, fun=function(x,...) fun.
   ForRowCropAdj(x, cellside) )

mpa1 <- aggregate(x ==1 | x==2,fac=fac, fun=function(x,...)
fun.MeanArea(x, cellside, na.rm=na.rm))
mpa3 <- aggregate(x ==3,fac=fac, fun=function(x,...)
fun.MeanArea(x, cellside, na.rm=na.rm))
mpa5 <- aggregate(x ==5,fac=fac, fun=function(x,...) fun.MeanArea
   (x, cellside,
na.rm=na.rm))
```

```
mpa6 <- aggregate(x ==6,fac=fac, fun=function(x,...) fun.MeanArea
   (x, cellside,
na.rm=na.rm))
mpa7 <- aggregate(x ==7,fac=fac, fun=function(x,...) fun.MeanArea
   (x, cellside,
na.rm=na.rm))
mpa_allmat <- cbind(getValues(mpa1),getValues(mpa3),getValues(
   mpa4),
getValues(mpa5), getValues(mpa6), getValues(mpa7))
mpa_allmat2 <- apply(mpa_allmat, 1, function(x) mean(x, na.rm=T))
mpa_all <- rasterFromXYZ(data.frame(x=coordinates(mpa1)[,1],
y=coordinates(mpa1)[,2], z= mpa_allmat2))

SHDI <- aggregate(x,fac=fac, fun=function(x,...) diversity(table(
   x),
+ index="shannon"))

stackras <- stack(fadjfph, fadjrc, gadjf, mpa_all, mpa4, prop7,
   prop1, prop3,
prop4, prop5, prop6, rcadjg, SHDI)
writeRaster(stackras, paste("CovariateStack_", spcode, ".tif",
   sep=''),
format='GTiff', overwrite=TRUE)
}
```

Specific functions

```
# Function to calculate mean patch size

fun.MeanArea <- function(x,cellside,...){
require(SDMTools)
x = try(as.matrix(x))
if (!is.matrix(x))
stop("objects must be a matrix")
if(sum(x, na.rm=T)==0) return(0)
if(all(x[!is.na(x)]==1)) return(sum(!is.na(x))*cellside^2)
x = ConnCompLabel(x)
patchIDs = as.numeric(na.omit(unique(as.vector(x))))
# Not interested in 0s
patchIDs = patchIDs[order(patchIDs)][-which(patchIDs[order(
   patchIDs)]==0)]
# This is a catch error -- if there's only the value of interest,
    and no zeroes,
# continue. If only zeroes, return zero
```

```
#if(1 %in% x & length(patchIDs)<1) return(0)
tmp <- NULL
for(j in 1:length(patchIDs)){
tmp[j] <- sum(as.numeric(na.omit(as.vector(x)))==patchIDs[j])*
   cellside^2

}
# just want mean area, also eliminate first row ('zero' patches)
return(mean(tmp, na.rm=T))
}

# Function to find adjacencies of forest and grassland cells,
   when forest == 1 or 2
# and grassland == 4.
fun.GrassForAdj <- function(x,cellside){
x = try(as.matrix(x))
if (!is.matrix(x))
stop("objects must be a matrix")
if(all(x[!is.na(x)]==4)) return(0)
if(all(x[!is.na(x)]==1 | x[!is.na(x)]==2)) return(0)

n_4adjto1 <- length(adjacent(x, cells=which(x==1 | x==2), target=
   which(x==4),
directions=8, pairs=F, sorted=TRUE, include=F))*cellside
return(n_4adjto1)
}

# Function to find adjacencies of forest and grassland cells,
   when forest == 1 or 2
and grassland == 4.
fun.RCAdjGrass <- function(x, cellside){
x = try(as.matrix(x))
if (!is.matrix(x))
stop("objects must be a matrix")
if(all(x[!is.na(x)]==4)) return(0)
if(all(x[!is.na(x)]==6)) return(0)

# Currently calculating distance in meters.
n_6adjto4 <- length(adjacent(x, cells=which(x==4), target=which(x
   ==6), directions=8,
pairs=F, sorted=TRUE, include=F))*cellside
return(n_6adjto4)
```

```
}


# Function to find adjacencies of forest and open cells, when
   forest == 1 or 2
and open == 3
fun.ForFPHAdj <- function(x, cellside){
x = try(as.matrix(x))
if (!is.matrix(x))
stop("objects must be a matrix")
if(all(x[!is.na(x)]==1 | x[!is.na(x)]==2)) return(0)
if(all(x[!is.na(x)]==3)) return(0)

n_1adjtoOpen <- length(adjacent(x, cells=which(x==3), target=
   which(x==1 | x==2),
directions=8, pairs=F, sorted=TRUE, include=F))*cellside
return(n_1adjtoOpen)
}

# Function to find adjacencies of forest and rowcrop cells, when
   forest == 1 or 2
and rowcrop == 6.
fun.ForRowCropAdj <- function(x, cellside){
x = try(as.matrix(x))
if (!is.matrix(x))
stop("objects must be a matrix")
if(all(x[!is.na(x)]==1 | x[!is.na(x)]==2)) return(0)
if(all(x[!is.na(x)]==6)) return(0)

n_1adjto6 <- length(adjacent(x, cells=which(x==6), target=which(x
   ==1 | x==2),
directions=8, pairs=F, sorted=TRUE, include=F))*cellside
return(n_1adjto6)
}
```

Validation. Class 1 (and 2) = Forest, Class 3 = Fescue Pasture/Hay, Class 4 = Grassland, Class 5 = Open Water, Class 6 = Row Crop, Class 7 = Developed

```
Confusion Matrix and Statistics

Reference
Prediction   1   3   4   5   6   7
1 227  12  11   7   0   4
3   8  85   2   1   9   2
4  16  25  18   1   4   5
5   3   0   0  49   0   0
6   3  17   5   0  69   6
7   2   5   2   0   1  12
```

```
Overall Statistics

Accuracy : 0.7529
95% CI : (0.7167, 0.7866)
No Information Rate : 0.4239
P—Value [Acc > NIR] : < 2.2e—16

Kappa : 0.6654
Mcnemar’s Test P—Value : NA

Statistics by Class:

                   Class: 1  Class: 3  Class: 4  Class: 5  Class: 6  Class: 7
Sensitivity           0.8764   0.5903  0.47368  0.84483   0.8313  0.41379
Specificity           0.9034   0.9529  0.91099  0.99458   0.9413  0.98282
Pos Pred Value        0.8697   0.7944  0.26087  0.94231   0.6900  0.54545
Neg Pred Value        0.9086   0.8829  0.96310  0.98390   0.9726  0.97114
Precision             0.8697   0.7944  0.26087  0.94231   0.6900  0.54545
Recall                0.8764   0.5903  0.47368  0.84483   0.8313  0.41379
F1                    0.8731   0.6773  0.33645  0.89091   0.7541  0.47059
Prevalence            0.4239   0.2357  0.06219  0.09493   0.1358  0.04746
Detection Rate        0.3715   0.1391  0.02946  0.08020   0.1129  0.01964
Detection Prevalence  0.4272   0.1751  0.11293  0.08511   0.1637  0.03601
Balanced Accuracy     0.8899   0.7716  0.69234  0.91970   0.8863  0.69831
```

A.4 JAGS Model Code for Chapter 3

```
model{

#1. Priors
psinobo ~ dunif(0,1)
beta0nobo ~ dunif(—10,10)
for(n in 1:ncov){
thetaLnobo[n] ~ dunif(—10,10)
}
theta0nobo ~ dunif(—10,10)
theta1nobo ~ dunif(—10,10)
kappa0nobo ~ dunif(—10,10)
kappa1nobo ~ dunif(—10,10)
sigma_cov_nobo ~ dunif(0,12)
for(t in 1:nyears){
sigmanobo[t] ~ dunif(0,10)
}
r ~ dunif(0,5)
rout <— log(r)

for(i in 1:nsites){
#ZIP
suit[i] ~ dbern(psinobo)

#3.1 Process model for abundance year 1
lambda[i,1] <— exp(beta0nobo)

prob[i,1] <— r/(r + lambda[i,1]*suit[i])
N[i,1] ~ dnegbin(prob[i,1], r)
#N[i,1] ~ dpois(lambda[i,1]*suit[i])

# PearsonâĂŹs residuals for model fit metric
Pres[i,1] <— (N[i,1]—lambda[i,1])/sqrt(lambda[i,1]+0.001)
N.new[i,1] ~ dnegbin(prob[i,1],r)
Pres.new[i,1] <— (N.new[i,1]—lambda[i,1])/sqrt(lambda[i,1]+0.001)
Pres2[i,1] <— pow(Pres[i,1], 2)
Pres.new2[i,1] <— pow(Pres.new[i,1], 2)
```

```
#3.2 Process model for abundance years 2...T
for(t in 2:nyears){
# If site went extinct in year t−1, flip the switch
# step = 1 if statement is >= to 0
switch[i,t] <− step(N[i,t−1]−1)

# If switch is off, estimate the expected amount of colonizers, given
# that the site is now occupied in year t
# If switch is on (site did not go extinct in year t−1),
# estimate growth rate

lambda[i,t] <− (1−switch[i,t])*exp(kappa0nobo +
kappa1nobo*Nmat_land.w[i,t−1])
+ (switch[i,t])*N[i,t−1]*exp(theta0nobo + theta1nobo*N[i,t−1] +
thetaLnobo[1]*covmat_land.w[i,1] + thetaLnobo[2]*covmat_land.w[i,2] +
thetaLnobo[3]*covmat_land.w[i,3]+ thetaLnobo[4]*covmat_land.w[i,4] +
thetaLnobo[5]*covmat_land.w[i,5]+ thetaLnobo[6]*covmat_land.w[i,6] +
thetaLnobo[7]*covmat_land.w[i,7] + thetaLnobo[8]*covmat_land.w[i,8] +
thetaLnobo[9]*covmat_land.w[i,9])

N[i,t] ~ dpois(lambda[i,t]*suit[i])

# Discrepancy
# 5.2 PearsonâĂŹs residuals for model fit metric
Pres[i,t] <− (N[i,t]−lambda[i,t])/sqrt(lambda[i,t]+0.001)
N.new[i,t] ~ dpois(lambda[i,t])
Pres.new[i,t] <− (N.new[i,t]−lambda[i,t])/sqrt(lambda[i,t]+0.001)
Pres2[i,t] <− pow(Pres[i,t], 2)
Pres.new2[i,t] <− pow(Pres.new[i,t], 2)
} #t

# 3.3 Scale of effect

for(u in 1:U[i]){
w0[i,u] <− exp(−D[i,u]^2 / (2*sigma_cov_nobo^2))
} #u
w[i,1:U[i]] <− w0[i,1:U[i]]/sum(w0[i,1:U[i]])

for(v in 1:ncov){
covmat_land.w[i,v] <− sum(w[i,1:U[i]]*covmat_land[i,1:U[i],v] )
}
for(t in 2:nyears){
for(u in 1:sU[i]){
wN[i,u,t−1] <− exp(−sD[i,u]^2 / (2*sigma_cov_nobo^2))
}
Nmat_land.w[i,t−1] <− sum(wN[i,1:sU[i],t−1]*N[sID[i,1:sU[i]],t−1])
}

#4.2 Observation process for abundance
for(t in 1:nyears){
y[i,t] ~ dbin(pCirc[t], N[i,t])
ydet[i,1:nBins,t] ~ dmulti(pi[1:nBins,t], y[i,t])
} # t
} #i


for(t in 1:nyears){
for(k in 1:nBins){
pr[k,t] <−
(exp(sigmanobo[t])^2*(1−exp(−db[k+1]^2/(2*exp(sigmanobo[t])^2)))−
exp(sigmanobo[t])^2*(1−exp(−db[k]^2/(2*exp(sigmanobo[t])^2))))*2*3.1416
/(point.area*pix[k])
pi[k,t] <− pr[k,t]*pix[k]
} #k
```

```
pCirc[t] <— sum(pi[1:nBins,t])
}#t

#5. Derived parameters
####

#5.1 Total occupied sites, population size, each species
for(t in 1:nyears){

Ntot[t] <— sum(N[,t])

# for(i in 1:nsites){
#     # Discrepancy
#     # 5.2 PearsonâĂŹs residuals for model fit metric
#     Pres[i,t] <— (N[i,t]—lambda[i,t])/sqrt(lambda[i,t]+0.001)
#     N.new[i,t] ~ dpois(lambda[i,t])
#     Pres.new[i,t] <— (N.new[i,t]—lambda[i,t])/sqrt(lambda[i,t]+0.001)
#     Pres2[i,t] <— pow(Pres[i,t], 2)
#     Pres.new2[i,t] <— pow(Pres.new[i,t], 2)
# }


fit[t] <— sum(Pres2[,t])
fit.new[t] <— sum(Pres.new2[,t])
b_pvalue[t] <— step(fit.new[t] — fit[t])
} #t
}
```

A.5 Spatial autocorrelation in woody cover and mowing

Below are figures describing spatial autocorrelation in mowing and woody cover measured by both observers. In each figure, there is no indication of spatial autocorrelation because semivariance (dissimilarity among measurements at sites) has a linear relationship with distance. There is no range (i.e., distance at which semivariance plateaus) and no sill (semivariance value at which semivariance plateaus). Additionally, there is a large nugget (i.e., y-intercept), indicating a relatively high degree of dissimilarity even among close-by sites.

A.6 Using Simulation to Determine Sample Size

Farm Bill biologists flew over the Kentucky CREP area on November 1–2 2012 to estimate compliance. Observers estimated whether or not a field was in compliance and then stated the reason why. We wanted to use information from the initial round of flights to inform sample size for the flights of 2016. We used a simulation-based approach. Estimates from a model of pilot data were used to simulate 20,000 data sets with different numbers of sampled fields within counties (1-20). For each simulated data set we used AIC to compare whether a model with a county effect was better supported than a null model.

```
#b0 are effects from pilot data
niter <— 1000
k <— length(levels(pilot.dat$GisCountyName))

#Simulation function
nc.powersim.fun <— function(beta, n, k){

# New beta values predicted at each site, based on sample size within each group
new.pred <— matrix(rep(beta[1:k], n))

#Design matrix

modmat <— array(dim = c(length(new.pred),length(beta)))
colnames(modmat) <— names(beta)
modmat[,1] <— rep(1, nrow(modmat))
for(i in 2:k—1){
```

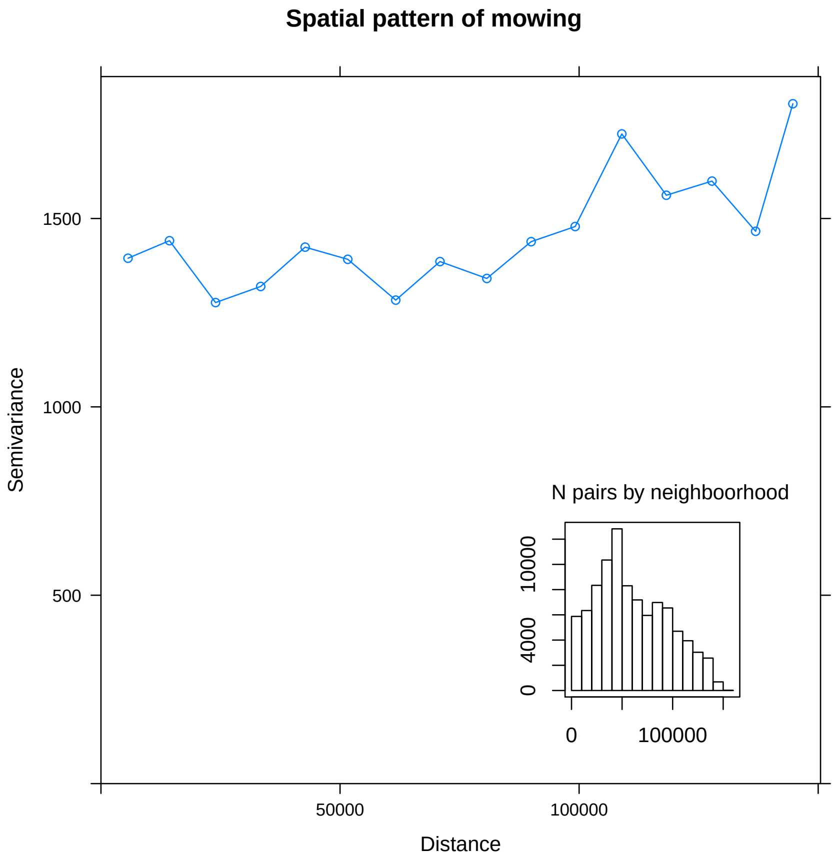

Spatial pattern of mowing

Figure A.1: Spatial autocorrelation in mowing based on measurements from observer 1.

```
modmat[,i] <− c(rep(0, n∗(i−1)), rep(1,n), rep(0,nrow(modmat)−(n∗(i−1)+n)))
}
modmat[,k] <− c(rep(0, (n∗k)−n), rep(1,n))
for(i in (k+1):length(beta)){
modmat[,i] <− rep(1, n)
}
# Linear predictions for each field, based on design matrix and beta
lin.pred <− modmat%∗%beta

#link function
p <− plogis(lin.pred)

# Simulate response based on p
resp <− rbinom(n∗k, 1, p)

simdat <− data.frame(modmat, resp)

# No information other than county effects...
fit1 <− glm(resp ~ modmat[,−c(1,13:19)], data= simdat,family=binomial)
fit2 <− update(fit1, resp~1 )
modsel <−  fit2$aic − fit1$aic

return(modsel)
```

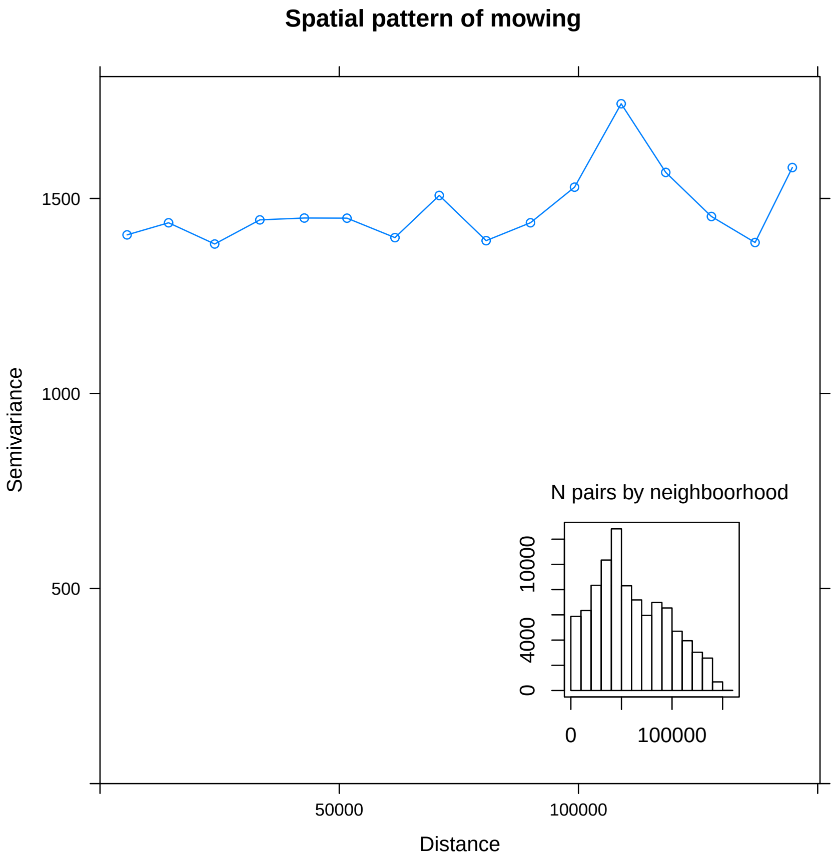


Figure A.2: Spatial autocorrelation in mowing based on measurements from observer 2.

```
}

# Results
# Function that calls modsel values from nc.powersim.fun then determines amount of support for
    that model based on AIC values. These are summarized and plotted (check working drive)
power.sim.out <- function(niter, beta, nsam, k){
out <- list()
top <- list()
substantial <- list()
less <- list()
none <- list()
pb <- txtProgressBar(min=0, max=nsam, style=3)

for(i in 1:nsam){
out[i] <- list(replicate(niter, nc.powersim.fun(beta, i, k)))

# Average support level for null hypothesis (analogous to power?)
# Delta AIC Numbers suggested by Burnham and Anderson 2002, page 70
top[i] <- list(mean(unlist(out[i]) < 0))
substantial[i] <- list(mean( (0 < unlist(out[i])) & (unlist(out[i]) < 2) ))
less[i] <- list(mean( (4 < unlist(out[i])) & (unlist(out[i])<7) ))
none[i] <- list(mean(10 < unlist(out[i])))
```

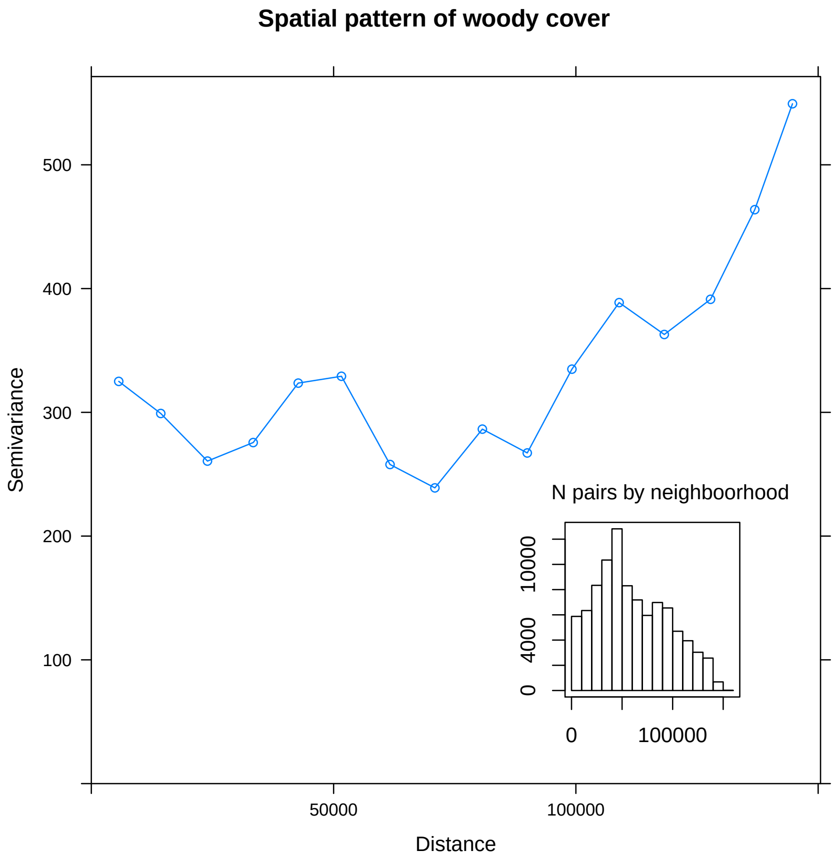


Figure A.3: Spatial autocorrelation in woody cover based on measurements from observer 1.

```
setTxtProgressBar(pb,i)
}
pdf("ResultsPowerSimulation.pdf")
plot(1:nsam, unlist(top),type=’n’, ylim=c(0,1), main=’Model performance versus Null’, ylab=’
    Proportion of simulations’, xlab=’Fields per County’)
lines(1:nsam, unlist(top), col=’red’, type=’o’)
lines(1:nsam, unlist(substantial), col=’orange’, type=’o’)
lines(1:nsam, unlist(less), col=’gray’, type=’o’)
lines(1:nsam, unlist(none), col=’green’, type=’o’)
legend(’right’, legend=c(’Null is top model’, ’Null model has substantial support’, ’Null model
    has considerably less support’, ’Null model has virtually no support’), col=c(’red’,’orange
    ’,’gray’,’green’), lty=1, pch=21, bty=’n’)
graphics.off()
return(data.frame("Fields per County" = 1:nsam, "Null model is top model" = unlist(top), "
    Substantial evidence for Null" = unlist(substantial), "Considerably less evidence for Null" =
     unlist(less), "No evidence for null" = unlist(none)))
}

results <- power.sim.out(niter=1000, b0, nsam=20, k)
```

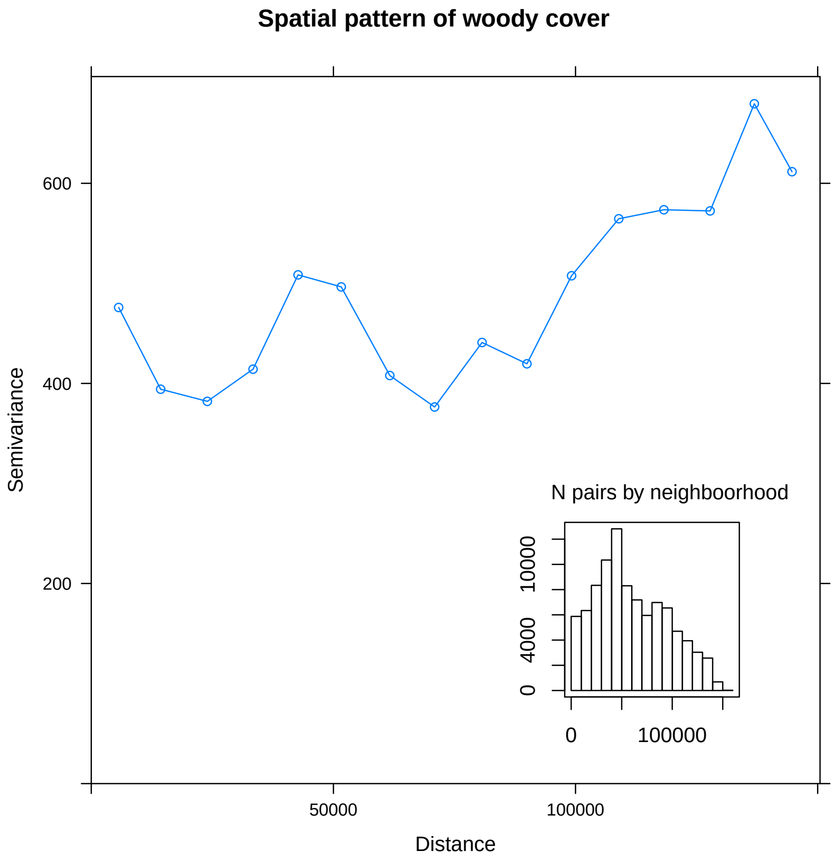


Figure A.4: Spatial autocorrelation in woody cover based on measurements from observer 2.

A.7 JAGS Model Code for Chapter 4

```
model
{
# priors
for(j in 1:ncounty){
alpha0[j] ~ dnorm(0,0.001)
beta0[j] ~ dnorm(0,0.001)
}
sd1 ~ dunif(0,10)
tau <- pow(sd1, -2)

alpha1 ~ dnorm(0, 0.001)
alpha2 ~ dnorm(0, 0.001)
alpha3 ~ dnorm(0, 0.001)
beta1 ~ dnorm(0, 0.001)
beta2 ~ dnorm(0, 0.001)
beta3 ~ dnorm(0, 0.001)

#likelihood
for(i in 1:N){
eps[i] ~ dnorm(0,tau)
```

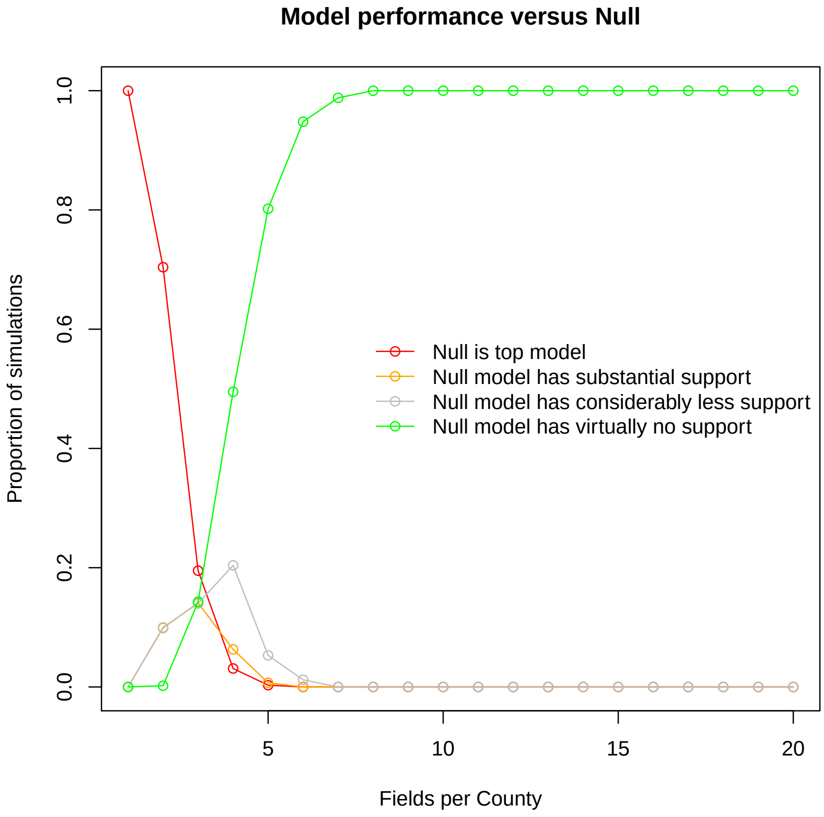


Figure A.5: Results of power simulation. After approximately 9 fields per county, the model with county effects (assuming effect sizes similar to what was found during the pilot study) outperformed the null model 100% of the time

```
logit(mu[i]) <–  alpha0[county[i]] + alpha1*road_dist[i] +
alpha2*field_size[i] + alpha3*crep[i] + eps[i]
logit(nu[i]) <– beta0[county[i]] + beta1*road_dist[i] +
beta2*field_size[i] + beta3*crep[i] + eps[i]

for(j in 1:2){
mow[i,j] ~ dbin(mu[i], 100)
wood[i,j] ~ dbin(nu[i] , 100)
}
}

}
```