

Birds and Bioenergy: A modeling framework for managed landscapes at multiple spatial scales

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*For my parents, the best warriors I know.
Everything I am is because of you.*

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Abstract

This dissertation examines the design and management of bioenergy landscapes at multiple spatial scales given numerous objectives. Objectives include biodiversity outcomes, biomass feedstock yields, and economic value.

Our study examined biodiversity metrics for 25 avian species in Iowa, including subsets of these species related to ecosystem services. We used our species distribution model (SDM) framework to determine the importance of predictors related to switchgrass production on species richness. We found that distance to water, mean diurnal temperature range, and herbicide application rate were the three most important predictors of biodiversity overall. We found that 76% of species responded positively to presence of grassland. We determined that a relationship between ecosystem service provided and potential species occurrence in a landscape does exist, with pollinators specifically benefiting from increased biomass production.

We explored predicted species occurrence under an alternative bioenergy landscape in which clustered corn/soy acres with a low return on investment (ROI) were replaced with grassland. We developed SDMs to predict changes in species occurrence for 28 birds. We compared results for three models: Random forest (RF), Stochastic gradient boosting (GBM), and Neural network (Nnet). Predicted species richness increased by 3.66% (RF), 2.79% (GBM), and 7.51% (Nnet) under the alternative landscape. If harvested, these areas could generate approximately 7.6 million dry tons/year of switchgrass for bioenergy. Unprofitable areas tended to occur along streams, suggesting that incorporating partially harvested riparian buffers can benefit avian biodiversity, while improving water quality and reducing unnecessary costs for farmers.

We explored effects of spatiotemporal harvest strategies at the field scale. We developed an agent-based model (ABM) that simulates ring-necked pheasants, tractors, hunters, and vegetation classes. Using this ABM, we assessed four different landscapes: corn-dominated, CRP-dominated, grassland-dominated, and mixed landscape. We determined that biomass yield and pheasant population size were sensitive to harvesting times, but unaffected by changes in spatial harvesting strategies. Specifically, harvesting in the fall yielded the most value because winter harvest resulted in lower yields and spring harvest resulted in decreases in pheasant population sizes. Trends were consistent across all landscapes. We discovered that corn (\$300,00/km²) and CRP (\$500,000/km²) landscapes had the highest-valued scenarios.

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Chapter 1

Introduction

The existential threat of climate change has spurred an increase in demand for energy from sources that are more sustainable than fossil fuels, like bioenergy. Sustainable bioenergy production is pursued by many countries because, if done well, both food and energy security can be obtained [60] in addition to mitigating the effects of climate change [158].

Bioenergy is a form of renewable energy that is produced from recently living organic materials known as biomass. Biomass feedstocks are resources that are used either directly as a fuel or converted to another form or energy product [18]. Biomass feedstocks include agricultural crop residues, corn grain, wood processing residues, dedicated energy crops, municipal waste, forestry residues, algae, and other types of wastes (e.g., industrial, urban) [4]. In this dissertation, we focus exclusively on biomass feedstocks from dedicated energy crops. Dedicated energy crops fall into two general categories: herbaceous and woody. Herbaceous energy crops are perennial grasses that take 2 - 3 years to reach maturity and then are harvested annually. Examples of herbaceous energy crops include switchgrass, miscanthus, sorghum, and bamboo. Short-rotation woody crops are fast-growing trees, like poplar and willow, that are harvested within 5 to 8 years of planting [19]. Dedicated energy crops, like switchgrass, have the potential to serve as a renewable source of transportation fuel and biomass-generated electricity [142]. The U.S. could produce 1 billion dry tons of non-food biomass resources annually by 2040 and still meet demands for food, feed, and fiber [46]. One billion tons of biomass could produce up to 50 billion gallons of biofuels, yield 50 billion pounds of bio-based chemicals and bio-products, generate 85 billion kilowatt-hours of electricity to power 7 million households, and contribute 1.1 million jobs to the U.S. economy [46].

Currently, the U.S. gets about 5% of its energy from biomass sources [20]. Despite this, no market for herbaceous energy crops currently exists, though they are predicted to in the next couple of years [46]. In

fact, there are now six biorefineries in Iowa that, together, have the capacity to produce 34 million gallons of cellulosic ethanol [74]. According to Jager and Kreig [75], until markets for dedicated energy crops become fully developed, economic incentives are likely to push biomass industries to either reduce capital inputs (e.g., growing crops on marginal land) or intensify production on more-valuable land. Here we focus on reducing capital inputs. One of the benefits of cultivating biomass feedstocks for energy purposes is that these feedstocks can be grown on marginal land where the profitability from traditional row-crops has become sub-optimal [23]. In this way, farmers can ensure that their resources are allocated to maximize their income. Incorporating biomass feedstocks into marginal lands also impacts biodiversity, like providing habitat to wildlife [167]. When considering avian species specifically, often the type of habitat provided is breeding or migratory stopover habitat [138]. Species can also be impacted if traditional rowcrops are converted to biomass feedstocks. Robertson [139] compared avian richness and abundance in fields of corn and two candidate biomass feedstocks (switchgrass and mixed-grass prairie) and found that bird species richness and species density increased with patch size in prairie and switchgrass, but not in corn. They conclude that, in contrast to corn, perennial biomass feedstocks have potential to provide benefits to grassland bird populations, especially if cultivated in large patches within relatively unforested landscapes [139].

The main question this dissertation examines is how do we holistically design and manage bioenergy landscapes at multiple spatial scales given numerous, potentially conflicting, objectives? When considering objectives, we are referring specifically to biodiversity outcomes, yield of biomass feedstocks, and economic value. Opportunities to improve coproduction of wildlife and biomass-for-energy exist at multiple spatial scales [75]. Therefore, we examine distributions of multiple avian species at the landscape scale and delve into the life process of an individual bird species at the field scale. In the first chapter we examine predictors, including management variables in the form of herbicide application, and their importance in predicting bird occurrence across Iowa. We also investigate the relationship between a species response to a predictor and the ecosystem service they provide. Such relationships could influence design guidelines for bioenergy landscapes. In the second chapter we create a future landscape where unprofitable areas have been converted to switchgrass and examine the impact on predicted bird occurrence. Finally, in the last chapter we focus on spatiotemporal harvest strategies of biomass feedstocks and a game species at the field scale. These questions are explored within a modeling framework that utilizes species distribution models and agent-based models.

1.1 Species distribution models

A species distribution model (SDM) spatially relates species occurrence with the environmental conditions in which the species was found [31]. Previously, SDMs have been used to model crop pollination services

[120, 125], evaluate pest management strategies on invasive species [92], and predict habitat suitability for rare plants at local scales [59], amongst other possible applications. The studies presented in Chapters 2 and 3 both utilize specie distribution models for subsets of farmland birds across Iowa.

1.2 Agent-based models

An agent-based model (ABM), also referred to as an individual-based model (IBM), is used for simulating the actions and interactions of autonomous individuals. Most ABMs are composed of four elements: (1) agents specified at a particular scale, (2) decision-making heuristics, (3) learning rules or adaptive processes, and (4) a clearly defined spatial environment [130]. ABMs are useful for problems that examine behaviors because they can examine and simulate agent behavior at different hierarchical levels. ABMs have been used to understand how populations respond to landscape heterogeneity with species as varied as red-cockaded woodpeckers [143], tigers [29], and wood mice [95].

The study exhibited in Chapter 4 uses an ABM that we built to examine interactions amongst tractors, pheasants, hunters, and the landscape. Unlike the SDM studies, this analysis is focused on a single species, the ring-necked pheasant (*Phasianus colchicus*), and at the field scale.

Chapter 2

Examining predictors of avian biodiversity for species providing different ecosystem services in Iowa's agricultural landscapes and the potential benefits of growing biomass feedstocks

2.1 Introduction

Policy directives focused on renewable fuel production in the United States often overlook any effects on biodiversity and ecosystem services that may occur by the land-use changes required to meet bioenergy production targets [14]. Through guidance on landscape management, negative effects could be mitigated and beneficial impacts could be enhanced [75]. A key management strategy utilized in agricultural landscapes is herbicide application. Herbicide application, while beneficial to agricultural crop yield, can have adverse effects on wildlife, including mammals [95], major aquatic taxa [141], and birds [105, 131]. Herbicide exposures can disrupt feeding behavior or lead to decrements in reproduction of a population. Herbicides

can also impact pollinators that are essential to grow some crops [127, 141].

In addition to herbicide application, species are also impacted by land use change [14, 17, 138, 157]. Warner [165] examined avian responses to land use change in Illinois and found that bird populations began to be impacted as early as the 1800s from changes in land management, mainly loss of grassland to agricultural production. The relationship between land use change and biodiversity is not always straightforward. Brandt et al., [25] showed that increasing energy corn production did not affect all birds in the same way; three of four bird species in the study experienced a decline when compared to a 2003 baseline. The fourth bird species experienced increases across all corn intensification scenarios, with a maximum increase of almost 70% [25]. Besides species-specific responses to transitions in land use, landscape composition must also be taken into account. Some farmland birds have been shown to respond positively to replacement of rowcrops with switchgrass and negatively to the conversion of conservation grasslands to switchgrass or rowcrops [157].

It is important to consider species reaction to landscape changes because of the ecosystem services that such species provide. Pollination is one ecosystem service that is incredibly important to human well-being [163]. Over three quarters of the world’s major crops benefit from pollination, with an economic value estimated to be around \$210 billion UDS globally in 2005 [125]. Insects, primarily bees, are major pollinators, though birds, mammals, and reptiles also play a role in pollination [128]. In fact, evolutionary shifts to bird-mediated pollination (ornithophily) have occurred in many types of flowering plants, being present in approximately 65 families [36]. Bird species that provide pollination services have been shown to be experiencing increased risk of extinction [132]. Besides pollination, ecosystem services can generate economic value. Mishra et al., [106] estimated the average annual values for wildlife viewing, water-based recreation, and pheasant hunting were \$1.24 million, \$0.17 million, and \$0.3 million, respectively in the Vermillion Basin in Illinois.

Given the variability in species’ responses to agriculture and the potential for species to be impaired by land conversion or changes in land management, this study asks to what extent potential biomass crops grown in Iowa landscapes would affect biodiversity. We hypothesize that incorporating biomass feedstocks into agricultural landscapes will benefit biodiversity. Incorporating perennial grasses into existing landscapes will increase heterogeneity. Pollinators may be more successful in bioenergy landscapes due to increased heterogeneity of vegetation cover and more opportunities for pollination. Bioenergy landscapes may provide habitat needed for species with conservation value, given that these species are generally at risk because of habitat loss. Finally, species with recreational value (e.g., hunting, bird watching) are valued in part from their interactions with humans, so converting some agricultural lands to biomass feedstocks may not substantially benefit these species.

The research questions of this study revolve around the central idea of generating guidelines for landscape

design of areas where bioenergy production could be introduced without adversely affecting biodiversity. If the goal is widespread introduction of biomass crops into the landscape, then we should know how much it could possibly affect biodiversity. First, we seek to find which environmental predictors are important in predicting bird occurrence. Additionally, knowing which variables are important to predicting bird occurrence can help inform and improve models in the future, or direct field research. Second, we want to know how avian species respond to environmental predictors. We can use grassland as a proxy for switchgrass to see how birds would respond to bioenergy production; whether it would positively or negatively affect their probability of occurrence. We also included management variables, in the form of herbicide application, as predictors that can help to discriminate the effects of lands growing perennial grasses for biomass from lands dedicated to other crops. We simulated herbicides that are used often in Midwest corn farming: 2,4-D, acetochlor, atrazine, dicamba, glyphosate, and metolachlor. Finally, we want to know if there are any relationships between a species response to a predictor and the ecosystem service they provide. If such relationship existed, it could influence guidelines on designing bioenergy landscapes with specific biodiversity goals in mind.

2.2 Materials and methods

2.2.1 Datasets

Our study spans the state of Iowa, USA, at 1 km² resolution. We included six types of environmental data as predictors (Table A.1).

Environmental data

Weather and climate have been shown to affect species typically found in agricultural settings, like grassland birds [62] and some mammals [115, 147]. Gorzo et al., [62] found that some congeneric birds responded significantly to weather with various significant responses to both precipitation and temperature. To model species responses, we selected a set of climatic variables that were expected to either directly or indirectly affect species occurrence. We acquired 19 climatic GIS data layers (1 km² resolution) from the WorldClim global climate database [170] and clipped them to the spatial extent of Iowa. We conducted a correlation analysis on pairs of predictors, and only included one from a pair due to high correlation (i.e., $r > 0.7$) [59]. All predictors that matched this criterion were investigated, and the predictor that was more important ecologically (e.g., maximum temperature would be more important than average temperature, because species have upper thermal tolerances) was kept. We found two types of correlated predictors: climatic predictors

(summarized in Table A.2), and herbicide data (discussed in next section).

There is strong evidence, especially for birds [22, 53, 118], that landscape structure and composition play a role in driving occurrences across the landscape. Land-use data were obtained from the 2009 National Agriculture Imagery Program (NAIP) [49] and resampled via nearest neighbor from 1 m to 1 km resolution. Nearest neighbor is an interpolation method that finds the closest subset of input samples to a query point and applies weights to them based on proportionate areas to interpolate a value [150].

Topography can affect the occurrence of birds [22]. Upland pastures generally support greater densities of grassland birds than lowland pastures [133]. Digital elevation data, originally 30 m and resampled using a nearest neighbor algorithm to 1 km, were acquired from an United States Geological Survey (USGS) National Map [99].

Snow depth can negatively affect some avian species [85]. We included snowfall accumulation (in meters) over a year (September 30 2016 – September 30 2017) as it was the most recent reported year. Snowfall data (1-km x 1-km resolution) were gathered from the National Snowfall Analysis which is a part of the National Weather Service under the National Operational Hydrologic Remote Sensing Center (National Weather Service, 2019).

Many predictors are needed to forecast the spatial distribution of wildlife, but not all of them can be considered important predictors of wildlife responses to perennial biomass crops. In addition to vegetation data from NAIP, we included distance to forest (m) and distance to water (m) as predictors. Proximity to forest and water are likely to be important for some wildlife taxa. Forests can buffer the effects of climate change on avian species [80] and distance to water can effect nesting success for some grassland birds [70]. These two layers were created by identifying water and forest features from the resampled NAIP 2009 land-use raster (1-km resolution), creating an empty mask grid, calculating the nearest distance between grid cells, and selecting features using the nearest neighbor algorithm in QGIS v3.10.3 (a free and open-source cross-platform desktop geographic information system application).

Herbicide downscaling

Herbicides are applied in Iowa and may have a substantial effect on the quality of habitat available to wildlife. As of 2019, herbicides were applied to 95% of corn acres and 100% of soybean acres planted in Iowa [110]. In comparison, fungicides and insecticides were applied on only 32% and 18% of corn acres, respectively, and both were applied to 19% of soybean acres [110]. Therefore, we focused on and included herbicide application information as a potential predictor of species success in agricultural landscapes, with all herbicide information, representing application for the year 2016, obtained from the Pesticide National Synthesis Project (PNSP) under the USGS National Water-Quality Assessment project [58]. We exam-

ined six herbicides (Figure A.1) chosen for their common occurrence on land uses prevalent in Iowa [114, 164]. The six herbicides were 2,4-dichlorophenoxyacetic acid, acetochlor, atrazine, dicamba, glyphosate, and metolachlor. 2,4-Dichlorophenoxyacetic acid (2,4-D) is one of the most widely used herbicides in the world and recommended for post control of annual and perennial broad-leaved weeds in cereals, corn (*Zea mays* L.), grain sorghum, grassland, orchards, sugar cane (*Saccharum officinarum* L.), and rice (*Oryza sativa* L.) as well as on non-crop land [129]. Acetochlor is a pre-emergence herbicide for control of annual grasses and broadleaf weed, used on a variety of food crops including all types of corn, and it is compatible with most other pesticides [123]. Atrazine is a selective pre- and post-emergence herbicide used for the control of broadleaf and grassy weeds in crops, such as corn, hay, range grasses for the establishment of permanent grass cover on range lands and pastures, wheat, sod farms, and sorghum [123]. Additionally, atrazine was the most widely used pesticide on corn in the state of Iowa in 2019, and was applied to 56 percent of all acres [110]. Dicamba controls annual and perennial broadleaf weeds in grain crops and grasslands, and it is used to control brush and bracken in pastures [123]. Glyphosate is a broad-spectrum, nonselective systemic herbicide used for control of annual and perennial plants [123] and it was the most widely used pesticide on soybean acres in 2019 [110]. Metolachlor is a selective herbicide that is usually applied to crops before plants emerge from the soil, and is used to control certain broadleaf and annual grassy weeds in field corn, soybeans, grain sorghum, highway rights-of-way, and some other food crops [123].

All available herbicide data are reported at the county scale, which is too coarse for our analysis given that the other input data has a resolution of 1 km. Thus, we downscaled herbicide data from the county scale to a 1 km x 1 km grid, as seen in Figure A.1. For each land use j , we took the reported amount X_j^k (kg) of herbicide k for the entire state and divided by the total reported area A_j (km²) to find the application rate r of herbicide k on land use j (kg km⁻²), denoted by r_j^k . We created a grid of 1 km x 1 km cells for Iowa and assigned each grid cell the dominant land use j in that grid cell, resulting in matrix S_j below. Land use was assigned from NAIP 2009, resampled to 1 km. Next, using this land use grid raster, we assigned the previously calculated application rate to each grid cell with corresponding land use j (e.g. a cell that represents corn will have the application rate of herbicide k for corn), creating matrix L . We then summed the cells in county c to find the total amount of herbicide k in that county giving P_c^k . Next, we subtracted the reported total amount T_c^k of herbicide k in county c to find the discrepancy δ between reported and calculated herbicide totals for the county. Finally, we divided the discrepancy δ by the total number of cells q with herbicide k application greater than 0 in county c and subtracted this from matrix L to arrive at the final downscaled landscape F for herbicide k . This process is detailed below in Equations 2.1-2.6.

$$\frac{X_j^k}{A_j} = r_j^k \quad (2.1)$$

$$S_j = \begin{bmatrix} j_{11} & \cdots & j_{1n} \\ \vdots & \ddots & \vdots \\ j_{m1} & \cdots & j_{mn} \end{bmatrix} \text{ assign calulated application rate via land use of grid cell } \begin{bmatrix} r_{j11}^k & \cdots & r_{j1n}^k \\ \vdots & \ddots & \vdots \\ r_{jm1}^k & \cdots & r_{jmn}^k \end{bmatrix} = L_k \quad (2.2)$$

$$P_c^k = \sum_j r_j^k, \text{ summing over the indices } j \text{ in county } c \quad (2.3)$$

$$P_c^k - T_c^k = \delta_c^k \quad (2.4)$$

$$r_{uv}^k - \frac{\delta_c^k}{q_c^k} = f_{uv}^k, \text{ for all } uv \text{ in county } c \quad (2.5)$$

$$\begin{bmatrix} f_{11}^k & \cdots & f_{1n}^k \\ \vdots & \ddots & \vdots \\ f_{m1}^k & \cdots & f_{mn}^k \end{bmatrix} = F_k \quad (2.6)$$

where,

j = index of land use (e.g., corn, soybean)

k = index of herbicides

c = index of counties in Iowa, grid cells (u, v) exist in county c

S_j = Matrix spanning Iowa with dimension $M \times N$, where $M = 1, \dots, m$ corresponds to $M = \min_{lat}, \dots, \max_{lat}$, and $N = 1, \dots, n$ corresponds to $N = \min_{long}, \dots, \max_{long}$, entry j_{sl} represents the land use of grid cell (s, l). ‘lat’ refers to latitude and ‘long’ refers to longitude. Each grid cell is 1 km x 1 km.

X_j^k = total amount (kg) of herbicide k applied to land use j in Iowa (reported)

A_j = total area (km²) of land use j in Iowa (reported)

r_j^k = application rate (kg/km²) of herbicide k on land use j

P_c^k = total amount (kg) of herbicides k in county c (calculated)

T_c^k = total amount (kg) of herbicide k in county c (reported)

q_c^k = total number of cells with nonzero herbicide k applied (kg) in county c

L_k = intermediate matrix of dimensions $M \times N$, where each element is the application rate of herbicides k applied to land use j in state grid cell (s, l)

F_k = final downscaled landscape matrix for herbicide k

We found that some of the downscaled herbicide layers were highly correlated. Of the 6 herbicides, 5 were found to be highly correlated. To reduce collinearity, we summed these 5 herbicide (acetochlor, atrazine, dicamba, glyphosate, metolachlor) layers together. We chose to linearly combine these layers as a sum because this is a way to deal with collinearity among predictors while retaining interpretability of results [44]. This summed layer, called “herb5”, was included with 2,4-D in the final stack of predictors.

Species data

Species distribution models (SDMs) require data on the presences and absences of a species across a landscape to estimate the probability of occurrence in a location [66]. We obtained species presence data from the Global Biodiversity Information Facility website (<https://www.gbif.org/>). The search area for recorded species occurrence was restricted to the state of Iowa. We excluded records without geographic coordinates. We included records dated between 1990 and 2019. Pseudo-absence data were generated by randomly selecting locations that were not presence points within the study area [9]. We selected an equal number of presence and absence points.

2.2.2 Species distribution modeling

After obtaining predictor values for locations of each recorded species presence as well as each inferred pseudo-absence we began the modeling process (Figure A.2). We used the Classification and Regression Training (caret) package in R [91] to fit generalized linear models (GLM) for each of the 25 bird species. The main dataset was divided into two smaller datasets: training datasets (75%) for model development, and testing datasets (25%) for model evaluation. Cross-validation was conducted with 5 replicates. We retained models that had accuracy > 0.7 [59].

Once we developed SDMs, we produced richness maps showing the number of species from the set of species that we modeled present in each grid cell. We estimated species richness in each grid cell by

summing presences across all species. We calculated the average richness of a landscape by summing across the landscape and dividing by the number of grid cells.

2.2.3 Model evaluation

We assessed the reliability of each SDM by calculating a confusion matrix using the test dataset. A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the outcomes are known [51]. From the confusion matrix, we calculated model accuracy and kappa. Accuracy is the proportion of correctly predicted sites [3] and any model with accuracy below 0.7 was discarded from further analysis [6]. Kappa, also known as Cohen’s kappa, compares an observed accuracy with an expected accuracy (i.e., that expected purely by chance). The kappa statistic ranges from -1 to +1, where +1 indicates perfect agreement and values of zero or less indicate a performance no better than random [51].

2.2.4 Species and ecosystem services

In this analysis, we developed models for 25 bird species (summarized in Table A.3). We classified species by the ecosystem service they provide to investigate whether if any relationship exists between grouped species and the possibility of occurrence in a bioenergy landscape. While species can provide more than one type of service, for the sake of simplicity, we assigned one service to each species. We examined three ecosystem services: pollination, conservation value, and recreational value. Species were classified as pollinators if they move pollen among plants. Species were marked as having conservation value if they are listed in either Iowa Department of Natural Resources’ list of Endangered and Threatened Species (Department of Natural Resources, 2019) or in the Iowa Gap Analysis Program (GAP) analysis [84]. Species were deemed to have recreational value if they are eligible for hunting in Iowa [42] or if they are associated with recreational activities (e.g. bird watching).

2.2.5 Importance of predictors

We estimated the contribution of each variable to the model by conducting a receiver operating characteristics (ROC) curve analysis on each predictor. An ROC curve shows the trade-off between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity). The trapezoidal rule was used to compute the area under the ROC curve, and this area is used as the measure of variable importance. We calculated variable importance for each of the 25 bird species in the analysis, as well as the average importance for each predictor over ecosystem service groupings. As mentioned previously, we are interested

in seeing which predictors are important in determining species occurrence and whether any patterns arise when considering species through the lens of the ecosystem services they provide. To this end, we present a ranking of importance of each predictor over each ecosystem service grouping and across all species in the analysis.

2.2.6 Logistic coefficients and odds ratios

Coefficients of logistic regressions determine the sign of response between species presence and the value of each predictor. For example, a positive coefficient would signal that when the predictor value increases, the probability of species presence also increases. To determine how much species presence probability changes given a one-unit change in the predictor value, we must calculate the odds ratio. The odds ratio is calculated by taking the exponential of the coefficient for a particular predictor (odds ratio = e^{β} , where β is the logistic coefficient for predictor j).

2.3 Results

2.3.1 Model evaluation

For our models, the accuracy and kappa values were high, which denotes good predictive power (Figure A.3). Accuracy values ranged between 0.71 and 0.88 with specific ranges of 0.71 – 0.85, 0.71 – 0.88, and 0.71 – 0.87 for pollinators, species with conservation value, and species with recreational value, respectively. Amongst all species, kappa ranged between 0.42 and 0.76. A similar range of kappa existed for pollinators (0.42 – 0.70), conservation value (0.42 – 0.76), and recreational value (0.42 – 0.73).

2.3.2 Importance of predictors

A ranking of the importance of each predictor (summarized in Table A.4) reveals that the top three predictors of species presence overall were distance to water, bio 2 (mean diurnal temperature range), and herb5, which is a summation of acetochlor, atrazine, dicamba, glyphosate, and metolachlor herbicide application over Iowa (kg). Mean diurnal temperature range describes the range between the highest temperature and the lowest temperature that occurs during the same day. This can be considered a descriptor of the weather on an average day. Herb5 was the only predictor that had the same ranking across all ecosystem service groupings.

Landscape predictors were the least importance predictors overall with presence of corn ranking last (15/15), presence of soybean ranking 11th of 15, and presence of grassland ranking at 13th of 15. When examining these rankings amongst ecosystem service groupings, presence of corn was not important to

predicting species presence across the board. Both soybean and grassland predictors exhibited nuanced behavior. Soybean presence was more important for species with conservation value (ranked 9/15) and grassland presence was more important for pollinators (9/15).

When analyzing large differences in response by ecosystem service groupings to various predictors, three predictors stand out: bio 9 (mean temperature of driest quarter), elevation, and presence of grassland. Interestingly, each of these predictors are substantially more important to one type of species over the others. Mean temperature of driest quarter was more important to species of conservation value, elevation was more important to species with recreational value, and presence of grassland was more important to pollinators).

2.3.3 Logistic coefficients and odds ratios

Logistic coefficients across all species and all predictors are displayed in Figure A.4. Graphing logistic coefficients allows us to determine what patterns, if any, occur among ecosystem service groupings. Species with recreation value tend to attain similar values for certain predictors, notably mean diurnal range, precipitation seasonality, precipitation of wettest quarter, elevation, and presence of soybean. Species of conservation value attain similar values for precipitation seasonality. Finally, pollinators displayed similar coefficient values for precipitation seasonality, presence of corn, presence of grassland, and distance to water.

To understand the value of a species response to a certain predictor, we must look at the odds ratio (summarized in Table A.5). For every increase of 1 unit in predictor values, the probability that a species is present increases by the odds ratio. For example, the estimated odds that a red-winged blackbird is present is 1.89 greater for each increase in the mean diurnal temperature range (Table A.5). By the same token, for each increase in the mean diurnal temperature range, the estimated odds of a gray partridge being present decreases by 0.94.

The majority of predictors displayed positive relationships to species presence. There were two exceptions to this, precipitation seasonality and precipitation of driest quarter, that both had generally negative responses on species. Only one predictor, distance to forest, had an almost even split amongst species response (52% responded negatively and 48% responded positively). Otherwise, the majority of species responded positively to predictors, with occasional negative responses sprinkled throughout. This speaks to the variability in responses by individual species to the same predictors.

2.3.4 Biodiversity mapping

The species richness maps (Figure A.5) display similar patterns with respect to areas of highest richness. Central Iowa and the eastern third of the state consistently came up as areas of high richness, whereas the western third of the state had lower richness across all groupings.

Differences in species richness over ecosystem service groupings do exist, though they are difficult to discern when looking at species richness across the entire extent of the study area. Main differences between the grouping exist in areas of moderate richness. Species of conservation value display moderate richness in the southern part of Iowa, while species with recreational value have moderate richness in the northern part of Iowa.

2.4 Discussion

We began this analysis with a simple question: which predictors are important to consider when thinking about future avian species occurrence in a bioenergy landscape? Of the predictors we considered, the top three most important predictors of species occurrence are distance to water, mean diurnal temperature range, and herbicide application rate (Table A.4). Neither distance to water nor mean diurnal temperature range tells us much about how biodiversity would be affected by future bioenergy production. Herbicide application rate, which was the only predictor to have every species respond positively to it, gives us information regarding land management and therefore allows us to make some conclusions about future bioenergy landscapes. Though herbicides are used on both traditional row crops and switchgrass plantings, the amount of herbicide used is much higher on annuals than perennials. This is because over a 15 year rotation, herbicides are applied yearly on annuals compared to once every 2-3 years on perennials [45]. Thus, the herbicide predictor can be thought of as antithetical to increased presence of perennial grasses. Positive odds ratios (Table A.5) for herbicide application mean that for every increase in herbicide application, the probability of species presence also increases, and by a factor larger than one. We can take this result to mean that increasing traditional row crops acreage on landscapes would result in higher biodiversity, which does not conform to much of the existing literature [146, 167]. However, when we look at species response to presence of corn and presence of grassland, we see a slightly different story: 32% of species exhibited a negative response to presence of corn, 36% of species exhibited a negative response to presence of soybean, and 76% of species displayed positive responses to presence of grassland. This seems to indicate that presence of traditional row crops is not always conducive to avian biodiversity. Additionally, increasing grassland, which could be thought of as a proxy for switchgrass or other perennial grasses, increases species richness.

Distance to water and mean diurnal temperature range are the other two top predictors of species occurrence. Unlike with herbicide application, the primacy of these predictors is somewhat self-explanatory. All species require water, and so water will naturally be a staple in any environment that supports life. Mean diurnal temperature range was the most important bioclimatic predictor of species presence. In thinking about long term resilience of wildlife populations, the dominance of mean diurnal range on species occurrence is concerning, given future climate change. With increasing temperatures, we can expect to see a shift in this particular climate-based predictor. Uncertainty about future climate conditions leads to uncertainty about future biodiversity.

The second question we sought to answer was whether grouping species by ecosystem service revealed any information on managing land for future bioenergy production. Overall, the rankings amongst these groups were similar, with three exceptions in mean temperature of driest quarter, elevation, and presence of grassland. Spatial variation in presence of species groups (Figure A.5) also exists. When considering predictor rankings, logistic coefficient clustering, and spatial patterns of species occurrence, we see that a relationship exists between the ecosystem service a species provides and their potential success in a landscape, though further work is required to tease out the intricacies of that relationship. This conclusion is supported by Rivas Casado et al. [137] in predicting the impacts of bioenergy production on farmland birds. They found that the response of the farmland bird community as a whole to the introduction of bioenergy production was small and broadly similar, but that the similarity in overall response masked significant intra- and inter-specific variations across the study area.

There were a number of limitations to this study. First is the lack of higher resolution pesticide data that required us to develop a downscaling protocol. More detailed information on pesticide application is required, but not currently available out of concern for farmer privacy. Policy and political implications surrounding privacy concerns is controversial and beyond the scope of this study. We also addressed correlated herbicide data layers by linearly combining said layers. There are more sophisticated ways of dealing with correlated herbicide layers, such as considering toxicity. Another limitation is the small sample size in the number of herbicides simulated. All the pesticides we examined were herbicides, and in future work we may include insecticides as well. Some insecticides that could be examined as potential predictors of species presence are chlorpyrifos, lambda-cyhalothrin, and methomyl. These three insecticides are commonly used on corn and generally applied via spray [45], which opens up the possibility of exposure from spray drift or particulates carried by wind and water. Additionally, studies have found these insecticides to have significant and long-term negative effects on pollinators [37, 96, 161]. An important caveat is the classification of some birds as pollinators. There are avian species that function as pollinators [128, 132], though when considering pollination in agricultural settings, insects like bees are more important [120]. In the future, we would like

to extend our species pool to include other taxa. This leads to another limitation: results were interpreted based on services to society rather than on taxonomic or life history differences.

Responses to environmental gradients are often unimodal (i.e., Gaussian distributions, where an intermediate value is best) [79]. Our models assumed a linear response. Alternative formulations may permit more varied responses. In addition, selected interactions may be important to include. Averaging snowfall data over multiple years would more align the temporal resolution in our data layers and is something we would do in the future. And finally, a subset of the tested species are migratory (e.g., neotropical migrant birds) and it may not make sense to include winter climate predictors for those that are not in the area in winter. In addition to the current climate variables, indicators of phenology may serve as important predictors of when species are likely to be observed in Iowa.

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Chapter 3

Growing perennial grasses in unprofitable areas of US Midwest croplands could increase avian richness and provide a cellulosic biofuel feedstock

3.1 Introduction

As the demand for low carbon fuels grows, it is imperative that the crops to meet this demand be deployed in sustainable ways [46]. More-sustainable options involve cellulosic feedstocks including crop residues, wood residues, dedicated energy crops, and industrial and other wastes [4]. These cellulosic feedstocks have the potential to serve as a renewable source of transportation fuel and biomass-generated electricity [142]. Currently, there are six biorefineries in Iowa that, together, have the capacity to produce 34 million gallons of cellulosic ethanol [74].

However, ethanol produced from corn grain far outpaces the production of biofuels from cellulosic feedstocks in the US [48]. In fact, approximately 25% of corn croplands in the US are used for ethanol production [108]. Growing corn for ethanol production reduces the area suitable for nesting birds [48]. Species react

differently to row-crop agriculture [12, 138, 167], with some species adversely affected in significant ways [17] through loss of habitat for reproduction and avoidance.

Cellulosic feedstock production from perennial grasses has many potential benefits. These feedstocks can be grown on marginal land where the profitability from traditional row-crops (e.g., corn and soy), grown for both food and ethanol, is sub-optimal [23]. There are areas of the landscape where row crop performance is poor—usually poorly drained or higher sloped soils—and that consistently lead to lost revenue for farmers [21]. These areas could be converted to switchgrass (*Panicum virgatum*) production for bioenergy. For example, Brandes et al. (2018) demonstrated that the conversion of low producing corn/soybean cropland to switchgrass in Iowa would net upwards of \$13.6 billion USD [24]. Besides energy and economic impacts, growing biomass feedstocks can also improve water quality [90]. Additionally, Gopalakrishnan et al. [60] found that perennial grasses could be grown on marginal land in redesigned agricultural landscapes to meet energy and environmental needs without major impacts on food and feed production. In terms of biodiversity, perennial and warm-season grasses, like switchgrass, can be used for biomass feedstocks and can provide habitat to wildlife [167]. Additional benefits that perennial grasses have on avian diversity specifically, in terms of providing breeding and migratory stopover habitat [138], and in comparison to traditional row-crops such as corn [139], has been well documented.

We asked to what extent potential biomass crops grown in Iowa landscapes could affect biodiversity. To examine the relationship between predictors and species’ probability of occurrence, we built upon a species distribution modeling (SDM) tool called BioEST (Bioenergy-biodiversity Estimation) [46, 77]. An SDM spatially relates species occurrence with the environmental conditions in which the species was found [31]. In this study, we build upon BioEST to create BioEST-Suite which fits SDMs using three commonly used algorithms: Random forests (RF), Stochastic gradient boosting (GBM), and Neural networks (Nnet). Utilizing multiple modeling methods has been used previously in species distribution studies [2, 9, 67]. Our goal here is to determine how different species would respond to planting switchgrass in areas of low return on investment (ROI). We hypothesize that incorporating perennial grasses managed as biomass feedstocks into agricultural landscapes will benefit avian biodiversity.

3.2 Materials and methods

3.2.1 BioEST-Suite

We built upon and implemented an enhanced species distribution model, BioEST-Suite (Figure B.6), tailored for bioenergy research [77]. BioEST-Suite estimates the effect of biomass crops on wildlife occurrence either

through incorporating response ratios that reflect how species densities vary among land management types or through direct use of relevant predictors (as here).

Inputs

The geographic distribution of bird species in agricultural settings has been shown to be affected by climate, topography, land cover and management. Our analysis includes these predictors (Table B.6) and spans the state of Iowa, USA, at 1 km² resolution. Topography can affect the occurrence of birds [22]. Upland pastures generally support greater densities of birds than lowland pastures [133]. Digital elevation data, originally at a 30-m resolution, was resampled using a nearest neighbor algorithm to 1 km, were acquired from an United States Geologic Survey (USGS) National Map [99].

Weather and climate have been shown to affect bird species typically found in agricultural settings, like grassland birds [62]. Gorzo et al., [62] found that some congeneric grassland birds responded significantly to weather with various significant responses to both precipitation and temperature. To model bird species responses, we selected a set of weather variables that were expected to either directly or indirectly affect species occurrence and abundance. We acquired precipitation and mean temperature data for the years 2009 to 2019 from the PRISM Climate Group [65]. We downloaded precipitation and mean temperature data (4 km² resolution), clipped them to the spatial extent of Iowa, averaged across the represented years, and then downscaled to 1 km² via bilinear interpolation. Snow depth can negatively affect some avian species [85]. We included snowfall accumulation (in meters) over a year (September 30 2016 – September 30 2017). Snowfall data (1-km x 1-km resolution) were gathered from the National Snowfall Analysis which is a part of the National Weather Service under the National Operational Hydrologic Remote Sensing Center [149].

There is strong evidence, especially for birds [22, 53, 118], that landscape structure and composition play a role in driving occurrences and abundances across the landscape. Therefore, we included land-use classification data obtained from the 2009 National Agriculture Imagery Program (NAIP) [49] and resampled via majority from 1 m² to 1 km² resolution. NAIP land classification categories include sorghum, wheat, winter wheat, wheat/soy rotation, rye, oats, alfalfa, hay, beans, peas, clover, sod, fallow, water, barren, evergreen forest, mixed forest, shrubland, woody wetland, herbaceous wetland, and developed/impervious. In addition to the land use in a particular cell, we also considered adjacency to important habitat categories. We included distance to forest (m) and distance to water (m) as predictors. Proximity to forest and water may affect species occurrence. Forests can buffer the effects of climate change on avian species [80] and distance to water can affect nesting success for some grassland birds [70]. These two layers were created by identifying water and forest features from the resampled NAIP 2009 land-use raster (1-km resolution), creating an empty mask grid, calculating the nearest distance between grid cells, and selecting features using

the nearest neighbor algorithm in QGIS v3.10.3 (a free and open-source cross-platform desktop geographic information system application).

Correlated predictors A common problem in building SDMs occurs when predictors are highly correlated. This results in unstable coefficient estimates. To examine collinearity among predictors, we calculated a correlation matrix (Figure B.7). We included only one predictor of a pair if any pairwise correlation were found to be highly correlated (i.e., $r > 0.7$) [59]. The value of the correlation coefficient describes the relationship between two predictors, with a positive coefficient arising between two correlated predictors and a value of zero between predictors that are not correlated. None of our predictors met this condition. Finally, we removed the predictors that had near-zero spatial variance, meaning they had very few unique values relative to the number of samples and the ratio of the frequency of the most common value to the frequency of the second most common value was large. The only predictors that met this condition were land use predictors like presence of wetlands or developed areas.

Species occurrence data SDMs require data on the presences and absences of a species across a landscape to estimate the probability of occurrence in a location [66]. We obtained species presence data for 28 birds (Table B.7) from the Global Biodiversity Information Facility (GBIF) website (<https://www.gbif.org/>). The search area for recorded species occurrence was restricted to the state of Iowa. We excluded records without geographic coordinates. We included records dated between 2009 and 2019. We calculated Moran’s I (Table B.7) to check for spatial autocorrelation. All species displayed near-zero Moran’s I values which denotes no autocorrelation [43].

Initially, pseudo-absences were generated using the “target-group background sampling” method [122]. These were created by sampling the presence data of species from the same taxa by a user-specified rank (i.e., order in this analysis). The reasoning behind this approach is that if the opportunity to observe the presence of a similar species exists, the opportunity to observe the target species also exists. However, these pseudoabsence data points were too similar, resulting in high omission error and poor models. Thus, we generated pseudo-absence data using an alternative approach by randomly selecting locations that were not recorded as species observations (‘presences’) within the study area [9]. This method of data generation has been widely utilized in previous studies [2, 9]. The same number of pseudo-absences were selected as the number of presences for a species.

Models

We obtained predictor values for locations of each recorded species presence as well as each inferred pseudo-absence (Figure B.6, middle panel). We used the Classification and Regression Training (caret) package in R [91] to fit SDMs for the suite of modeling methods. The three algorithms we utilized in our suite modeling were Random forest (RF), Stochastic gradient boosting (GBM), and Neural network (Nnet). Random forest is an ensemble machine learning method for classifications and regressions that operates by constructing a multitude of decision trees at training time, then merges them together to get a more accurate and stable prediction. Gradient boosting is a machine learning technique for both classification and regression tasks, which produces a prediction model in the form of an ensemble of weak prediction models. Stochastic gradient boosting is a variation of gradient boosting where at each iteration a subsample of the training data is drawn at random (without replacement) from the full training dataset. The randomly selected subsample is then used, instead of the full sample, to fit the model. A neural network is a series of algorithms that attempts to recognize underlying relationships in a set of data through a process that mimics the human brain. The dataset was randomly divided into two datasets: training datasets (75%) for model development, and testing datasets (25%) for model evaluation. Cross-validation was conducted with 5 replicates.

Outputs

We used the SDMs with current and alternative landscapes to predict species occurrence. If the probability that a species will occur in a grid cell is greater than or equal to 0.5, that species is deemed “present” for that grid cell. We used that information to produce richness maps under the current and alternative landscapes. This was done by summing predicted presences in each grid cell. Note that richness can also be estimated by summing probabilities, though this method was not utilized here. We also examined the change in richness between the two landscapes. We can also calculate the average richness of a landscape by dividing the total richness by the total number of grid cells.

3.2.2 Model evaluation

We assessed the reliability of each SDM by calculating a confusion matrix using the test dataset. From the confusion matrix, we calculated model accuracy, kappa, and True skill statistic (TSS). For a discussion of accuracy and kappa, please see Section 2.2.3. TSS range from -1 to +1, where +1 indicates perfect agreement and values of zero or less indicate a performance no better than random [3]. Unlike kappa, TSS is not affected by sampling prevalence (proportion of samples representing species presence [104]) or by the size of the validation set and is a special case of kappa [3].

3.2.3 Alternative landscape

To create the alternative landscape, we identified Iowa land that can be economically and practically converted to perennial switchgrass to achieve bioenergy production goals. We used ArcGIS analyses of two 2013-2016 Iowa datasets provided by EFC Systems: a Profit Zone Manager (PZM) dataset that describes subfield profitability for all of Iowa’s corn/soy acres [23] and an AgSolver dataset that describes subfield agroecosystem management and associated process-based biogeochemistry [21]. Subfields with a positive ROI value are considered profitable, with higher values indicating greater profitability. In order to target land growing corn and/or soy (often in rotation) for potential management as grassland, we started by identifying subfields with low ROI values that totaled 10% of Iowa’s total corn/soy acres based on an understanding that this could potentially lead to 3 million acres of perennial grass production across the state and sufficient biomass for commercial-scale cellulosic ethanol production. We found 688,596 subfields with an $\text{ROI} < 0.365$ averaged across years 2013-2016, and these low-ROI subfields totaled 9,415 km². In order to find clusters of low ROI land that would make biomass harvesting logistically feasible, we aggregated adjacent subfields and subfields with very close proximity (i.e., within 0.2 miles) and excluded clusters with areas smaller than 20,234 m² (5 acres). This resulted in a final set of low ROI subfield clusters totaling 7,689 km², representing approximately 3% of Iowa’s agricultural land area. These clusters had an average size of 56,656 m² (14 acres). We converted the shapefile layer of clustered low ROI polygons into a 15 m x 15 m grid. This grid was then resampled via nearest neighbor from 15 m to 1 km resolution. The grid of the alternative grassland layer, which includes existing grasslands and the identified low-ROI lands as grassland, replaced the grid of current grassland layer in the predictor stack. Then each of the SDMs (RF, GBM, and Nnet) was projected on alternative conditions to obtain alternative distributions for each of the 28 species.

3.3 Results

3.3.1 Model evaluation

BioEST-Suite models for our 28 avian species performed well across a variety of measures (Figure B.8). The average accuracy of GBM, Nnet, and RF algorithms were 0.82, 0.78, and 0.87, respectively. Kappa and TSS values were on average less than accuracy measures—the GBM model attained an average kappa of 0.65 and an average TSS of 0.64; the Nnet model had average kappa and TSS values of 0.56 and 0.57; the RF model had average kappa and TSS values of 0.75 and 0.74.

Across all three measures, the RF model consistently had the highest values and the Nnet model had the lowest. In addition, RF consistently had the smallest variation amongst the modeling algorithms.

3.3.2 Current versus alternative landscapes

Richness maps for the avian species produced by BioEST-Suite of both current and alternative landscapes are displayed in Figure B.9. Although predictions differ among models, they all generally agree on two areas of high richness: the Des Moines area and the state’s eastern border. The average richness of the current landscape was 3.27 (RF), 5.34 (GBM), and 5.88 (Nnet), compared to an average richness of 3.38 (RF), 5.49 (GBM), and 6.32 (Nnet) for the alternative landscape.

Most areas in the state did not experience much of a change in richness (Figure B.9). We made a difference map to highlight the areas where species richness changed between the current and alternative landscapes (Figure B.10). Many of the areas that did experience an increase aligned with unprofitable areas. Over the landscape, species richness increased by 3.66% (RF), 2.79% (GBM), and 7.51% (Nnet) when we simulated management of unprofitable areas as grassland.

We calculated the occurrence of each individual species under current and alternative landscapes (Figure B.11). Of 28 birds, only 1 (Forster’s tern, *Sterna forsteri*) saw a decrease in predicted prevalence in response to managing unprofitable areas as grassland, and this was true for all three modeling methods. Five other birds did exhibit some declines in occurrence between scenarios, however in no cases did all of the algorithms predicted a decrease. Of the species that did experience a decline in richness, the average decline for each of the three methods was 1.16% (RF), 0.67% (GBM), and 8.37% (Nnet).

3.4 Discussion

We used BioEST-Suite to evaluate a alternative Iowa landscape that simulated a potential landscape for cellulosic bioenergy production created by managing low ROI lands to grassland. We examined species richness predictions to determine how avian biodiversity would be affected. By converting unprofitable areas in Iowa to grassland, BioEST-Suite predicted anywhere from 2.79% to 7.51% increase in species richness. Our results are consistent with previously reported benefits of increasing grassland acreage on birds [17, 39, 72, 138, 139]. Additionally, the potential distributions of species that did not increase either stayed the same or decreased a small amount (Figure B.10, B.11). From a conservation standpoint, increasing the amount of grassland in the landscape is advantageous to grassland birds prevalence.

It is important to note that we simulated grassland as defined in the NAIP classification, rather than perennial grasses specifically managed (i.e., harvested) as a bioenergy feedstock. Individual bird species may have different responses to unmanaged versus managed grasslands. However, Murray & Best [109] evaluated bird abundance and nest success in totally harvested, partially harvested, and non-harvested CRP

switchgrass fields in northern Iowa and found that no major shifts in species richness resulted from the harvest of switchgrass fields because in harvested areas, the absence of species that are common in tall, dense vegetation was offset by the presence of species that prefer shorter, sparser vegetation. Additionally, Jungers et al., [83] studied the effect of grassland biomass harvest on nesting pheasants and ducks and found that nest success was not influenced by biomass harvest, though nest density was greater in unharvested refuge regions. Roth et al., [140] determined that both harvested and unharvested switchgrass fields have habitat value for birds, concluding that a good compromise would be to leave some fields unharvested each year to provide habitat for a larger number of birds. Projected improvement in biodiversity is not the only benefit to an alternative bioenergy landscape.

Areas of low ROI tended to occur in riparian areas, suggesting that incorporating bioenergy riparian buffers into the landscape would be beneficial to avian biodiversity. These riparian buffers could also potentially be harvested as biomass crops [76]. Besides improved soil [55, 144] and improved water quality [61, 90] that can arise from incorporating bioenergy riparian buffers into a landscape, farmer income can also increase [21, 24]. Under the alternative landscape, we determined that the revenue lost across all the low ROI land identified averaged approximately \$110 million USD per year from 2013 to 2016. If these targeted areas, totaling just 3% of Iowa’s agricultural land, were planted with switchgrass yielding an average of 0.00089 tonnes/m² (4 tons/acre), we would expect an annual harvest of approximately 7.6 million tons y⁻¹ of switchgrass biomass that could be used for cellulosic ethanol production. This is a substantial sum to “leave on the field”. As with any scientific endeavor, there were several limitations to this study. First, SDM performance is constrained by quantity and quality of species occurrence data. Second, BioEST-Suite may overpredict a single species occurrence because there is no limit on the number of species allowed in the environment. Essentially, the model operates as if there is no carrying capacity. Finally, we only considered birds in this study.

Through this study, we demonstrated that BioEST-Suite can successfully project biodiversity implications of alternative landscape designs and can be useful for illustrating those effects through biodiversity maps. BioEST-Suite can be applied to any geographic location if suitable data are available, and BioEST-Suite has shown that it can effectively evaluate the biodiversity of alternative landscapes. Thus, BioEST-Suite can potentially be a useful tool for evaluating other types of landscapes and future scenarios that can be represented through changes in its predictors.

3.5 Future directions

In addition to crop cover, there is evidence that the arrangement and juxtaposition of habitat can influence species presence [47, 100]. We did consider proximity for two predictors (forest and water). However, future research might also consider how perennial grasses can be optimally arranged in the matrix of croplands and natural vegetation to improve habitat for wildlife. Such a study could produce guidelines for incorporating biomass crops into existing agricultural landscapes in ways that can improve conditions for birds at a finer resolution than the ones produced here.

Biofuels are part of the portfolio of low-carbon renewable energy sources that are being considered as a path to avoid a ‘sixth extinction’ [76]. Including bioenergy riparian buffers in future landscape designs is an essential recommendation considering the energy, economic, and ecological impacts of planting bioenergy riparian buffers, especially under future wetter climate conditions that prevent or delay spring planting of corn [76]. A next step in this research would be to examine how sensitive species presence might be to climate change by evaluating a assembly of possible future climate scenarios. Such an analysis would allow us to investigate the extent to which planting cellulosic bioenergy crops could mitigate possible negative biodiversity effects of future climate scenarios.

3.6 Acknowledgements

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Chapter 4

Spatially-explicit agent-based modeling to evaluate the effects of planting and harvesting biomass and hunting on ring-necked pheasant (*Phasianus colchicus*) populations.

4.1 Introduction

Perennial grasses provide more wildlife habitat compared to traditional row crops, resulting in increased bird diversity [13]. Additionally, perennial grasses can be harvested as biomass feedstocks [54]. Thus, the opportunity with perennial grasses exists to contribute to wildlife conservation while simultaneously providing additional value to farmers. Biodiversity in agricultural landscapes has high value, however it can also provide economic value [106]. This value is revealed through hunters buying hunting licenses, paying farmers to hunt on their lands, and contributing to the tourist economy in many Midwestern states [106, 159].

One species that is highly valued by hunters in the Midwest US is the ring-necked pheasant (*Phasianus colchicus*). Thanks in part to its popularity as a game bird, there are programs, such as the US Conservation

Reserve Program (CRP) that is administered by the United States Department of Agriculture (USDA) and funded under the Farm Bill, that seek to recover and maintain pheasant populations [39, 102, 109, 116]. One CRP program in Iowa, CRP SAFE, encourages farmers to grow perennial grasses on parts of their land to provide pheasant habitat [41] via yearly rental payments to the farmers. It has been demonstrated that pheasant populations respond positively when previously agricultural land is managed according to requirements of CRP [71, 101, 102, 113]. Specifically, interspersed local grassland patches within landscapes containing small grains and row crop agriculture, a requirement of CRP, is a critical element in maintaining ring-necked pheasant populations [82].

An added benefit and further economic incentive to landowners to participate in this conservation program, is that perennial grasses can be harvested as biomass [54]. Avian nesting habitat is severely limited in agriculturally dominated landscapes in the Midwestern US [116, 165]. Traditional row crops can provide some cover to birds, at least until the field is disturbed by harvest [27]. Unlike traditional row crops, perennial grasses not only provide nesting habitat, but harvesting can also be delayed so as not to disturb the nesting season for most wildlife species, including pheasants [109]. It has been suggested that leaving standing biomass over winter provides important wildlife cover and seed forage. Postponing harvest until later in a season does not come without consequences; there is a peak window in which to harvest biomass feedstocks, such as perennial grasses, and delays past that period result in degradation of biomass [57]. This does not mean the biomass is not useful as a feedstock for bioenergy production. Rather, the energy content decreases, and a larger amount of feedstock is required to achieve an equivalent amount of energy production that would have occurred if the bioenergy crops were harvested during the peak time. When considering trade-offs inherent in managing landscapes where biomass harvesting and pheasant harvesting (i.e., hunting) both take place, we expect to see an inverse relationship (e.g., if biomass yield increases then pheasant population size will decrease and vice versa). We expect this because biomass harvesting disturbs pheasants but delaying biomass harvest so not to disrupt pheasant life process allows that biomass to degrade.

Harvest strategies also contain a spatial component which can affect yield outcomes and population dynamics. Hunting has been shown to have a direct impact on spatial dynamics of farmland birds [30]. Inclusion of a hunt-free reserve near hunting grounds has been shown to benefit the long-term sustainability of wildlife populations [26, 30, 87]. Additionally, hunting methods, like the use of a pointing dog or movement within a hunting area, can impact hunters success [153]. Spatial aspects of harvesting biomass can affect wildlife. Traditionally, switchgrass is harvested by beginning at the edge of a field and moving inward following the perimeter of the field [52]. This method pushes wildlife inward and does not allow them easy egress from a field [52]. Solutions to this problem have been proposed, like beginning in the middle of a field and moving outward [50, 52, 89] or using a flushing bar [155]. A flushing bar creates a disturbance in

advance of the tractor to allow extra time for wildlife to flush from the field to avoid injury or death [155].

The complex interactions between individuals present in these multifunctional agricultural landscapes makes this a situation ideal for employing an agent-based model (ABM) is ideal. We utilize an ABM that model pheasants, vegetation, hunters, and tractors in various agricultural landscapes and a set of eight scenarios (4 time-based, 4 space-based) to investigate trade-offs between pheasant population size and biomass yield. Landscape composition and size affect agricultural yield [12, 100], profitability [23, 124], and wildlife [12, 25, 124]. We test all scenarios across four different landscapes to examine how landscape composition impacts model outputs. We expect that landscapes with more crops and CRP land will have higher yields of biomass and pheasants overall because these lands are harvestable and do an adequate job of providing some habitat to pheasants [13, 39, 71, 88, 102, 103, 113, 116].

The goal of this study is to assess the effect of various spatiotemporal harvest strategies on biomass yield, pheasant harvest, and average pheasant population size over a 5 year period, and to investigate how landscape-design impacts the outcomes of such strategies. We are also interested in how scenario outcomes compare in economic terms, including appropriate valuation of ecosystem services, which includes provision of biomass for energy and provision of game. It is important to understand the dynamics of complex field-scale interactions between multiple agents both for developing better management practices and ensuring optimal outcomes.

4.2 Materials and methods

4.2.1 Study area

A selection of agricultural fields in Iowa, USA were chosen as the base landscape for this analysis. The simulated area contains CRP SAFE in the form of nesting cover, winter cover (switchgrass), and a food plot. Through collaboration with the Antares project, geospatial data of the chosen area were acquired and imported into the ABM. The Antares project is a multi-lab and -university project sponsored by the Bioenergy Technologies Office of the US Department of Energy that seeks to create a comprehensive landscape design handbook for bioenergy production in Iowa. The study region represents a typical agricultural area in Iowa. Most land is used to grow corn and soybeans with some patches of deciduous forests, wetlands (herbaceous and woody), hay, alfalfa, oats, and grasslands interspersed on the landscape. The CRP SAFE Pheasant program has strict requirements on the design of enrolled land and the types of species that can be planted. All blocks of land must be at least 20 acres (8.09 ha) and no larger than 160 acres (64.75 ha) with winter cover taking up 25% of the block, a food plot on 10% of the land area, and the rest of the land

being used for nesting cover [111]. Establishing winter cover and a nearby food plot is key to ensuring that pheasants survive through the winter [166]. The winter cover protects pheasants from predation and cold temperatures, while the food plot ensures they can access enough high caloric food to survive the cold. Nests and broods have greater changes of survival if adequate nesting cover is provided and left undisturbed until hens have finished nesting and brooding [11, 28, 34].

This area is normally managed for corn and soybean. Typically, corn planting begins in April and continues through June, with harvest commencing in October and finishing by the end of November [38]. The optimum time to plant soybeans in Iowa is the last week of April for the southern two thirds of Iowa and the first week of May for the northern one third of Iowa [117]. Similar to corn, soybeans should be harvested beginning near the end of September and finish by the end of November [117].

4.2.2 ODD Protocol

The model description follows the Overview, Design concepts, Details (ODD) protocol for describing agent-based models as laid out by [63]. The model was implemented in NetLogo version 6.0.4 [168].

Purpose

The main purpose of this model is to simulate ring-necked pheasants in agricultural landscapes that include bioenergy crops and determine the trade-offs between biomass yield and pheasant harvest. This is done in order to determine how bioenergy crops, which can provide pheasant habitat, affect pheasant population dynamics and their spatial life history.

Entities, state variables, and scales

An entity is a distinct or separate object or actor that behaves as a unit and may interact with other entities or be affected by external environmental factors [63]. This model has four entities: pheasants (both male and female), tractors, and hunters, and vegetation. All state variables characterizing these entities are listed in Table C.8. Multiple landscapes are simulated, and a detailed description of each can be found in 4.2.4. Each landscape is approximately 5 km² because this is roughly equal to the home range of a ring-necked pheasant [82]. The world is represented by 120 x 175 patches, thus each patch is approximately 270 m².

Both female and male pheasants have attributes that are state variables in the model. These include age (days), mass (in kg), the number of attempts at acquiring food in a day, whether or not they have established a territory for mating, the area (in cells) of their territory (set to 0 if they have not established a territory), identity of their mother, the flock they belong to during the winter, and the identity of the

nearest pheasants of the same gender (used to help them form flocks). The dynamic state of each female pheasant is tracked by the following variables: the harem she belongs to, whether she has established a nest, the number of eggs she lays in a year, and the location of her nest. Each male pheasant has state variables describing his desirability to females, the number of attempts to attract females (lekking behavior), whether he has established a harem, and the area (in cells) of his harem (set to 0 if he has not established a harem).

The dynamic state of tractors is tracked by variables that describe the amount of biomass and corn they have harvested (dry ton/km²). The state of hunters is described by the current target of their hunting efforts, their accuracy in hitting their target, the number of attempts they have to successfully hunt male pheasants, the radius around themselves in which they can look for male pheasants to hunt, and the total number of successfully killed roosters. Hunter's accuracy and the distance in which they may look for male pheasants to hunt are randomly assigned. Additionally, hunters may only kill up to three roosters per day, per bag limits in Iowa.

Grid cells (i.e. patches) describe the landscape composition. The dynamic value of patches are recorded via state variables that describe the amount of energy provided to pheasants if consumed (measured in percent crude protein), the amount of cover provided to pheasants (simulated as plant height in meters), the amount of potential biomass yield to be harvested (dry ton/km²), and Boolean variables that represents whether pheasants are allowed to nest in the specific type of vegetation and whether that vegetation is eligible for harvest by tractor. Other landscape variables detail individual patches interactions with pheasants and tractors and are outlined in Table C.8. The state of each patch varies with the season. To account for this, the food, cover, and biomass of certain vegetation types are presented as time-dependent functions. We gathered data from the literature regarding these three attributes for vegetation types simulated by the model, and then constructed functions that represent these processes over the year. The food parameter for vegetation is represented as percent crude protein and shown in Figures C.12 and C.13. We represent the cover provided by vegetation structure, in this instance as the vertical plant height (m), in the model (Figures C.12, C.13) to account for the effect that vegetation has on bird survival.

Both types of CRP lands (switchgrass and food plot) are eligible for harvesting. Additionally, we simulate corn harvest because as the largest producer of corn in the country [160] tractor impact on pheasant populations in corn fields is important to consider. The biomass parameter for these three land uses (Figure C.13) is represented as dry ton/km².

Process overview and scheduling

The following processes are run on a daily time step in the order shown in Figure C.14. Activities related to reproduction and parenting are described in detail in the Submodels section. Seasons determine which

submodels are executed in the model, because pheasant life cycles and harvesting are time dependent. First, all input data are imported, and the model landscape is constructed. The model is initialized and then all following processes occur randomly within their particular season. Each submodel within a season is run on a daily time step. Once each submodel is completed, then time will advance, and the cycle will begin again. The model will continue to run until the designated stop time. Seasons are defined as follows: Winter (December 1 – February 28), Spring (March 1 – May 31), Summer (June 1 – August 31), and Autumn (September 1 – November 30).

Design concepts

Basic principles The basic principle of this simulation is to replicate pheasant dynamics in combination with biomass harvesting and pheasant hunters in agricultural fields in Iowa. Ring-necked pheasant life history stages and processes form the basis of the modeling framework. Pheasants breed during the spring. In March, males begin to establish crowing grounds. These are areas where they lek—display various courtship behaviors in an attempt to attract females. Rarely do these displays result in violent confrontations, though they can occur. Males mate with any receptive hen that enters their territory. Harems can get as large as twelve hens. After spring, female pheasants rear their broods. Young chicks can leave the nest and follow their mother within a few hours of hatching. Young chicks can make short flights at 12-14 days of age and resemble adults by 16 weeks of age [50]. Hens take their broods to good insect hunting areas and warn chicks of impending danger. Mortality of young chicks is high. The mortality between hatching and 2 weeks of age may be as high as 25% and may increase to almost 50% by 9 weeks of age [119]. As winter approaches, broods disperse and pheasants search for winter cover. Suitable winter cover is close to a winter food source because pheasants will forage only short distances during this season. Mortality does not increase during winter, since pheasants can survive bouts of freezing temperatures, as long as they are able to consume enough high caloric food to keep their body temperatures high [166].

Both biomass harvesting and hunter behavior are varied according to user input. Geotagged tractor paths from various fields in Iowa [personal communication with Mike Griffel (Idaho National Laboratory) on February 7, 2019] informed the biomass harvesting simulations. Hunter behavior is modeled after hunter testimonials and how-to guides [40, 41].

Adaptation Male pheasants determine the size of their territory based on surrounding vegetation and the level of their desirability to potential mates. Female pheasants adopt the territory of their male mates after joining a male’s harem. In the model, pheasant have limited attempts to find an unoccupied, habitable territory in which to establish a harem. For details, see the “Lek” submodel.

Objectives The objective of a pheasant is to mate and successfully reproduce. Their territory decisions are based on the vegetation around them. Mating decisions depend on availability of mates near and within their territory. Pheasants also seek out food. A tractor’s objective is to harvest as much feedstock as possible in the allotted harvest season. A hunter’s objective is to kill as many male pheasants as possible given the daily limit of a haul.

Sensing Pheasants can sense the gender and the mating status of other pheasants within their search radius. This information drives movement and mating. They can also sense whether adjacent patches are occupied by other pheasants and the vegetation type there. Tractors can sense field boundaries (i.e., is patch eligible for mowing?) and whether an area has been mowed or not. Hunters can also sense any male pheasants that are within their search radius.

Interaction Pheasants utilize vegetation to provide cover, as a food source, and to satisfy habitat requirements of various life stages. Ring-necked pheasant habitat is associated with areas of high soil fertility where agricultural crops and other vegetation provide the basic food and cover requirements [15]. Pheasants occupy crop fields of corn, sorghum, oats, wheat and barley stubble, unmowed haylands, native grasslands of big and little grasses with a healthy forb component, grassy roadside ditches and field drainage channels, dense vegetation growing along overgrown fence-rows, windbreaks, shelter-belts, woodlots, and field corners. CRP management requires maintaining grass-like habitat (small grains and perennial grasses), which serve as breeding habitat for pheasants [82].

Hunters hunt pheasants during a specified hunting season. Tractors harvest various types of vegetation that result in agricultural yield. Tractors can also kill pheasants during the harvest process.

Stochasticity There are many stochastic events in this model. Whenever any entity (agent or patch) executes a procedure, the order in which the agents execute that procedure is randomized. Additionally, there are decisions made by the agents or patches that are stochastic. Within this model, stochastic decisions by entities (agents and patches) are determined by drawing from a discrete number of available options with equal probability (i.e., from a uniform probability distribution) as described below.

Let X be a decision made with probability p . Each time decision X is to be made, the uniform distribution $U[0, 1]$ is sampled to generate $y \in R$. The event X occurs if $y \leq p$ and does not occur otherwise.

Each individual is selected randomly with probability 50% of completing the following procedures on any given day.

- Male pheasants initiating courtship behavior (i.e. execute submodel 4.2.2)

- Female pheasants begin nesting
- Eggs in a nest hatch (submodel 4.2.2)

Observation At each time step, we record the pheasant population size (both female and male counts), the current day, week, and year. When tractors are active on the landscape, we keep track of the total biomass yield that is harvested (dry tons/km²). When hunters are active on the landscape, we track the cumulative pheasants killed by each hunter (count).

Initialization and input data

The model begins on January 1 of year 1. Initially, 40 pheasants (20 male and 20 female) are randomly placed in patches on the landscape, given the 5 km² area [73]. Each pheasant is assigned an age, energy, and desirability (males only) at random upon creation (Table C.8). All state variables for entities are initialized during the set-up procedure. Hunters and tractors are initialized when the Hunt and Biomass Harvest or Corn Harvest submodels are executed, respectively. All agents, except hatchlings, are placed randomly on the landscape when initialized.

The landscape of this model is created by importing GIS land data; however, this data only defines the extent of the study area and the static spatial distribution of land use categories. The GIS Extension in NetLogo is used to import a shapefile of the landscape, which is then displayed and assigned appropriate patch values depending on land use.

Submodels

The submodels of the ABM are described here in detail.

Forage This procedure is executed by male and female pheasants. Initially, all agents set their food trials to zero. Until pheasants have either acquired food or used all their trials to find food, they will continue to search for food. Pheasants are allowed 4 trials so they do not exceed their average activity radius of 0.25 km [69]. If the patch a pheasant is inhabiting has food (denoted by patch variable food), the pheasant will increase their energy level by consuming the available food on that patch. The patch variable energy will decrease by the equivalent amount. Pheasants will then choose a random heading and move forward a random amount that depends on the amount of energy they have to move.

Even though young chicks resemble adults relatively fast, they will stay with their mother for 3 months after hatching and during this time the mother will still display protective behavior over her young. Therefore,

if an individual pheasant is a juvenile (age ≤ 77 days), then it must stay within 100 m of its mother [134]. If a juvenile is further from its mother than the threshold, it will move towards her.

Lek In March, males begin to establish crowing grounds. These are areas where they lek or display various courtship behaviors to attract females. Rarely do these displays result in violent confrontations, though they can occur. Males mate with any receptive hen that enters their territory. Harems can get as large as twelve hens.

Thus, this procedure is executed by male pheasants only. Males are allowed two attempts to establish a harem. If they are unable to establish a harem within the two trials, they will not mate during the reproductive season. Males possess a desirability parameter that is between 0 and 1, which is randomly assigned at birth. Each male also has a harem-radius (measured in patches) which describes how large an area each male may search during a given time step in order to establish a harem. The radius of that circular area is given by multiplying a male's desirability value by 20 to ensure that crowing territories stay within appropriate bounds of possible size [50].

During a lekking trial, each male will check the patches that occur within their harem-radius for ownership by other males and whether the vegetation is suitable for nesting. If all requirements are met, then five things will happen. First, the male pheasant will set their parameter determining whether they are able to establish mating territory to true to indicate that they are in the process of moving through the reproductive cycle. Second, every patch within the harem radius will change owner from 'nobody' to the ID of that particular male. The patches will also set patch-harem-num to the ID of the male owner. Next, each male will set his territory size to the number of patches within his harem. Finally, all female pheasants that are currently within the male's breeding territory and not part of another male's harem will move towards that male, set their territory parameter to true, set territory size as that of the male, and set harem-num to the ID of the male owner. If a female is within the breeding territory of more than one male, she will mate with the male who has a larger desirability value. Only one male pheasant is allowed on a patch at a time. If a male is unable to establish a harem in the trials, territory parameter will remain FALSE and they will not participate in reproductive activities for the season.

Nest Nesting can begin as early as March in southern Iowa, but egg laying usually begins in mid to late April [154]. Only hens take part in nesting. After constructing a nest, a hen lays 6 to 15 eggs, often 10 to 12 [15]. Hens lay one egg per day until the clutch is complete, and then incubation begins. This procedure is executed by female pheasants who belong to a harem only. Females move randomly around in their harem territory and if they find a patch that is inside their harem territory and not occupied by another female,

they will establish a nest in that patch. Once a female has established a nest, she will lay between 7 and 15 eggs at that site. The number of eggs that a female lay is randomly chosen. Females will continue to execute this procedure until either the nesting period ends, or they establish a nest.

Incubate Peak incubation occurs in May [50], and hens incubate eggs for 23 to 25 days [15]. This procedure is only executed by female pheasants who have establish a nest and laid eggs. Each day, females who have established nests will move ≤ 5 patches away from her nest in search of food and then move immediately back to their nest, regardless of whether their search for food was successful. This will continue through the entire incubation period.

Birth This procedure is only executed by female pheasants who have established a nest and laid eggs. Female pheasants will execute the “Birth” process at some point during the hatching period (see Stochasticity). When “Birth” is initiated, each egg within a hen’s nest will hatch in the same timestep (i.e. day). There is a 50% that each hatchling will be female. Each new pheasant, depending on its sex, is initialized with the appropriate parameters (Table C.8) and within the mother’s harem territory.

Check death This procedure is executed by both male and female pheasants. The baseline daily risk of mortality is determined based on the pheasants age and relation to their mother if a juvenile. There is a 0.005 probability of the death of a juvenile with a mother, and a 0.0078 probability of death of a juvenile whose mother has died or abandoned them to die [134]. Adults die with probability 0.0021 [119], and senior adult pheasants (older than 2 years) die with probability 0.975 [135]. However, vegetation may provide some cover to pheasants which could reduce their risk of mortality. The daily mortality risk for pheasants (Figure C.15), decreases in patches with higher cover because increased vegetation decreases rate of predation [94].

If the daily mortality risk is greater than a random number between 0 and 1, then the pheasant will execute the “Death” submodel. Otherwise, the pheasant survives. Additionally, if a pheasant’s energy reaches zero, then the pheasant dies immediately.

Death This procedure is executed by both male and female pheasants based on the submodel “Check death”. Any patches within the territory of the dead pheasant will be reset to have no owner and thus be eligible for other pheasants to use in reproduction.

Flock by sex By winter, chicks no longer rely on their mothers for food and protection, and broods break up. All pheasants, both males and females seek out appropriate winter cover in which to spend the winter. This is also the only season in which pheasants will associate with other members of the same-sex; pheasants

flock by sex as they search for winter habitat [50]. In this procedure, each pheasant will look for other pheasants of the same sex in a radius of 5 patches from themselves. If there are other pheasants in the search radius, the individual will move towards them to form flocks of same-sex pheasants.

Corn harvest Tractors execute this procedure by determining if the current patch is corn and then harvesting that corn if the patch has not yet been mown. The tractor then examines the adjacent patches, looking for patches with corn vegetation that have not been mown. Based on this, the tractor will either move forward and harvest or turn right, move forward, and harvest. Tractors mow in a spiral pattern that turns inward, with a tractor finishing harvest at the center of the field. If a pheasant is occupying a patch that a tractor is harvesting, then that pheasant will die, and the tractor will continue with its harvesting.

Biomass harvest This procedure is executed by tractors. First, the tractor will check to see if the current patch is eligible for harvest (vegetation is either switchgrass or CRP food plot) and whether it has been mown. If both criteria are met, the tractor will harvest the current patch. If a pheasant is occupying this patch, then it will die. The tractor will then examine the parameters of the next patch to determine if it should move to said patch, or a different patch. Choosing the next patch to investigate is different depending on which submodel (base-harvest or theory-harvest) is currently being executed. They are represented as two separate submodels in order to execute different rules of movement. In the base-harvest submodel, tractors emulate the typical harvest practices by mowing the entire boundary of the field and then spiraling inward, to end the mowing patch at the center of the field. The theory-harvest submodel can be thought of as the opposite of base-harvest in that the tractor begins at the center of the field and then spirals outward to end at the boundary of the field.

Hunt This procedure is executed by hunters. All hunters begin with no hunt trials yet attempted. Each hunter will continue to search for male pheasants to kill in each time step until they have killed 3 roosters or have used all of their hunt trials. If there is a rooster within a hunter's hunt-distance than that rooster becomes the hunters target. Each hunter possesses an accuracy parameter that is between 0 and 1, which is randomly assigned. If a random number between 0 and 1 is less than a hunter's accuracy than the pheasant dies and the hunter's rooster count increases by one. Otherwise, the rooster gets away and the hunter increments their hunt trials by one and try again if they are eligible. This is the way that the hunter submodel operates. To introduce spatial variation, the hunt submodel is represented as two separate submodels (hunt-strip and hunt-radius) which are identical expect for the rules that govern hunter movement. In the hunt-strip submodel, hunters begin at one part of the field and move forward, flushing pheasants out of the field. Hunter's hunt-distance is limited to only 180 heading north in front of them and this is the only

direction in which they move. In the hunt-radius submodel, hunters movement and hunt-distance are not restricted by orientation. Wherever a hunter senses a potential target, they may turn and move towards it. The first target they sense determines in which direction they move.

4.2.3 Model evaluation

We conducted pattern-oriented validation [64, 78] on three separate patterns: population dynamics, habitat usage, and populations under hunting. We ran the model with no tractors or hunters on the landscape for 25 years to ensure that pheasant population dynamics mirrored field observations. Beginning with an initial population of 50, the model exhibited a stable pheasant population over simulation time. When compared to 36 years of pheasant data from Nebraska, the population dynamics produced by the model fit the overall pattern of pheasant counts and the seasonality captured by the data and is reflected our population results [169]. Additionally, demographic data from a 5 year field study in Iowa followed trends of our model output [33]. Specifically, the boom and bust nature of pheasant populations was well-captured in the model, with populations increasing in the spring during the reproductive season and then steadily declining over the year until spring the next year.

During these baseline model simulations, pheasant seasonal use of habitat was documented. In examining field data, hens preference for grassland, and occasional use of woody habitat, over the years was confirmed [121, 145]. Winter and nesting season are the two periods during the pheasant life cycle when habitat is especially important. During winter, pheasants tended to prefer grassy, woody habitat, and habitat that provided adequate cover [121]. For the nesting season, hens will nest in many types of habitat (e.g. grassland, pasture, fence line), though our percent of habitat used for nesting was similar to field data [34].

We also examined 17 years of pheasant hunting data from Iowa [56] to determine how well our model was able to reproduce hunting patterns. Overall, the hunting data produced by our model was typically within range of the Iowa hunting data (Figure C.16). The variability of the observed hunting data arises in part from the fluctuation of hunters each season, which can be influenced by a myriad of external factors such as shifting national demographics or depressed economic growth [159]. Our modeled results are within an order of magnitude of the observed hunting data.

4.2.4 Experimental design

Simulation experiments were devised to explore the effects of various harvest strategies of both biomass and pheasants. Additionally, we created four different landscapes (Figure C.17)—dominated by corn, CRP, grassland, and mixed land uses—to determine how landscape composition affects outcomes from various

spatiotemporal harvest strategies. Each landscape is approximately 5 km², a spatial scale that is biologically relevant to pheasants [32, 151]. We averaged 50 replicates simulated for each scenario; each scenario (4 time based and 4 space based) was run on all four landscapes.

The scenarios (summarized Figure C.18) vary biomass harvest timing, tractor’s spatial harvesting, and hunter’s spatial strategies. Harvest timing was broken into four date ranges: fall (September 2 - October 5), winter (November 10 - December 31), early spring (March 14 - April 16), and late spring (May 1 - May 20) [57, 83]. Tractors harvest biomass via the base-harvest method (see “Harvest” submodel) and hunters use the hunt-strip method (see “Hunt” submodel). The spatial rules for biomass harvest are varied between base harvest and theory harvest. The inward-spiral mowing pattern represents the typical way fields with bioenergy crops are mowed, as opposed to back-and-forth row mowing for traditional crops (e.g. corn harvest). The tractor will begin at a point on the outskirts of the field and mow around the edges of the field, making its way to the center of the field. This is the most common way to mow a non-corn field for a couple of reasons: (1) by following the natural curves of the field, the tractor does not have to slow down while making turns, (2) it is easy to pick a starting point for mowing, and (3) the mowing path is simple to follow without the need for technology or prior planning. However, this mowing path is not ideal for wildlife as it pushes them to the center of the field and traps them there. Conversely, the outward-spiral is, theoretically, considered the best mowing strategy for protecting wildlife [50, 52, 89]. By beginning in the center of the field and slowly moving outward, wildlife can be flushed from the field. Although it may be the best path for wildlife, it may not be the most efficient or practical. First, prior to mowing, the farmer must determine where the center of the field is and then physically move the tractor to that spot. Second, without being able to see the boundary of the field, the path the tractor is to follow is less certain, resulting in the need for additional planning beforehand, slower mow-times, or, GPS-enabled tractors, all of which translate to lost productivity. The hunters’ spatial patterns are varied between strip hunting and radial hunting (see “Hunt” submodel for more information).

4.2.5 Experiment execution

Since ABM’s are inherently stochastic, we simulated 50 replicates of each scenario consisting of 1) a crop landscape, 2) a harvest season, and 3) a hunter strategy. This requires running the model 1,600 times and with one model run taking about 4 hours to compute, it would be time-consuming to simulate all these model runs on a single machine. An often utilized solution to this computationally-expensive problem is to use computing clusters to enable parallelization and speed up execution time. We simulated our model in a cluster environment using the computing cluster available at the Advanced Computing Facility (ACF), a

high-performance computing facility at the University of Tennessee.

We created our scenarios in Behavior Space, a tool inherent in NetLogo, that allows users to vary model parameters across model simulations. Within this setup, the recorded output includes pheasant population size (male and female breakdown), total harvested biomass, total harvested corn, total number of deaths via tractor (male and female breakdown), and total hunted roosters. Output is recorded approximately every 2 weeks during the 5 year simulation. Annual values are calculated by summing each variable over a simulated year (e.g., day 1 to day 365). We created the appropriate setup file via BehaviorSpace. Then, to submit the job to the cluster, we used a Portable Batch System (PBS) file that does the following: (1) specifies the file path for the ABM, NetLogo, and the setup file, (2) calls the specified setup file, (3) specifies a maximum run-time and number of nodes to use, and (4) includes code for calling the Python file that orders and organizes the resulting simulation outputs according to each parameter combination. This cluster framework was created and implemented by Eduardo Ponce [126].

4.2.6 Ecological valuation

Ecological valuation is the practice of assigning monetary value to an ecosystem and/or its ecosystem services that accounts for the full economic (real or subtextual) value of that ecosystem. This practice has been applied across a diverse range of topics, from assigning value to best management practices like prairie contour stripping [156] to the environmental impacts of geothermal power projects [35]. Other studies have assigned monetary value to species to aid in the conservation of that species [148] or to ensure a sustainable harvest of that species [136]. In this study, we present a valuation approach for pheasant related services, like hunting, in addition to crop yields. Bartkowski [10] utilized a similar method in valuing biodiversity. While ecological valuation can be a useful tool for assigning economic value to ecosystems, it is important to be cognizant of the fact that even the direct impacts of wildlife management actions are difficult to quantify, which limits the scope of economic analyses involving wildlife [5].

In order to calculate the monetary value of one pheasant in dollars (ρ), we found that the annual pass for a non-resident to hunt pheasant in Iowa is \$144/year [42]. Assuming that all hunters are non-residents who spend approximately 5 days hunting and bags 3 roosters over each of those days, we calculate ρ to be \$9.60. This value is applied to the number of roosters that are successfully bagged by hunters ($+r$ because hunters are spending money to hunt pheasants) and the number of accidental pheasant deaths from tractors ($-d$). We subtract the number of accidental pheasant deaths because those pheasants are no longer available for hunting, decreasing the pool of potential targets and representing lost money that could have been reaped had the pheasant been alive. We assumed a price of \$84.45 per dry ton for biomass feedstock (β) [18] and

a price of \$26.78 per ton for corn feedstock (γ) [16]. Finally, we calculate the total of each scenario (EV) using Equation 4.1. Note that money is not all flowing to a single beneficiary; license fees go to the state and profits from agricultural yield go to farmers.

$$EV = \beta(h_b) + \rho(r - d) + \gamma(h_c) \quad (4.1)$$

where,

β = price (in dollars) per dry ton for biomass feedstock

γ = price (in dollars) per ton for con feedstock

h = amount of harvested feedstock (dry ton); b for biomass and c for corn

ρ = “worth” of one pheasant (in dollars)

r = number of roosters bagged by hunters

d = number of accidental pheasant deaths from tractors

4.3 Results

4.3.1 Scenarios

To look at the relationship between pheasant population size and biomass yield, we plotted annual values of these two outputs across all landscapes (Figures C.19, C.20, C.21, C.22). The simulation was run for 5 years so each figure displays 5 data points. We encircled all results from a scenario with a line to highlight the range and potential clustering of results. On the corn-dominated landscape, the scenarios varying timing of biomass harvest (Figure C.19, left) display a more direct relationship between pheasant population size and biomass yield than the scenarios varying spatial movement strategies of hunters and tractors (Figure C.19, right). The Time2 (winter harvest) scenario has lower reported biomass than the other scenarios which report higher biomass values. There is no discernible relationship between pheasant population and biomass yield among the scenarios that vary spatial movement strategies of hunters and tractors. The time-varied scenarios simulated on the CRP landscape (Figure C.20, left) exhibit similar clustering behavior as those simulated on the corn landscape. Again, the scenario that simulates biomass harvest in the winter has distinctly lower biomass than biomass yields from other biomass harvest times. However, these low biomass values coincide with high pheasant values which follows expected behavior. The other time scenarios on the CRP landscape have higher biomass values and a wide range of pheasant population sizes. The space

scenarios on CRP land, similar to the space scenarios on corn landscape, do not display any relationship between pheasant population size and biomass yield. On the grass landscape (Figure C.21), we again see lower biomass yield during winter harvest compared to all other scenarios. Similar to on the CRP landscape, these lower biomass values are associated with higher pheasant population sizes. Additionally, the other time scenarios have higher biomass values but also a wide range of pheasant population values. The space scenarios on the grass landscape display more clustering than on other landscapes, though still display no discernible relationship between the two measured values. Finally, we examine the mixed landscape (Figure C.22) and again see that harvesting biomass in winter generated lower biomass values, though the difference is not as wide as on other landscapes. Time3 and Time4 scenarios, both spring harvests, had lower pheasant values than other time scenarios. The mixed landscape is the only landscape to exhibit the kind of trade-offs that we initially expected: lower pheasant population values with higher biomass yield and vice versa. Unlike the other landscapes, the space scenarios on the mixed landscape produced results that occur in distinct regions. Space3 and Space4 scenarios (both had tractors use theory harvest) had comparable to slightly higher biomass yield than the other space scenarios, which was unexpected. However, Space3 and Space4 did not result in higher pheasant populations, which was expected for these scenarios.

We also looked at average annual biomass yield against average annual pheasant population (Figures C.23, C.24). Error bars in these figures represent the standard deviation among annual biomass yield (vertical bars) and annual pheasant population (horizontal bars). Comparing all time-based scenarios across all landscapes (Figure C.23), we see clear indications that biomass yields are lower when harvesting occurs in winter. We also see that harvesting in the fall consistently yielded better outcomes: higher biomass yields and larger pheasant populations than other scenarios. None of the scenarios were agents spatial movements are varied (Figure C.24) distinguished themselves in performance.

Time series figures display the pheasant population (Figures C.25, C.26, C.27, C.28, top row) and biomass yield (Figures C.25, C.26, C.27, C.28, bottom row) over simulation time (total 5 years). These figures highlight the modeled processes. For example, each of the harvest periods simulated in scenarios that varied harvest timings can be seen as spikes across the simulation (e.g., biomass yield is zero throughout the year expect in winter when harvesting occurs). In comparison, biomass is harvested in the fall for all scenarios that vary spatial movements of some agents. Hence, the overlap among simulated scenarios displayed in the time series figure of biomass yield. The cyclic nature of pheasant populations is also well illustrated in the time series figures.

We investigated mortality causes across all scenarios and looked at the number of pheasants (males only) killed by hunters and the number of pheasants killed by tractors broken down by sex (Figure C.29). Tractors killed more pheasants than hunters did in these simulations. Across all scenarios on the corn landscape, the

maximum number of pheasants killed by tractors was 660 ± 58.21 compared to a maximum of 272 ± 31.58 pheasants killed by hunters. Similar results occur on the CRP landscape (502 ± 29.52 deaths caused by tractors vs. 270 ± 10.89 deaths caused by hunters), grass landscape (405 ± 37.23 deaths caused by tractors vs. 266 ± 23.29 deaths caused by hunters), and mixed landscape (590 ± 39.07 deaths caused by tractors vs. 241 ± 26.28 deaths caused by hunters). The number of pheasants killed by hunters were fairly consistent across all scenarios and all landscapes. Space3 and Space4 represent scenarios that utilized the ‘theory-harvest’ strategy for tractors. This strategy did not seem to have any effect on tractor death by sex.

We plotted cumulative and average values with error bars representing variation across replicates for a variety of outputs across all the landscapes (Figure C.30). First, we looked at the amount of biomass feedstock produced for bioenergy production. We see a confirmation of our previous finding that biomass values were lower when the harvest occurs in winter (Time2), and that this holds across all landscapes. Otherwise, the total amount of biomass feedstock was fairly consistent over all the other scenarios. Next, we examined the amount of corn that was harvested. These values should be similar across scenarios since nothing was varied with respect to harvest strategies. Finally, we determined the “average pheasant abundance” value for each scenario by dividing the total pheasant population summed over all time-steps and then dividing by the total number of time-steps. The behavior of pheasant populations varies greatly over time, so the “average pheasant abundance” value can provide information that is easily comparable across scenarios. Interestingly, we see one type of behavior from corn landscape scenarios and another type of behavior from CRP, grass, and mixed landscape scenarios. On the corn landscape, scenarios that utilized theory harvest (Space3 and Space4) had the highest average pheasant abundance. On all the other landscapes, spring harvests (Time3 and Time4) had the lowest average pheasant value. For CRP, grass, and mixed landscapes, the average pheasant value associated with theory harvest scenarios (Space3 and Space4) fall within the distribution of average pheasant values among the scenarios.

4.3.2 Ecological valuation

We calculated the total monetary value per square km associated with each scenario across all landscapes (Table C.9). The valuation was incredibly dependent upon landscape. The CRP landscape had the highest valued scenarios at approximately \$500,000 per km². Next was the corn landscape scenarios with around \$300,000 per km². Third was the mixed landscape scenarios at approximately \$100,000 per km². The lowest valued scenarios, with approximately \$35,000 per km², came from the grass landscape. Even though scenario valuations occur in various ranges for different landscapes, when examining across scenarios within a landscape, all the total values are pretty close together. Naturally, winter harvest scenarios (Time2) had

lower monetary values than the other scenarios given that it consistently reported lower biomass yields than other scenarios.

4.4 Discussion

Overall, we found that fall harvesting may provide the most value. Our results suggest that harvesting in winter will result in less biomass yield, and that this reduction in yield is not landscape dependent. This is in agreement with Gamble et al., [57] who found that biomass yield was lowest when harvested in winter across seven sites in Minnesota. Biomass yield is lower when harvested in winter because of the degradation in plant material. Additionally, other studies have found that biomass yield is less in winter [1, 7]. We also found that harvesting in spring will result in fewer pheasants, because this is when reproduction occurs and more chicks (individuals) are added to the population [154]. We expected an inverse relationship between biomass yield and pheasant populations associated with changing biomass harvest time. We did not see an such a relationship, rather we saw some clustering of output, creating distinct regions associated with each time scenario. In general, we find that harvesting biomass in the fall results in the highest combined values of both pheasant population and biomass generation.

We also examined the effect of varying spatial harvest strategies of both biomass and pheasants. The results from the scenarios where spatial movement of some agents were varied were inconclusive. Among the spatial strategies for tractors, we expected to see similar biomass yields but larger pheasant populations when a theory harvest strategy is utilized. Biomass yield values did remain fairly constant among scenarios, but pheasant populations did not increase between base harvest and theory harvest scenarios. The theory harvest strategy does not impart any additional benefits. Varying spatial hunting strategies did not have any effect on hunter's yield.

We found ecological value to be landscape dependent. Our scenarios totaled between \$18,000 per km² (minimum) and \$550,000 per km² (maximum) over all landscapes. CRP landscape- and corn landscape-scenarios were among the most lucrative and far surpassed values from grass landscape- and mixed landscape-scenarios, even without accounting for direct payments to farmers for enrolling land in CRP. The majority of value in these scenarios came from biomass yield from switchgrass and other non-corn harvested lands. No market for such products currently exists, it is predicted to exist in the future [18, 46]. Nevertheless, farmers cannot realize profits from feedstocks yet. Additionally, pheasants were valued in a limited capacity in our valuation framework. The true value would include the value in sustaining pheasant populations in an environmental sense and all of the other money that is associated with hunters traveling as tourists to hunt. Hunter's willingness-to-pay (WTP) for the experience of hunting was excluded in this study but could

arguably provide additional value. Both of these valuation methods are beyond the scope of this study.

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Chapter 5

Conclusions

We began this dissertation with the overarching question: How do we holistically design and manage bioenergy landscapes at multiple spatial scales given numerous, potentially conflicting, objectives? We then explored this question through three studies that utilized both species distribution modeling and agent-based modeling methods.

The first study investigated which predictors are important to consider when thinking about future avian occurrence in a bioenergy landscape. We downscaled county-level herbicide application data and included it along with climatic and landscape predictors in modeling occurrence of 25 avian species across Iowa. We found the three most important predictors of species occurrence to be distance to water, mean diurnal temperature range, and herbicide application rate. When contemplating future bioenergy feedstock production from perennial grasses, we envision an increase in grassland-like acres on the landscape. In our study, 76% of species responded positively to presence of grassland. This leads us to conclude that producing perennial grasses as biomass feedstocks will not negatively impact avian biodiversity. We also examined whether grouping species by ecosystem service revealed any information on managing land for future biomass feedstock production. We did find a relationship between the ecosystem service a species provides and their potential success in a landscape, though further work is required to determine the nature of that relationship. This is supported by the conclusion that responses of the farmland bird community as a whole to the introduction of bioenergy production is small and broadly similar, but that similarity in overall responses masks significant intra- and inter-specific variations [137].

In the second study we built a species distribution modeling tool called BioEST-Suite. BioEST-Suite utilizes three different algorithm methods: random forest, stochastic gradient boosting, and neural network. We then used BioEST-Suite to evaluate a potential future Iowa landscape where cellulosic bioenergy is

produced. This future landscape is created by managing low ROI lands to grassland. We examined species richness predictions to determine how avian biodiversity would be affected. By converting unprofitable areas in Iowa to grassland, BioEST-Suite predicted anywhere from 2.79% to 7.51% increase in species richness. We also found that areas of low ROI tended to occur in riparian areas, suggesting that incorporating bioenergy riparian buffers into the landscape would be beneficial to avian biodiversity. Under the future landscape, we determined that the revenue lost across all the low ROI land identified averaged approximately \$110 million USD per year from 2013 to 2016. If these targeted areas, totaling just 3% of Iowa's agricultural land, were planted with switchgrass yielding an average of 0.00089 tonnes/m² (4 tons/acre), we would expect an annual harvest of approximately 7.6 million tons y⁻¹ of switchgrass biomass that could be used for cellulosic ethanol production.

Finally, in the last study we varied spatiotemporal harvest strategies at the field scale and examined resultant biomass yield, pheasant yield, and pheasant population size. Through utilization of an agent-based model that represented pheasants, tractors, hunters, and vegetation at the field scale, we were able to assess effects of management practices on four different landscapes. We determined that biomass yield and pheasant population size were sensitive to changes in harvesting times, but unaffected by changes in spatial movement of harvesting strategies. Specifically, harvesting in the fall may yield the most value because winter harvest results in depressed biomass yields due to biomass degradation and spring harvest results in decreases in pheasant population sizes because of disruptions to pheasant reproduction. Landscapes dominated by corn and CRP were orders of magnitude more profitable than grassland dominated or mixed landscapes.

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Appendix

Appendix A: Examining predictors of avian biodiversity for species providing different ecosystem services in Iowa’s agricultural landscapes and the potential benefits of growing biomass feedstocks

Table A.1: All 19 predictors used in modeling, including the name of the predictor, a description of the predictor, and the original data source.

Predictor Name	Description	Temporal Resolution	Source
Bio 2	Mean diurnal rage	1970 - 2000	[170]
Bio 4	Temperature seasonality	1970 - 2000	[170]
Bio 8	Mean temperature of wettest quarter	1970 - 2000	[170]
Bio 9	Mean temperature of driest quarter	1970 - 2000	[170]
Bio 15	Precipitation seasonality	1970 - 2000	[170]
Bio 16	Precipitation of wettest quarter	1970 - 2000	[170]
Bio 17	Precipitation of direst quarter	1970 - 2000	[170]
Bio 18	Precipitation of warmest quarter	1970 - 2000	[170]
Bio 19	Precipitation of coldest quarter	1970 - 2000	[170]
DEM	Digital elevation model, elevation (m)	2020 (1 year)	[99]
Corn	Presence of corn	2009 (1 year)	[49]
Soybean	Presence of soybean	2009 (1 year)	[49]
Grassland	Presence of grassland	2009 (1 year)	[49]
Forest	Presence of decidous forest of varying heights	2009 (1 year)	[49]
2,4-D	2,4-D herbicide applied (kg)	2016 (1 year)	[58]
Herb5	Summation of acetochlor, atrazine, dicamba, glyphosate, and metolachlor herbicide application over Iowa (kg)	2016 (1 year)	[58]
Forest dist	Distance to forest (m)	2009 (1 year)	[49]
Water dist	Distance to water (m)	2009 (1 year)	[49]
Snow	Season accumulation of snow fall (ft)	September 30 2016 - September 30 2017	[149]

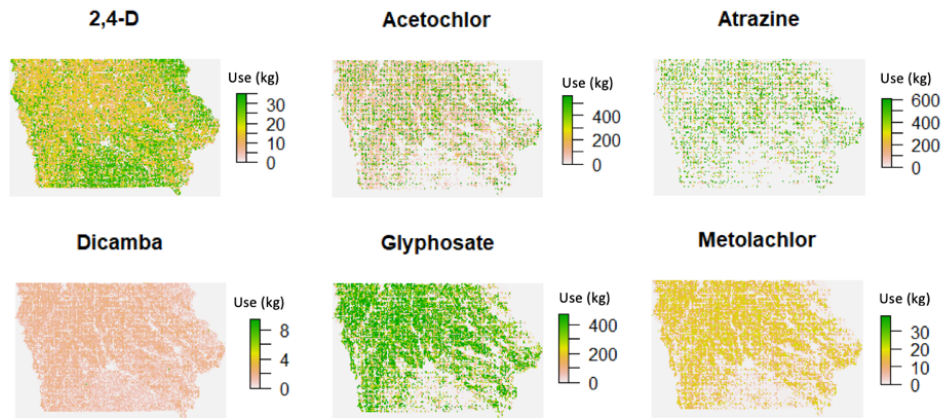


Figure A.1: Downscaled herbicide application maps of Iowa; the six herbicides are (beginning in top left corner) 2,4-D, acetochlor, atrazine, dicamba, glyphosate, and metolachlor, application of herbicide in is kg.

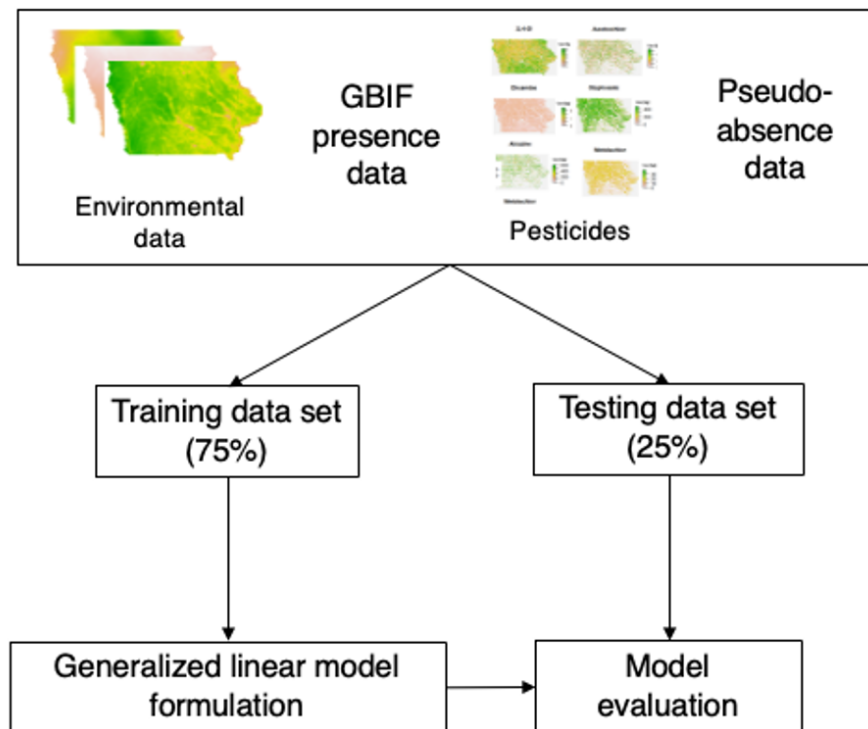


Figure A.2: Modeling framework overview.

Table A.2: Correlations amongst predictors considered for incorporation into the model.

Predictor 1	Predictor 2	Correlation coefficient
Annual mean temperature	Max temperature of warmest month	0.905
Annual mean temperature	Mean temperature of warmest quarter	0.962
Annual mean temperature	Min temperature of coldest month	0.984
Annual mean temperature	Mean temperature of driest quarter	0.993
Annual mean temperature	Mean temperature of coldest quarter	0.994
Mean diurnal range	Isothermality	0.734
Isothermality	Max temperature of warmest month	0.754
Temperature seasonality	Temperature annual range	0.939
Max temperature of warmest month	Min temperature of coldest month	0.840
Max temperature of warmest month	Mean temperature of driest quarter	0.869
Max temperature of warmest month	Mean temperature of warmest quarter	0.975
Max temperature of warmest month	Mean temperature of coldest quarter	0.870
Min temperature of coldest month	Mean temperature of driest quarter	0.993
Min temperature of coldest month	Mean temperature of warmest quarter	0.914
Min temperature of coldest month	Mean temperature of coldest quarter	0.993
Temperature annual range	Precipitation seasonality	0.783
Mean temperature of driest quarter	Mean temperature of coldest quarter	0.999
Mean temperature of driest quarter	Mean temperature of warmest quarter	0.931
Mean temperature of warmest quarter	Mean temperature of coldest quarter	0.931
Annual precipitation	Precipitation of driest quarter	0.868
Annual precipitation	Precipitation of coldest quarter	0.868
Annual precipitation	Precipitation of driest month	0.844
Annual precipitation	Precipitation of wettest quarter	0.752
Precipitation of wettest month	Precipitation of wettest quarter	0.817
Precipitation of wettest month	Precipitation of warmest quarter	0.783
Precipitation of driest month	Precipitation of coldest quarter	0.979
Precipitation of driest month	Precipitation of driest quarter	0.979
Precipitation of wettest quarter	Precipitation of warmest quarter	0.956
Precipitation of driest quarter	Precipitation of coldest quarter	1

Table A.3: A summary of the abbreviation of common name used in figures, scientific name, common species name, number of presence points used in modeling, and the ecosystem service each species provides.

Abbreviation	Scientific name	Species	Number of presences	Ecosystem service
RWB	<i>Agelaius phoeniceus</i>	Red-winged black-bird	16291	Conservation value
WD	<i>Aix sponsa</i>	Wood duck	6707	Recreational value
LEO	<i>Asio otus</i>	Long-eared owl	160	Conservation value
RND	<i>Aythya collaris</i>	Ring-necked duck	3501	Recreational value
GS	<i>Aythya marila</i>	Greater scaup	466	Recreational value
RSH	<i>Buteo lineatus</i>	Red-shouldered hawk	970	Conservation value
BT	<i>Chlidonias niger</i>	Black tern	886	Conservation value
NB	<i>Colinus virginianus</i>	Northern bobwhite	1028	Conservation value
AC	<i>Fulica americana</i>	American coot	5629	Recreational value
BE	<i>Haliaeetus leucocephalus</i>	Bald eagle	52301	Conservation value
BO	<i>Icterus galbula</i>	Baltimore oriole	7084	Pollinator
OO	<i>Icterus spurius</i>	Orchard oriole	1924	Pollinator
HM	<i>Lophodytes cucullatus</i>	Hood merganser	2976	Recreational value
WT	<i>Meleagris gallopavo</i>	Wild turkey	5451	Recreational value
BHC	<i>Molothrus ater</i>	Brown-headed cowbird	9309	Recreational value
GP	<i>Perdix perdix</i>	Gray partridge	308	Recreational value
SCT	<i>Piranga olivacea</i>	Scarlet tanager	1732	Pollinator
SUT	<i>Piranga rubra</i>	Summer tanager	542	Pollinator
GTG	<i>Quiscalus mexicanus</i>	Great-tailed grackle	480	Pollinator
CG	<i>Quiscalus quiscula</i>	Common grackle	13337	Pollinator
VR	<i>Rallus limicola</i>	Virginia rail	315	Recreational value
AW	<i>Scolopax minor</i>	American woodcock	519	Recreational value
FT	<i>Sterna forsteri</i>	Forster's tern	1020	Conservation value
EM	<i>Sturnella magna</i>	Eastern meadowlark	5681	Conservation value
MD	<i>Zenida macroura</i>	Mourning dove	15192	Recreational value

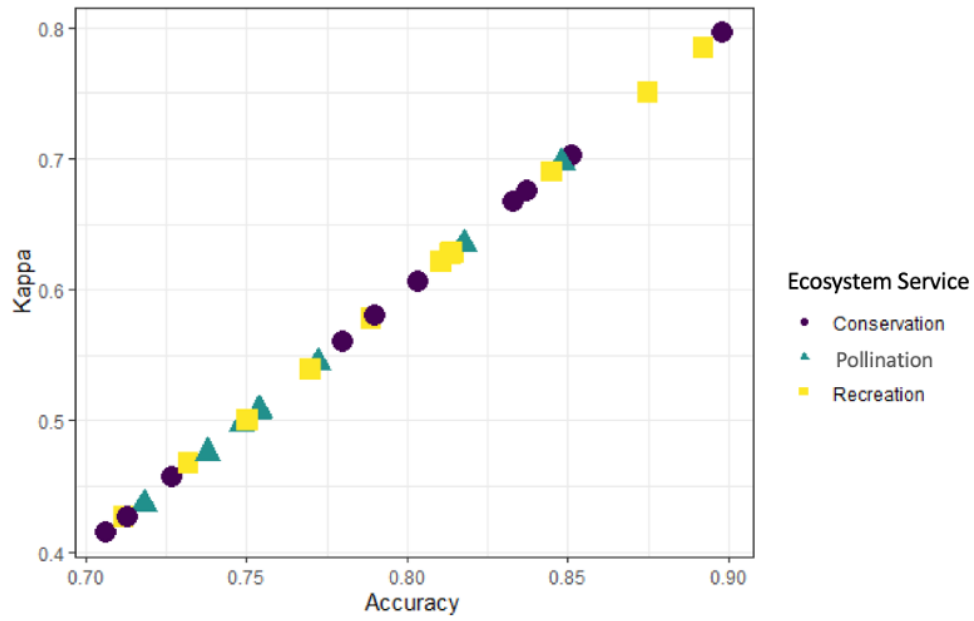


Figure A.3: Accuracy versus kappa for 25 bird species. Each point represents one species with each color/shape combination representing a different ecosystem service grouping.

Table A.4: Ranking of importance for each predictor over all ecosystem groups and total species.

Predictor Name	Pollinators	Conservation Value	Recreational Value	Total
Bio 2	1	2	2	2
Bio 8	12	11	12	12
Bio 9	13	6	10	10
Bio 15	8	8	7	9
Bio 16	7	7	9	6
Bio 17	15	13	11	14
DEM	10	12	5	8
Corn	14	15	13	15
Soybean	11	9	14	11
Grassland	9	14	15	13
2,4-D	4	5	4	4
Herb5	3	3	3	3
Forest dist	6	10	8	7
Water dist	2	1	1	1
Snow	5	4	6	5

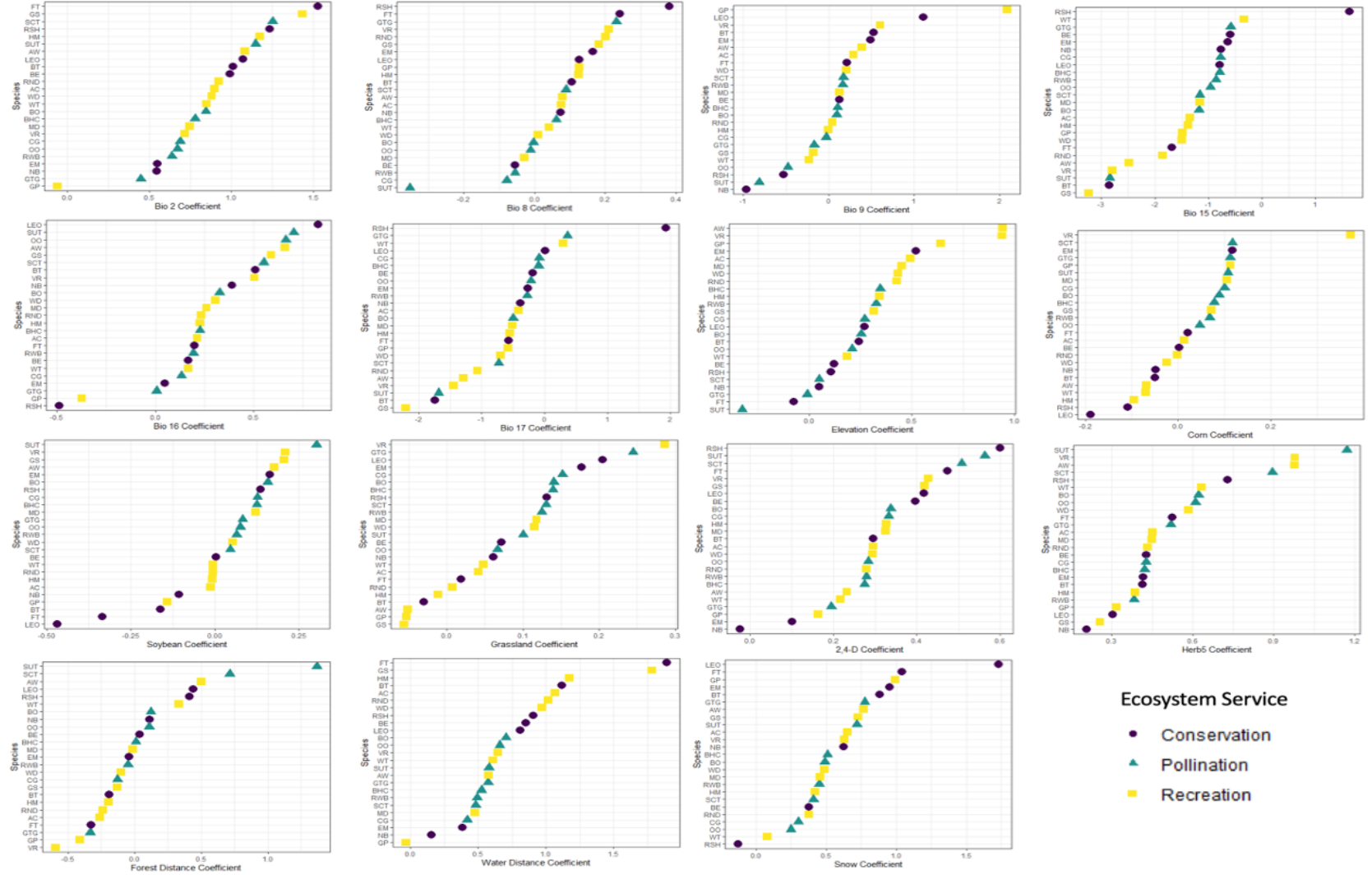


Figure A.4: Logistic coefficient values across all 15 predictors for all 25 species. Each point represents one species, the species abbreviation key can be found in Table A.3. Beginning in the top left corner and moving left to right, the predictors are bio 2, bio 8, bio 9, bio 15, bio 16, bio 17, DEM, corn, soybean, grassland, 2,4-D, herb5, forest distance, water distance, and snow.

Table A.5: The odds ratio across each species and predictor. Values ≥ 1 denote that an increase in that predictor corresponds to an increase in the probability of presence of that species. Values < 1 denote that a decrease in that predictor corresponds to a decrease in the probability of presence of that species

Species	Bio 2	Bio 8	Bio 9	Bio 15	Bio 16	Bio 17	DEM	Corn	Soybean	Grassland	Water	Herb	Forest	Water	Snow
RWB	1.89	0.95	1.18	0.42	1.21	0.76	1.39	1.07	1.07	1.13	1.32	1.47	0.95	1.64	1.57
WD	2.41	1.01	1.23	0.22	1.36	0.5	1.54	0.98	1.06	1.12	1.34	1.79	0.9	2.64	1.63
LEO	2.92	1.13	3.02	0.46	2.29	1.01	1.31	0.83	0.63	1.23	1.52	1.36	1.55	2.25	5.64
RND	2.52	1.22	1.04	0.16	1.26	0.34	1.53	1	0.99	1.01	1.32	1.54	0.79	2.76	1.46
GS	4.19	1.2	0.84	0.04	1.8	0.11	1.37	1.07	1.23	0.95	1.52	1.29	0.88	5.93	2.06
RSH	3.43	1.46	0.59	5.11	0.61	6.85	1.11	0.9	1.15	1.14	1.82	2.07	1.51	2.48	0.88
BT	2.74	1.11	1.69	0.06	1.66	0.18	1.28	0.95	0.85	0.97	1.34	1.51	0.83	3.06	2.41
NB	1.73	1.08	0.38	0.47	1.48	0.68	1.06	0.95	0.9	1.06	0.98	1.23	1.12	1.17	1.87
AC	2.45	1.08	1.34	0.26	1.24	0.66	1.64	1.01	0.99	1.04	1.34	1.57	0.77	2.91	1.92
BE	2.69	0.95	1.14	0.55	1.18	0.83	1.13	1	1	1.07	1.49	1.53	1.04	2.34	1.46
BO	2.33	1	1.1	0.31	1.39	0.61	1.29	1.09	1.17	1.15	1.4	1.86	1.13	2.02	1.63
OO	1.96	0.99	0.62	0.38	1.94	0.81	1.23	1.05	1.08	1.07	1.33	1.84	1.12	1.93	1.28
HM	3.23	1.13	0.99	0.25	1.26	0.58	1.41	0.91	0.99	0.99	1.39	1.47	0.82	3.24	1.52
WT	2.34	1.04	0.8	0.71	1.18	1.34	1.2	0.93	0.99	1.05	1.24	1.88	1.39	1.84	1.08
BHC	2.18	1.06	1.11	0.45	1.26	0.91	1.41	1.08	1.13	1.15	1.32	1.52	1.01	1.69	1.66
GP	0.94	1.13	8.04	0.23	0.69	0.56	1.9	1.12	0.87	0.95	1.18	1.37	0.66	0.97	2.7
SCT	3.49	1.09	1.19	0.31	1.74	0.48	1.05	1.12	1.05	1.14	1.66	2.45	2.04	1.62	1.51
SUT	3.15	0.7	0.44	0.06	2.02	0.19	0.72	1.11	1.35	1.11	1.76	3.23	3.93	1.79	2.05
GTG	1.57	1.26	0.84	0.56	1.01	1.44	0.99	1.12	1.09	1.28	1.22	1.68	0.72	1.77	2.17
CG	1.99	0.92	0.97	0.46	1.14	0.92	1.31	1.11	1.14	1.16	1.39	1.53	0.88	1.52	1.35
VR	2.04	1.23	1.83	0.06	1.66	0.23	2.56	1.45	1.23	1.33	1.53	2.66	0.55	1.91	1.87
AW	2.96	1.08	1.48	0.08	1.93	0.28	2.57	0.93	1.19	0.95	1.26	2.66	1.65	1.78	2.16
FT	4.6	1.27	1.24	0.19	1.22	0.56	0.93	1.02	0.72	1.02	1.61	1.69	0.72	6.62	2.83
EM	1.73	1.18	1.63	0.53	1.05	0.77	1.68	1.12	1.18	1.19	1.11	1.52	0.96	1.47	2.59

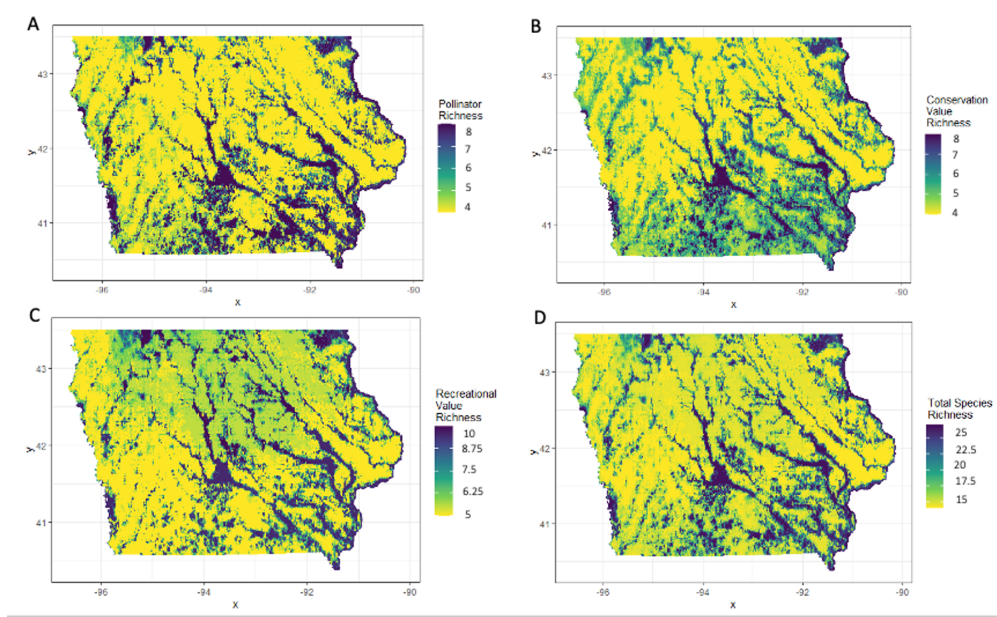


Figure A.5: Species richness maps for (A) pollinators ($n=8$), (B) species of conservation value ($n=7$), (C) species of recreational value ($n=10$), and (D) total species richness ($n=25$). Here ‘ n ’ is the maximum number of species that can be present.

Appendix B: Growing perennial grasses in unprofitable areas of US Midwest croplands could increase avian richness and provide a cellulosic biofuel feedstock

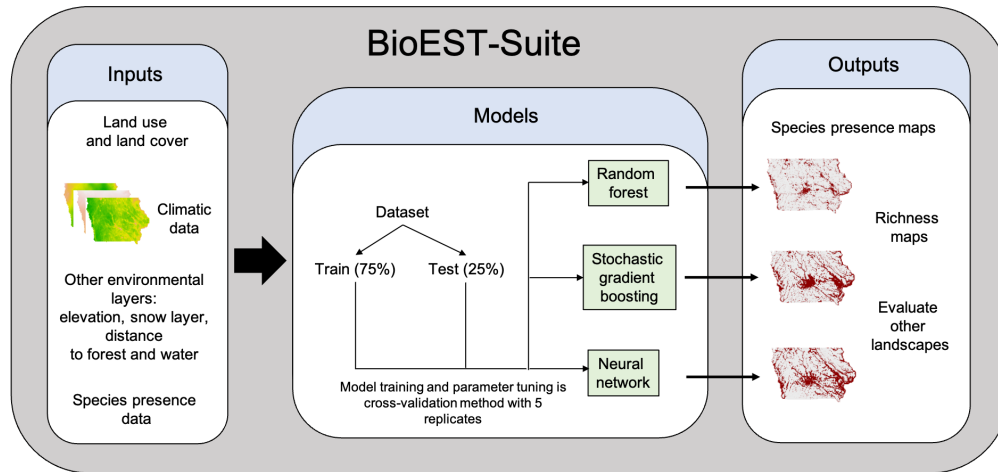


Figure B.6: BioEST-Suite model diagram including inputs, model formulation, and outputs. BioEST-Suite outputs can be used to compare current and future scenarios.

Table B.6: Predictors included in BioEST-Suite.

Predictor Name	Description	Temporal Resolution	Source
Precip	Precipitation (mm)	2009 - 2019	[65]
Temp mean	Mean daily temperature (degC)	2009 - 2019	[65]
DEM	Digital elevation model, elevation (m)	2020 (1 year)	[99]
Corn	Presence of corn	2009 (1 year)	[49]
Soybean	Presence of soybean	2009 (1 year)	[49]
Grassland	Presence of grassland	2009 (1 year)	[49]
Forest dist	Distance to forest (m)	2009 (1 year)	[49]
Water dist	Distance to water (m)	2009 (1 year)	[49]
Snow	Season accumulation of snow fall (m)	Sept 30 2016 - Sept 30 2017	[149]

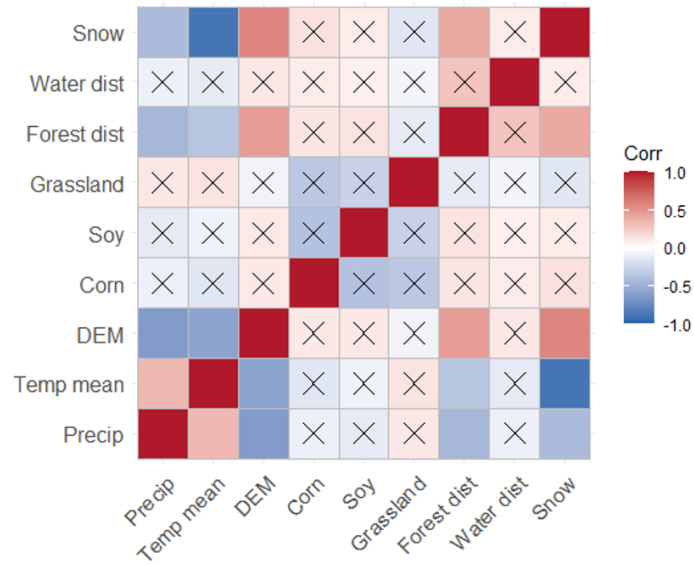


Figure B.7: Correlation matrix depicting the correlation coefficients between all predictors. Cells without crosses in them represent statistically significant correlations. See Table B.6 for description of predictors.

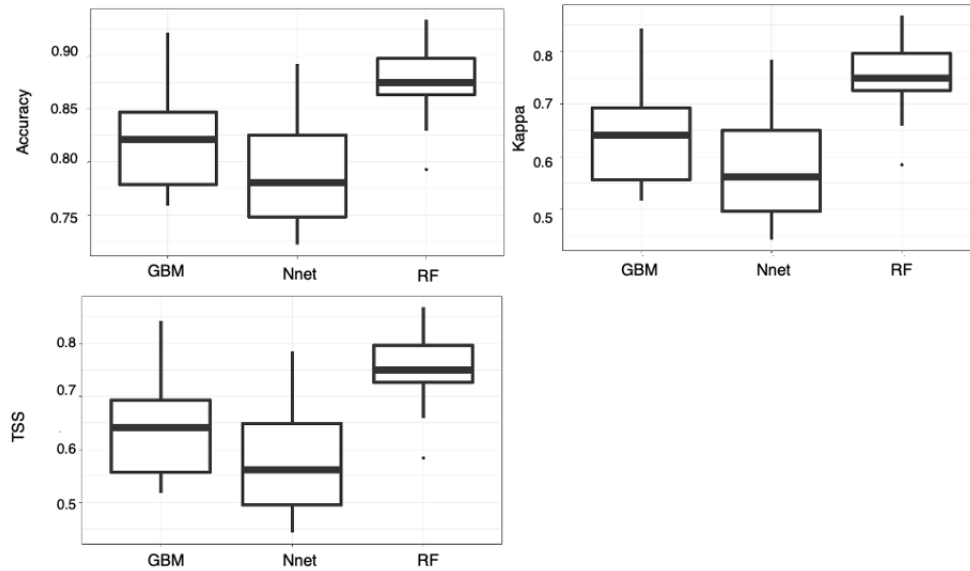


Figure B.8: Accuracy, kappa, and True skill statistic (TSS) values averaged across 28 avian species for BioEST-Suite models (GBM - Stochastic gradient boosting, Nnet - Neural network, RF - Random forest)

Table B.7: A summary of the 28 species characterized with data obtained from the Global Biodiversity Information Facility, including the abbreviation of common name used in figures, scientific name, common species name, number of presence points used in modeling, and Moran’s I value.

Abbreviation	Scientific name	Species	Number of presences	Moran’s I value
RWB	<i>Agelaius phoeniceus</i>	Red-winged blackbird	16419	0.07524
WD	<i>Aix sponsa</i>	Wood duck	7877	0.07925
RTH	<i>Archilochus colubris</i>	Ruby-throated hummingbird	5237	0.01186
LEO	<i>Asio otus</i>	Long-eared owl	132	0.00548
RND	<i>Aythya collaris</i>	Ring-necked duck	3621	0.09727
GS	<i>Aythya marila</i>	Greater scaup	485	0.06729
RSH	<i>Buteo lineatus</i>	Red-shouldered hawk	1088	-0.0222
BT	<i>Chlidonias niger</i>	Black tern	771	0.01244
HH	<i>Circus cyaneus</i>	Hen harrier	3118	0.08931
NB	<i>Colinus virginianus</i>	Northern bobwhite	1056	0.10531
ACR	<i>Corvus brachyrhynchos</i>	American crow	17839	0.05942
ACO	<i>Fulica americana</i>	American coot	5815	0.01431
BE	<i>Haliaeetus leucocephalus</i>	Bald eagle	16157	0.08371
BO	<i>Icterus galbula</i>	Baltimore oriole	8412	0.09317
OO	<i>Icterus spurius</i>	Orchard oriole	2384	0.07158
HM	<i>Lophodytes cucullatus</i>	Hooded merganser	3270	0.10044
WT	<i>Meleagris gallopavo</i>	Wild turkey	6144	0.07036
BHC	<i>Molothrus ater</i>	Brown-headed cowbird	10999	0.0768
SCT	<i>Piranga olivacea</i>	Scarlet tanager	2038	0.08648
SUM	<i>Piranga rubra</i>	Summer tanager	666	0.07064
GTG	<i>Quiscalus mexicanus</i>	Great-tailed grackle	45	0.021331
CG	<i>Quiscalus quiscula</i>	Common grackle	15311	0.08019
AW	<i>Scolopax minor</i>	American woodcock	580	0.10529
AG	<i>Spinus tristis</i>	American goldfinch	14362	0.09943
FS	<i>Spizella pusilla</i>	Field sparrow	5492	0.08626
FT	<i>Sterna forsteri</i>	Forster’s tern	945	0.10612
EM	<i>Sturnella magna</i>	Eastern meadowlark	6605	0.07363
MD	<i>Zenaida macroura</i>	Mourning dove	15014	0.07586

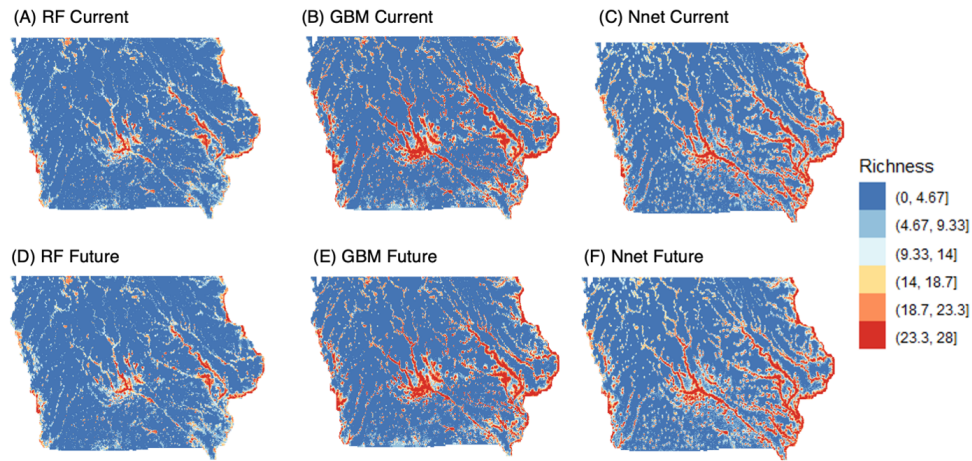


Figure B.9: BioEST-Suite maps of avian species richness for the current (A, B, C) and alternative (D, E, F) landscape. BioEST-Suite models include (A, D) Random forest (RF), (B, E) Stochastic gradient boosting (GBM), and (C, F) Neural network (Nnet).

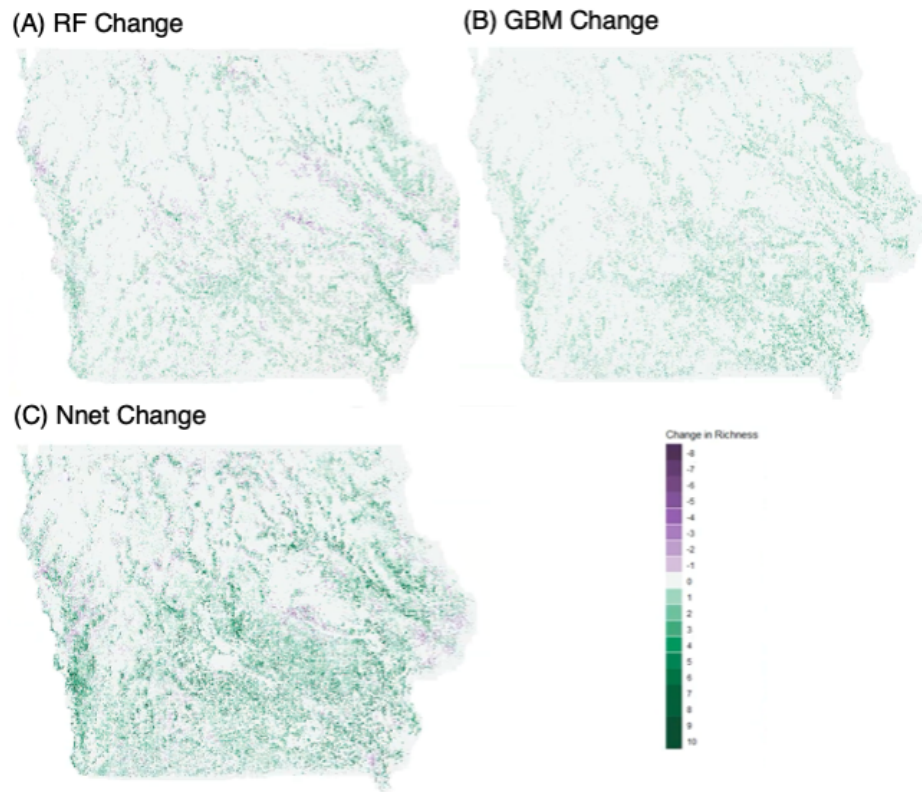


Figure B.10: Different map showing predicted changes in richness that occurred between the alternative and current landscape for BioEST-Suite models (RF - Random forest, GBM - Stochastic gradient boosting, Nnet - Neural network.)

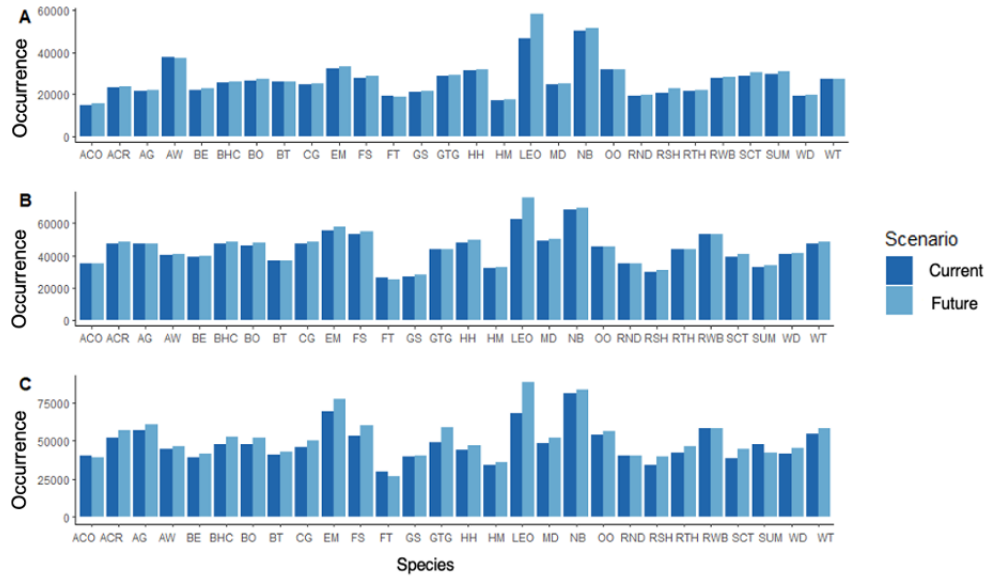


Figure B.11: Species occurrence under current and alternative landscapes for (A) Random forest, (B) Stochastic gradient boosting, and (C) Neural network. Species abbreviations are detailed in Table B.7.

Appendix C: Spatially-explicit agent-based modeling to evaluate the effects of planting and harvesting biomass and hunting on ring-necked pheasant (*Phasianus colchicus*) populations.

Table C.8: All entities with descriptions of the state variables and corresponding values.

Variable	Description	Value(s)
<i>Pheasant Entity</i>		
energy	Total mass (kg) of individual pheasant	$[0, \text{inf}]$; female average is 0.8 kg, male average is 1.95
age	Age (in days) of pheasant	$[0, 1095]$
food-trials	Number of attempts to find food per day	4
mom	Identifies the mother of each pheasant	female pheasant ID
lek-trials	For males only, the number of attempts to establish a harem	2
desirability	For males only, a random value assigned at birth that describes how attractive they are to female pheasants	$[0, 1]$
territorial?	Established territory for mating	True/False
terr-size	Area (in cells) of mating territory	$0 \cup [5, 7]$
harem-radius	For males only, the area in which they may search for females and attempt to establish a harem, dependent on their desirability	$[5, 7]$
harem-num	For females only, identifies which male's harem they belong to	male-pheasant ID
est-nest?	For females only, established a nest	True/False
nest-site	For females only, the location of their nest site	patch ID
eggs	For females only, the number of eggs a female pheasant has laid	$[7, 15]$
Continued on next page		

Table C.8 continued

Variable	Description	Value(s)
<i>Tractor Entity</i>		
bio-yield	The amount of biomass a tractor can harvest (dry ton/km ²)	[0, inf)
corn-yield	The amount of corn a tractor can harvest (dry ton/km ²)	[0, inf)
<i>Hunter Entity</i>		
target	Identifies the male pheasant that an individual hunter is trying to kill	male pheasant ID
accuracy	The probability that a hunter will hit their target	[0, 1]
hunt-trials	The number of attempts one hunter has in a day to successfully bag a male pheasant	6
hunt-distance	The radius (in cells) around each hunter in which they may look for male pheasants to treat as a target	[0, 1]
roosters	The total number of male pheasants that a hunter has successfully bagged, cumulative over a hunting season	[0, ∞)
<i>Vegetation</i>		
owner	Current male pheasant that is claiming ownership of patch in attempt to form a harem	male pheasant ID
patch-harem-num	Identifies all the patches that belong to one harem	male pheasant ID
nest?	Whether pheasants can nest in this vegetation type	True/False
luse	Type of land use on a patch	Alfalfa, hay, soybean, grass/shrubland, woody wetland, herbaceous wetland, forest, corn, switch- grass (CRP), CRP food plot
Continued on next page		

Table C.8 continued

Variable	Description	Value(s)
food	Amount of food provided to pheasants by vegetation (crude protein)	Day dependent, see Figure C.12
cover	Amount of cover (c) provided to pheasants by vegetation, plant height (m)	Day dependent, see Figure C.13
biomass	Amount of potential biomass yield that is available for harvest by tractors	Day dependent, see Figure C.13
harvestable?	Whether the vegetation type may be harvested for biomass	True/False
been-mowed?	Whether a patch has been harvested (by tractor) for the current season	True/False

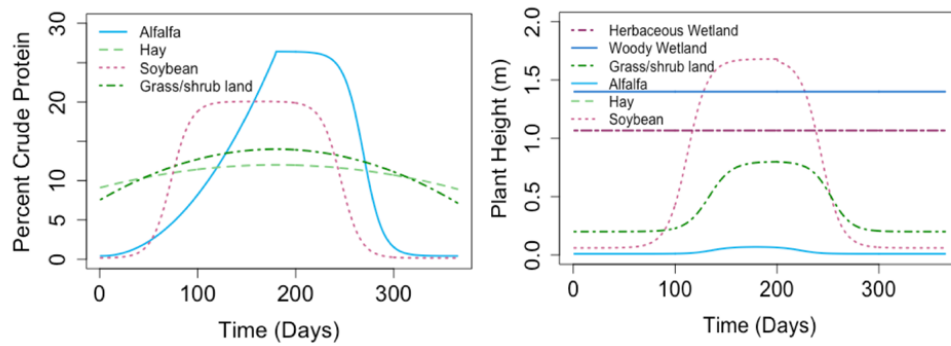


Figure C.12: Food provided by land use (left) and cover provided by land use (right), seasonal food and cover values determined from the literature [8, 68, 81, 86, 97, 98, 107, 112, 152, 171].

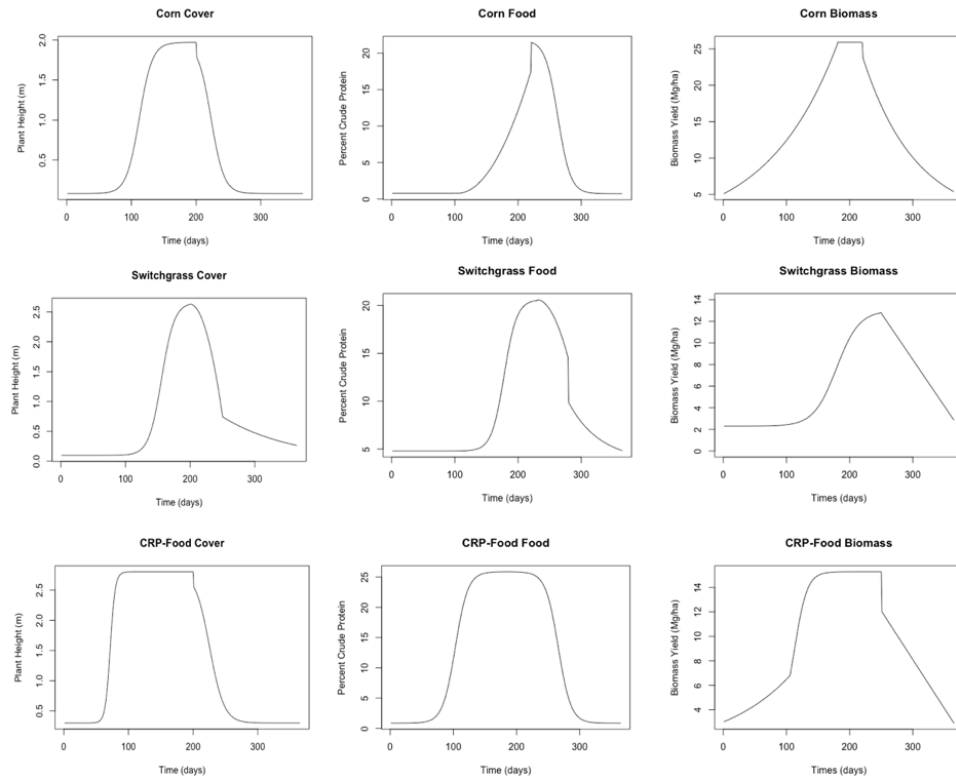


Figure C.13: Available cover, food, and biomass (left to right), for corn, switchgrass (CRP), and CRP food plot (top to bottom) [7, 93, 162, 172, 173]

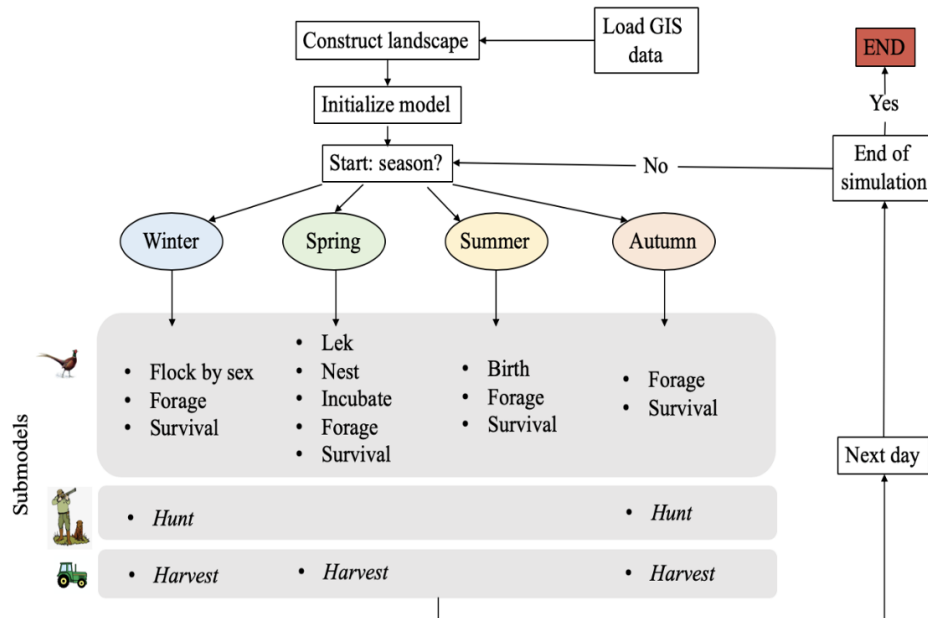


Figure C.14: Diagram of ABM scheduling, italicized submmodels represent operation that may change time of execution depending on the analysis being run

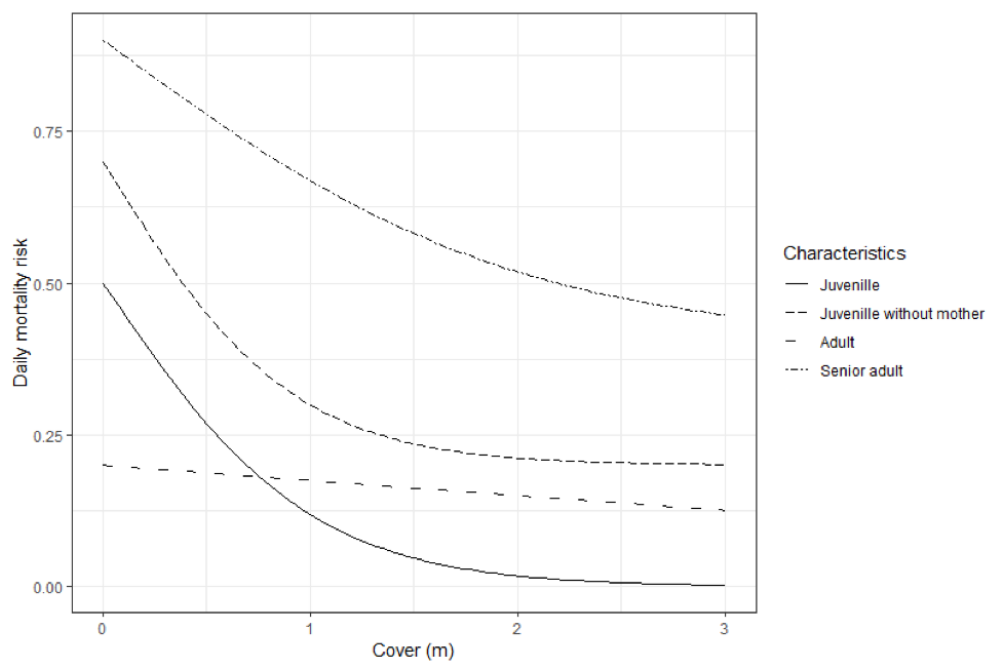


Figure C.15: The daily mortality risk (probability of death) for pheasants, given bird-specific characteristics and the cover from vegetation of current patch that the pheasant is occupying

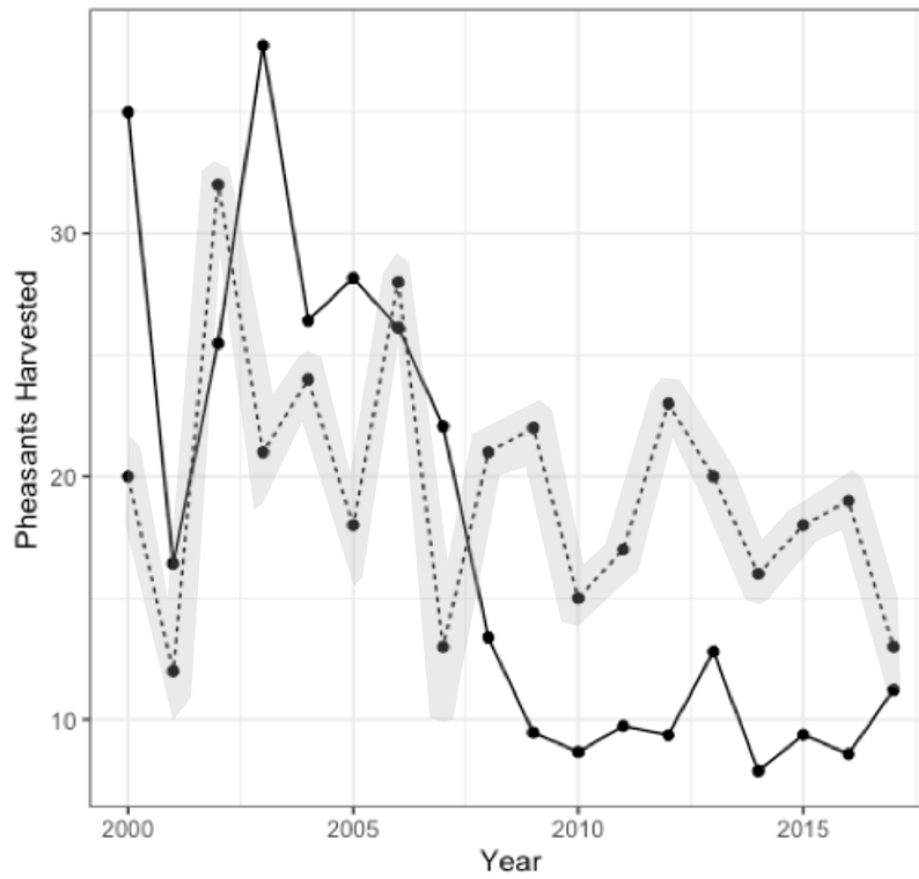


Figure C.16: Simulation results averaged across 50 replicates (dashed line, grey region is standard deviation) compared to observed pheasant hunting data from Iowa 2000-2017 (solid line).

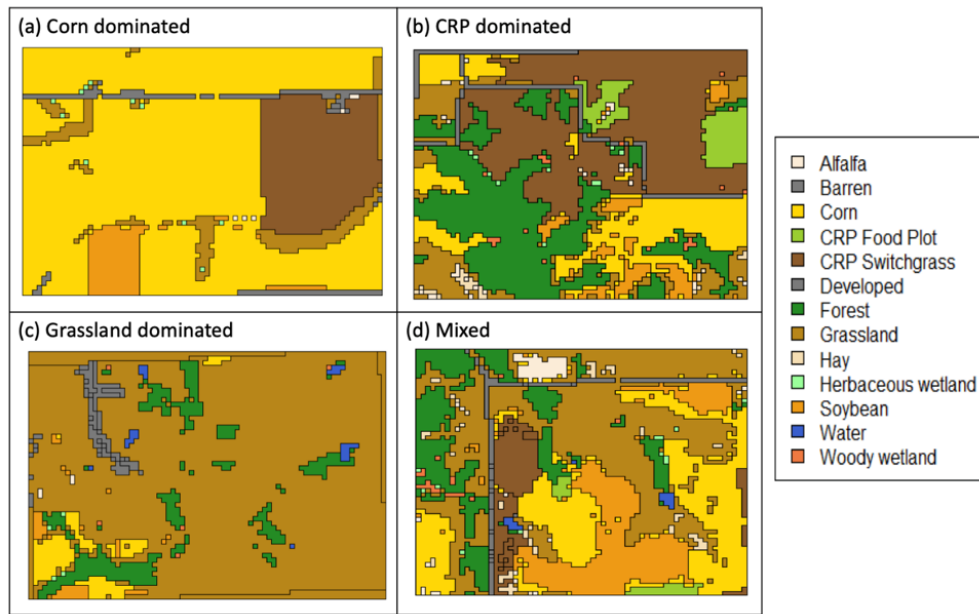


Figure C.17: The four landscapes, all approximately 5 km², used in the simulation experiments with (a) corn dominated, (b) CRP dominated, (c) grassland dominated, (d) mixed

Scenario	Tractors Temporal	Tractors Spatial	Hunters Spatial
Time1	Fall	Base harvest	Strip hunt
Time2	Winter	Base harvest	Strip hunt
Time3	Early spring	Base harvest	Strip hunt
Time4	Late spring	Base harvest	Strip hunt
Space1	Fall	Base harvest	Strip hunt
Space2	Fall	Base harvest	Hunt radius
Space3	Fall	Theory harvest	Strip hunt
Space4	Fall	Theory harvest	Hunt radius

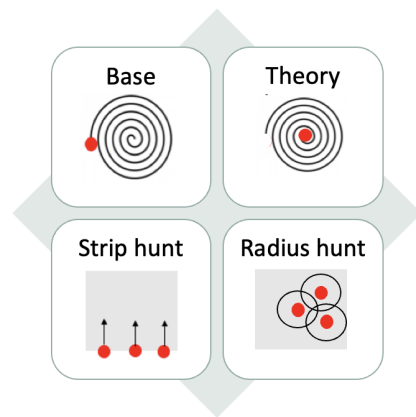


Figure C.18: Summary of all scenarios. The described tractors spatial movement and hunters spatial movement are illustrated as figures on the right.

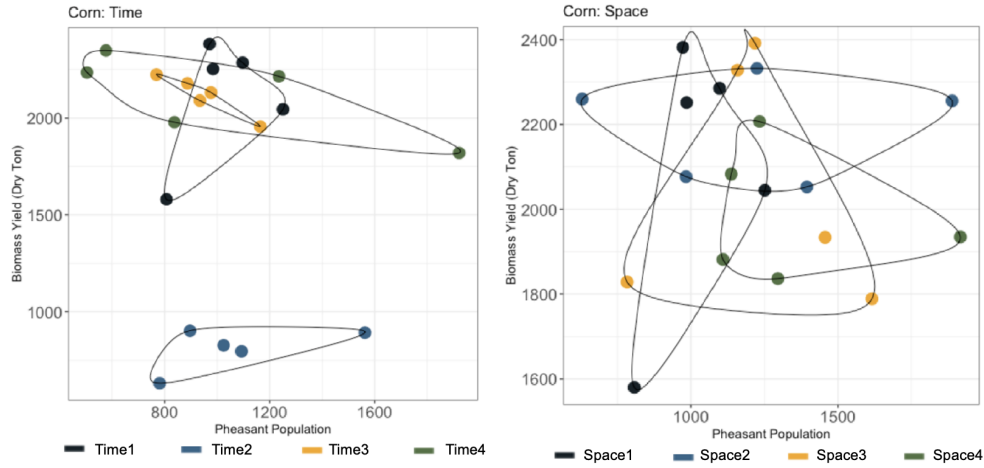


Figure C.19: Cumulative annual biomass yield (dry ton) versus cumulative annual pheasant population (number of individuals) for five simulated years for each scenario that is simulated on the corn landscape, averaged across 50 replicates. Lines encircle each grouping of scenario values. Time scenarios are represented in the left figure and space scenarios are in the right figure. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

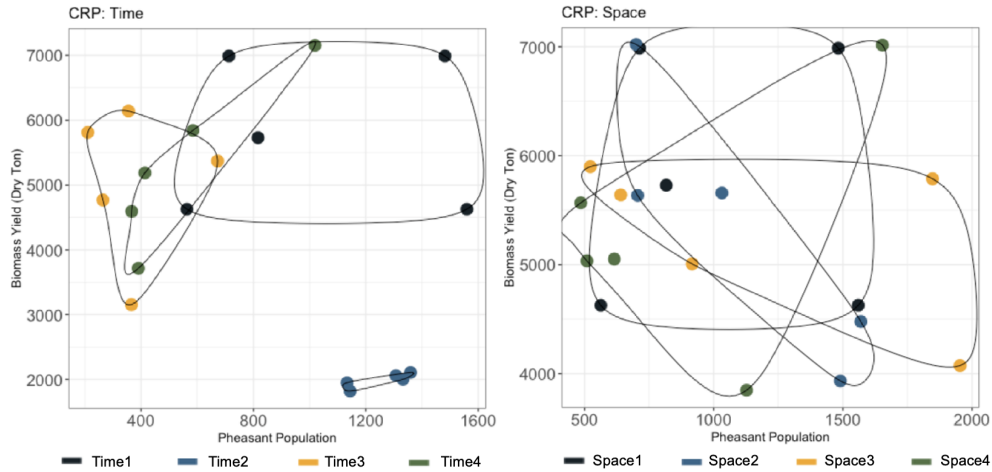


Figure C.20: Cumulative annual biomass yield (dry ton) versus cumulative annual pheasant population (number of individuals) for five simulated years for each scenario that is simulated on the CRP landscape, averaged across 50 replicates. Lines encircle each grouping of scenario values. Time scenarios are represented in the left figure and space scenarios are in the right figure. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

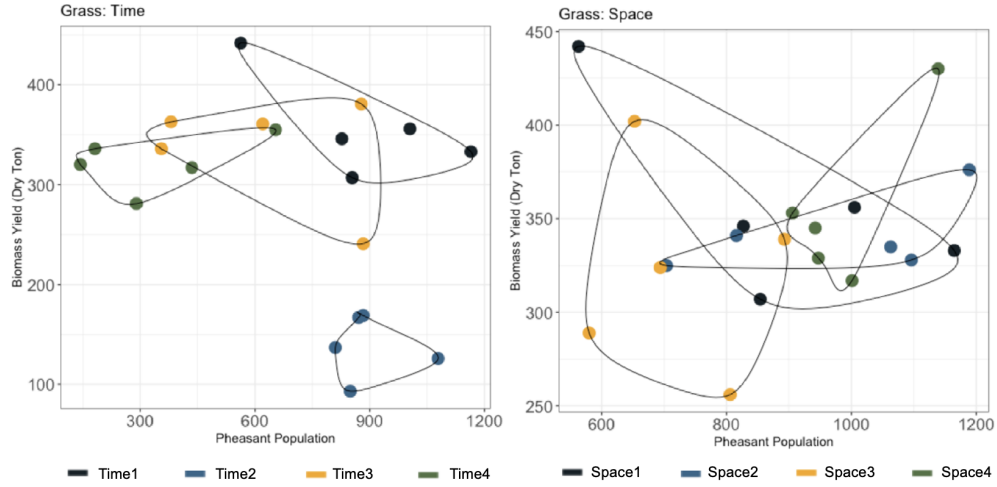


Figure C.21: Cumulative annual biomass yield (dry ton) versus cumulative annual pheasant population (number of individuals) for five simulated years for each scenario that is simulated on the grassland landscape, averaged across 50 replicates. Lines encircle each grouping of scenario values. Time scenarios are represented in the left figure and space scenarios are in the right figure. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

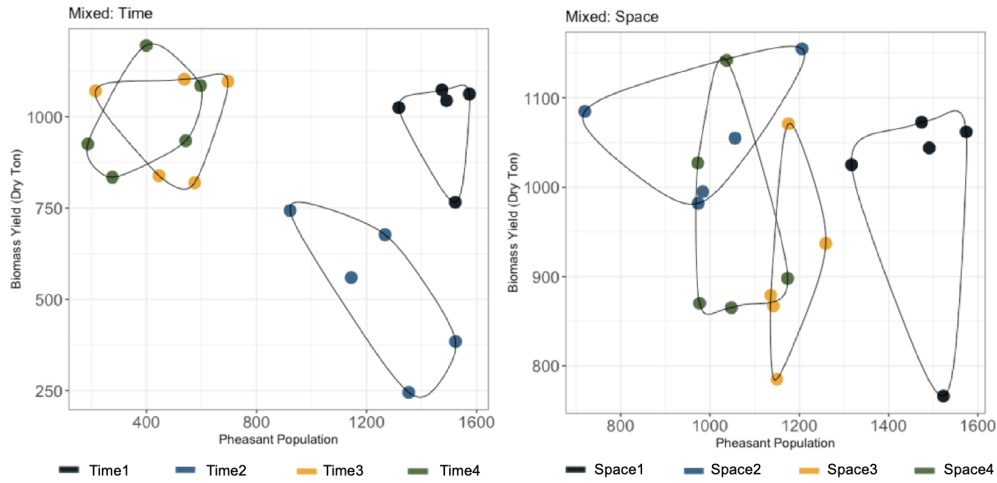


Figure C.22: Cumulative annual biomass yield (dry ton) versus cumulative annual pheasant population (number of individuals) for five simulated years for each scenario that is simulated on the mixed landscape, averaged across 50 replicates. Lines encircle each grouping of scenario values. Time scenarios are represented in the left figure and space scenarios are in the right figure. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

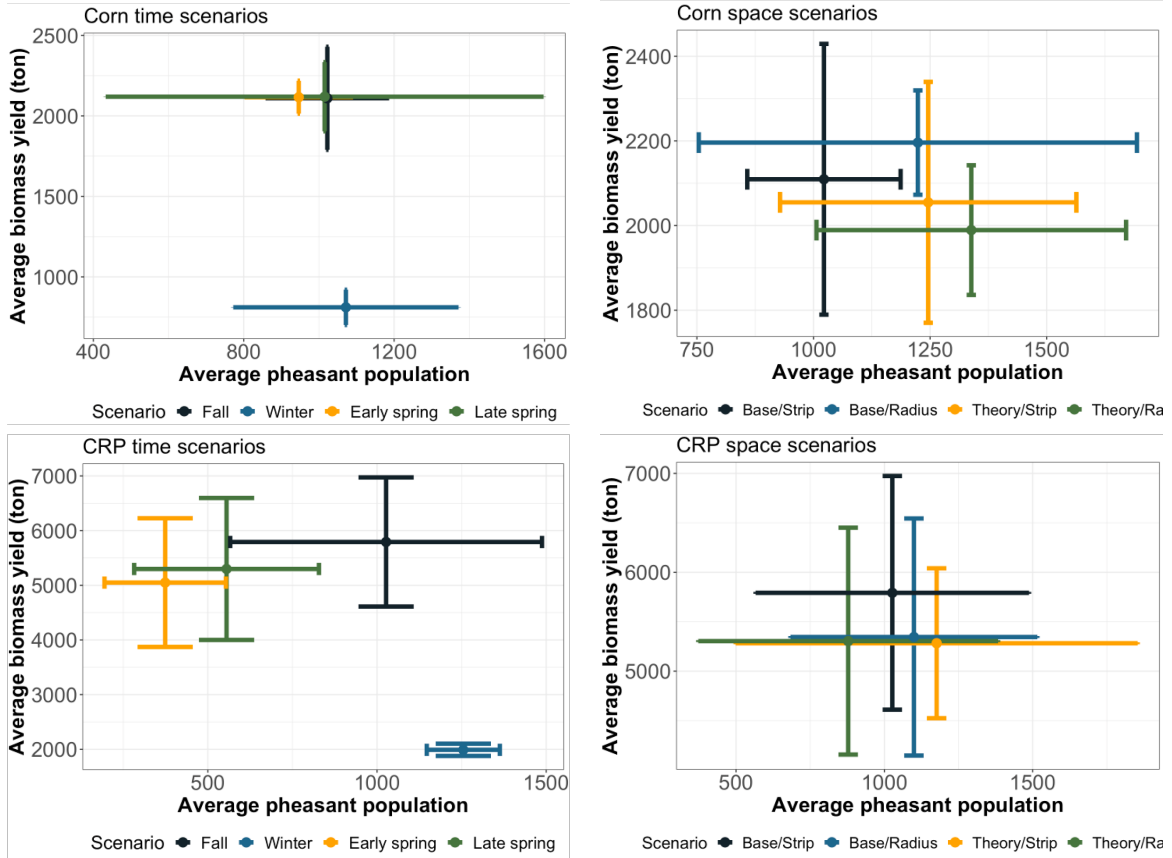


Figure C.23: Each figure displays the average biomass yield and average pheasant population size over total simulation time for each scenario. Error bars show variation among annual averages across 50 replicates. Time scenarios are on the left and space scenarios are on the right. Landscapes are corn (top row) and CRP (bottom row).

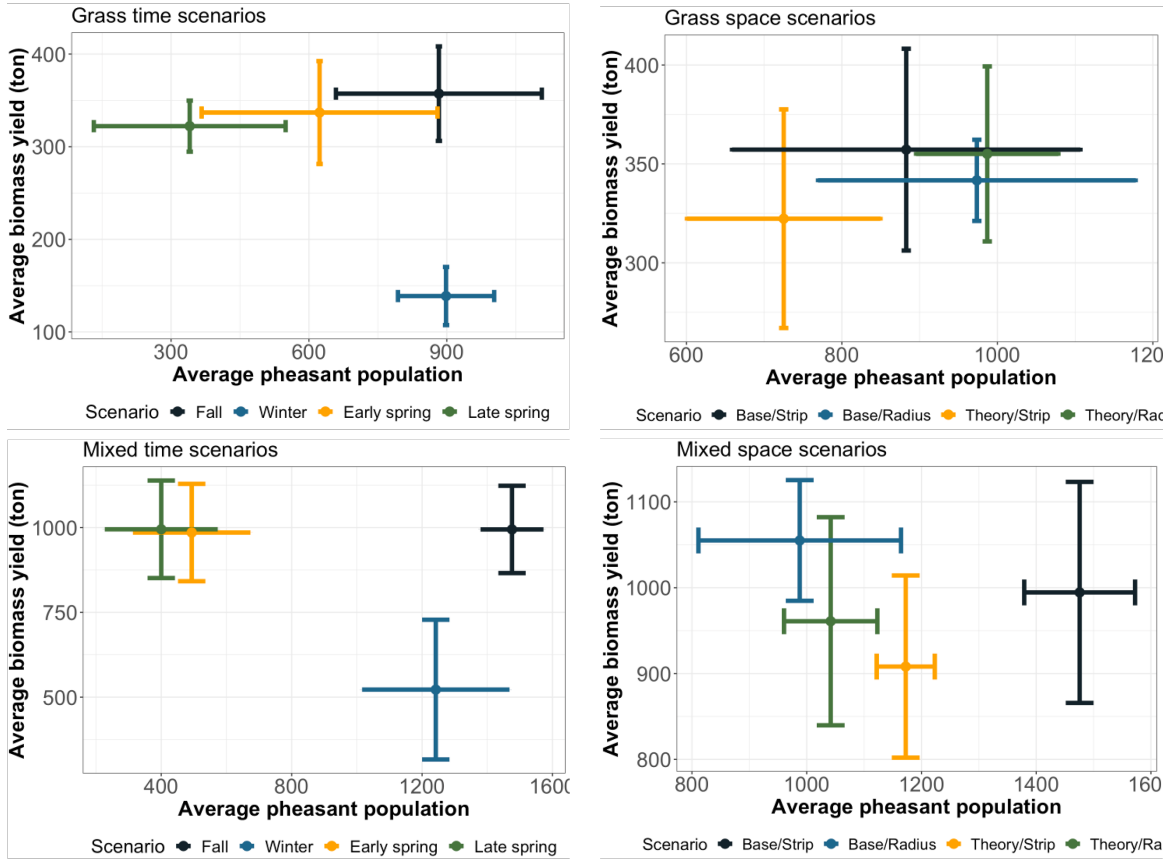


Figure C.24: Each figure displays the average biomass yield and pheasant population size over total simulation time. Error bars show variation among annual averages across 50 replicates. Time scenarios are on the left and space scenarios are on the right. Landscapes are grassland (top row) and mixed (bottom row).

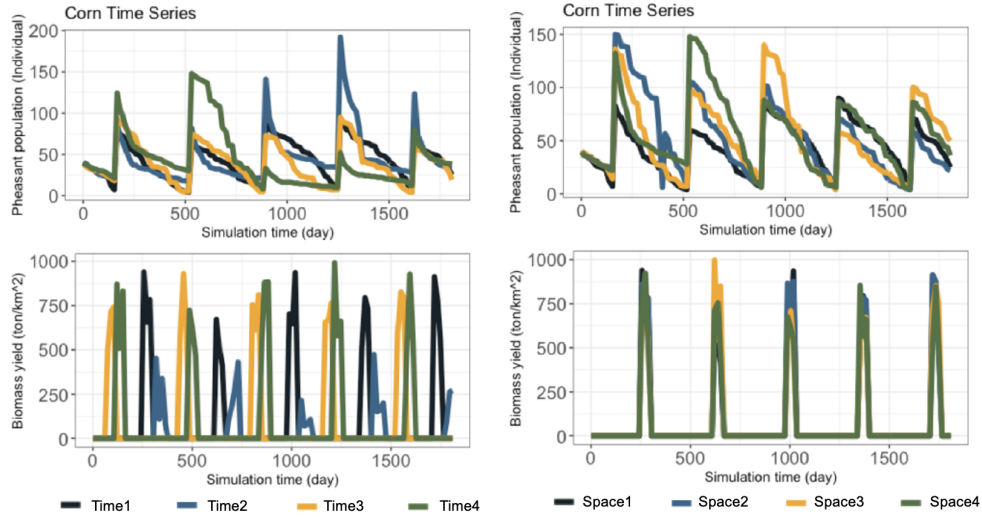


Figure C.25: Pheasant population (top row) and biomass yield (bottom row) over simulation time for all scenarios on the corn landscape. Time scenarios are on the left and space scenarios are on the right. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

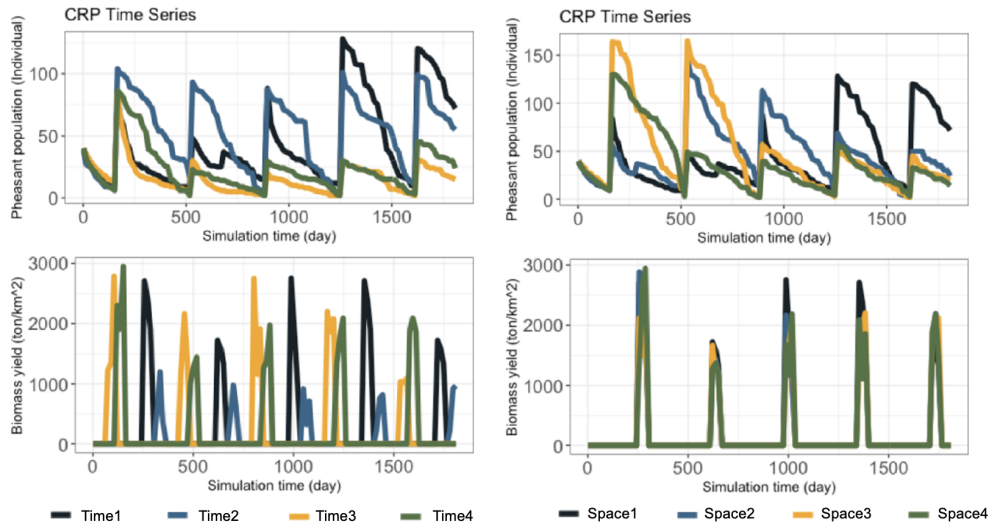


Figure C.26: Pheasant population (top row) and biomass yield (bottom row) over simulation time for all scenarios on the CRP landscape. Time scenarios are on the left and space scenarios are on the right. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

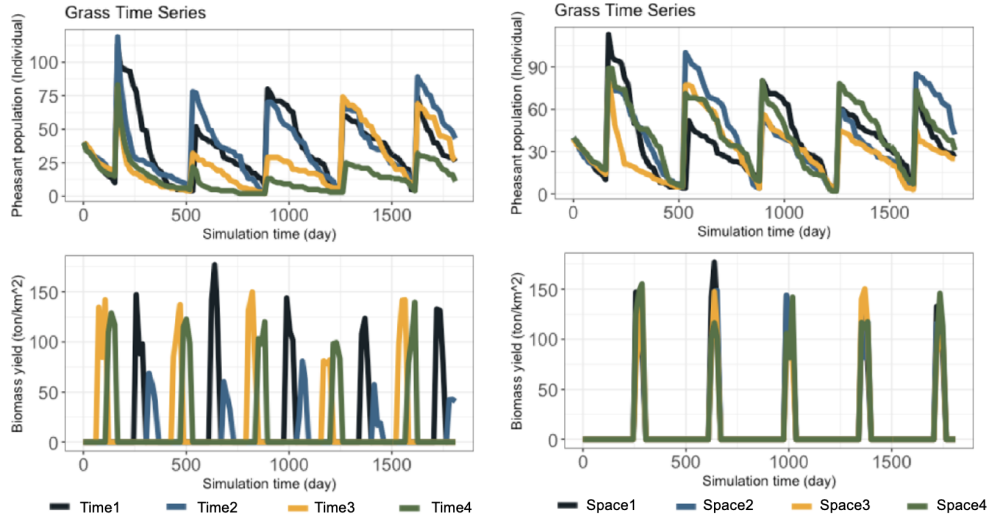


Figure C.27: Pheasant population (top row) and biomass yield (bottom row) over simulation time for all scenarios on the grass landscape. Time scenarios are on the left and space scenarios are on the right. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

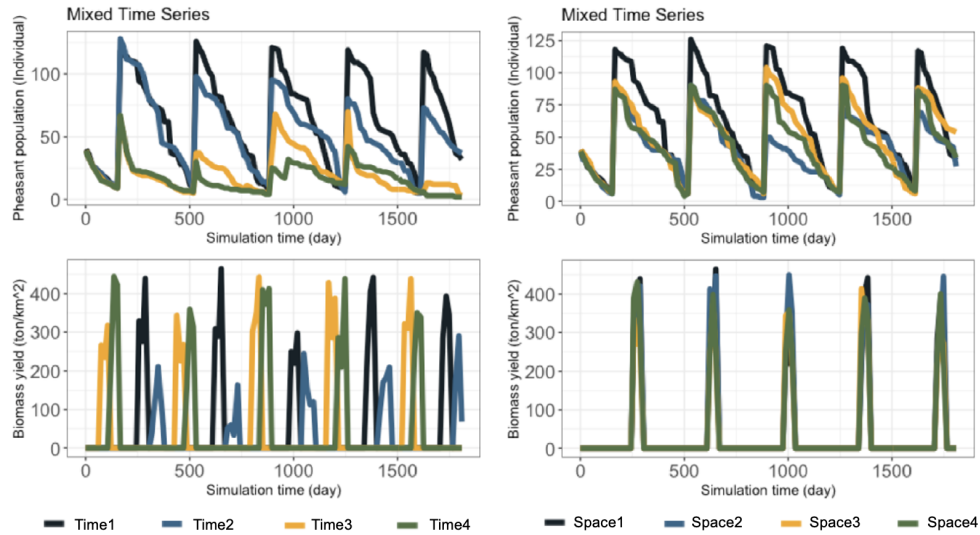


Figure C.28: Pheasant population (top row) and biomass yield (bottom row) over simulation time for all scenarios on the mixed landscape. Time scenarios are on the left and space scenarios are on the right. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

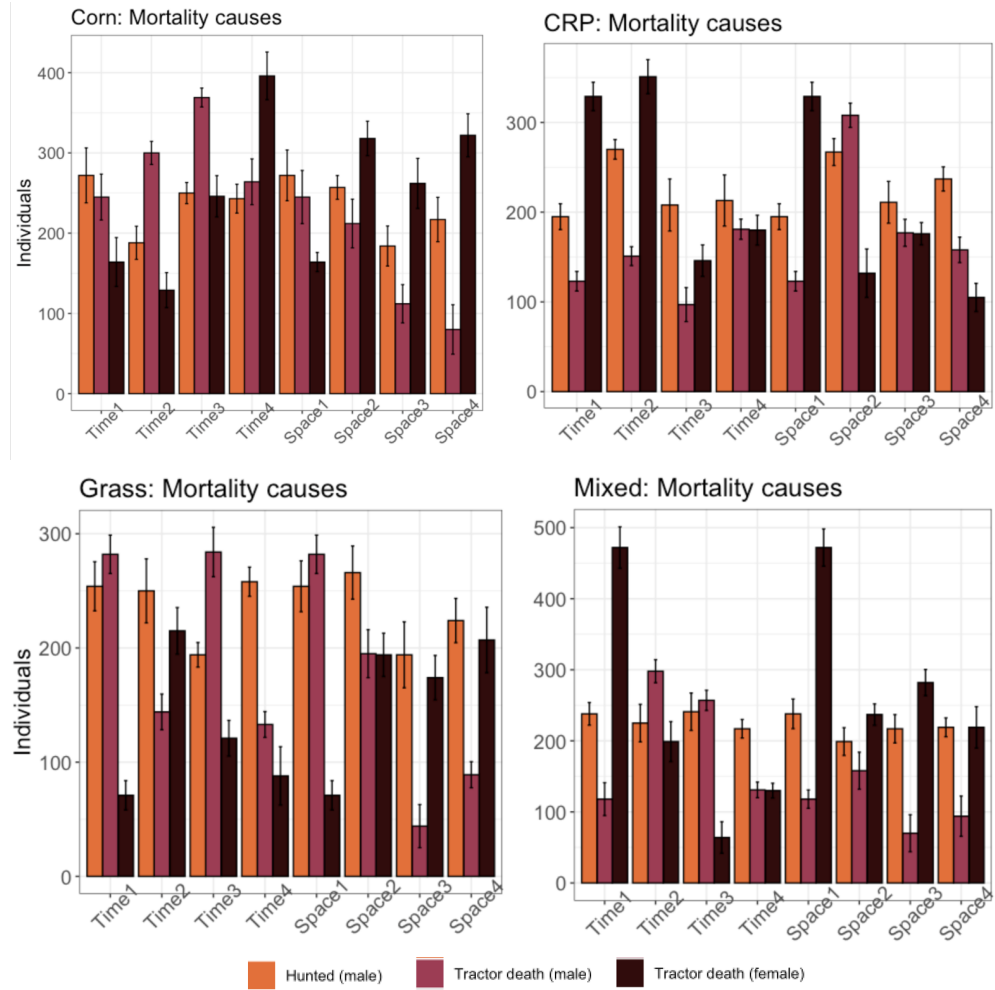


Figure C.29: Breakdown of mortality causes across scenarios and landscapes. Mortality causes are hunted (male pheasants), tractor death (male pheasants), and tractor death (female pheasants). Error bars represent standard deviation across replicates. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

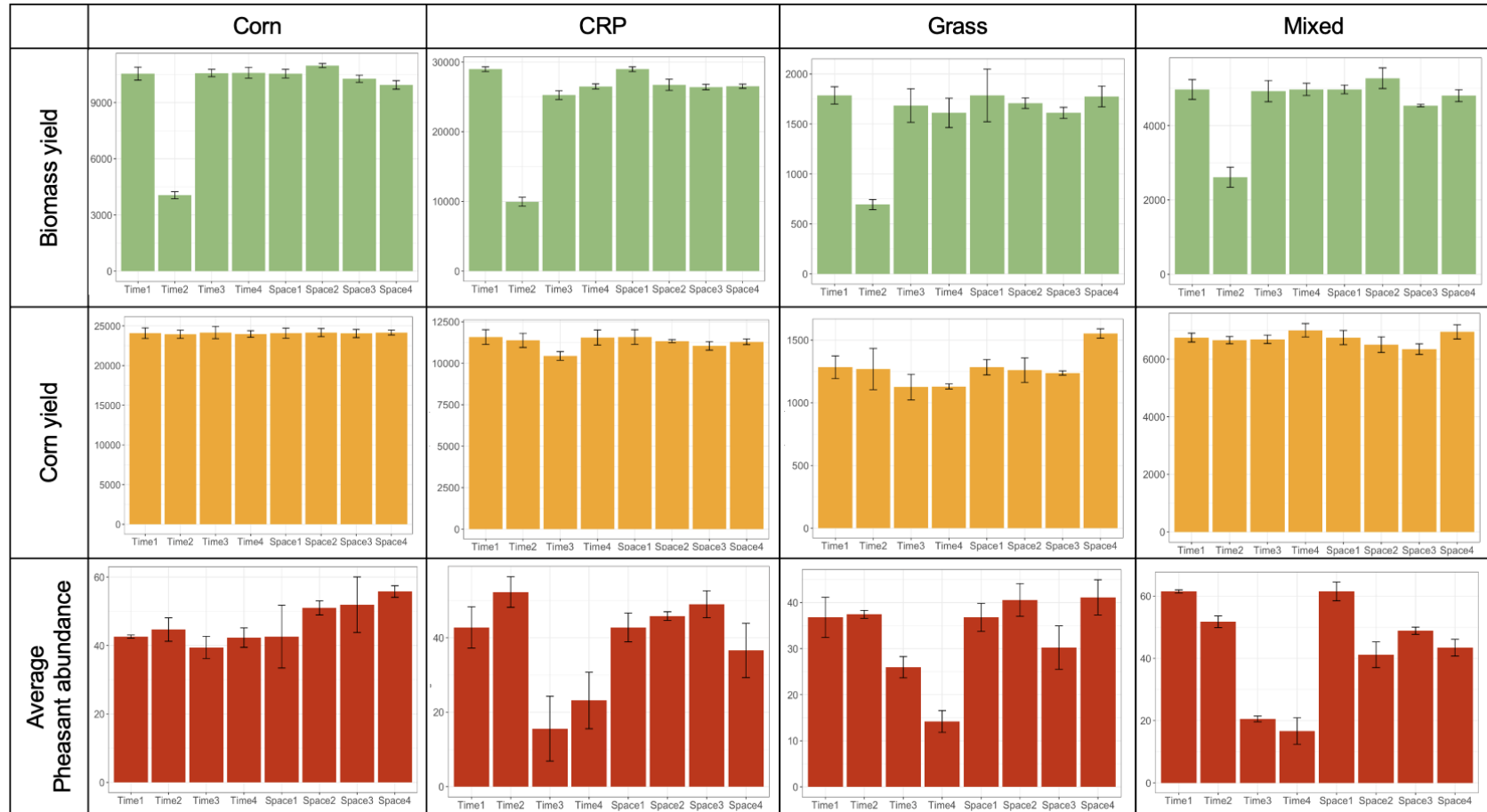


Figure C.30: Total biomass yield (ton) (top row) for all scenarios over each landscape. Total corn yield (ton) (middle row) for all scenarios over each landscape. Average pheasant abundance (bottom row) for all scenarios over each landscape. Average pheasant abundance for a scenario is calculated by summing pheasant population values over the entire simulation and dividing by the total number of timesteps. Landscapes are corn-dominated (first column), CRP-dominated (second column), grassland-dominated (third column), and mixed (last column). Error bars represent standard error across replicates. Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

Table C.9: Monetary valuation of each scenario and landscape as dollar/km². Time1 is fall harvest, Time2 is winter harvest, Time3 is early spring harvest, Time4 is late spring harvest, Space1 is base harvest and strip hunt, Space2 is base harvest and radius hunt, Space3 is theory harvest and strip hunt, and Space4 is theory harvest and radius hunt.

Scenario	Corn land	CRP land	Grass land	Mixed land
Time1	\$306,836	\$550,763	\$36,853	\$119,447
Time2	\$196,253	\$228,581	\$18,308	\$79,724
Time3	\$307,416	\$482,246	\$34,843	\$119,194
Time4	\$306,602	\$509,038	\$34,077	\$120,075
Space1	\$306,836	\$550,763	\$36,853	\$119,447
Space2	\$314,303	\$511,795	\$35,420	\$124,857
Space3	\$301,895	\$504,979	\$33,973	\$112,570
Space4	\$297,045	\$508,371	\$36,646	\$117,107

Vita

Jasmine Kreig received her Bachelor's of Science degree in Environmental Science and Bachelor's of Arts degree in Mathematics in 2014 from the University of North Carolina at Chapel Hill. After graduating, she worked as a research assistant in Dr. Larry Band's Hydrology Lab at UNC Chapel Hill. In October 2014, Jasmine moved to Oak Ridge, TN to work as a post-bachelor researcher for Dr. Henriette Jager in the Environmental Sciences Division at Oak Ridge National Laboratory. While there, she contributed to two chapters of the Department of Energy's 2016 Billion-Ton Report, Volume 2: Environmental Sustainability Effects of Select Scenarios from Volume 1.

Jasmine came to the University of Tennessee in August 2016 to pursue her Ph.D. in Energy Science and Engineering through the University of Tennessee, Knoxville and Oak Ridge National Laboratory's Bredesen Center for Interdisciplinary Research and Graduate Education. While working towards her Ph.D., she also earned her Master's of Science in Mathematics in August 2019 under Dr. Suzanne Lenhart. She earned her doctorate in Summer 2021 under Dr. Jager.