# Optimizing timber harvest revenue with wildlife constraints for old-forest species using a spatially explicit habitat model and open source GIS

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A thesis
submitted in partial fulfillment of the requirements for the degree of

Master of Science

University of Washington

2007

Program Authorized to Offer Degree:

College of Forest Resources

University of Washington
Graduate School

This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,
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## Abstract

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The current study presents a spatial forest planning framework that combines a stand level management simulation and a landscape level harvest scheduling. This spatial forest planning framework includes conflicting management goals such as a net present value of timber harvesting (*NPV*) and threshold levels of wildlife habitat capacity. An optimization algorithm, simulated annealing, was adopted to search for efficient relationships between two conflicting objectives. Ecologically Scaled Landscape Indices (*ESLI*, Vos *et al*. 2001) and the landscape suitability score (*LS*, Polasky *et al*. 2005) were adopted to translate landscape changes from forest management activities into biologically meaningful measurements. The entire analysis framework was built on various open source computer programs including PostGIS. I chose two old-forest species, the northern flying squirrel (*Glaucomys sabrinus*) and the winter wren (*Troglodytes troglodytes*), to test the framework. Both dispersal distances and habitat compatibility settings were varied to examine the sensitivity of key parameters. Production possibility frontiers were constructed to present trade-off relationships between *NPV* and *LS*. Opportunity costs of timber harvesting increased as the level of habitat conservation increased. However, changes in costs were not linear with the changes in the level of habitat protection. In the case of the northern flying squirrel, an opportunity cost to maintain 300 breeding pair

became $ 366,446 and costs became close to 30 million dollars as the level of conservation reached 550 breeding pairs. The conservation level could be increased with relatively less cost between 300 and 450 breeding pair levels. A similar trend was observed for the winter wren. In both cases, opportunity costs became higher when species dispersal distances were reduced. On the other hand, increased sensitivity of wildlife to the presence of old-forest altered the shape and range of the production possibility frontier. The incremental opportunity cost was lower as the level of conservation increased. These results suggest the importance of not only spatial composition and the arrangement of management units but also species' ecological traits such as a habitat preference and dispersal distance in landscape level forest planning. Although the spatial forest planning process presented in this study required a large amount of computing power, it was feasible to examine economically and ecologically optimized forest planning goals.

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# ACKNOWLEDGEMENTS

I am most grateful to my chair Professor Bruce Lippke for his constant support in giving me the freedom to pursue my own interest and financial support for my entire study. Professor Lippke encouraged me to continue this study topic and was always available for discussion. Without Professor John Perez-Garcia's friendly approach and deep insights on optimization, the author could not have completed the data analysis. Professor Perez-Garcia was especially helpful in elevating beyond the complications of the optimization world. Professor John Marzluff deserves my special thanks for sharing his tremendous knowledge of wildlife and conservation for my project. Professor Marzluff also emersed me in his field research and made me realize the importance of knowing the species I modeled. As a wildlifer from Japan, I was grateful to have a chance to work with Professor Marzluff.

I greatly appreciate the advice on optimization techniques from Dr. Joshua Lawler and Dr. Sandor Toth. Dr. Lawler's optimization code became a core module in my program. Josh Livni's vision and knowledge on open source GIS and geospatial techniques enable me to construct my entire analysis framework by open source applications. Kevin Ceder Dr. Betsy Bancroft, Dr. Monika Moskal, Akira Kato, CFR computer lab staff provided me invaluable technical support and shared their computer resources. Thank you to Larry Mason, Kevin Zobrist, Clara Burnett and Jim McCarter for their ongoing friendship, critiques, and assistance. I am grateful to Dr. Tim Beechie for his understanding and assistance on this project.

Thank you to all of my family and friends who have supported me in countless ways. I greatly appreciate Chris and Gregg Angeli for supporting my family when I needed to concentrate on the work. Finally, I just want to say thank you to my wife, Caitlin, and two lovely daughters Chiharu and Ayaka.

# DEDICATION

To my wife Caitlin and two daughters, Chiharu and Ayaka.

# Introduction

In forest management, spatial and temporal arrangements of harvest units influence not only revenue from timber harvesting but also the viability of wildlife. Since "new forestry" practices were proposed by Franklin (1989), many studies have focused on landscape level (>1000 ha) considerations in forest management to enhance structural and compositional forest diversity. Methods such as variable retention harvesting (Aubry *et al*. 2004), variable density thinning and leaving key elements such as large diameter trees, snags and understory species (Hagar 2007) have been proposed. These various forest treatments were proposed to improve biological diversity or habitat functions for certain species; however, as is often the case, these approaches did not include spatial or temporal implementation of those techniques. Additionally, the economic feasibility of implementing those techniques is usually ignored. Therefore, a forest management framework that integrates spatial, temporal and economic aspects of forest management is necessary.

The biodiversity pathways proposed by Carey *et al*. (1996, 1999) provide one approach that pursues both better economic and ecological output through forest management. The biodiversity pathways were developed to create forest structural diversity through silvicultural treatments such as variable-density thinnings, long rotations, and structural retention (Carey *et al*, 1996, 1999). Because of active stand management, the biodiversity pathway also creates cash flow by managing timber removals. The Washington Forest Landscape Management Project (Carey *et al*. 1996, Lippke *et al*. 1996) illustrated the potential to conserve biodiversity in managed landscapes without maintaining large reserves through an exploratory simulation study. The Landscape Management Project examined a few spatial patterns derived from their simulations, but did not develop criteria suitable for improving spatial impacts.

Some tools to evaluate economic and ecological trade-offs under various management regimes have provided critical insights for improving forest management. For example, the Landscape Management System (LMS) developed by McCarter *et al.* (1998) at the University of Washington provides a useful tool to evaluate economic and ecological trade-offs at the stand level (~ 50 ha). Using LMS, forest managers can simulate alternative management treatments and compare economic and ecological outcomes such as wildlife habitat suitability. Similar tools and methods have been developed (Jordan and Baskent 1991, Moore and Lockwood 1990, Li *et al.* 1993), however, it is difficult to connect outcomes from stand level analysis to landscape level management. This is because landscape level management requires different management variables to characterize the spatial arrangement of harvest units and spatial relationships among adjacent units.

In addition to economic considerations, planning for spatial and temporal arrangements of harvest activities at a landscape level is a particularly complex aspect of landscape-scale forest management and therefore it is often an unrecognized and poorly understand area in forest management (Lindenmeyer and Franklin 2002). This complexity in spatial and temporal factors of harvest scheduling is characterized by diverse parameters that need to be taken into account such as harvest unit size, shape, location, contiguity, rotation period, treatment, and ecological and economic constraints.

Spatial forest planning provides an approach to support complex landscape level forest management decisions including economic and ecological goals. Spatial forest planning is defined as a forest modeling approach that accommodates spatial requirements as well as multiple, often conflicting management objectives over the landscape (Baskent and Keles 2005). It often uses a mathematical optimization approach such as linear programming, simulation, and/or meta-heuristics to resolve conflicting goals in an optimal manner. Various ecological constraints are considered in the search for efficient management decisions. Spatial requirements such as harvest unit location or habitat patch size, shape and distribution (Cox and Sullivan 1995; Başkent and Jordan 1995, 2002; Başkent 1997, Gustafson *et al*. 2006; Hurme *et al*. 2007, Hof and Raphael 1997; Holzkamper *et al*. 2006; Kurttila 2001; Kurttila *et al*. 2002; Rempel and Kaufmann 2003; Authaud and Rose 1996; Bettinger *et al*. 1997, 2003a), adjacency restrictions (Jones *et al*. 1991; Weinbraub *et al*. 1994; Yoshimoto and Brodie 1994; Murray and Church 1995, 1996; Snyder and Revelle 1997; Hoganson and Borges 1998; McDill and Braze 2000, 2001), connectivity and proximity (Nelson and Finn 1991; Sessions 1992; Hof and Joyce 1993; Church *et al*. 1998; Williams 1998; Lu and Eriksson 2000, Weintraub *et al*. 2000; Richards and Gunn 2000, 2003), interior and edge habitat (Hof and Joyce 1992, 1993; Bevers and Hof 1999), habitat attributes (Rohweder *et al*. 2000), habitat effectiveness (HEI, Bettinger *et al*. 1999), and wildlife population (Moore *et al*. 2000; Calkin *et al*. 2002; Juutinen *et al* 2004; Nalle *et al*. 2004; Polasky *et al*. 2005; Loehle *et al* 2006) have been taken into account along with economic goals.

Spatial forest planning also connects all forest planning from the highest strategic planning level to tactical and operational levels in one place (Bettinger and Sessions 2003b). Outputs from spatial forest planning can be graphically presented using a geographic information system (GIS) and utilized in planning processes as well as a communication tool among interest groups (Bettinger and Sessions 2003b; Baskent and Keles 2005). Spatial forest planning has proven that a large portion of ecological goals can be achieved with a small amount of economic sacrifice or sometimes without none at all (Junntinen *et al*. 2004; Nalle *et al*. 2004; Polasky *et al*. 2005; Hurme *et al*. 2007).

Wildlife or habitat models adopted in spatial forest management studies range from a single species (Moore *et al*. 2000; Calkin *et al*. 2002; Arthaud and Rose 1996; Hof and Raphael 1997; Bettinger *et al*. 1999; Hurme *et al*. 2007;) to multi-species models (Kurttila *et al* 2002; Nella *et al* 2005), and models that simulate the persistence probability of a wide range of species in a landscape (Juutinen *et al*. 2004; Polasky *et al*. 2005; Loehle *et al* 2006). Recently, ecological models used in spatial planning have become more complicated and sophisticated by estimating population size and persistence in different forest plans (Juutinen *et al*. 2004; Nella *et al*. 2005; Polasky *et al* 2005) compared to previously used habitat index based modeling such as available habitat area and edge-interior ratios. Therefore, spatial forest planning has the potential to provide spatial and temporal criteria to achieve both ecological and economic goals for forest management.

The current study introduced two new aspects of spatial forest management: ecologically scaled landscape indices (ESLI; Vos *et al.* 2001) and open source GIS capability. Landscape indices and wildlife models that evaluate the impact of landscape properties on wildlife populations are the key components needed to develop for a spatial forest planning. ESLI are species specific landscape metrics that incorporate species area requirements and dispersal abilities (Verboom *et al*. 1991; Hanski 1994; Vos *et al*. 2001, Verboom *et al*. 2001). ESLI were developed to evaluate landscape qualities from a wildlife perspective using average patch carrying capacity and average patch connectivity. Using the ESLI approach, Polasky *et al*. (2005) integrated spatial land allocation planning with ESLI and further developed two landscape indices: a landscape suitability score that represents the carrying capacity of a landscape and a biodiversity score that indicates multi-species persistence probability in a landscape.

For most spatial forest planning studies, a geographic information system (GIS) and advanced computer technology are essential components. GIS can offer not only spatial modeling capability, but also visualization of management plans and alternatives. GIS can be an essential tool to communicate with different stakeholders to create a comprehensive management plan. Since GIS can serve as a database, all inventory data and other associated management information can be stored in one place. Recent rapid growth in open source GIS (e.c.. http://www.osgeo.org) has made GIS capability available to anyone who wants it to implement landscape level forest management and spatial forest planning without complex computer programming. High performance and reasonable computer hardware enables anyone to tackle the intensive optimization processes of spatial forest planning.

My first objective was to provide a method to search for optimal forest management strategies with species specific habitat conservation goals. I developed a spatial forest planning framework to explore economically and ecologically efficient management decisions from pre-existing tree inventory data, spatially explicit wildlife habitat models, and freely distributed open source software. Optimal trade-off relationships between timber revenue and conserved wildlife habitat were explored by a simulated annealing algorithm. Based on

Polasky *et al*. (2005), I integrated a spatially explicit wildlife habitat model and an economic model into a simulated annealing optimization process to find a series of efficient solutions by maximizing revenue from timber harvesting under various ecologically scaled carrying capacities.  The method can explore optimal or near-optimal relationships where economic output cannot be improved without decreasing ecological output. A second objective of this study was to provide examples of the developed method. I chose two species, the northern flying squirrel (*Glaucomys sabrinus*) and the winter wren (*Troglodytes troglodytes*), that prefer old-forest structures because their life history features tends to conflict with forest management activities. I searched efficient management alternatives for these two species and a production possibility frontier was constructed to depict economic and ecological trade-offs under different management regimes and ecological parameter settings.

# Material and methods

## Modeling framework

A set of forest management regimes assigned to 195 stands was an input for both biological and economic models and an optimal management set was explored. I prepared three management regimes, a 45-year rotation, a short biodiversity pathway, and a no-harvesting alternative. Through the biological model, I calculated the number of breeding pairs that can be supported by a landscape, the landscape suitability score (*LS*), for a given set of management regimes each decade for a 100-year time period and averaged it to represent the ecological performance of a given management set. Simultaneously, the economic model calculated the net present value (NPV) from timber harvests for 100 years. I used a simulated annealing algorithm to find efficient points between ecological and economic outcomes from an enormous number of choices in harvest scheduling and constructed production possibility frontiers to examine ecological and economic tradeoffs under various ecological and economic constraints.

## Stand level simulations to translate stand treatments into ecological and economic outputs

Three management regimes, no-harvesting, 45-year rotation, and the short biodiversity pathway, were chosen for the management simulations. The purpose of this simulation were: 1) to trace changes in habitat structural conditions and 2) to calculate cash flow from management activities. Habitat structural conditions categorize forest growth processes into the 26 stages that correlate with the life histories of Oregon and Washington’s wildlife (Johnson and O’Neil 2002). The no-harvesting regime did not treat the stand for the entire100 years (Table 1). In the 45-year rotation, stands were clear-cut every 45 years and seedlings were replanted immediately after the stand was treated (Table 1). I set 435 trees per acre as the planting density with 75 % of Douglas-fir (*Psuedotsuga menziesii*) and 5 % each of other species including western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), red alder (*Alnus rubra*), big leaf maple (*Acer macrophyllum*), and black cotton wood (*Populus balsamifera ssp.trichocarpa*). No thinning was conducted in this regime. The short biodiversity pathway aims to create vertical and horizontal forest structural diversity through multiple thinnings (Carey and Curtis 1996; Carey *et al*. 1996, Lippke *et al*. 1996). The first commercial thinning reduced the tree density to 150 trees per acre by cutting smaller diameter trees in year 30, followed by a second thinning to 35 trees per acre at year 55 (Table 1). Additionally, 25 trees per acre of Douglas-fir, 50 of western hemlock, and 50 of western red cedar seedlings were planted after the second thinning. Then, all stands were clear-cut at year 100.

Table 1. Three management regimes used in the stand level management simulation and their stand treatment schedules

| Management regime | Year of stand treatments within the 100-year simulation period | | | | | |
|---|---|---|---|---|---|---|
| | 0 | 35 | 45 | 55 | 90 | 100 |
| 45-year rotation | P (435) | - | C & P (435) | - | C & P (435) | - |
| Short biodiversity pathway | P (435) | T (150) | - | T (35) & P (150) | - | C & P (435) |
| No-harvesting | - | - | - | - | - | - |

P: planting, T: thinning, C: clear-cutting

The numbers in parentheses indicate a target planting or thinning density in the number of trees per acre

Stand structure and composition changes along the various stand treatments were simulated using the Landscape Management System version 3.1 (University of Washington, 2007; http://lms.cfr.washington.edu/lms.html). The Landscape Management System (LMS) uses the Forest Vegetation Simulator (FVS, Donnelly 1997) to virtually grow trees based on current inventory data, site index, topography, and geography. User can set management regimes to simulate forest growth, management activities and associated cost and revenue, forest structure, and wildlife habitat characteristics (McCarter *et al.*, 1988). Johnson and O'Neil's habitat structural conditions was implemented in the LMS. Based on tree size, canopy cover (%), and the number of canopy layers from the stand structure analysis functions, LMS assigns one of 26 habitat structural conditions to each stand in a given year (Table 2). Structural conditions estimated through LMS analysis were used to identify the degree of association between wildlife species and their habitat as defined by Johnson and O'Neil (2001). The degree of association between wildlife and their habitat was labeled as closely associated (CA), generally associated (GA), and present (P) degrees to indicate species dependence on the habitat structural condition. All wildlife-habitat relationship tables from Johnson and O'Neil (2001) were imported as database tables in Microsoft Access. Then, all results from the forest structural condition analysis in the LMS were joined to the wildlife-habitat association table to find an association degree in a given stand and year for a target species. This degree of wildlife – habitat association under different management regimes and years was stored as a database table and used in the following optimization process.

Table 2. Forest structural conditions and degree of association of the northern flying squirrel and the winter wren from Johnson and O'Neil (2002)

| Forest structural conditions | | | | Habitat association degree *,** | |
|---|---|---|---|---|---|
| | Tree size (cm) | Canopy cover (%) | Canopy layers | Northern Flying Squirrel | Winter Wren |
| Grass/Forb-Open | - | 0 ~ 9 | 0 | GA | GA |
| Grass/Forb-Closed | - | 0 ~ 9 | 0 | GA | GA |
| Shrub/Seedling-Open | 0 ~ 2.5 | 10 ~ 39 | 1 | NP | GA |
| Shrub/Seedling-Closed | 0 ~ 2.5 | 70 ~ 100 | 1 | NP | GA |
| Sapling/Pole-Open | 2.5 ~ 24.0 | 10 ~ 39 | 1 | GA | GA |
| Sapling/Pole-Moderate | 2.5 ~ 24.0 | 40 ~ 69 | 1 | GA | GA |
| Sapling/Pole-Closed | 2.5 ~ 24.0 | 70 ~ 100 | 1 | NP | GA |
| Small Tree-Single Story-Open | 25.0 ~ 37.0 | 10 ~ 39 | 1 | GA | GA |
| Small Tree-Single Story-Moderate | 25.0 ~ 37.0 | 40 ~ 69 | 1 | NP | GA |
| Small Tree-Single Story-Closed | 25.0 ~ 37.0 | 70 ~ 100 | 1 | NP | GA |
| Small Tree-Multi-Story-Open | 25.0 ~ 37.0 | 10 ~ 39 | 2 ~ | GA | GA |
| Small Tree-Multi-Story-Moderate | 25.0 ~ 37.0 | 40 ~ 69 | 2 ~ | GA | GA |
| Small Tree-Multi-Story-Closed | 25.0 ~ 37.0 | 70 ~ 100 | 2 ~ | NP | GA |
| Medium Tree-Single Story-Open | 38.0 ~ 49.0 | 10 ~ 39 | 1 | GA | GA |
| Medium Tree-Single Story-Moderate | 38.0 ~ 49.0 | 40 ~ 69 | 1 | GA | GA |
| Medium Tree-Single Story-Closed | 38.0 ~ 49.0 | 70 ~ 100 | 1 | GA | GA |
| Medium Tree-Multi-Story-Open | 38.0 ~ 49.0 | 10 ~ 39 | 2 ~ | GA | GA |
| Medium Tree-Multi-Story-Moderate | 38.0 ~ 49.0 | 40 ~ 69 | 2 ~ | GA | CA |
| Medium Tree-Multi-Story-Closed | 38.0 ~ 49.0 | 70 ~ 100 | 2 ~ | GA | CA |
| Large Tree-Single Story-Open | 50.0 ~ 75.0 | 10 ~ 39 | 1 | GA | GA |
| Large Tree-Single Story-Moderate | 50.0 ~ 75.0 | 40 ~ 69 | 1 | GA | GA |
| Large Tree-Single Story-Closed | 50.0 ~ 75.0 | 70 ~ 100 | 1 | NP | GA |
| Large Tree-Multi-Story-Open | 50.0 ~ 75.0 | 10 ~ 39 | 2 ~ | CA | CA |
| Large Tree-Multi-Story-Moderate | 50.0 ~ 75.0 | 40 ~ 69 | 2 ~ | CA | CA |
| Large Tree-Multi-Story-Closed | 50.0 ~ 75.0 | 70 ~ 100 | 2 ~ | CA | CA |
| Giant Tree-Multi-Story | 76.0 ~ | - | 2 ~ | NP | CA |

* Not present was assigned if there was no information about the degree of association

** CA: Closely associated, GA: Generally associated, P: Present, NP: Not present

### The spatially explicit ecological model

The goal of the ecological model was to calculate the number of breeding pairs that can be sustained in a given landscape. I calculated landscape suitability scores (*LS*) by adopting the method proposed by Polasky *et al.* (2005). The idea of *LS* originated with the ecologically scaled landscape indices (ESLI) proposed by Vos *et al*. (2001). The landscape score needs three biological parameters and two threshold values to calculate. Those biological parameters are 1) territory or home range size, 2) dispersal ability, and 3) habitat compatibility among different habitat types. I estimated the amount of area required of a breeding pair by territory sizes or home range sizes from the literatures. A territory size is preferable for ESLI calculation; however, home range size was used without any calibration if a selected species was not territorial. I estimated the compatibility of different habitat types based on Johnson and O'Neil's wildlife-habitat relationship matrix (Johnson and O'Neil, 2001). This matrix uses expert opinions to associate wildlife with 26 habitat structural conditions by 3 degrees such as closely associated (CA), generally associated (GA) and present (P) (Table 2). I converted those 3 categories into a 0 to 1 scale to use as a habitat compatibility score (CA = 1.0, GA = 0.5, P = 0.25, no association information was set to 0). Johnson and O'Neil (2001) composed their habitat model of three factors: Wildlife Habitats = wildlife cover type(s) + structural condition(s) + habitat element(s) (O'Neil *et al*. 2001). Wildlife cover types refer to a group of vegetation cover types that were determined based on similarity of wildlife use (O'Neil and Johnson, 2001). Since the current study focused on the South Puget Sound region, I assumed that the study area belonged to the Westside Lowlands Conifer-Hardwood Forest type (Chappell *et al.* 2001). While wildlife cover types represent the broadest habitat scale in the model, structural conditions describe the forest structure on a stand level. There are a total of 26 structural conditions which were defined by tree size, percent canopy cover, and the number of canopy layers (O'Neil *et al*. 2001). The most fine scale habitat features are habitat elements. Site specific habitat features such as downed logs and snags belong to this level. Although habitat elements are critical components in the habitat model, I did not include them in the current analysis because ecological models were not available.

**Steps in the ecological model**

Here I simplified and modified Polasky *et al*. (2005) to explain the ecological modeling process. First, the suitable score for each stand *j*, $Z_{sj}$, that represents the number of breeding pairs of species *s* supported under a given forest stand structural condition, $SC_j$, was calculated.

$$Z_{sj} = \frac{A_j C_{sj}\left(SC_j\right)}{AR_s} \qquad (1)$$

where $A_j$ is the area of stand *j*, $C_{sj}\ (SC_j)$ is the habitat compatibility score of stand *j* for species *s* given the forest structural condition $SC_j$, and $AR_s$ is the area of territory or home range for a breeding pair of species *s*. Habitat compatibility scores $C_{sj}\ (SC_j)$ range from 0 to 1 and convert categorical forest conditions into a comparable numerical scale.

After I calculated the *Z* scores for each stand, I merged adjacent stands that possessed higher habitat compatibility scores, $C_{sj}\ (SC_j)$, than a specified threshold together as habitat patches. The threshold used here functioned to drop less preferable stands from the habitat patch designation process. Each species may have different habitat compatibility thresholds, however, I set thresholds to only include stands that reached CA and GA, or only CA association degrees, depending on a model setting. Then, I calculated the habitat-patch suitability score, a summation of $Z_{sj}$ scores for each habitat patch, $n_s$.

$$Z_{sn_s} = \sum_{j \in n_s} Z_{sj}. \qquad (2)$$

To evaluate forest management decisions at the landscape level, I calculated the landscape suitability score (*LS*) that takes the dispersal ability of a species to a neighboring habitat patch into account. The *LS* represents the expected number of breeding pairs that a landscape will support. First, the potential maximum *LS* was calculated by assuming species had unlimited dispersal ability. When this is the case, the species can utilize all habitat patches within the landscape.

$$L\max_s = \sum_{n_s=1}^{N_s} Z_{sn_s} \qquad (3)$$

Secondly, the minimum possible *LS* was calculated by assuming a species had no dispersal ability from its natal patch. This is the case where a threshold ($\gamma$) plays a role. Gamma is the minimum number of breeding pairs for a species that a patch must support. Each patch has to have enough carrying capacity to sustain a species by itself without immigration. When the $L_{max}$ was calculated, habitat patches that cannot self-sustain a population for a certain period of time can still contribute as a habitat patch because of species dispersal capability. However, $L_{min}$ simply does not count habitat patches that did not reach the threshold $\gamma$.

$$L\min_s = \sum_{N_s=1}^{N_s} Z_{sn_s} \quad \text{and} \quad Z_{sn_s} \geq \gamma_s \qquad (4)$$

where $\gamma_s$ represents the threshold number of breeding pairs for species *s* that a patch must support on its own before the habitat patch contributes to the landscape score.

Landscape suitability scores, *LS*, ranged between *Lmax* and *Lmin* depending on species dispersal ability and the degree of habitat connectivity. To scale the degree of habitat fragmentation in a species specific manner, the index *C* (Verboom *et al.* 1991, Hanski 1994, Verboom *et al.* 2001, Vos *et al.* 2001) was introduced.

$$C_{sn_s} = \sum Z_{sm_s} \cdot e^{-\alpha_s \cdot dm_s n_s} \qquad (5)$$

where $C_{sns}$ is the connectivity of a species $s$ in a patch $n_s$, which is the sum of all contributions of patches $m_s$ weighted both by their effective area, $Z_{sms}$, and the distance between patch $m_s$ and $n_s$. $\alpha_s$ depends on the species dispersal ability and can be calculated as the reciprocal of the mean dispersal ability. When an animal has poor dispersal ability, influences from habitat patches far from a focal patch are minimal (Fig. 1).

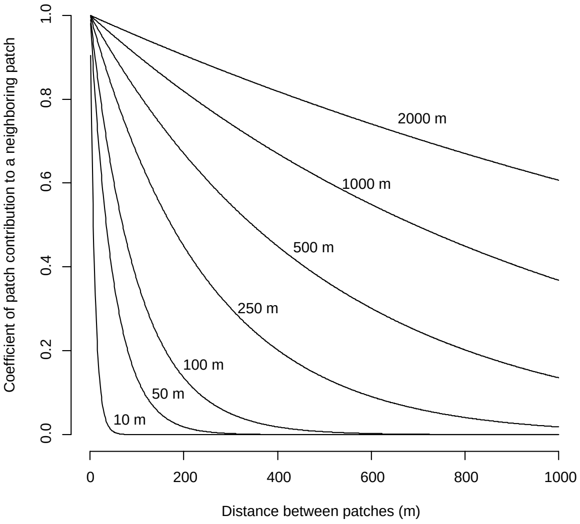


Figure 1 Contributions of neighboring habitat patches under different dispersal abilities. The numbers above the lines indicate species dispersal ability in meters. An effect of neighboring habitat patches depends on the species' dispersal ability and a distance between habitat patches (Vos *et al.* 2001).

Then the landscape connectivity score, $LC$, was calculated from $C_{sns}$ and $Lmax_s$. The landscape connectivity score ranges between 0 and 1, where a score of 1 indicates a completely connected landscape.

$$LC_s = \frac{\sum_{n_s=1}^{N_x} C_{sn_s} - L\max_s}{(N_s - 1) \cdot L\max_s} \qquad (6)$$

where $N_s$ represents the total number of habitat patches for species $s$ and $C_{sns}$ is the index $C$ as explained above. In a completely connected landscape by the physical patch arrangement or the species dispersal ability, all habitat-patch connectivity scores for species $s$, $C_{sns}$, would equal $Lmax_s$, and the aggregate patch score summing over all suitable habitat patches would be $N_sLmax_s$ since all habitat patches should have $Lmax_s$. On the other hand, in a completely isolated landscape, the sum of the $C$ index becomes $Lmax_s$, which is the total $Z$ scores of all the patches, in which case $LC_s$ will be 0.

Finally, I calculated the landscape suitability score, $LS_s$, assuming the number of breeding pairs that a given landscape can sustain. $LS_s$ ranges between $Lmin_s$ and $Lmax_s$ and it depends on the landscape connectivity score, $LC_s$.

$$LS_s = (1 - LC_s) \cdot L\min_s + LC_s \cdot L\max_s \qquad (7)$$

## Wildlife parameters

The northern flying squirrel (*Glaucomys sabrinus*) and winter wren (*Troglodytes troglodytes*),which prefer old forest structures, were selected for the analysis. Northern flying squirrels prefer old-growth forest areas where there are more tree cavities available for nest sites (Demboski *et al*, 2000). The winter wren is not only an old-forest species, but also a forest edge sensitive species (Brand and George 2001) that requires an intact native understory and woody debris (Donnelly and Marzluff 2006). In coastal redwood forests in California, their density was lower in the area from forest edge to 120m toward the forest interior (Brand and George, 2001). Therefore, these two species represent others that are susceptible to forest operations such as clear-cutting and thinning. Species that prefer old forest structures tend to be negatively affected by forest management activities that aim for higher economic returns, whereas species that prefer open structures may show a positive relationship (Nalle *et al*. 2004). Other criteria for species selection included the degree of dispersal ability. Since the study area was 17.4 km$^2$ with 195 stands, species that show high dispersal ability were not sensitive enough to detect landscape changes.

Home range size and average dispersal distance of the northern flying squirrel are 0.025 ha (average of 16 animals in north-western British Columbia, Takats *et al*. 1999) and 0.5 km. Dispersal distances of the two species were estimated by their average body mass and biometric relationships between body weight and dispersal distance as proposed by Sutherland *et al*. (2000) (Table 3).

Mammals (herbivores and omnivores)

$$\text{Median dispersal distance}_{(\text{km})} = 1.45 \times \text{body mass}_{(\text{kg})}{}^{0.54}$$

Birds (herbivores and omnivores)

$$\text{Median dispersal distance}_{(\text{km})} = 2.10 \times \text{body mass}_{(\text{kg})}{}^{0.18}$$

The average body mass of the northern flying squirrel used for analysis was 133.2 g (n = 13, Villa *et al.*, 1999).

Territory size and dispersal distance of the winter wren were 0.013 ha (average of two study seasons in British Columbia, McLachlin, 1983) and 2.0 km. The dispersal distance for the winter wren was estimated using their average body mass, 9.1 g (n = 30, McLachlin, 1983).

Both the northern flying squirrel and winter wren prefer old forest structures, however, the winter wren was further assumed to use only interior habitat where the distance from the forest edge was greater than 100 m. The criteria of 100 m from forest edge was adopted since the

first-order biotic effects seem to extend less than 100 m from forest edge (Kremsater *et al.* 1999) and close enough to the 130 m criteria in Brand and George (2001).

Table 3. Ecological parameter settings adopted in the optimization process for the northern flying squirrel and the winter wren

| Species | Ecological parameter setting* | Territory size ($km^2$) | Dispersal distance (km) | Interior species analysis | Habitat compatibility setting ** |
|---|---|---|---|---|---|
| Northern Flying Squirrel | Standard | 0.025 | 0.5 | no | CA & GA |
| | Short dispersal | 0.025 | 0.25 | no | CA & GA |
| Winter Wren | Standard | 0.013 | 2.0 | yes | CA & GA |
| | Short dispersal | 0.013 | 0.5 | yes | CA & GA |
| | Old-forest sensitive | 0.013 | 2.0 | yes | CA |
| | Old-forest sensitive & short dispersal | 0.013 | 0.5 | yes | CA |

* The ecological parameters of the standard settings were based on other ecological studies and all other settings were derived from the standard settings for the sensitivity analysis.

** CA & GA: select both closely associated and generally associated habitat structure as a habitat patch. CA: select only closely associated habitat structure as a habitat patch.

Both the northern flying squirrel and winter wren prefer old forest structures, however, the winter wren was further assumed to use only interior habitat where the distance from the forest edge was greater than 100 m. The criteria of 100 m from forest edge was adopted since the first-order biotic effects seem to extend less than 100 m from forest edge (Kremsater *et al.* 1999) and close enough to the 130 m criteria in Brand and George (2001).

### The non spatially explicit economic model

Net present value of timber harvest revenue for 100 years was calculated to evaluate an economic performance for a given forest management regime set for each stand.

$$NPV = \sum_{i=1}^{N} \sum_{y=o}^{n} \left[ \frac{R_y}{(1+r)^y} - \frac{C_y}{(1+r)^y} \right]$$

where $R_y$ represents revenue from harvested timber in year $y$, $C_y$ is the cost in year $y$, $r$ is the rate of return, and $N$ is the number of stands. Revenue from timber harvests was calculated based on tree species and total harvest volume from commercial thinning and harvesting. Total harvest volume of a given tree species and year was translated into a board foot measure using the Landscape Management System and multiplied by the stumpage price of each tree species. Stumpage prices, planting cost, site preparation cost, commercial thinning cost, harvesting cost, and annual costs from the Future of Washington's Forests and Forest Industries (College of Forest Resources, University of Washington, 2007) were used in this study (Table 4). The rate of return was set as 5.00 %. Only Douglas-fir was selected for planting. Net present value from timber harvesting and other management activities for each stand under different management regimes were calculated and stored in the database table for the optimization exercise.

Table 4. Parameters used in the economic model

| | Cost or stumpage price |
|---|---|
| Base cost | \$ 100 / Mbf |
| Harvest cost ( <10 Mbf ) | + \$ 35 / Mbf |
| Harvest cost ( 10 ~ 30 Mbf ) | + \$ 15 / Mbf |
| Harvest cost ( > 30 Mbf ) | + \$ 0 / Mbf |
| Commercial Thinning | \$ 100 / Mbf |
| Annual Costs | \$ 17 / acre |
| Planting (Douglas-fir) | \$ 215 / acre |
| Other Site Preparation | \$ 34 / acre |
| Annual Interest rate | 5.00% |
| Stumpage – Douglas-fir | \$ 476 / Mbf |
| Stumpage – Western red ceder | \$ 513 / Mbf |
| Stumpage – Western hemlock | \$ 302 / Mbf |
| Stumpage – Red alder | \$ 324 / Mbf |
| Stumpage – Black cottonwood | \$ 21 / Mbf |

### Landscape level optimization process: Constructing a production possibility frontier using a simulated annealing algorithm

The stand level simulation, the ecological model, and the economic model described above composed a part of an optimization process (Figure 2). An objective function of optimization was NPV and constraints were various levels of *LS*. Near optimal points were estimated by maximizing NPV while constraining *LS* at a certain level.

$$\text{Max} \sum_{i=1}^{Y} NPV$$

subject to

$$\frac{\sum_{i=1}^{Y} LS}{Y} \geq C_{LS}$$

where $Y$ is the number of decades and $C_{LS}$ is a constant at a certain $LS$ between potential maximum and minimum values. I averaged landscape suitability scores from each decade to evaluate an ecological performance of a management regime allocation to 195 stands.

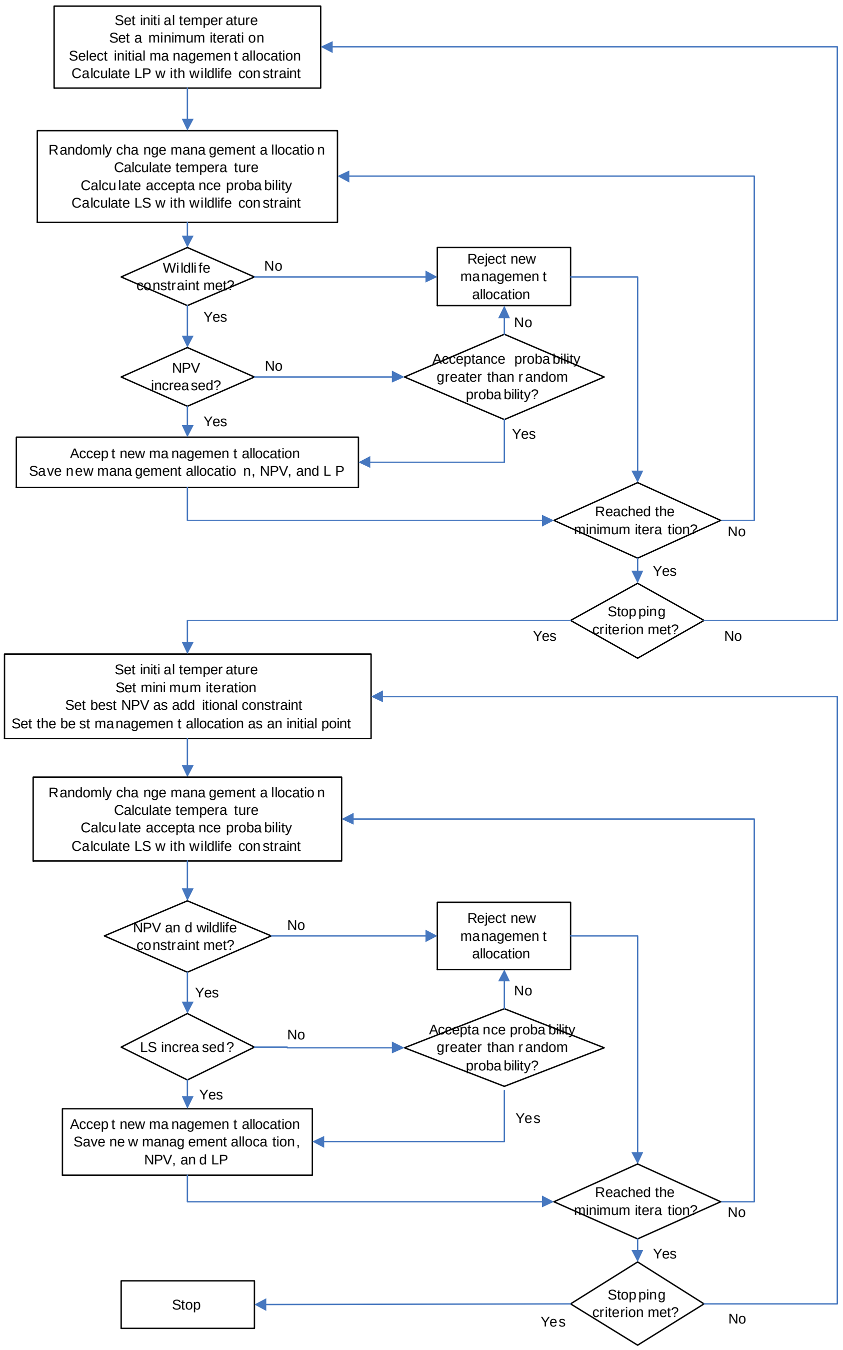


Figure 2 . Optimization processes using simulated annealing algorithm

To search maximum NPV values with different level of *LS* constraints, I used a simulated annealing algorithm (SA; Fig. 2). SA is a meta-heuristic optimization algorithm and is recommended as an optimization method for harvest scheduling that includes spatial constraints (Boston and Bettinger 1999; Bettinger *et al*. 2002). Since SA is a heuristic procedure, solutions through SA do not necessarily guarantee its optimality (Hillier and Lieberman 2005). However, SA is suitable for large size and complex problems including spatial constraints as used in this study (Calkin *et al*., 2002). Simulated annealing is based on the analogy to a physical annealing process. An annealing process initially involves melting a metal or glass at a high temperature and then slowly cooling the substance until it reaches a low-energy stable state with desirable physical properties (Hiller and Lieberman 2005). SA algorithms imitate this annealing process to find a near-optimal solution while escaping from being trapped in local optima. Although a better solution, in my case, a management set, is always accepted, a worse solution also sometimes is accepted with some probability in order to escape from local optima. That probability is as follows.

$$\text{Acceptance probability} = e^{\frac{Zn-Zc}{T}}$$

where *Zc* is an objective function value for the current trial solution, *Zn* is an objective function value for the current candidates to be the next trial solution, and *T*, or temperature, is a parameter that measures the tendency to accept the current candidates to be the next trial solution if this candidate is not an improvement on the current trial solution (Hiller and Lieberman, 2005). As a SA process proceeds, the temperature decreases with a schedule. This schedule is called a temperature schedule or a cooling schedule and various functions can be used. I set a cooling schedule to decrease the temperature exponentially as the number of iterations proceeded. Since *Zn* is always smaller than *Zc*, *T* becomes smaller as the iteration process proceeds, and the acceptance probability rapidly decreases as the iteration process proceeds. If the acceptance probability exceeds a randomly generated probability, the inferior solution is accepted to escape from a local optima.

Additionally, I adopted the $\varepsilon$-Constraining technique (Haimes *et al*., 1971, Tóth *et al*., 2006) to reach a solution as close to the efficient point as possible. This method is constructed by 4 steps; First, determining the ideal solution by optimizing each objective without any constraints (*MaxNPV*, *MaxLS*). Second, maximize NPV while constraining *LS* to be equal to or greater than *MaxLS*. Similary, maximize *LS* while constraining NPV to be equal to or greater than *MaxNPV*. These two points through the second step should be the two ends of the possibility frontier. Third, set the *LS* constraint at a certain level between minimum and maximum *LS* and search for the maximum NPV. Since this process results in a weak Pareto-optimal solution, one additional step is needed; fourth, maximize *LS* while using the maximum NPV value as a constraint. I repeated this process until the maximum NPV value did not increase or increased but an improvement occurred within the first 5 % of iteration after the rotation (Figure 2). I observed that the amount of NPV increase was negligible with the 5 % criteria.

The initial temperature and point settings in SA are critical to reach optimal points. I used 10,000,000 and 200 as initial temperatures for each run before and after each rotation, respectively. I chose the initial temperatures after several test runs. To find better initial points for each SA run, I first depicted point clouds in a searching space using a random search algorithm with a large number of iterations (Fig. 3). I selected two initial points for the random search. One initial point was all 45-year rotation and another was all no-harvesting because those two points represents the two extreme management sets, i.e. the highest and lowest NPV management sets (Fig. 3). Then, I chose one initial point from a point cloud for each constraint level.

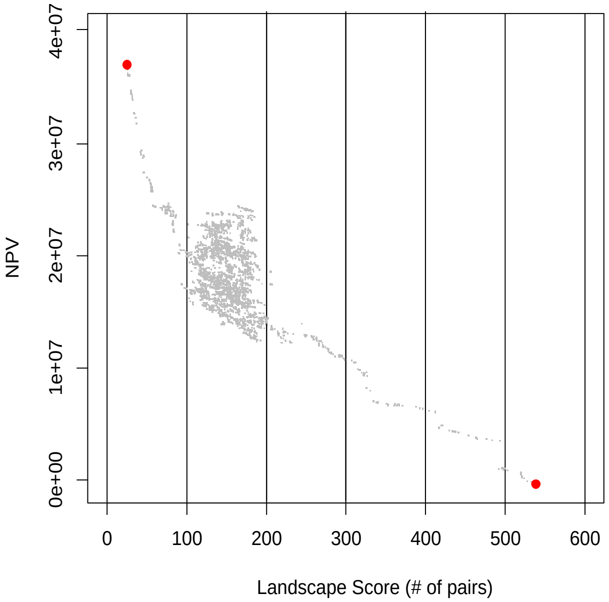


Figure 3. One example of a random search to explore the two dimensional NPV - *LS* space. Two initial points were set to all 45-year rotations and all no-harvesting regimes management for all 195 stands. This figure combined outputs from two optimization processes starting from two reference points with 4000 iterations. Almost all searching time was spent between the 100 and 200 landscape scores.

The number of iterations of each SA run was set to 1000. If the best solution in a given run was no better than the last best value, the program proceeded to the next step (Fig. 2). If the best solution in a current run was better than the last best value, the program looped back to another 1000 iterations using the last best solution as an initial input. Once the process exited from the first loop, the axis was rotated and the same process described above was repeated except for different initial parameters. If the algorithm could not find a better solution after the rotation, the entire process was stopped and the last best solution became the final solution. If the algorithm could find a better solution, I manually restarted the whole process described above using the best solution from the last run as an initial point for the next run. I repeated these processes until I could not find a better solution. Figure 4 describes 4 trials to reach a near-optimal point.

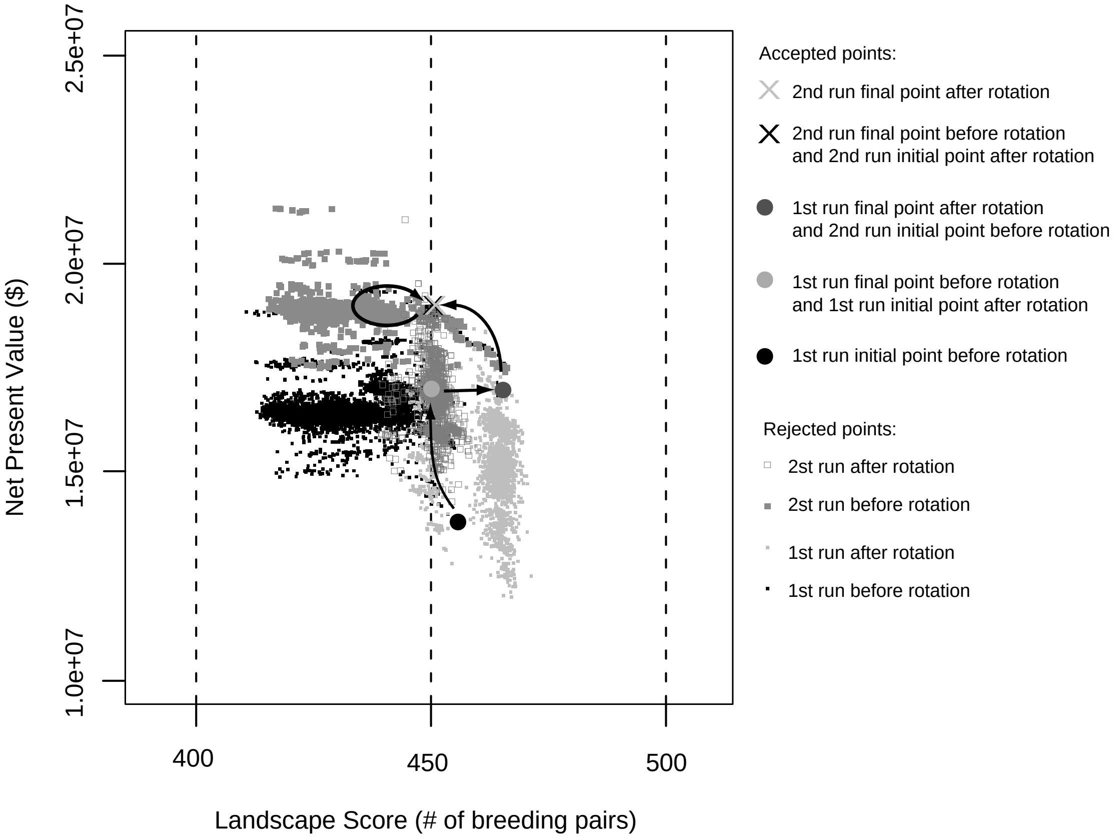


Figure 4. An example of the process of simulated annealing (SA)
In this example, two SA runs are presented. For each run, SA searched maximum NPV while keeping *LS* level at 450 or greater. After finding the maximum NPV, axis were rotated and SA continued searching maximum LS while keeping NPV equal or greater than the maximum value found before axis rotation.

In this example, two SA runs are presented. For each run, SA searched maximum NPV while keeping *LS* level at 450 or greater. After finding the maximum NPV, axis were rotated and SA

continued searching maximum *LS* while keeping NPV equal or greater than the maximum value found before axis rotation.

A production possibility frontier is a curve depicting all maximum outputs for two or more goods given a set of inputs. In this analysis, the two competing goods are NPV and *LS* for a set of inputs that are management decisions on 195 forest stands. This is a convenient way to describe trade-offs between two conflicting goals that share the same resources. I selected 6 or 7 constraint levels to search maximum NPV at each level. Then I subtracted the maximum NPV values from the highest NPV value among all management sets. I calculated the logical highest NPV by assigning the 45-year rotation to all stands. I drew a production possibility frontier by plotting the costs at each constraint level. In addition to the production possibility frontier, chronological changes in the timber harvest volume, landscape suitability scores, landscape connectivity scores, the total area of available habitat and the geographic habitat distribution for each species were examined.

I varied the habitat compatibility thresholds and the dispersal distance of the two species to examine the model's sensitivity to the ecological parameter settings. The habitat compatibility threshold was changed to only include mature forest structural conditions for the winter wren (Table 3). I included stands categorized as CA and GA in a standard analysis setting, whereas only CA habitat was included in the old-forest sensitive setting. I also changed dispersal distance settings from the distances in the literature (standard setting) to a much shorter distance (short dispersal setting, Table 2). Gamma represents the minimum number of breeding pairs for species that a patch must support on its own before the habitat patch contributes to the *LS* (Polasky *et al*. 2005). I set gamma to 5 breeding pairs for all model settings. Each step in the ecological model is described below.

### Study area and inventory data

I used forest inventory data from University of Washington's Charles Lathrop Pack Demonstration Forest (Pack Forest) for the simulation. Pack Forest is located in the southeast part of the Puget Lowland (Figure 5). Elevations range from 200 to 600 m and the vegetation zone is in the *Tsuga heterophylla* zone (Franklin and Dyrness 1988). Predominant forest cover at Pack Forest was Douglas-fir with some red alder, western hemlock, and western red cedar. Pack Forest contains 193 stands and total area is 17.4 km$^2$ (4306.8 acres). Stand age ranged from new plantations to 205 year old stands (Figure 6). Pack Forest's tree inventory data included 193 stands and the inventory was updated in 2005. One hundred and thirty one stands (67.9 %) were younger than 45 years old and 9 stands were older than 100 years in 2005.

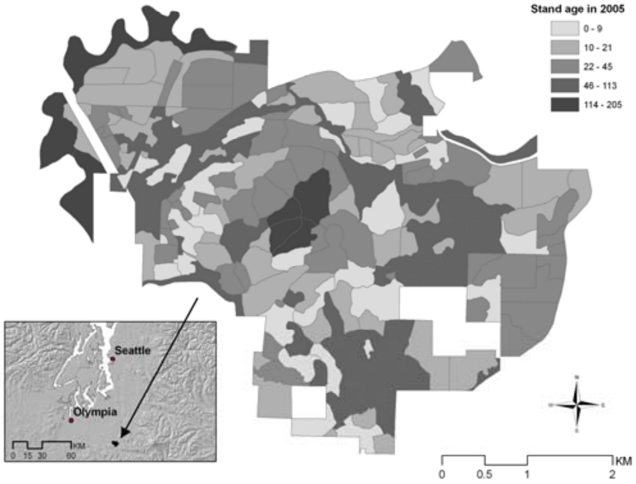


Figure 5. University of Washington Pack Forest

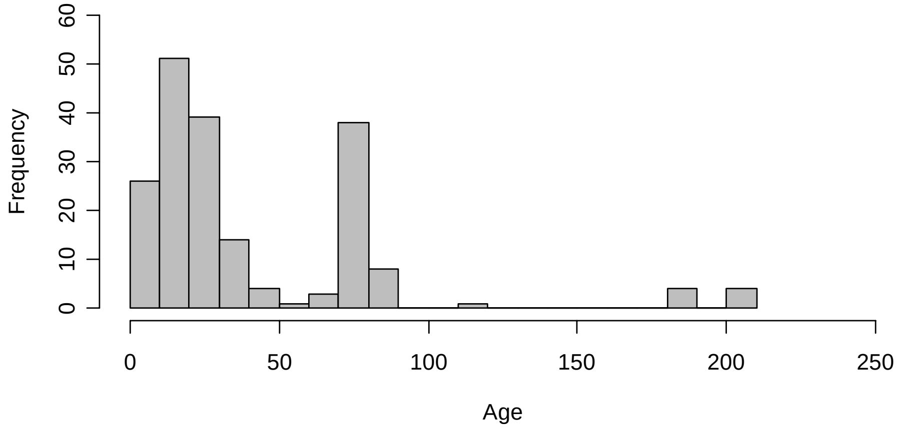


Figure 6. Stand age distribution of Pack Forest in 2005

**Software and computers**

I used various types of open source software to build a spatial forest management framework. Open source is a development method for software that harnesses the power of distributed peer review and the transparency of the process (Open Source Initiative 2007). Open source software is always free; therefore, open source technologies are suitable for projects that require transparency, since anyone interested in the project can examine the analysis processes. I used Python (http://www.python.org) to integrate GIS processes, an optimization process, a stand level management simulation, statistical analysis, and output presentations. Results from each analysis were delivered through a Python code. I used PostGIS (http://postgis.refractions.net) for the ecological modeling. PostGIS offers geographic analysis capability. PostGIS is a program library to process geographic information stored in PostgreSQL (http://www.postgresql.org). PostGIS is especially suitable for simple geoprocessing tasks, but needs a large number of iterations because it uses SQL for data process and storage. I used psycopg2 (http://www.initd.org/tracker/psycopg) to communicate between Python and PostgreSQL. Since PostGIS does not have visualization capability, I used MapServer and MapScript (http://mapserver.gis.umn.edu) to visualize habitat patch distributions under different management sets. MapServer excels at rendering spatial data (maps, images, and vector data) on the web and MapScript functions as the programming environment for MapServer. For the statistical analysis and its presentation, I used a statistical package, R (http://www.r-project.org). I used Rpy (http://rpy.sourceforge.net) to communicate between Python and R.

In addition to independent desktop computers, I used an elastic computer cloud provided by Amazon (http://www.amazon.com). Amazon's elastic computer cloud, EC2 (http://www.amazon.com/gp/browse.html?node=201590011), allows users to boot as many virtual computers as they want in the cloud. Entire analysis processes were packed into a instance, which is a image file that includes an operating system and software, and uploaded to the virtual computer space. Each instances can be controlled over the internet. Because I only used open source software, I was able to start several instances without any licensing issues. At most, I used a total of 20 CPUs at one time, including both desktop machines and EC2 instances.

## Results

### Forest management simulation at stand level

Both the short biodiversity pathway (short bio) and *no-harvesting* regimes created large tree forest structure, however, the 45-year rotation only reached the medium tree – multi story structure condition within the 100-year projection period (Table 5). The 45-year rotation created closed and vertically simple forest structure through the projection period (Figure 5). With the 45-year rotation setting, a stand could not reach the large tree structural stage or create a multi-story forest structure at least for 5 years within the rotation period.  The percentage of  forest canopy closure increased until the next clear-cutting (Table 5). The short bio followed the forest structural development described above to year 40 after clear-cutting, however, the first thinning at year 35 created a more open and large tree forest structure (Figure 5). The second thinning at year 55 even decreased canopy closure to 34.6 % and kept open forest structure. However, the no-harvesting regime created a longer multi-layer forest structure than the short-bio and reached higher QMD at the end of the projection period (Table 6).

**Table 5**. Changes in forest structural conditions and habitat association of northern flying squirrel and winter wren under the 45-year rotation regime in a sample stand*

| Year | Operation | QMD (in$^2$) | Canopy closure (%) | Canopy layer | Forest structural conditions | Habitat association degree ** | |
|---|---|---|---|---|---|---|---|
| | | | | | | Northern flying squirrel | Winter wren |
| 2005 | Clear-cut | - | - | - | Grass-Forb-Open | GA | GA |
| 2010 | | 0.12 | 24.6 | 1 | Seedling-Single-Open | NP | GA |
| 2015 | | 2.5 | 39.5 | 1 | Sapling-Pole-Single-Open | GA | GA |
| 2020 | | 4.26 | 62.0 | 1 | Sapling-Pole-Single-Moderate | GA | GA |
| 2025 | | 7.38 | 79.8 | 1 | Sapling-Pole-Single-Closed | NP | GA |
| 2030 | | 10.17 | 87.5 | 1 | Small-Single-Closed | NP | GA |
| 2035 | | 12.69 | 90.7 | 1 | Small-Single-Closed | NP | GA |
| 2040 | | 14.92 | 91.9 | 1 | Small-Single-Closed | NP | GA |
| 2045 | | 16.93 | 92.1 | 2 | Medium-Multi-Closed | GA | CA |
| 2050 | Clear-cut | - | - | - | Grass-Forb-Open | GA | GA |
| 2055 | | 0.12 | 24.6 | 1 | Seedling-Single-Open | NP | GA |
| 2060 | | 2.5 | 39.5 | 1 | Sapling-Pole-Single-Open | GA | GA |
| 2065 | | 4.26 | 62.0 | 1 | Sapling-Pole-Single-Moderate | GA | GA |
| 2070 | | 7.38 | 79.8 | 1 | Sapling-Pole-Single-Closed | NP | GA |
| 2075 | | 10.17 | 87.5 | 1 | Small-Single-Closed | NP | GA |
| 2080 | | 12.69 | 90.7 | 1 | Small-Single-Closed | NP | GA |
| 2085 | | 14.92 | 91.9 | 1 | Small-Single-Closed | NP | GA |
| 2090 | | 16.93 | 92.1 | 2 | Medium-Multi-Closed | GA | CA |
| 2095 | Clear-cut | - | - | - | Grass-Forb-Open | GA | GA |

* A sample stand represent a typical stand in study area

** CA: closely associated, GA: generally associated, P: present, NP: not present

Table 6. Changes in forest structural conditions and habitat association of northern flying squirrel and winter wren under the short biodiversity pathway regime in a sample stand*

| Year | Operation | QMD (in2) | Canopy closure (%) | Canopy layer | Forest structural conditions | Habiat association degree ** | |
|---|---|---|---|---|---|---|---|
| | | | | | | Northern flying squirrel | Winter wren |
| 2005 | Clear-cut | - | - | - | Grass-Forb-Open | GA | GA |
| 2010 | | 0.12 | 24.6 | 1 | Seedling-Single-Open | NP | GA |
| 2015 | | 2.5 | 39.5 | 1 | Sapling-Pole-Single-Open | GA | GA |
| 2020 | | 4.26 | 62.0 | 1 | Sapling-Pole-Single-Moderate | GA | GA |
| 2025 | | 7.38 | 79.8 | 1 | Sapling-Pole-Single-Closed | NP | GA |
| 2030 | | 10.17 | 87.5 | 1 | Small-Single-Closed | NP | GA |
| 2035 | | 12.69 | 90.7 | 1 | Small-Single-Closed | NP | GA |
| 2040 | Thinning | 14.92 | 68.9 | 1 | Small-Single-Moderate | NP | GA |
| 2045 | | 17.07 | 72.0 | 1 | Medium-Single-Closed | GA | GA |
| 2050 | | 18.95 | 73.5 | 1 | Medium-Single-Closed | GA | GA |
| 2055 | | 20.82 | 74.4 | 1 | Large-Single-Closed | NP | GA |
| 2060 | Thinning | 22.59 | 34.6 | 1 | Large-Single-Open | GA | GA |
| 2065 | | 22.41 | 37.1 | 2 | Large-Multi-Open | CA | CA |
| 2070 | | 23.61 | 43.7 | 2 | Large-Multi-Moderate | CA | CA |
| 2075 | | 24.78 | 48.3 | 2 | Large-Multi-Moderate | CA | CA |
| 2080 | | 25.94 | 51.1 | 2 | Large-Multi-Moderate | CA | CA |
| 2085 | | 27.01 | 52.7 | 2 | Large-Multi-Moderate | CA | CA |
| 2090 | | 28.06 | 54.3 | 2 | Large-Multi-Moderate | CA | CA |
| 2095 | | 29.05 | 55.6 | 2 | Large-Multi-Moderate | CA | CA |

* A sample stand represent a typical stand in study area

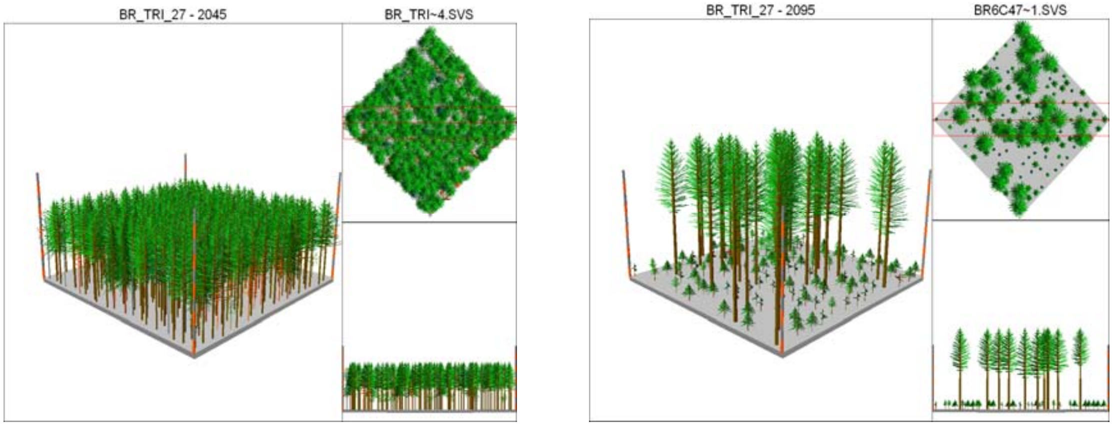
** CA: closely associated, GA: generally associated, P: present, NP: not present

Table 7. Changes in forest structural conditions and habitat association of northern flying squirrel and winter wren under the *no-harvesting* regime in a sample stand*

| Year | Operation | QMD (in2) | Canopy closure (%) | Canopy layer | Forest structural conditions | Habitat association degree ** | |
|---|---|---|---|---|---|---|---|
| | | | | | | Northern flying squirrel | Winter wren |
| 2005 | Clear-cut | - | - | - | Grass-Forb-Open | GA | GA |
| 2010 | | 0.12 | 24.6 | 1 | Seedling-Single-Open | NP | GA |
| 2015 | | 2.5 | 39.5 | 1 | Sapling-Pole-Single-Open | GA | GA |
| 2020 | | 4.26 | 62.0 | 1 | Sapling-Pole-Single-Moderate | GA | GA |
| 2025 | | 7.38 | 79.8 | 1 | Sapling-Pole-Single-Closed | NP | GA |
| 2030 | | 10.17 | 87.5 | 1 | Small-Single-Closed | NP | GA |
| 2035 | | 12.69 | 90.7 | 1 | Small-Single-Closed | NP | GA |
| 2040 | | 14.92 | 91.9 | 1 | Small-Single-Closed | NP | GA |
| 2045 | | 16.93 | 92.1 | 2 | Medium-Multi-Closed | GA | CA |
| 2050 | | 18.75 | 91.7 | 2 | Medium-Multi-Closed | GA | CA |
| 2055 | | 20.38 | 90.8 | 2 | Large-Multi-Closed | CA | CA |
| 2060 | | 21.91 | 89.8 | 2 | Large-Multi-Closed | CA | CA |
| 2065 | | 23.28 | 88.6 | 2 | Large-Multi-Closed | CA | CA |
| 2070 | | 24.52 | 87.4 | 2 | Large-Multi-Closed | CA | CA |
| 2075 | | 25.68 | 86.0 | 2 | Large-Multi-Closed | CA | CA |
| 2080 | | 26.78 | 84.6 | 2 | Large-Multi-Closed | CA | CA |
| 2085 | | 27.77 | 83.1 | 2 | Large-Multi-Closed | CA | CA |
| 2090 | | 28.73 | 81.7 | 2 | Large-Multi-Closed | CA | CA |
| 2095 | | 29.63 | 80.1 | 2 | Large-Multi-Closed | CA | CA |

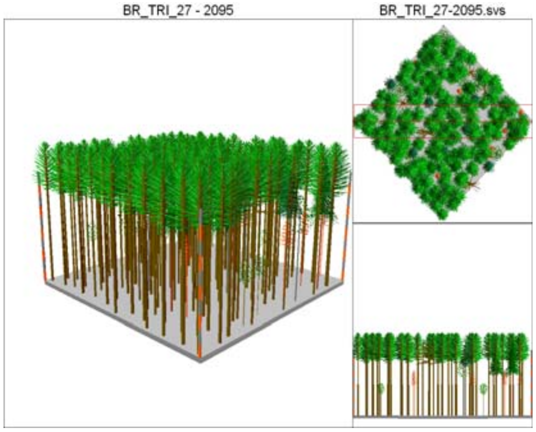
* A sample stand represent a typical stand in study area

** CA: closely associated, GA: generally associated, P: present, NP: not present



45-year rotation

Short biodiversity pathway



*No-harvesting*

Figure 7. Visualization of stand condition at the end of rotation period for three management regimes

Since the northern flying squirrel does not prefer small trees or single canopy layer structure, more than half of the projection period (53 %) in the 45-year rotation the landscape resulted in a “not present (NP)” condition (Figure 8). On the other hand, both short bio and no-harvesting regimes created preferable habitat conditions for a longer time period. Although the degree of association was similar between the short-bio and the no-harvesting, the no-harvesting regime created the “closely associated (CA)” condition 10 years longer for the northern flying squirrel. Since the winter wren was more of a habitat generalist than the flying squirrel in Johnson and O'Neil's model (Table 2), habitat conditions were always equal to or better than "generally associated (GA)" under all management regimes (Figure 8). A winter wren's preference of a multi-layer forest structure resulted in a higher percentage of the CA condition under the no-harvesting (58 %) than that of the short-bio (37 %).

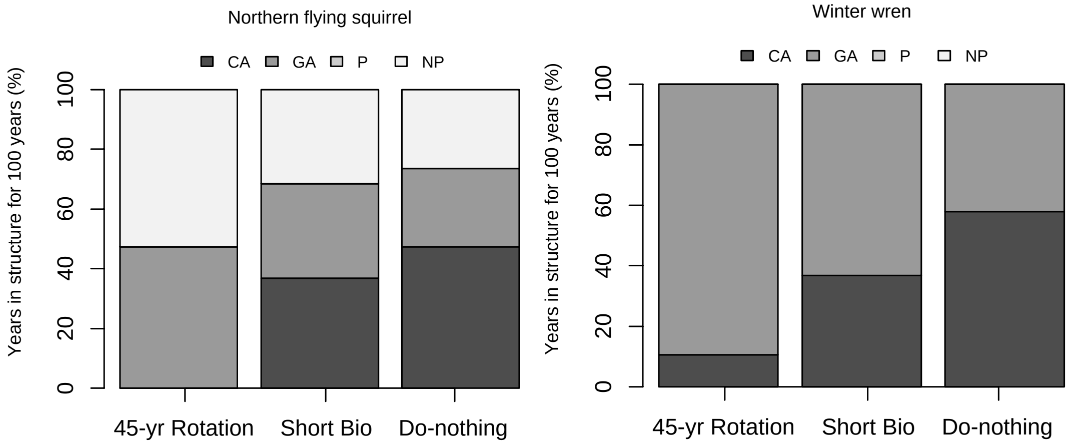


Figure 8. Habitat structural condition for the northern flying squirrel and the winter wren at a sample plot. CA: Closely Associated, GA: Generally Associated, P: Present, NP: Not Present

### Landscape level analysis

To overview species responses to different management sets, i.e. the various management regime assignments to the 195 stands, two reference management sets, the no-harvesting regime and the 45-year rotation regime for all stands, were examined (Table 8). Costs of both management sets were calculated by subtracting each NPV value from the highest possible NPV (base line: $ 36,875,380) and ranged from $ 0 to $ 371,211,030 (Table 8). The higher cost compared to the base line price was calculated under the all no-harvesting simulation because I assumed that there were minimum annual management fees (Table 4) even without any forest treatments. The range of landscape scores clearly differed among the northern flying squirrel with the standard setting (254 – 572) and the winter wren with the standard (601 – 900) and old-forest sensitive (26 – 537) settings, however the short dispersal variation results were the same or similar to their standard settings (Table 8). Therefore, the *LS* was sensitive to changes in territory size, habitat compatibility settings and the interior habitat use setting, whereas it was insensitive to the dispersal distance setting. The range of *LS* was the largest in the old-forest sensitive settings and only 22 or 26 breeding pairs could be supported when NPV was maximized (Table 8).

Table 8. The range of costs and the landscape suitability scores with two extreme management sets (all 45-year rotation and all no-harvesting for 195 stands) for the northern flying squirrel and the winter wren

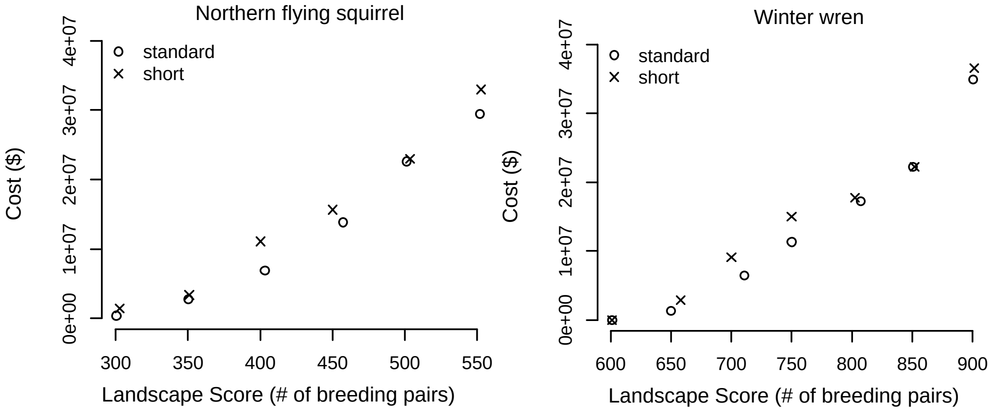
| | Species | Wildlife parameter setting** | All 45-year rotation | All no-harvesting |
|---|---|---|---|---|
| Cost ($)* | Both species | All settings | $ 0 | $ 37,211,030 |
| Landscape suitability score (# of breeding pairs) | Northern flying squirrel | Standard | $ 254 | $ 572 |
| | | Short dispersal | $ 254 | $ 572 |
| | Winter Wren | Standard | $ 601 | $ 900 |
| | | Short dispersal | $ 601 | $ 900 |
| | | Old-forest sensitive | $ 26 | $ 537 |
| | | Old-forest sensitive & short dispersal | $ 22 | $ 536 |

* Costs were calculated by subtracting NPV from a baseline price $36,875,380.

** The standard setting uses ecological parameters that represent typical numbers founded in the literatures.

** Other settings are derivatives from the standard setting to examine parameter's sensitivity (see Table2).

The costs to conserve habitat for both northern flying squirrel and winter wren increased as the carrying capacity of habitat (*LS*) increased in all ecological parameter settings, although the range and changing patterns of costs differed (Figure 9). Changes in costs were not linear to the changes in conservation level for all cases. The costs to conserve habitat for the northern flying squirrel slowly increased at the lowest end of the conservation level and gradually the rate of increase became higher as the conservation level increased. The short dispersal setting for the winter wren cost was always higher than the standard setting and especially higher, by about 2 to 4 million dollars, around the middle of the conservation level. Although the range of *LS* (601 – 900 breeding pairs) was different from the northern flying squirrel (300 – 553 breeding pairs), production possibilities of the winter wren habitat changed in a similar manner as described above in the case of standard and short dispersal settings (Figure 9). On the other hand, the patterns shown in the production possibility frontier for winter wren with old-forest sensitive settings were different from others. The increase rates in cost were generally higher in the lower conservation levels and the rates became lower as the conservation level increased for both old-forest sensitive settings (Figure 9). The additional short dispersal setting did not always result in higher costs in the case of the old-forest sensitive setting for the winter wren.



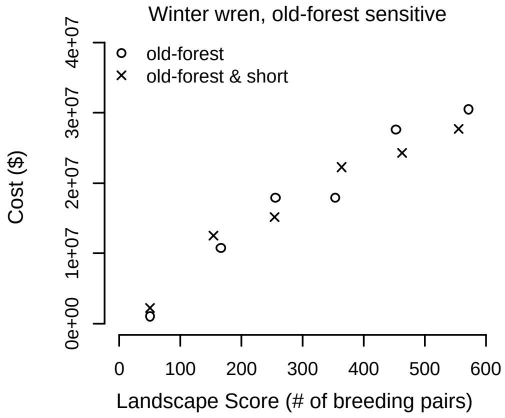


Figure 9. Costs of conserving habitat for northern flying squirrel and winter wren at different population sizes

The possible range of the landscape connectivity was narrow across the entire conservation levels for the flying squirrel (Figure 10; 0.84 – 0.98). The habitat patches were completely connected to each other through all conservation levels for the winter wren with standard and short dispersal settings (Figure 10). Therefore, it is difficult to connect the landscape scores alone to the conservation strategies in these cases. On the other hand, costs to create habitat connectivity depended on the level of connectivity for the winter wren with old-forest sensitive settings (Figure 10). The possible ranges in landscape connectivity were distinct between the old-forest sensitive setting (0.46 – 0.75) and the old-forest sensitive with short dispersal setting (0.11 – 0.44). The additional short dispersal setting clearly reflected the higher costs in creating habitat connectivity. In both cases, the patterns of changes were similar to each other and the costs did not increase linearly to the levels of connectivity.

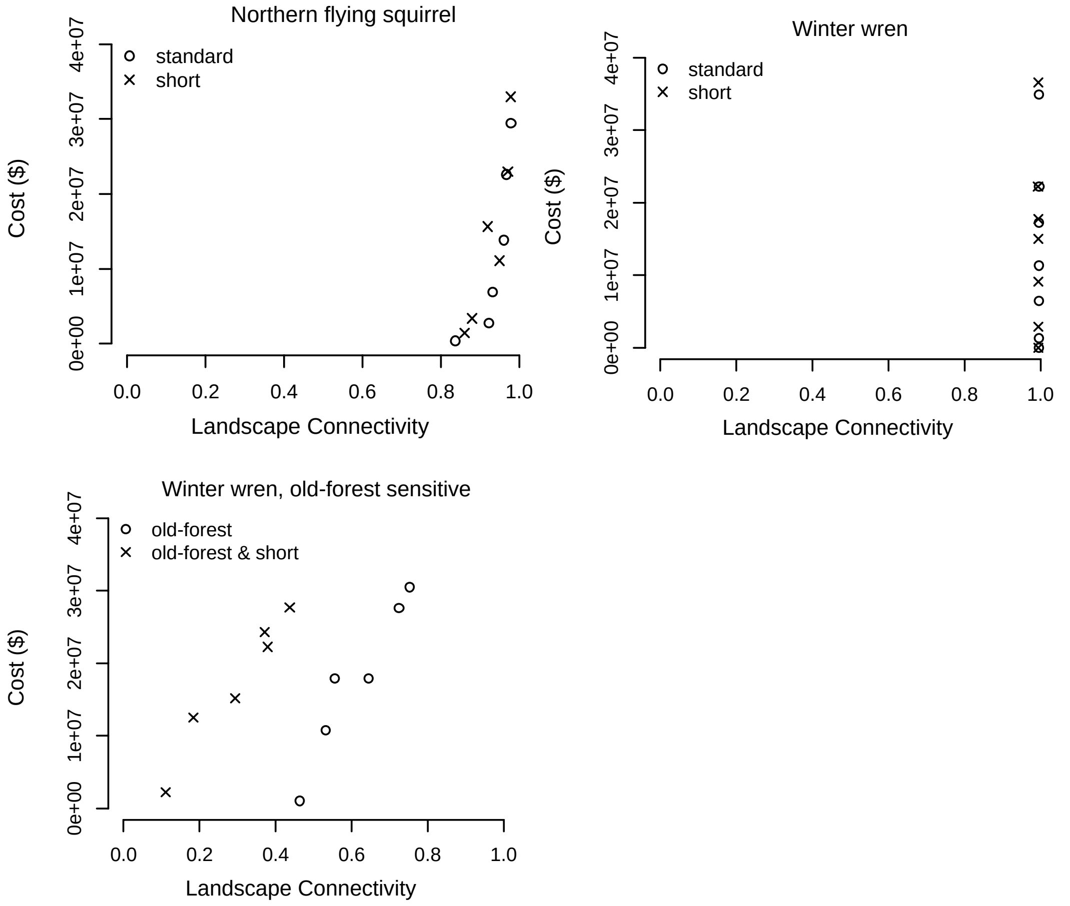


Figure 10. Cost to create landscape connectivity at different population levels for northern flying squirrel and winter wren

Chronological changes in economic and ecological measures indicated similar patterns between standard and short dispersal variations for both species (Figure 11). Therefore, I described the results only among the northern flying squirrel with standard setting, the winter wren with standard setting, and the winter wren with old-forest sensitive setting. In all three cases, the harvested timber volumes rapidly increased in 2005 and 2095 (Figure 11, 12, 13). The level of harvest volumes reflected the order of conservation degrees and the volumes were usually higher in the lower conservation levels. On the other hand, chronological changes in the habitat connectivity, habitat area, and the landscape score were variable among the three ecological settings (Figure 11, 12, 13). Habitat connectivity and the habitat area reflected the harvest volume changes in the flying squirrel, however; ecological measurements did not correspond to the level of harvest volumes for the winter wren. In spite of the rapid changes in the habitat connectivity and the habitat area for the northern flying squirrel, the landscape scores gradually increased by the year 2075 and decreased slightly after 2075. Both the habitat connectivity and habitat areas were constant and the highest through the all conservation levels in case of the winter wren with the standard parameter setting (Figure 13). Patterns of chronological changes in the connectivity, habitat area, and the landscape score in the winter wren with the old-forest sensitive setting were largely different from others explained above (Figure 15). The differences in the connectivity and habitat area became gradually larger among different conservation levels as time went by. The chronological changes in the *LS* were even more distinct among the conservation levels. The range of changes in the *LS* was minimal at the lowest end of conservation level, however; it became larger at the highest conservation level. Since the landscape score is partly calculated from each habitat connectivity and total habitat areas, the changes shown in the higher conservation levels appeared in a synergistic manner. The series of GIS outputs also show chronological changes in the habitat connectivity and the habitat areas (Appendix 1).

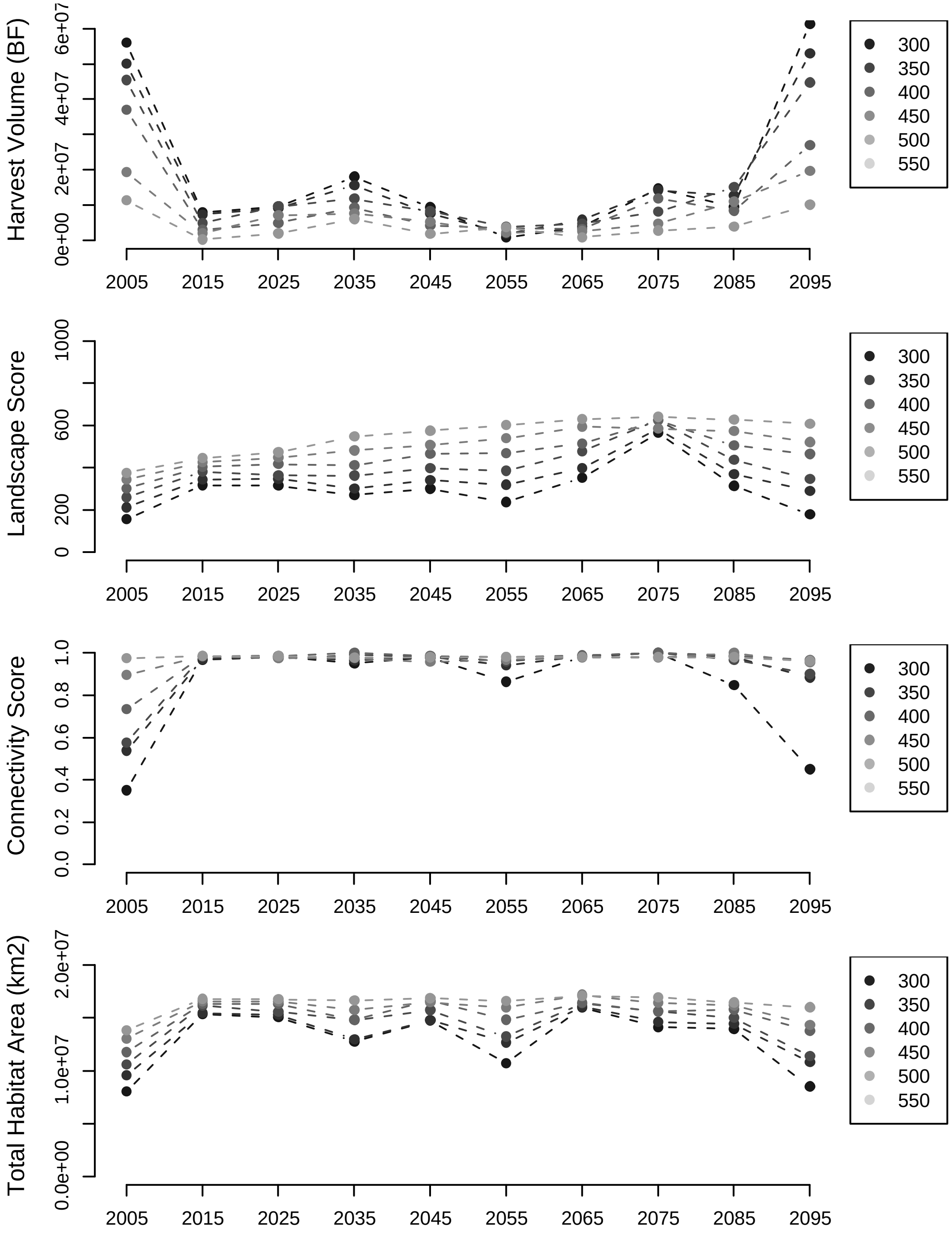


Figure 11. Chronological changes in economic and ecological measures for northern flying squirrel under the standard setting

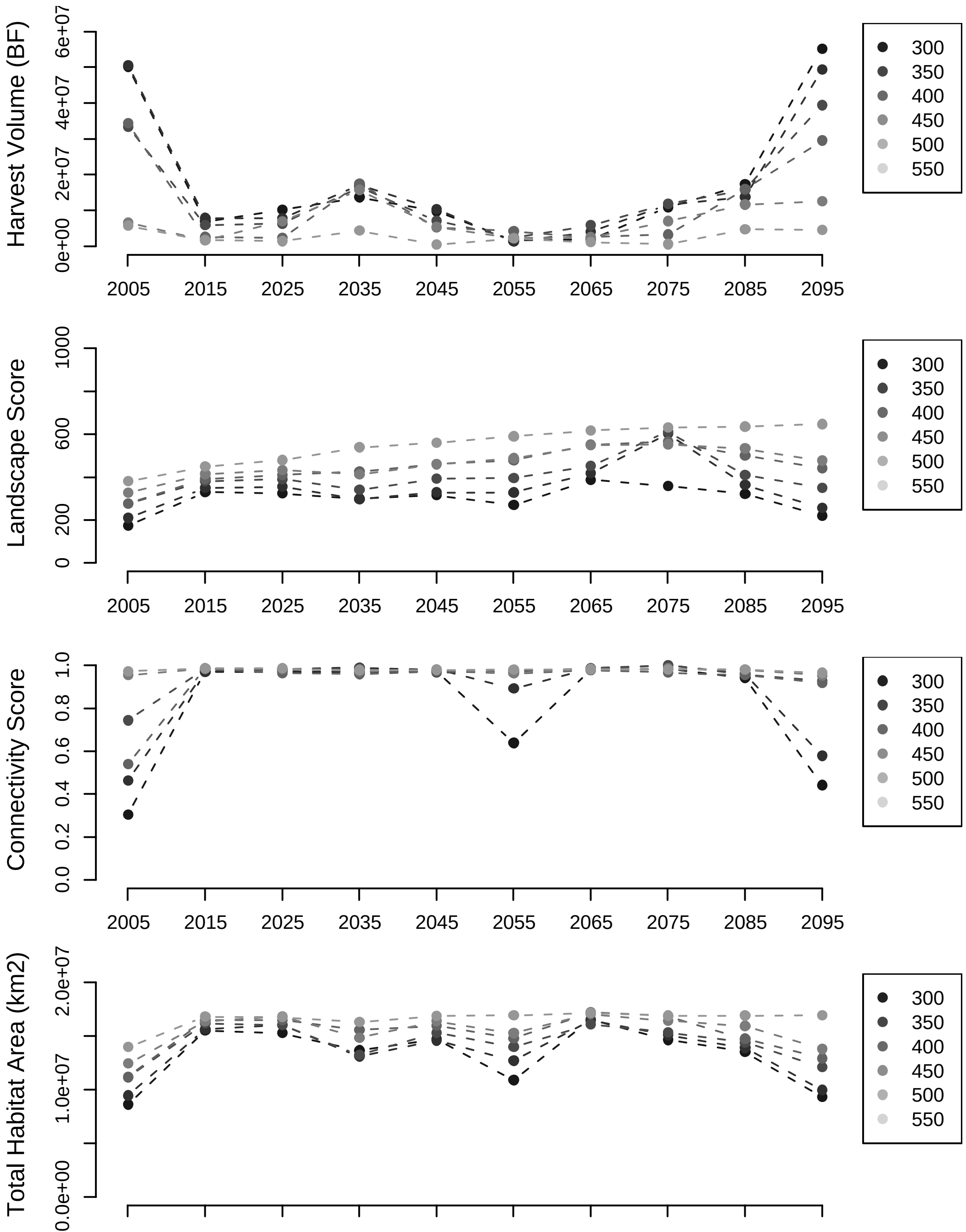


Figure 12. Chronological changes in economic and ecological measures for northern flying squirrel under the short dispersal setting

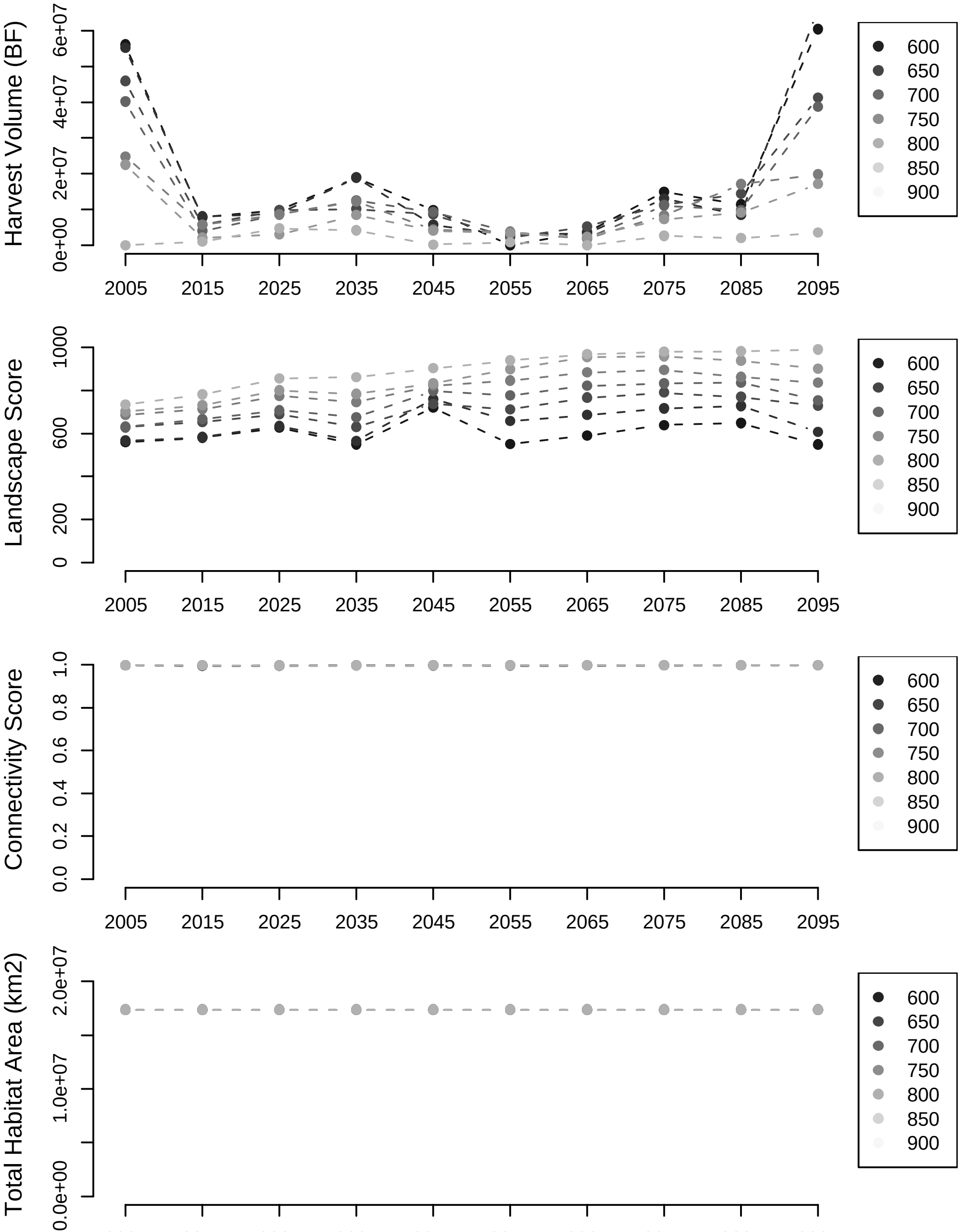


Figure 13. Chronological changes in economic and ecological measures for winter wren under the standard setting

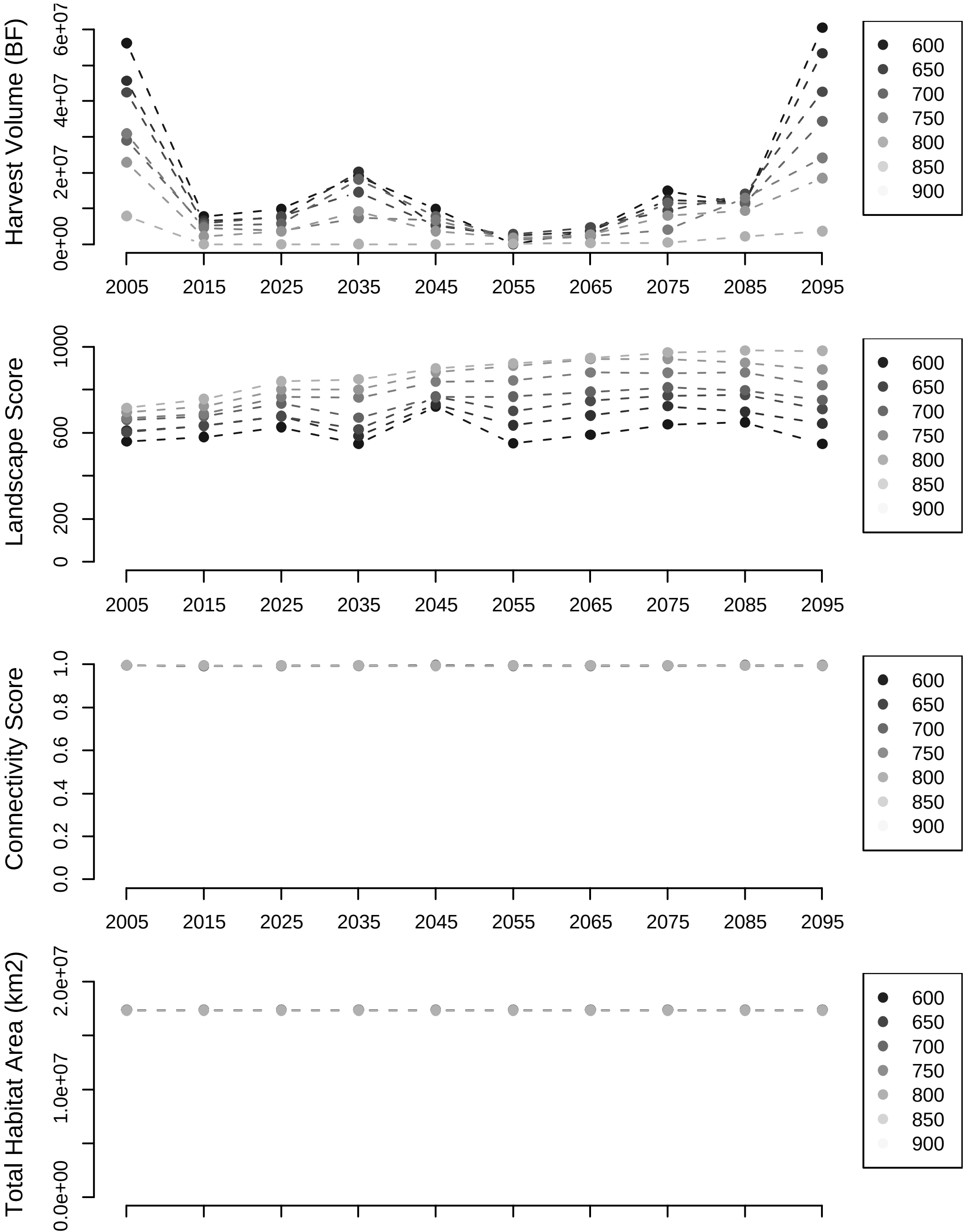


Figure 14. Chronological changes in economic and ecological measures for winter wren under the short dispersal setting

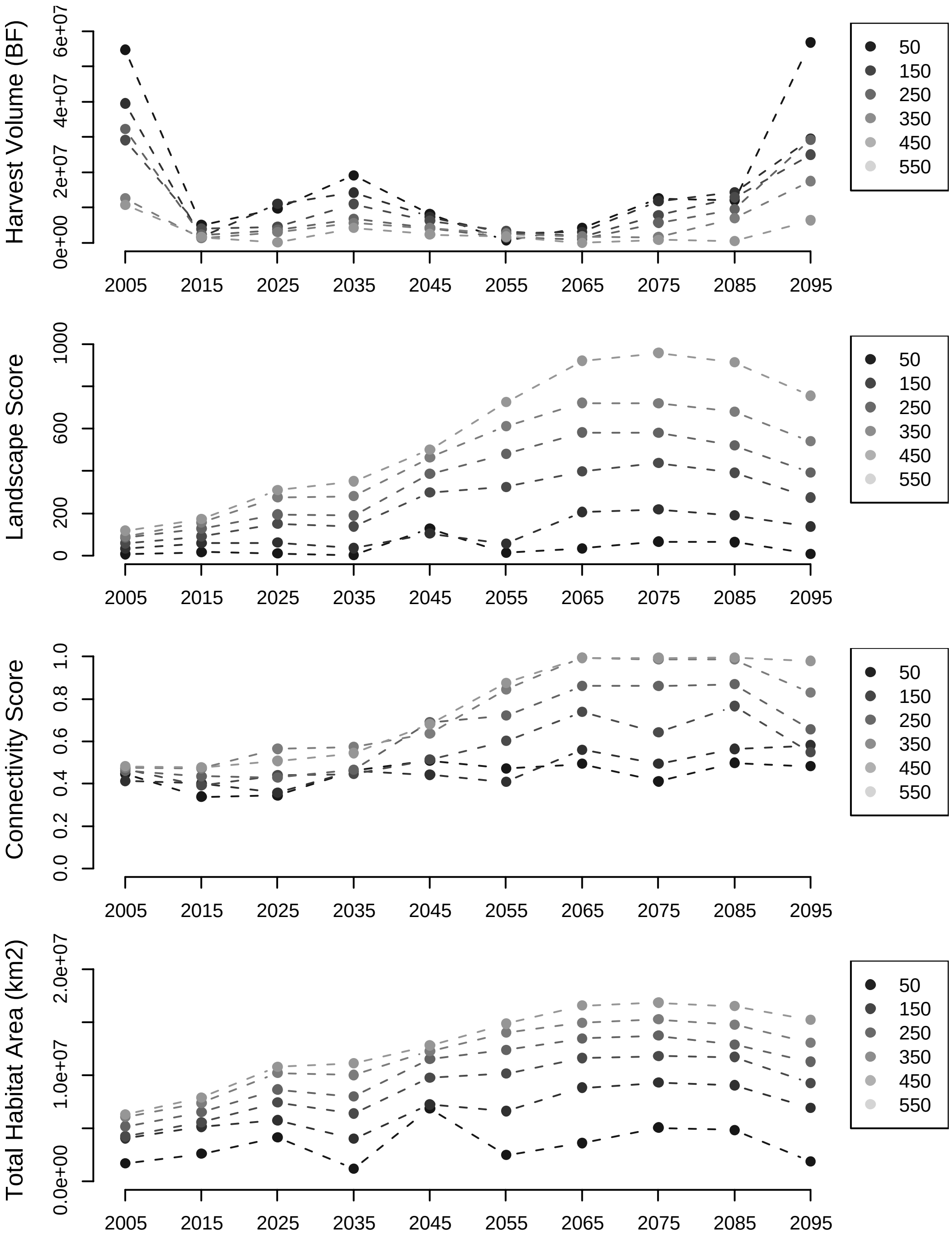


Figure 15. Chronological changes in economic and ecological measures for winter wren under the old-forest sensitive setting

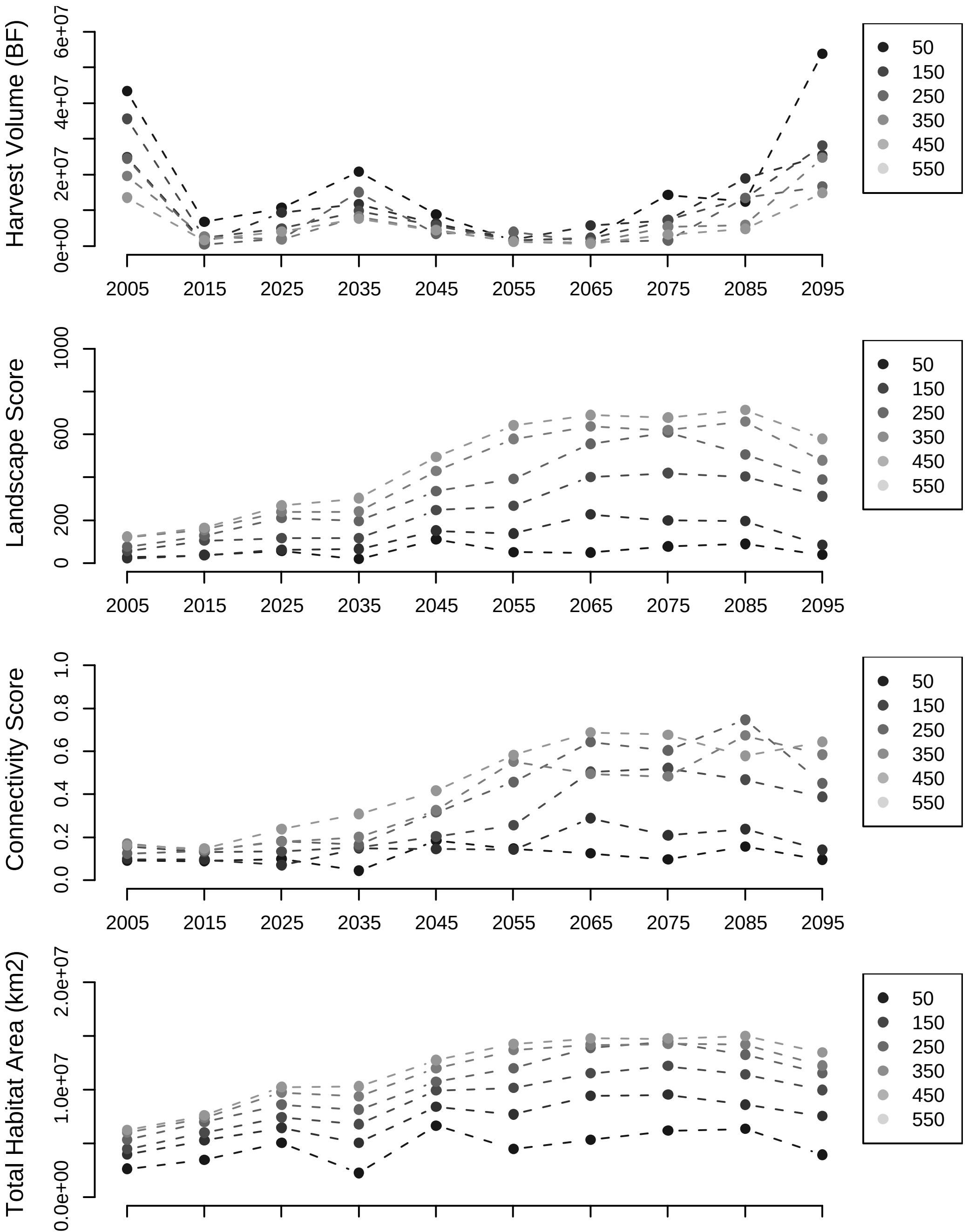


Figure 16. Chronological changes in economic and ecological measures for winter wren under the old-forest sensitive with short dispersal setting

Figure 17 showed the allocation of three management regimes at each optimal points. For all cases, the 45-year rotation became the dominant management regime at the lowest end of wildlife constraints (Fig. 17). On the other hand, the no-harvesting regime gradually increased as the conservation level increased and it became the dominant management regime at the highest conservation level for all cases. Therefore, the short bio regime was usually high around the middle constraint levels.

Sensitivity of conservation cost to ecological parameters was examined by comparing NPV increases at the lowest end of *LS* levels. The lowest end was chosen because it is not realistic to assume that the highest *LS* level becomes management goals in working forest. The largest cost increased occurred in habitat compatibility settings (Table 8). After changing habitat compatibility setting from standard to the old-forest sensitive, costs became almost three times than that of standard setting. On the other hand, changes in dispersal distances did not always result in a substantial differences in conservation costs except in one case for the winter wren (Table 8). Effects of territory size on costs could not be isolated, however, the cost difference to conserve northern flying squirrels (territory size: 0.025 $km^2$) relative to winter wren (0.013 $km^2$) was nearly double.

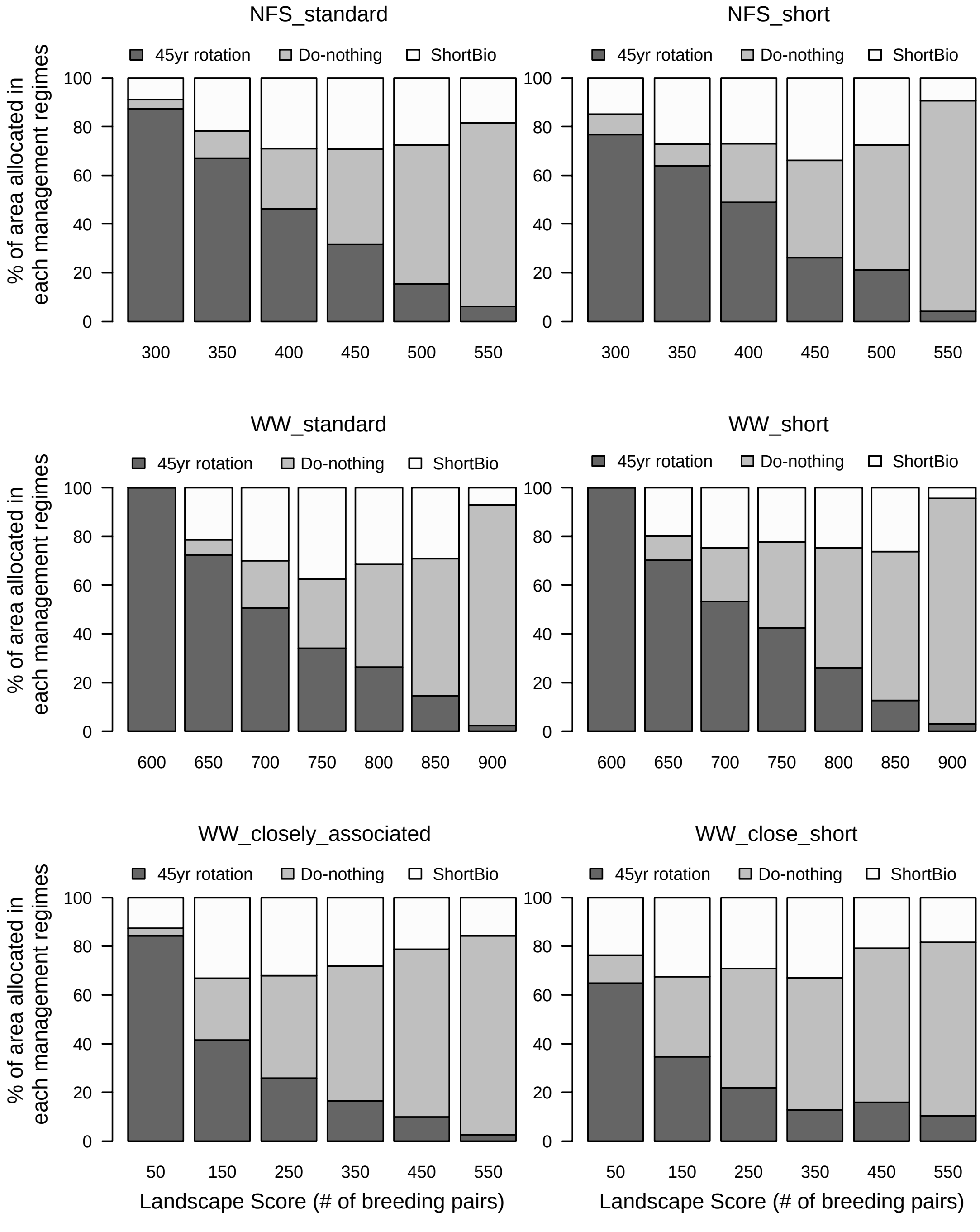


Figure 17. Management regime allocations at different population levels

Table 8. Cost performance of habitat conservation under different ecological settings at the lowest end of population size

| Differences in | Parameter setting* | | Cost increase per breeding pair** |
|---|---|---|---|
| Dispersal distance | | | |
| Northern flying squirrel | Standard | $ | 48,139 |
| Northern flying squirrel | Short dispersal | $ | 40,885 |
| Dispersal distance | | | |
| Winter weren | Standard | $ | 26,388 |
| Winter wren | Short dispersal | $ | 50,796 |
| Dispersal distance | | | |
| Winter wren | Old-forest sensitive | $ | 83,840 |
| Winter wren | Old-forest sensitive & short dispersal | $ | 99,210 |
| Habitat selection | | | |
| Winter wren | Standard | $ | 26,388 |
| Winter wren | old-forest sensitive | $ | 83,840 |
| Habitat selection and territory size | | | |
| Northern flying squirrel | Standard | $ | 48,139 |
| Winter wren | Standard | $ | 26,388 |

* Standard setting uses a territory size and a dispersal distance parameters from literatures or estimations based on allometric relationships. Ecological parameters were changed to examine responses in habitat parameters for other cases.

** The amount of increase was calculated by comparing the costs between the lowest wildlife constraint level and next constraint level.

# Discussion

## Spatial forest planning

The current study presented a spatial forest planning framework that combined a stand level management simulation and landscape level harvest schedule optimization with wildlife constraints. I used various readily available tools including open source GIS, a stand level forest management simulator (Landscape Management System), and other programming environments to build the analysis framework. Spatial forest planning focuses on forest management activities and the specific tools used to develop, implement, and evaluate spatial forest plans and alternative policies (Bettinger and Sessions 2003b). Spatial objectives were directly included in an optimization processes instead of checking the spatial feasibility of non-spatial optimal solutions afterwards (Bettinger *et al*. 1996).

Various types of spatial goals and constraints such as size, shape, juxtaposition, stand distribution, minimum and maximum harvest size, adjacency restrictions, habitat connectivity and the ratio of interior habitat can be considered with traditional non-spatial goals such as revenue from timber harvesting. I used the landscape suitability score developed by Polasky *et al*. (2005) based on the ESLI ( Vos *et al*. 2001) to include spatial wildlife goals into the optimization process. Since ESLI was developed to take into account uniqueness in species response to landscape (Vos *et al*. 2001) by including carrying capacity of habitat and habitat patch connectivity, indices were suitable to evaluate landscape changes through silvicultural operations from the wildlife point of view. The ESLI approach I used enables forest managers to evaluate a forest management plan efficiently compared to examining several landscape measurements separately. Additionally, the optimization process can reduce millions of management choices to many fewer choices. The spatial forest planning framework presented in this study facilitates efficient forest planning that includes multiple management goals.

### Integrating stand level and landscape level approaches

Integrating a stand level forest management simulation and a landscape level spatial forest planning process give us the advantage of designing a forest management plan with great detail. Therefore, researchers and managers can now pay close attention to the stand level management design to achieve landscape level management goals. In the current analysis, the short biodiversity pathway, which aims to create old-forest structure through a series of forest treatments (Ceary 1996, 1999; Lippke 1996), was created based on the management regime used in the Future of Washington's Forests And Forestry Industries study (College of Forest Resources, University of Washington, 2007). However, the short diversity pathway could not create the "closely associated" habitat condition (Johnson and O'Neil 2001) long enough to compete with the no-harvesting regime . Therefore, the short biodiversity pathway used in this study could not be a dominant management regime under the highest wildlife constraint level. By the end of the 100 years, as the ecological constraint level increased gradually the proportion of the no-harvesting regime increased. However, this long term consequence of stand level management design can be altered by tuning stand treatments to enhance forest structures for a specific wildlife species as shown in Marzluff *et al*. (2002). When the viability of a species becomes one of the management goals, an optimization process of stand level treatments also becomes a requirement. Recent spatial forest planning studies have proven that ecological and economic goals do not necessarily contradict each other (Nalle *et al*. 2004). Therefore, we may have the potential to increase ecological or economic outcomes at the same time without sacrificing other management objectives in currently managed forests.

### Spatially explicit ecological model

Habitat compatibility was the most sensitive parameter in the current study. Sensitivity changes from a habitat generalist to an old-forest sensitive species largely affected the shape of production possibility frontiers in the winter wren. Therefore, I hypothesized that the short dispersal setting, in addition to the old-forest sensitive setting, also greatly influenced a species sensitivity to landscape fragmentation; however, the results did not support this hypothesis. One reason for this unexpected result may be attributable to local optima. Since the optimization algorithm used in this study is one of meta-heuristics, the solutions from optimization do not guarantee a global optimality. In order to reach global optima or near global optima, parameters used in optimization need to be tuned and an optimization process needs to be iterated. However, I did not iterate several runs to choose the best solution from several outputs. Repeating the optimization process and fine optimization parameter settings should be part of future research. In spite of this caveat, differences shown in the habitat conservation costs in respect to landscape scores are suggestive. Instead of large increases in opportunity cost at the higher end of landscape scores, the rate of cost change was rather decreased for the old-forest sensitive settings for the winter wren. Kurttila *et al*. (2001) pointed out that the spatial arrangement of habitat needs to be seriously considered when landscapes have less than 20 % suitable habitat because the distance between the remaining habitat patches increases exponentially below this point (Andren 1994). As more stands reached the structures and compositions for species that prefer the old-forest structure, connectivity of habitat patches and total habitat area both increased in the current case. Especially, habitat connectivity rapidly increased 40 years after a large amount of timber harvesting in 2005. Therefore, the landscape suitability score, which is composed of habitat area and connectivity, increased in a synergistic manner after 40 years of large scale clear-cutting. While the loss of habitat has a far greater effect than the fragmentation of habitat on population survival in many cases (Fahrig 1999), habitat fragmentation can affect population survival under certain conditions as shown in this study. The landscape configurations, including fragmentation, had especially large influences in the case of short dispersal species. Therefore, a forest manager who needs to consider wildlife habitat is required to pay close attention to not only landscape conditions but also to species' ecological attributes as well as their responses to landscape changes.

### Ecological indices

My results suggest that species specific “Ecologically Scaled Landscape Indices (ESLI)” can effectively evaluate a changing landscape from silvicultural operations. Habitat suitability index (HSI) is another habitat measurement that has been used in spatial forest planning studies (Arthaud and Rose 1996; Bettinger *et al*. 1999; Marzluff *et al*. 2002 ). However, HSI approaches in spatial forest planning needs to include additional mechanisms to include spatial criteria since HSI itself usually does not contain spatial landscape parameters. Bettinger *et al*. (1997, 1999, 2003a) and Arthaud and Rose (1996) improved HSI with a spatial criteria such as a distance from other resources for their forest planning processes. Bettinger *et al*. (1997, 2003) specified the percentage of foraging and cover habitat within a certain distance from a focal habitat patch and used them as constraints in an optimization process. Individual landscape ecological measures such as total habitat areas, total edge / interior habitat areas, and landscape connectivity, were also used as optimization goals (Hof and Joyce 1993; Cox and Sullivan 1995; Bevers and Hof 1999; Gustafson *et al*. 2006). Individual landscape measures are simpler than ESLI and HSI approaches, however; it is more difficult to interpret multiple measures for forest and wildlife conservation planning. Since individual landscape indices represent general landscape conditions, those measurements may be more appropriate for broader biological measures such as species diversity, biological diversity or biological integrity (Karr 1993) than single or multiple species base approaches. There are still few studies that use population indices as ecological measurements rather than the more widely used habitat indices. Nalle *et al*. (2004) rather directly modeled a detailed wildlife population simulation model into a harvest scheduling problem. They used Program to Assist in the Tracking of Critical Habitat (PATCH) to evaluate landscape structures and compositions for two wildlife species. Because they used a spatial population model, they succeeded in implementing spatial landscape considerations into their forest management planning processes in an intuitive way. Because of its intuitive presentation and direct measurement of population status, methodologies that use a population index may have the potential to be developed.

### Habitat compatibility

The differences in habitat compatibility contributed to the highest variability in cost among all parameters in this study. Therefore, a habitat compatibility setting and its function in the modeling process needs to be closely examined. The current study used four habitat association degrees from Johnson and O'Neil (2001) and converted them into habitat compatibility scores ranging from 0 to 1. Johnson and O'Neil's (2001) habitat model was used because its extensive species coverage and simplicity. Additionally, their model works with widely available forest inventory data. However, the resolution of their model is coarse and requires additional criteria to convert habitat association degrees into numerical habitat compatibility measures.

The purpose of habitat compatibilities are to translate various forest structure and composition into comparable variables. By using habitat compatibilities, we can evaluate forest stands as species-specific wildlife habitats. Ideally, habitat compatibility should explain how much each habitat type contributes to species fitness. However, it may be difficult to measure the direct relationship between habitat compatibility and species fitness because of complex relationships between species and habitat. Instead of measuring direct fitness, we can use habitat selection studies. By examining how species budget their time spent in specific habitat types and locations, researchers can use species time allocation in each habitat type as a measure of habitat compatibility. Species coverage may not be extensive compared to Jonson and O'Neil's model,  but plenty of habitat selection studies have been conducted. Species abundance models such as Hansen *et al*. (1995) can provide another approach to evaluate habitat compatibility. An abundance model should be constructed by common measurements such as trees per acre, diameter at breast height, and canopy closure for data transferability between forest inventory data and an ecological model. Habitat suitability indices are another candidate. Instead of using HSI as an ecological criteria for an optimization process, HSI can be used as habitat compatibility measures. However, the species coverage becomes even smaller than other approaches. I proposed three alternative approaches for habitat compatibility estimations and selection should depend on management goals.

## Economic approaches in forest planning and wildlife conservation

Various concepts from economics are useful when creating plans for forest management and wildlife conservation. Net present value (NPV) of timber or the soil expectation value (SEV) of stands are commonly used as economic measurements, however; there are no similar common ecological measurements for wildlife. Since NPV and SEV use a discounting concept to convolve time series data into one measurement, it may be appropriate to apply the "discounting" concept to ecological measurements as well. A population index of species and its intrinsic growth rate may be good candidates. Discounting population size by its intrinsic growth rate give us a single value to evaluate population response to landscape through a period of time. Therefore, discounted population size becomes directly comparable to NPV or SEV instead of averaging ecological measures.

A production possibility frontier is another useful tool for spatial forest management. A production possibility frontier presents various levels of input measured by ecological and economic outcomes. All combinations of ecological and economic values on the production possibility frontier are assumed to be efficient. By identifying places on the frontier, managers reduce the number of plans they need to consider. For example, since there were 195 stands and three management regimes, $1.093 \times 10^{93}$ management decisions were available in the current study. I was able to choose an efficient management option from a limited number of choices. A production possibility frontier between economic and ecological values was also constructed in other spatial forest planning studies (Arthaud and Rose 1996; Rohweder *et al*. 2000; Juutinen *et al*. 2004; Nalle *et al*. 2004; Polasky *et al*. 2005; Toth *et al*. 2006; Hurme *et al*. 2007). These studies and the current study proved that the combination of optimization and production possibility frontiers is a useful tool for forest and wildlife managers who need to consider landscape management.

## Optimization

In contrast to linear programming, meta-heuristics cannot guarantee optimality in solutions; however, meta-heuristics can deal with non-linear, complex, and large size problems. A spatial ecological model are often non-linear and their optimization presents problem like the current study. Traditionally, linear programming such as integer programming and mixed integer programming have been used for harvest scheduling. Since solutions from linear programming guarantee their optimality, linear programming is suitable for harvest scheduling without spatial constraints. However, standard linear programming approaches are unable to deal with some of the non-linear formulations needed to express spatial relationships (Lockwood and Moore 1993, Bettinger *et al*. 2002). Decision variables can be split into fractions, and spatially inaccurate stratumwise data are sometimes used (Kurttila 2001). On the other hand, meta-heuristics such as simulated annealing, tabu search, threshold accepting and genetic algorithm are becoming common in spatial forest planning (Bettinger and Chung 2004) because they can overcome some of the shortcomings found in linear programming. Among various meta- heuristics, simulated annealing is one of the recommended optimization methods for spatial forest planning (Bettinger *et al.* 2002; Boston and Bettinger 1999).

Simulated annealing was adopted in the current study because of its simplicity, its theoretical capability to find optimal solutions (Aarts and Korst 1989: George 2003) and recommendations from Bettinger *et al*. (2002) and Boston and Bettinger (1999). Although, the performance of heuristic solution algorithms is always sensitive to one or more parameter values (Baskent and Jordan 2002, George 2003), I did not find any studies that conducted a parameter optimization in advance. Therefore, parameters used in an optimization also need to be optimized in the future studies. A parameter optimization method for simulated annealing was proposed by George (2003) and we need to adopt his approach or other parameter optimization approaches before starting the optimization process.

The current study only used one ecological constraint, the landscape suitability score. However, various kinds of ecological and economic constraints can be included in the optimization for more realistic forest planning. An even timber harvest volume flow is one of the common economic constraints in spatial forest planning (Bettinger *et al*. 2003a, 2007). Other types of economic constraints such as minimum and maximum harvest volume (Bettinger *et al*. 2007), minimum clear-cut age and green-up delays (Boston and Bettinger 2001; Bettinger *et al*. 2003a) can be formulated into the optimization process. Spatial constraints such as the maximum clearcut size (Kurttila 2001), Compared with the various economic constraints available, only a few types of ecological constraints have been considered. Minimum habitat area for certain species is a common constraint (Bettinger *et al*. 2003). Bettinger *et al*. (1997, 2003) set wildlife habitat quality goals based on minimum habitat area and distance from habitat patches. The geometric mean of various habitat measures such as habitat suitability index and habitat effective index have also been used as constraints (Arthaud and Rose 1997; Bettinger *et al*. 1999). The current study implemented the landscape suitability score (Polasky *et al*. 2005) as an ecological constraint. However, I did not use *LS* to constrain variability in ecological and economic outcomes presented in their chronological changes. The landscape suitability score is a simple numerical measure even though it includes species life history parameters and landscape indices. Therefore, the *LS* approach offers a way to implement complex ecological constraints in simple manner.

### Geographic information systems and technical insights

A GIS plays a critical role in spatial forest planning (Bettinger 2003, Baskent and Keles 2005). The current study used GIS not only for spatially explicit ecological modeling, but also to present habitat patch distributions as a map format. Ducheyne *et al*. (2006) suggested the importance of describing spatial details during the optimization process and operational forest planning to be able to implement a plan created through spatial forest planning processes. Ducheyne *et al*. (2006) presented three management plans (a maximum timber production, a maximum abundance of mature forest animals, and a maximum abundance of edge-dependent animals) through a genetic algorithm optimization in a detailed map format using an open source GIS system, GRASS (Neteler and Mitasova 2002). The current study also integrated an open source GIS system, PostGIS, as a spatial data processing engine and MapServer as a visualization engine to not only analyze spatial information but also interpret analysis results into a geographic representation. Detailed maps are useful not only for implementing forest plans on the ground but also for communicating management plans to interest groups (Bettinger 2003b). Therefore, combining an optimization process and a GIS may become a requirement for future forest planning (Kurttila 2001, George 2003, Ducheye *et al*. 2006). It is my hope that the current study contributes to the further integration of harvest scheduling and a GIS.

Integrating open source GIS capabilities into the analysis framework resulted in flexible spatial modeling functions and data processing abilities. I developed the entire analysis framework by open source software such as PostgresSQL, PostGIS, MapServer, QGIS, Python, and R. Open source is a development method for software that harnesses the power of distributed peer review and transparency of the process (Open Source Initiative 2007). Open source software are freely distributed and source codes are open to public. Therefore, open source applications are usually easily communicable among interested parties and can be customized by each user. I selected PostGIS as a spatial analysis engine and python as the coding environment. Because of Python’s flexible module extensibility, I could integrate all other open source programs to build a data processing system. Because of the flexibility and transparency of the open source environment, anybody who wants to improve or check my analysis methods can access the entire process. As I prove in this study, it is feasible to use an open source environment to build forestry and conservation tools. With increasing contribution from private, public agencies and universities, open source environments offer great opportunities to develop transparent and free forest management tools for the forestry field.

Even though I conducted our simulation and optimization process with a small area, the optimization processes needed a large amount of CPU power to find efficient points within a given time period. Future programmers should note that throughout all the processes, the sections that required that most CPU power were a series of GIS processing such as dissolving adjacent stand polygons to make patch polygons, calculating distances among all patch polygons, and spatially transferring stand attributes to an overlapping patch. Although some of the processing time was dramatically reduced by SQL query optimization, GIS processes that involved a large size of geometric information were still relatively slow. Additional SQL query optimization and developments of new geo-processing algorithms, as well as more powerful CPUs,  may be required to solve larger size problems.

The maximum number of CPUs used at one time was 20. In order to add more CPU power, I used an elastic computer cloud which is a web service that provides resizable computer capacity in clouds from amazon.com (Amazon EC2; **http://www.amazon.com**). Amazon EC2 service enables the public to use a large number of CPUs through the internet environment. Therefore, an elastic computer cloud is suitable for projects that need a high CPU power like the current study. Once the user sets an instance that is an entire environment including an operating system and application programs, users could activate as many instances as they want with “virtual computers.” Instead of purchasing and maintaining computers, the user can purchase CPU power depending on the user’s needs.  The open source environment was the key to using the elastic computer cloud. Since I developed the entire data analysis process with open source software, there was no user license issue. Therefore, even with an optimization process that takes several days to obtain one efficient point, the entire analysis can be finished in a relatively short time by activating a large number of instances at the same time. This is a great technological advantage for computer intensive calculations such as an optimization process in spatial forest planning.

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## Appendix A: Ecological and economic performance at near optimal points at various levels of wildlife constraints for northern flying squirrel and winter wren

Northern flying squirrel - Standard ecological setting
(Territory size = 0.025, Dispersal distance = 0.5, Compatibility threshold = 0.49, non-interior species setting)

| Wildlife constraint level | Total harvest volume (BF) | Cost ($) | Landscape Suitability Score | Landscape connectivity | Total habitat area ($m^2$) |
|---|---|---|---|---|---|
| 300 | 190,470,782 | 366,446 | 300 | 0.84 | 12,933,426 |
| 350 | 176,575,719 | 2,758,530 | 350 | 0.92 | 13,552,452 |
| 400 | 155,729,310 | 6,872,728 | 403 | 0.93 | 14,195,121 |
| 450 | 111,616,714 | 13,829,117 | 457 | 0.96 | 15,223,961 |
| 500 | 80,595,352 | 22,601,674 | 501 | 0.97 | 15,710,217 |
| 550 | 41,796,246 | 29,431,052 | 552 | 0.98 | 16,132,688 |

Northern flying squirrel - Short dispersal setting
(Territory size = 0.025, Dispersal distance = 0.25, Compatibility threshold = 0.49, non-interior species setting)

| Wildlife constraint level | Total harvest volume (BF) | Cost ($) | Landscape Suitability Score | Landscape connectivity | Total habitat area ($m^2$) |
|---|---|---|---|---|---|
| 300 | 186,856,126 | 1,387,357 | 303 | 0.86 | 13,369,159 |
| 350 | 173,639,433 | 3,359,029 | 351 | 0.88 | 13,560,753 |
| 400 | 144,131,898 | 11,073,452 | 400 | 0.95 | 14,222,920 |
| 450 | 117,061,323 | 15,651,672 | 450 | 0.92 | 15,115,908 |
| 500 | 80,873,800 | 22,965,632 | 503 | 0.97 | 15,542,957 |
| 550 | 26,184,424 | 32,994,338 | 553 | 0.98 | 16,431,115 |

Winter wren - Standard setting
(Territory size = 0.013, Dispersal distance = 2.0, Compatibility threshold = 0.49, interior species setting)

| Wildlife constraint level | Total harvest volume (BF) | Cost ($) | Landscape Suitability Score | Landscape connectivity | Total habitat area ($m^2$) |
|---|---|---|---|---|---|
| 600 | 192,938,638 | (0) | 601 | 1.00 | 17,374,975 |
| 650 | 190,342,681 | 1,286,852 | 650 | 1.00 | 17,374,975 |
| 700 | 154,749,285 | 6,450,754 | 711 | 1.00 | 17,374,975 |
| 750 | 140,017,923 | 11,322,856 | 750 | 1.00 | 17,374,975 |
| 800 | 106,422,536 | 17,243,449 | 807 | 1.00 | 17,374,975 |
| 850 | 79,287,766 | 22,211,792 | 850 | 1.00 | 17,318,323 |
| 900 | 19,019,179 | 34,901,088 | 900 | 1.00 | 17,318,323 |

Winter wren - Short dispersal setting
(Territory size = 0.013, Dispersal distance = 0.5, Compatibility threshold = 0.49, interior species setting)

| Wildlife constraint level | Total harvest volume (BF) | Cost ($) | Landscape Suitability Score | Landscape connectivity | Total habitat area ($m^2$) |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 600 | 192,938,638 | (0) | 601 | 0.99 | 17,374,975 |
| 650 | 183,206,926 | 2,888,322 | 658 | 0.99 | 17,374,975 |
| 700 | 149,382,062 | 9,120,666 | 700 | 0.99 | 17,318,323 |
| 750 | 126,878,063 | 15,001,903 | 750 | 0.99 | 17,374,975 |
| 800 | 97,769,006 | 17,750,399 | 802 | 0.99 | 17,318,323 |
| 850 | 81,655,091 | 22,249,588 | 852 | 0.99 | 17,318,323 |
| 900 | 6,855,487 | 36,593,083 | 901 | 0.99 | 17,318,323 |

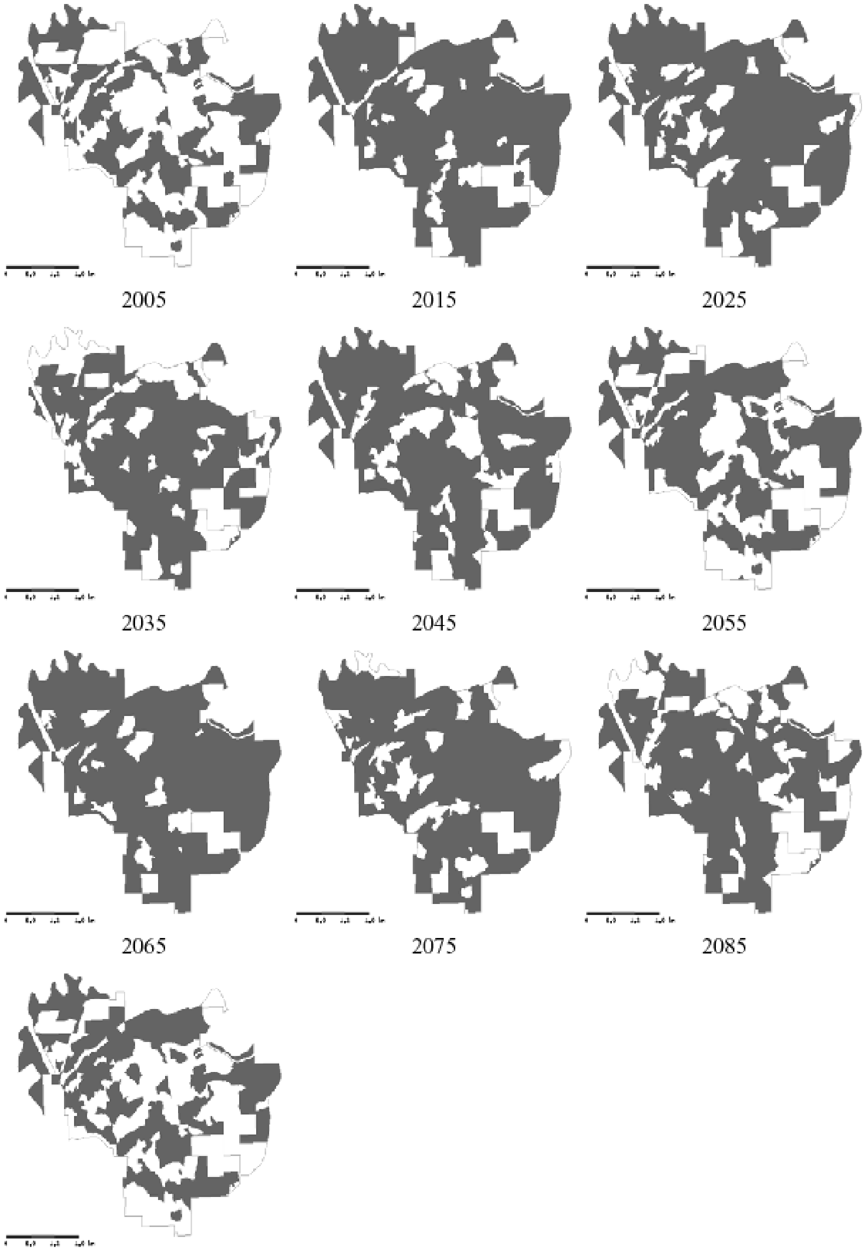
Winter wren - Old-forest sensitive setting
(Territory size = 0.013, Dispersal distance = 2.0, Compatibility threshold = 0.5, interior species setting)

| **Wildlife constraint level** | **Total harvest volume (BF)** | **Cost ($)** | **Landscape Suitability Score** | **Landscape connectivity** | **Total habitat area ($m^2$)** |
|---|---|---|---|---|---|
| 50 | 188,825,265 | 1,019,375 | 50 | 0.46 | 3,905,956 |
| 150 | 135,284,542 | 10,737,378 | 166 | 0.53 | 7,000,726 |
| 250 | 105,569,154 | 17,906,648 | 256 | 0.56 | 8,294,891 |
| 350 | 96,196,726 | 17,895,327 | 353 | 0.64 | 9,163,902 |
| 450 | 56,141,478 | 27,581,508 | 453 | 0.72 | 10,653,159 |
| 550 | 28,663,427 | 30,461,846 | 572 | 0.75 | 12,059,105 |

Winter wren - Old-forest Sensitive & Short Dispersal setting
(Territory size = 0.013, Dispersal distance = 0.5, Compatibility threshold = 0.5, interior species setting)

| **Wildlife constraint level** | **Total harvest volume (BF)** | **Cost ($)** | **Landscape Suitability Score** | **Landscape connectivity** | **Total habitat area ($m^2$)** |
|---|---|---|---|---|---|
| 50 | 184,772,909 | 2,192,729 | 50 | 0.11 | 4,640,965 |
| 150 | 132,250,313 | 12,494,504 | 154 | 0.18 | 7,715,744 |
| 250 | 111,265,901 | 15,164,128 | 254 | 0.29 | 9,014,224 |
| 350 | 82,300,705 | 22,252,279 | 364 | 0.38 | 9,257,628 |
| 450 | 75,299,831 | 24,297,025 | 463 | 0.37 | 9,860,853 |
| 550 | 56,059,270 | 27,682,452 | 555 | 0.44 | 10,741,178 |

## Appendix B: GIS outputs



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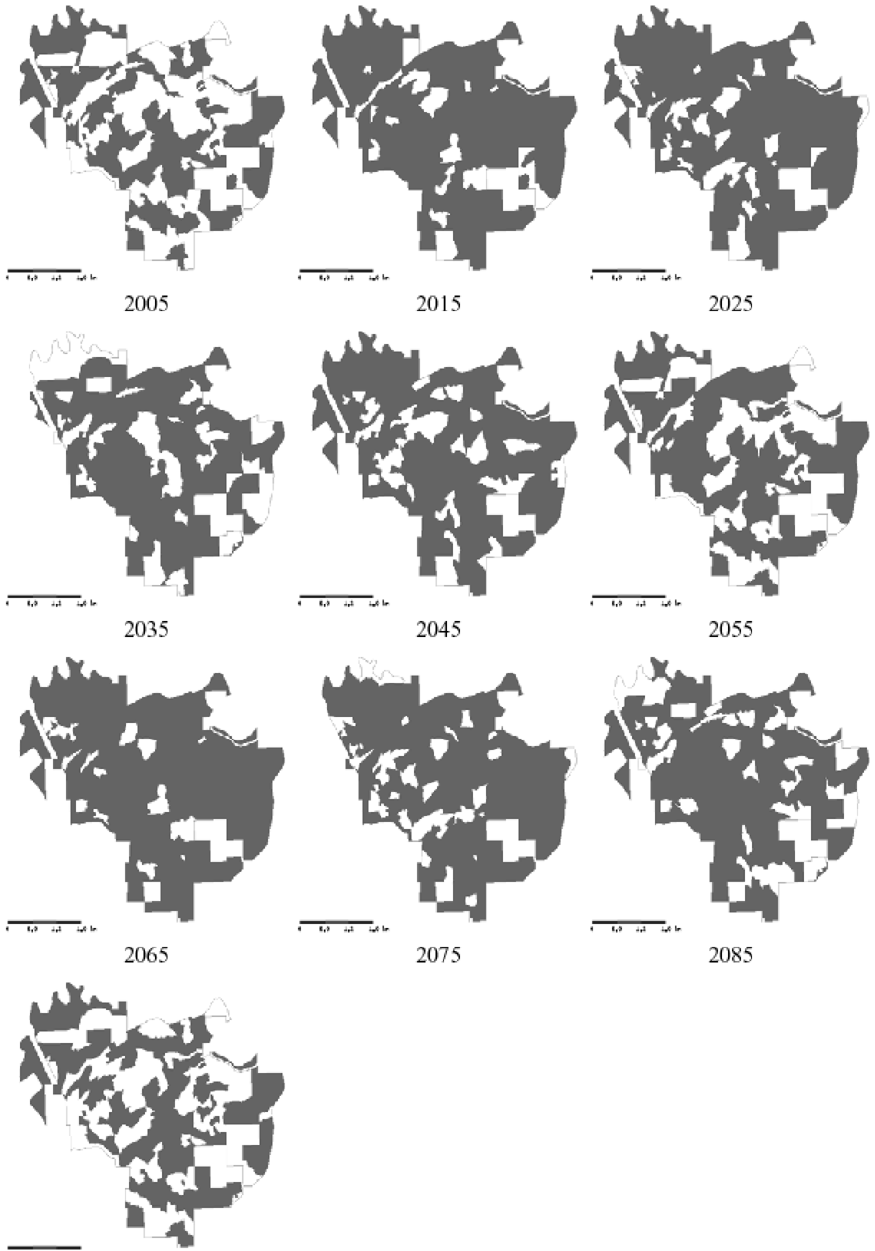
Appendix B-1. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 300 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).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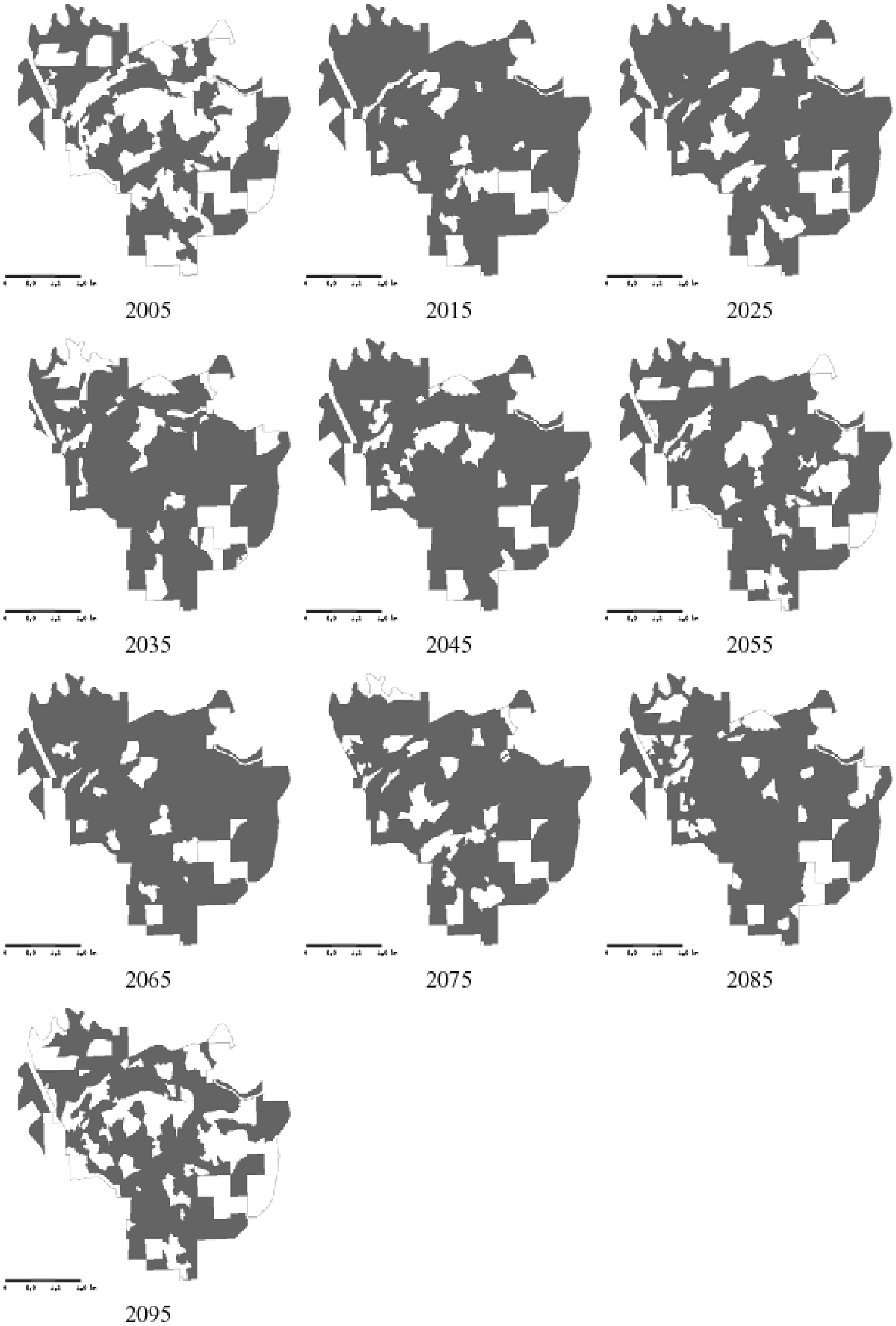
Appendix B-2. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 350 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).



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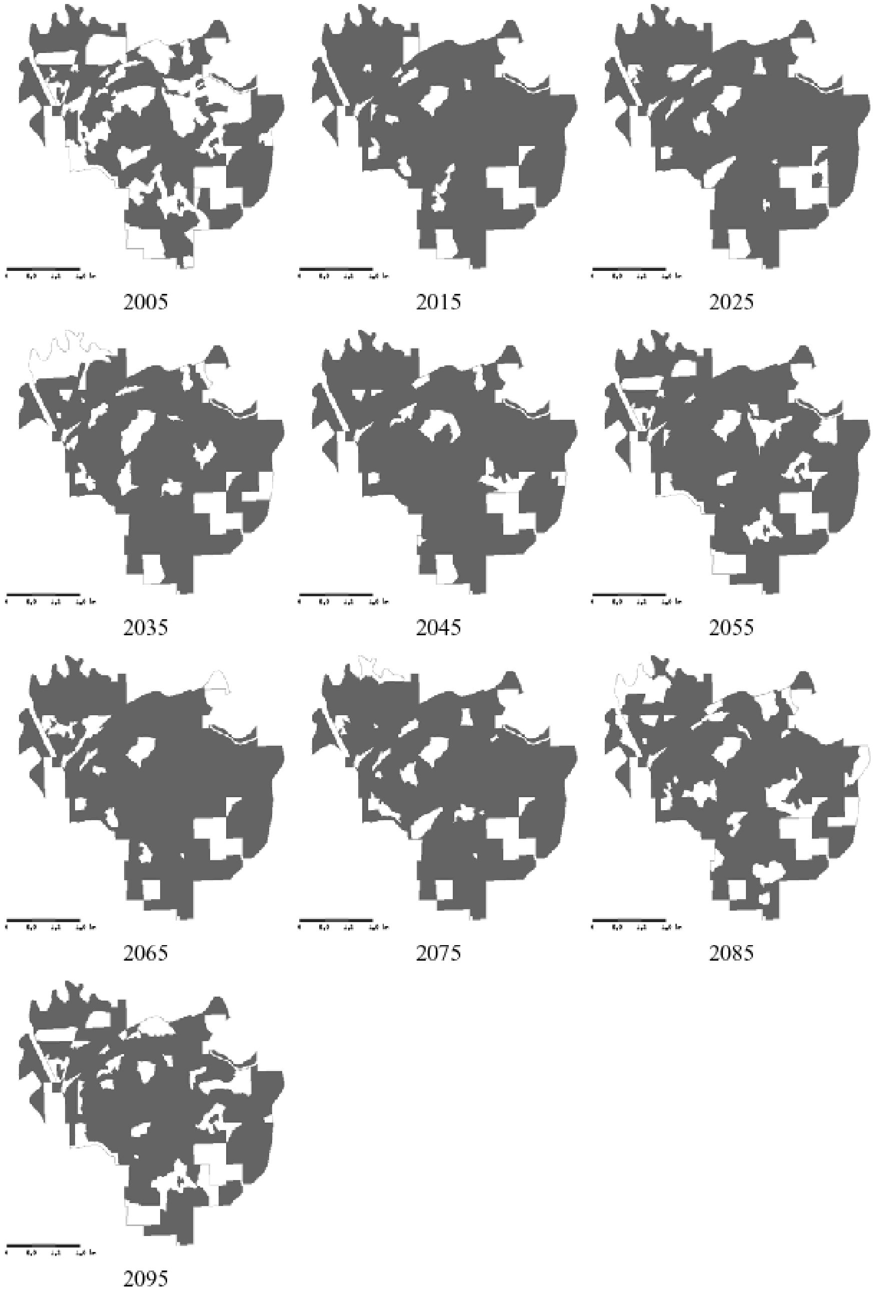
Appendix B-3. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 400 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).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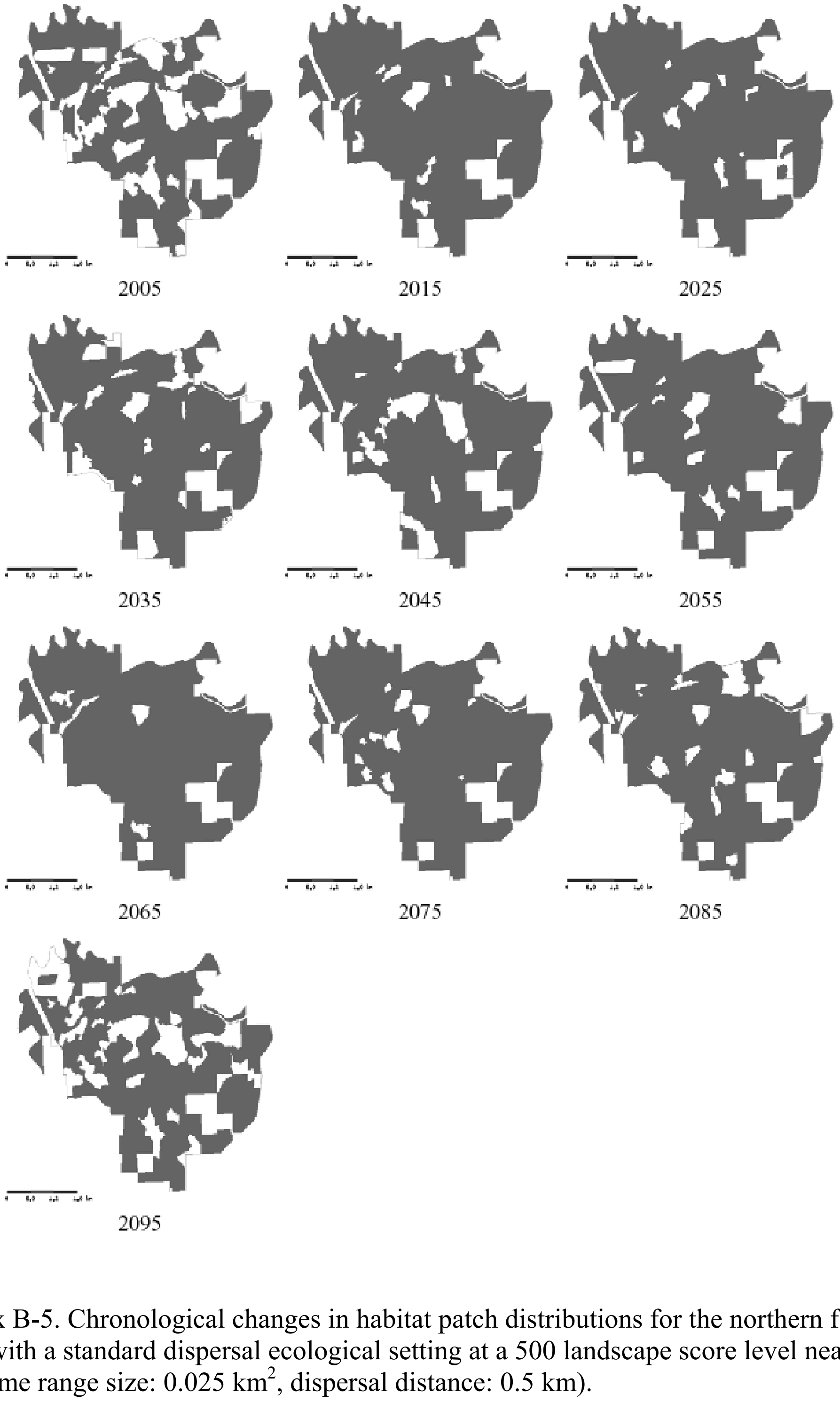
Appendix B-4. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 450 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).



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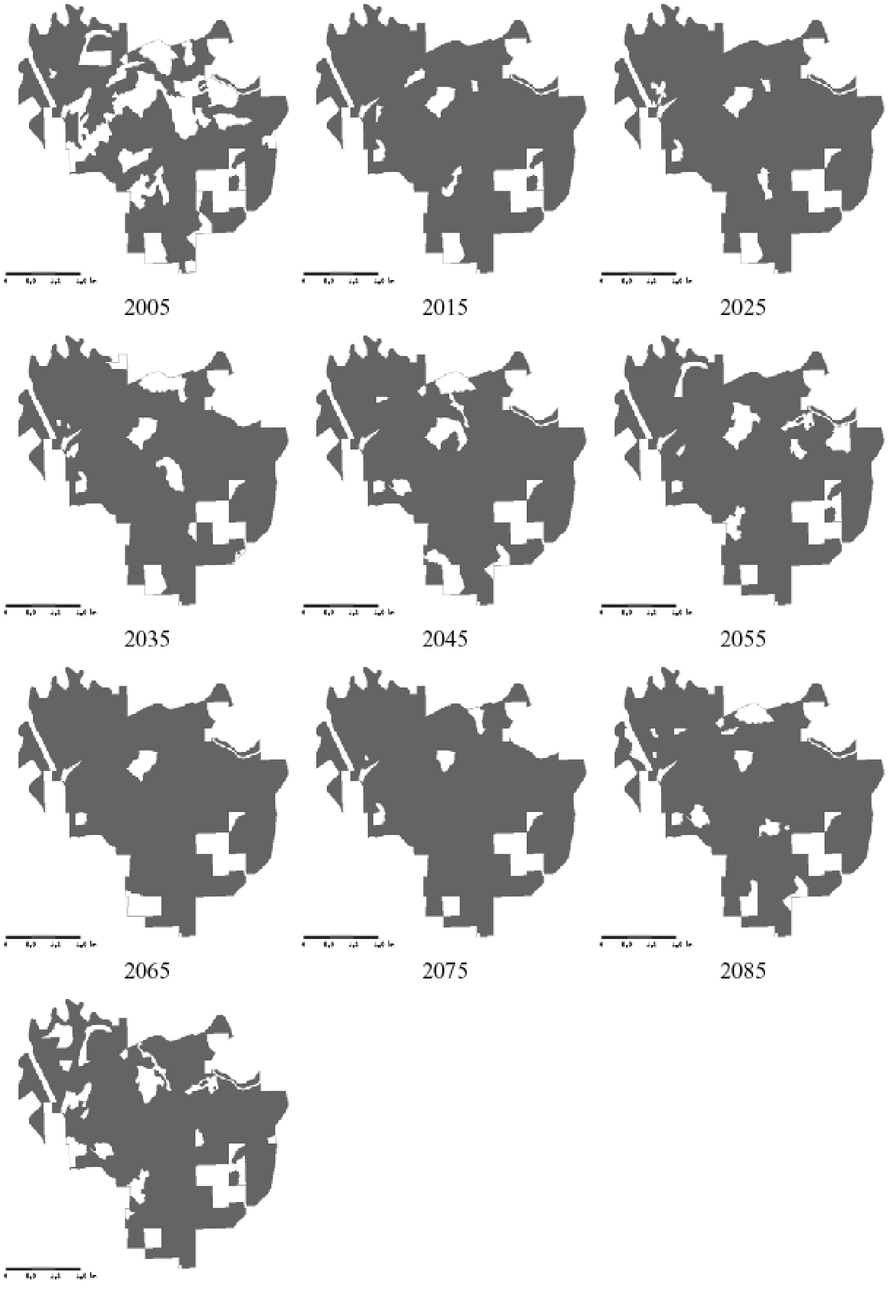
Appendix B-5. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 500 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).



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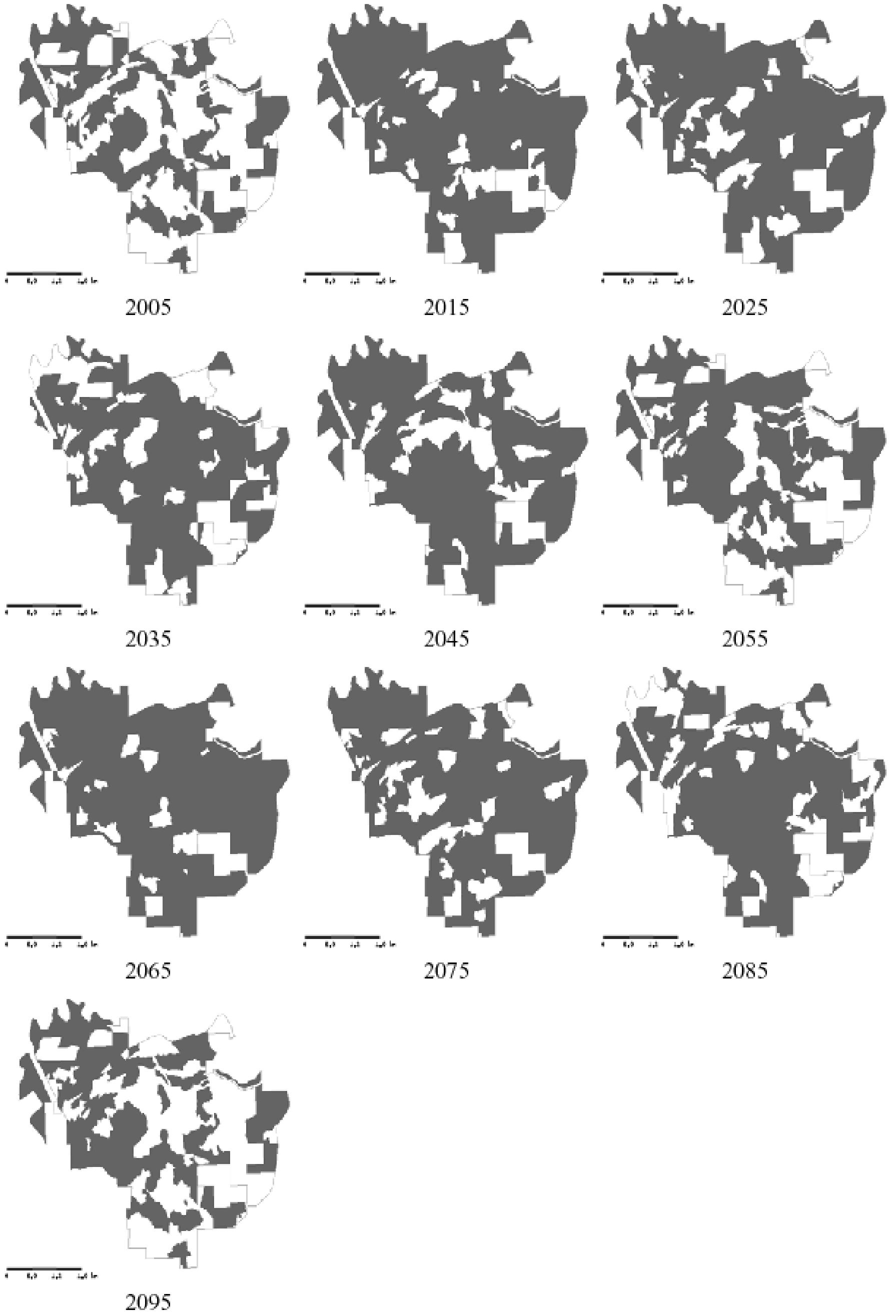
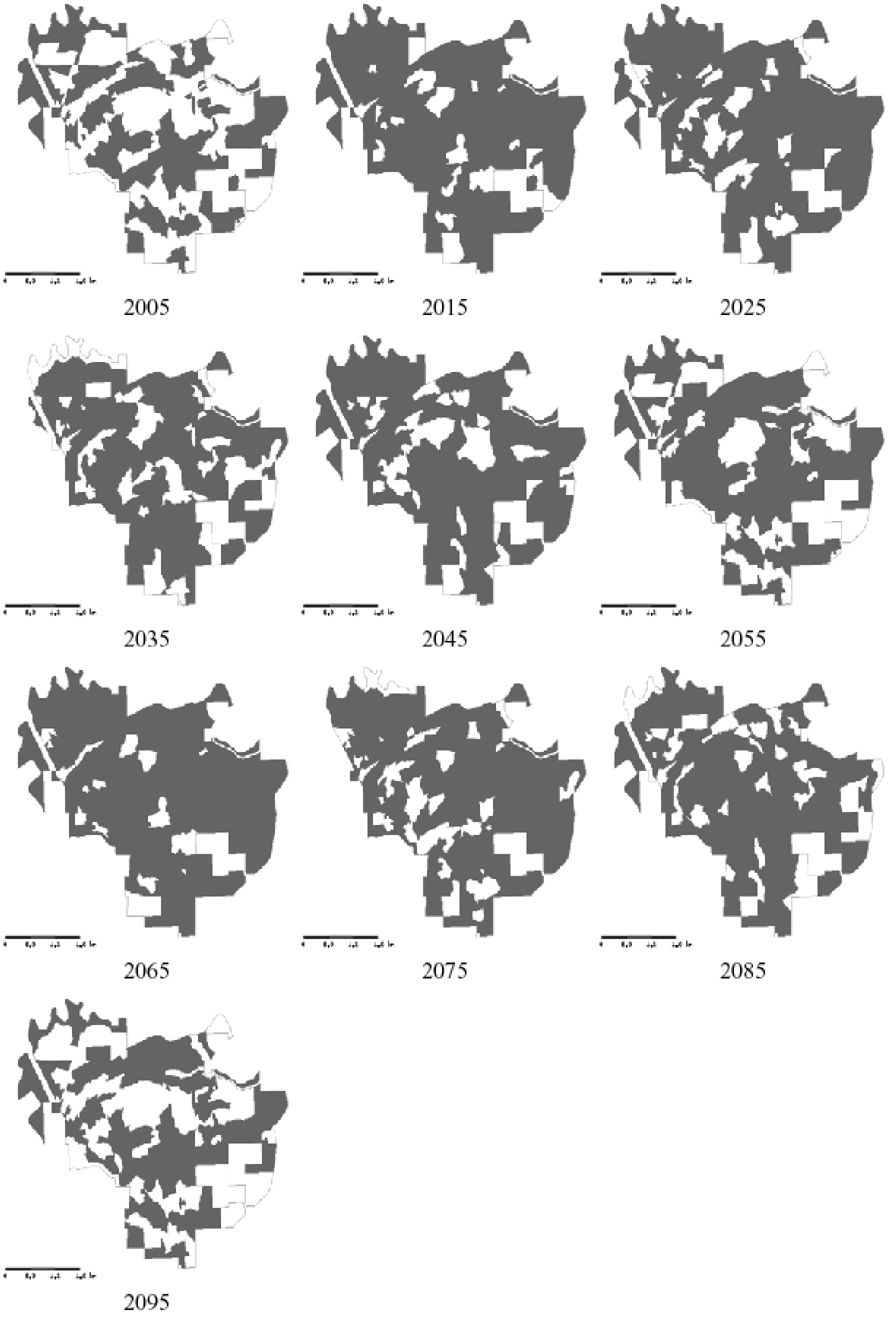
Appendix B-6. Chronological changes in habitat patch distributions for the northern flying squirrel with a standard dispersal ecological setting at a 550 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.5 km).



Appendix B-7. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 300 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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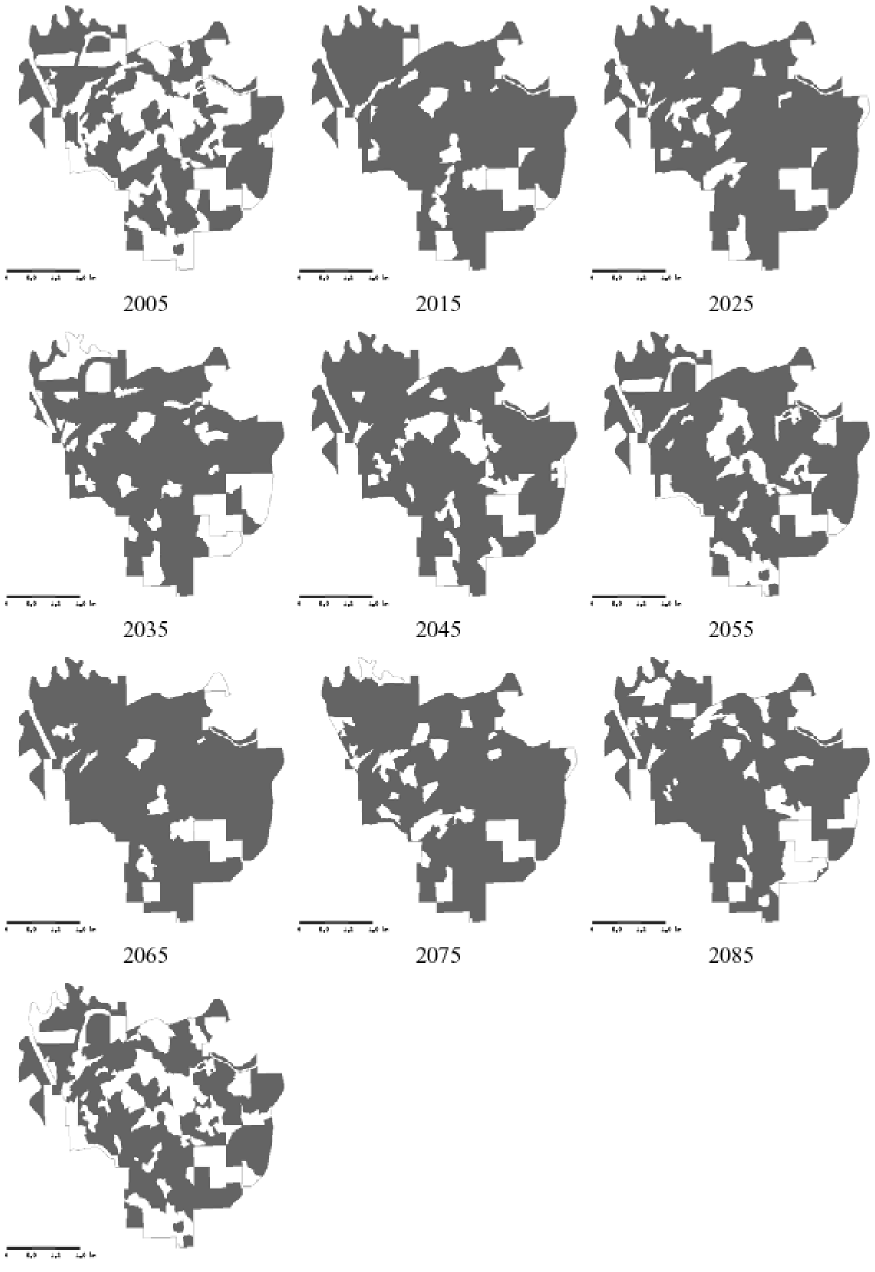
Appendix B-8. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 350 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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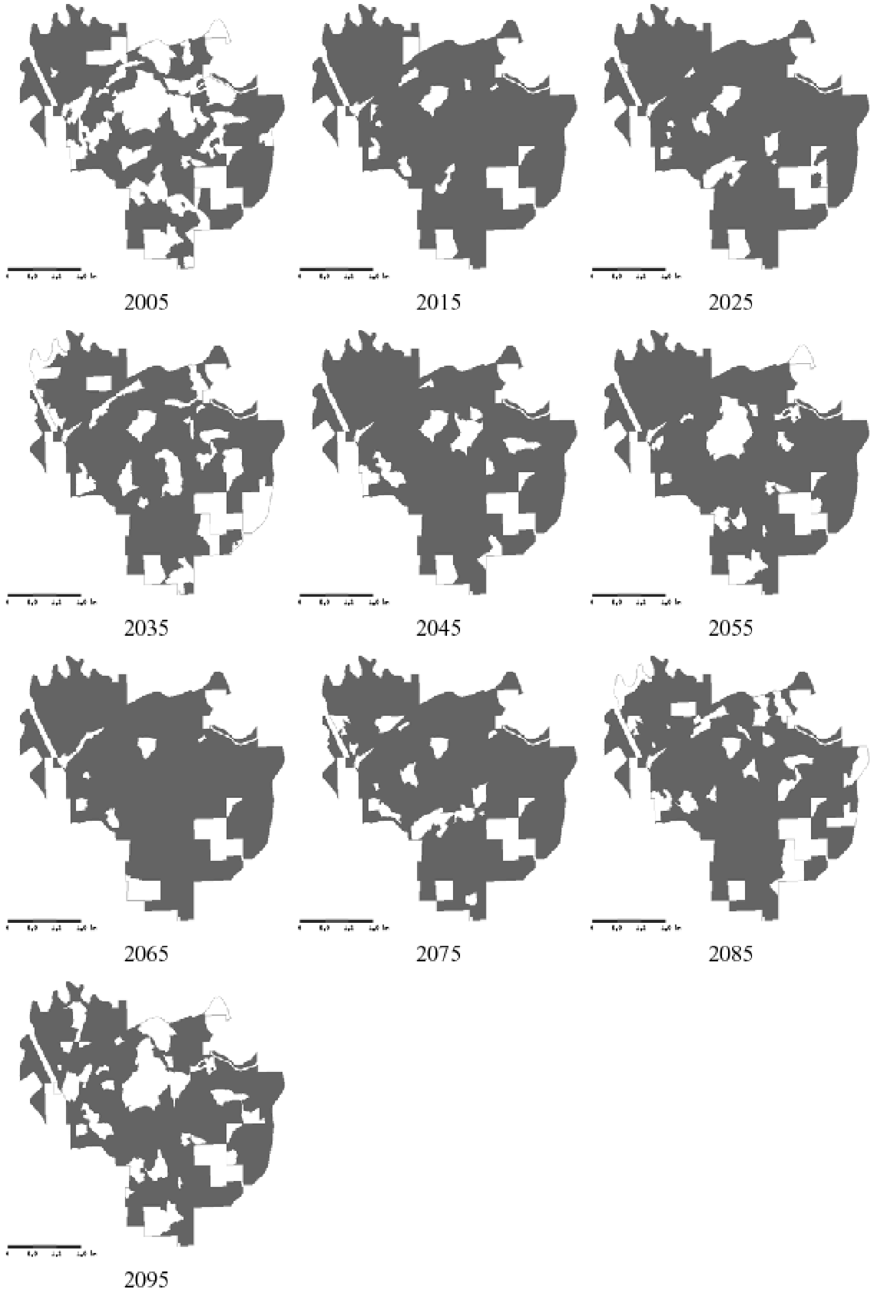
Appendix B-9. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 400 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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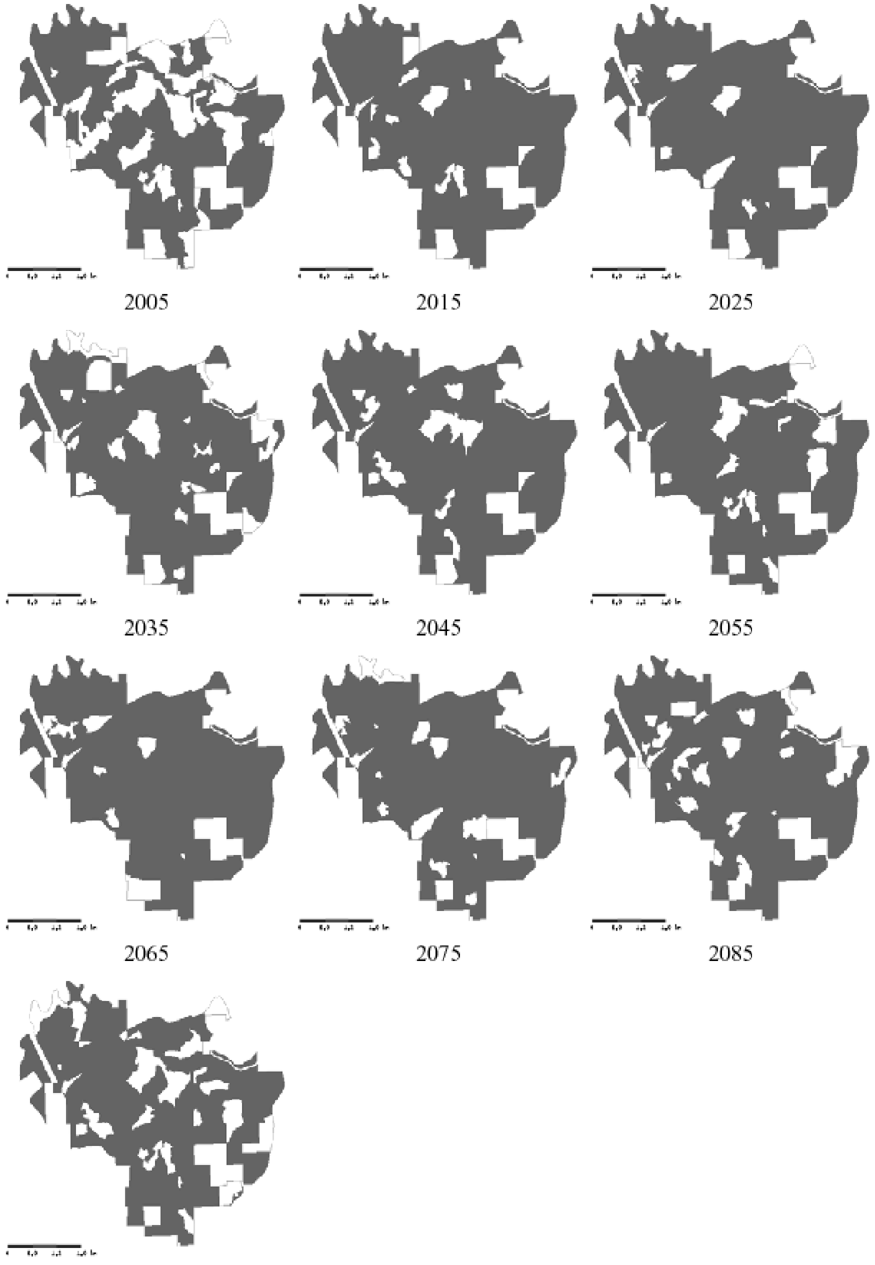
Appendix B-10. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 450 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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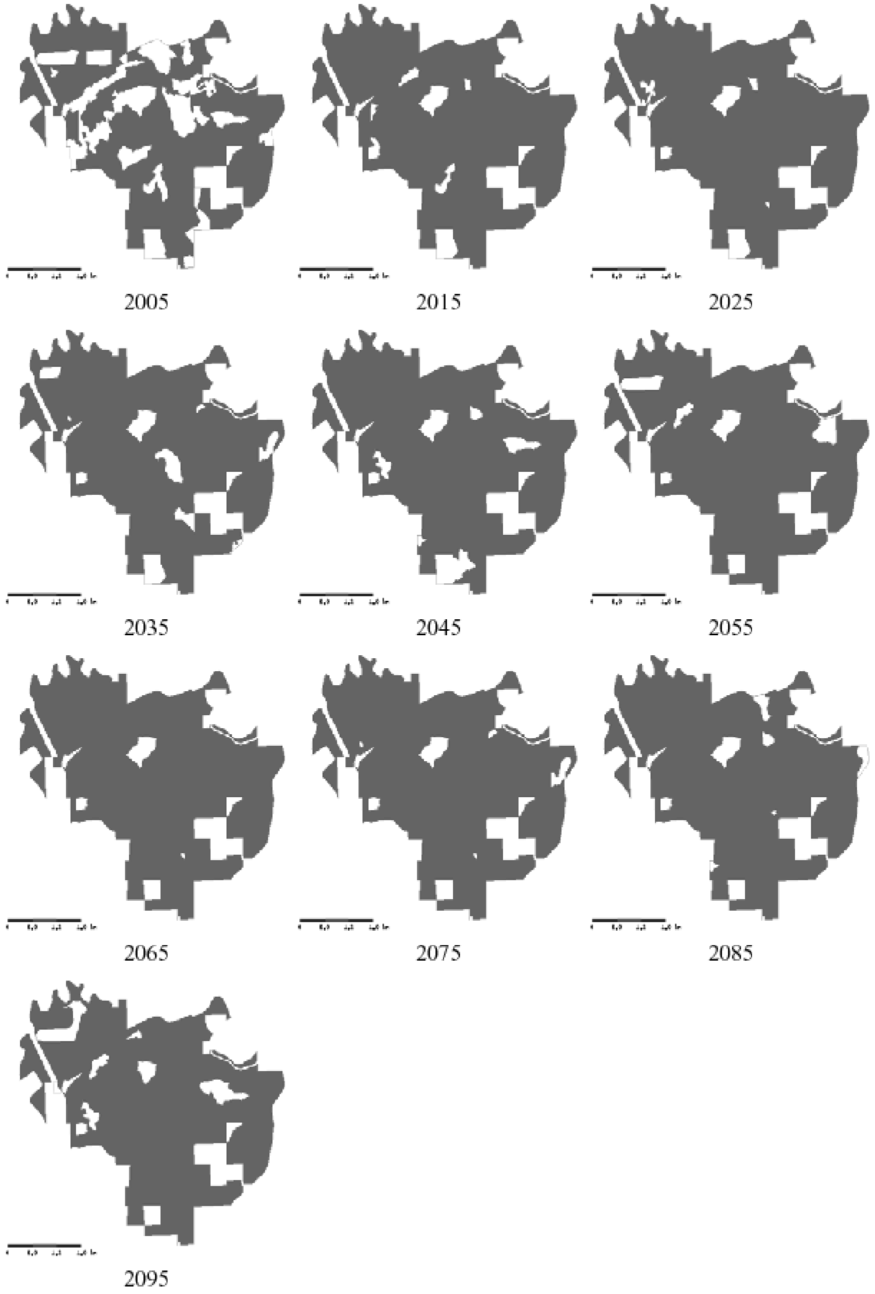
Appendix B-11. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 500 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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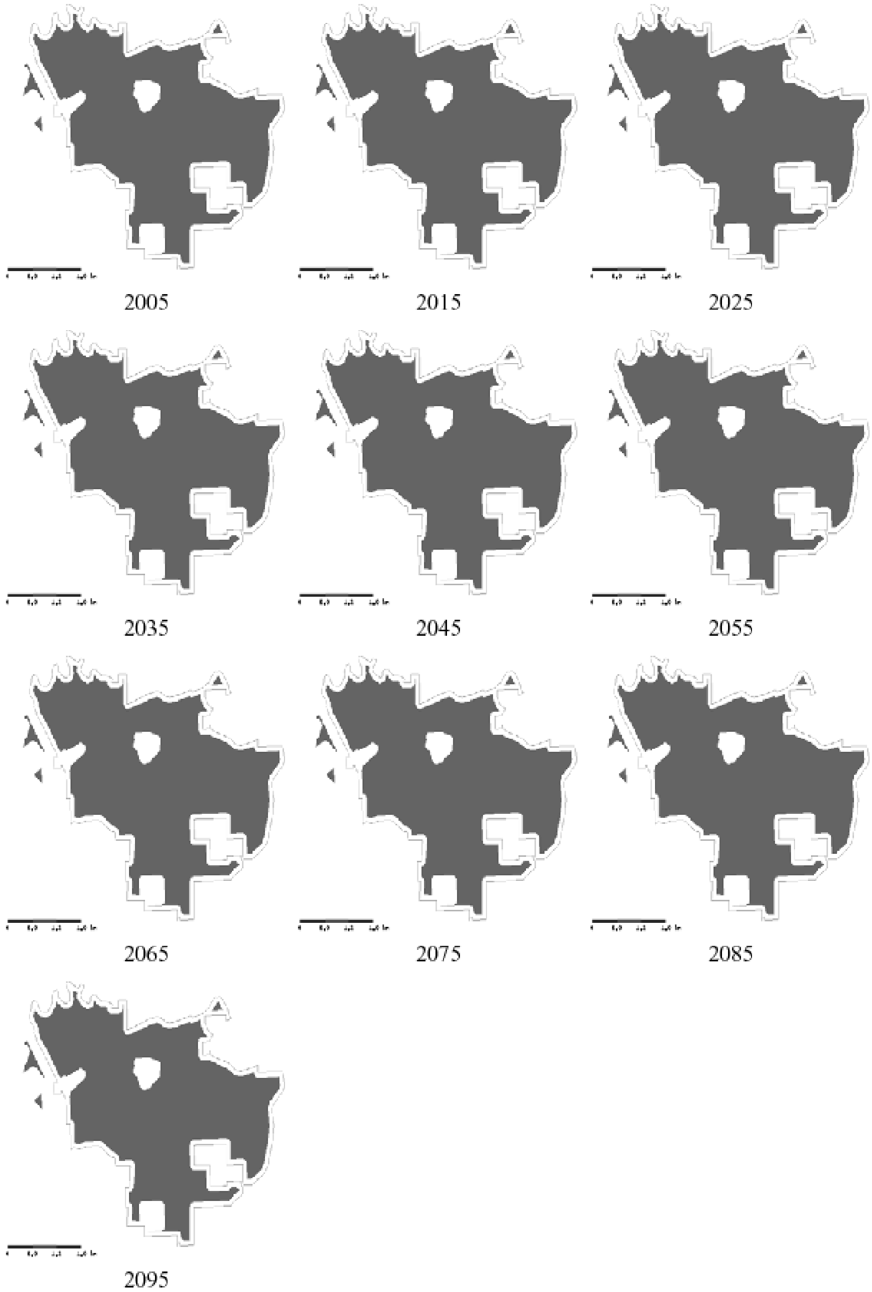
Appendix B-12. Chronological changes in habitat patch distributions for the northern flying squirrel with a short dispersal ecological setting at a 550 landscape score level near optimal point (home range size: 0.025 km$^2$, dispersal distance: 0.25 km).



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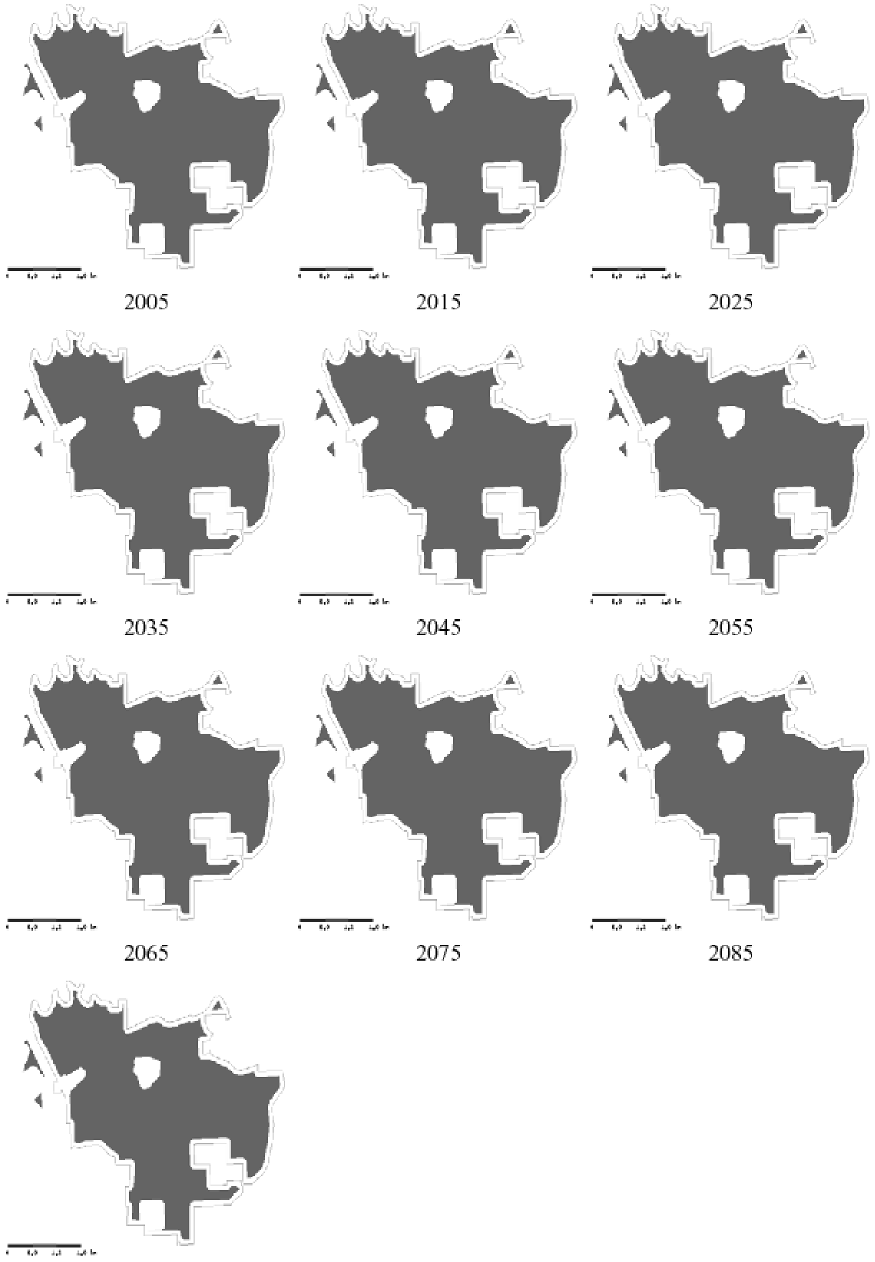
Appendix B-13. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 600 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



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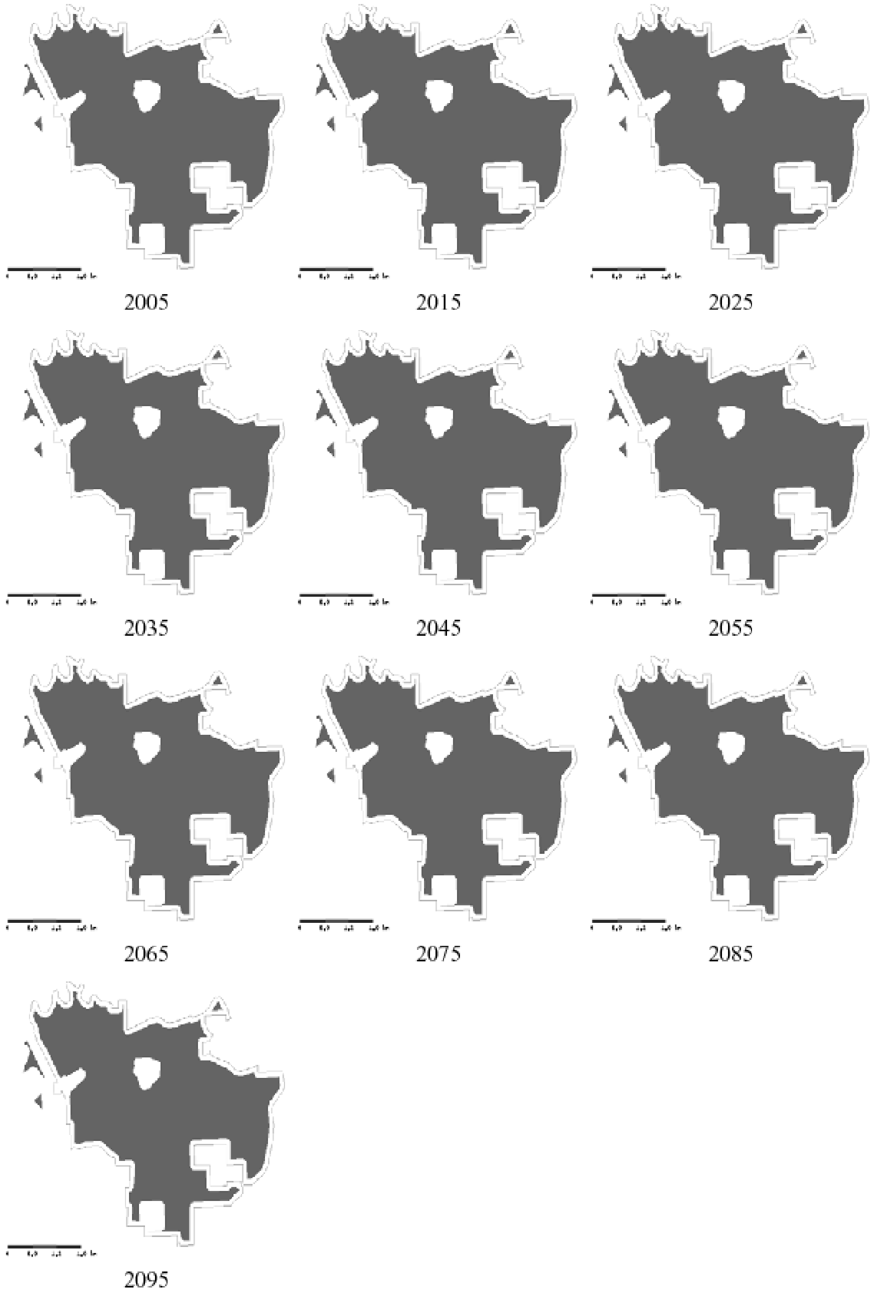
Appendix B-14. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 650 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



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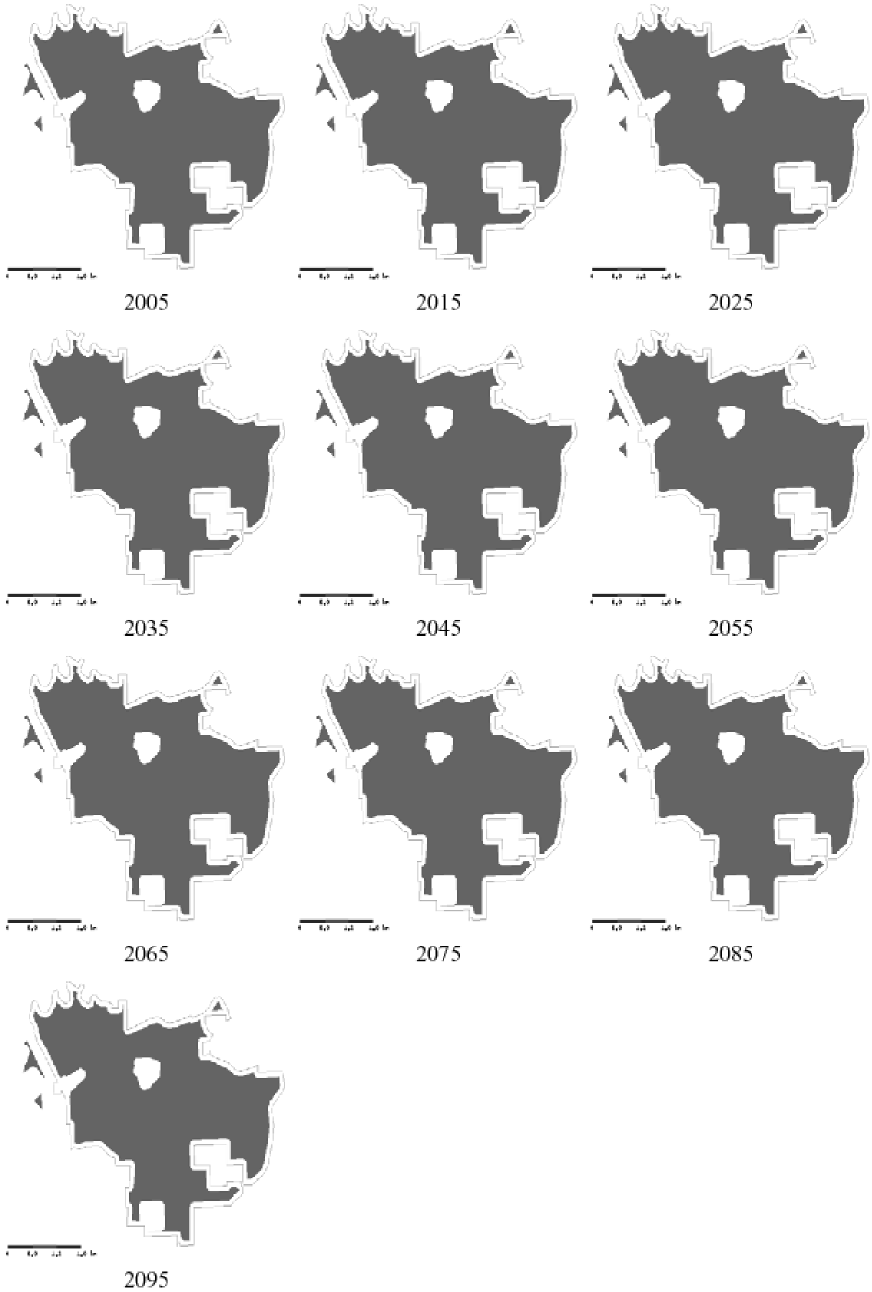
Appendix B-15. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 700 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



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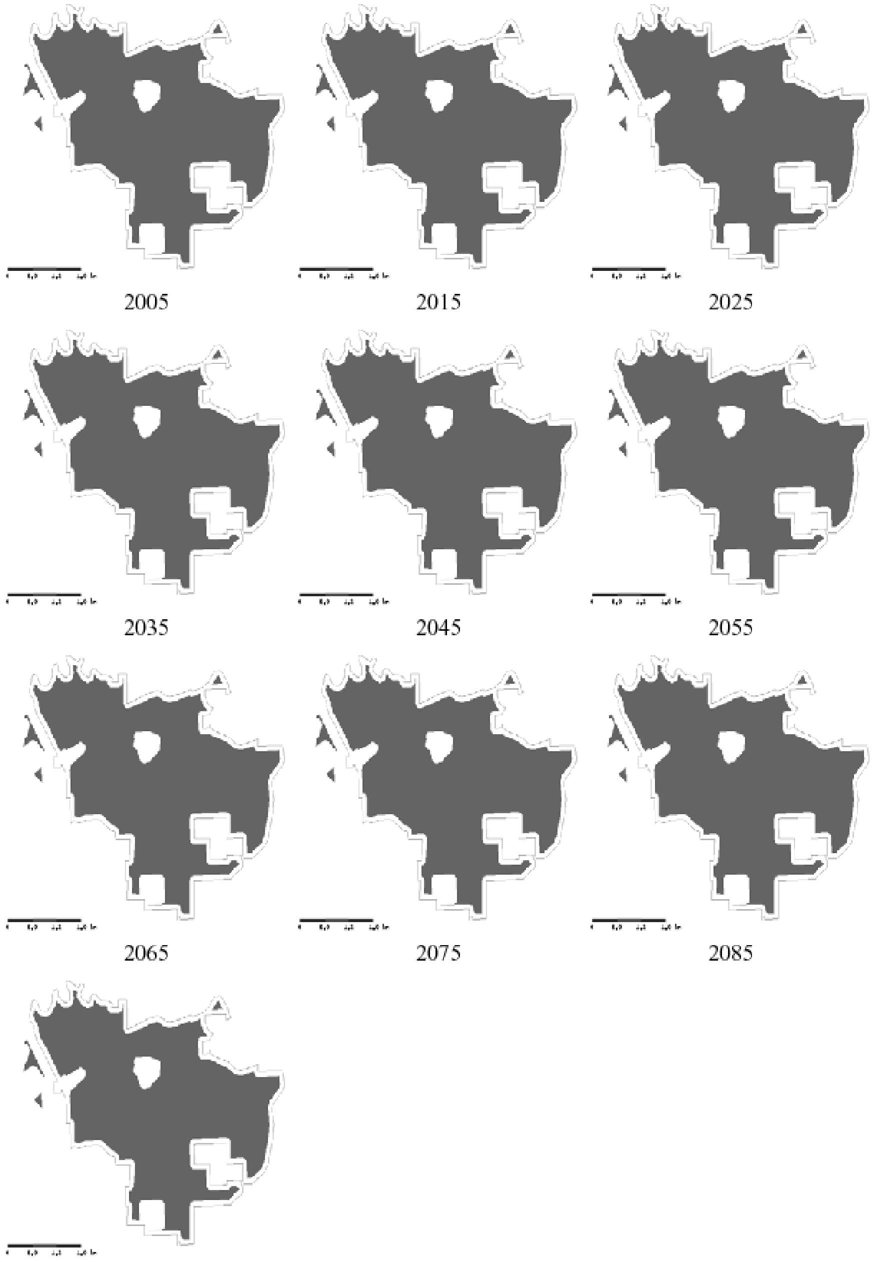
Appendix B-16. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 750 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



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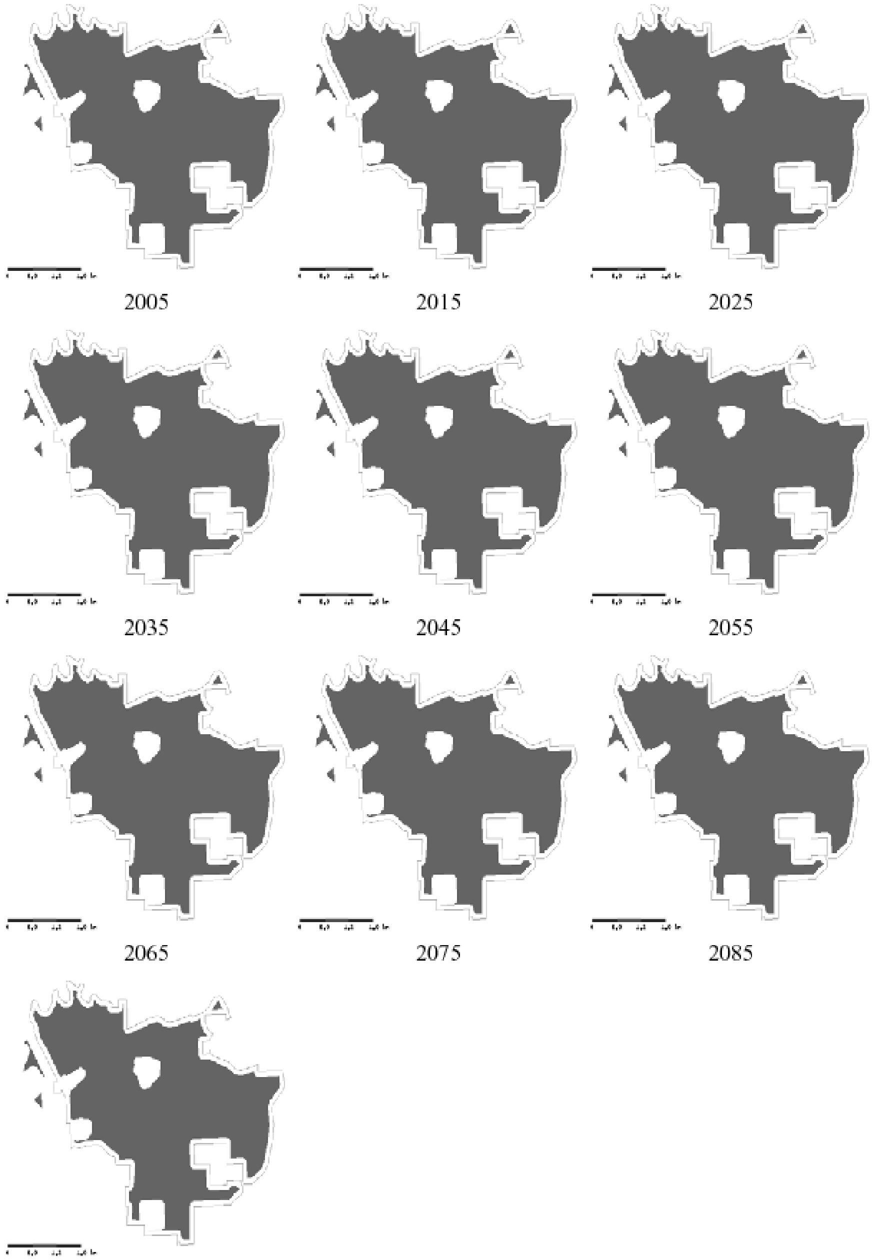
Appendix B-17. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 800 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



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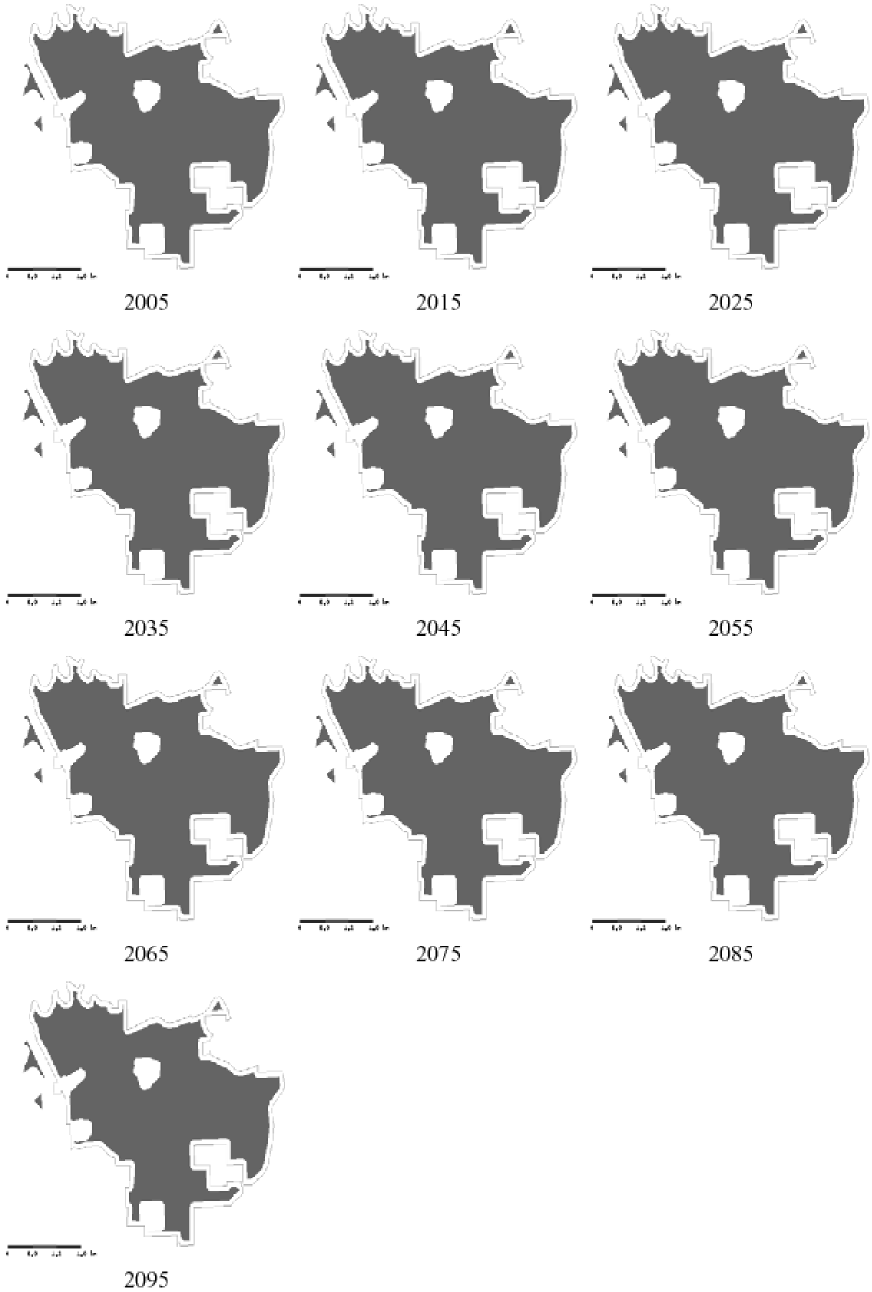
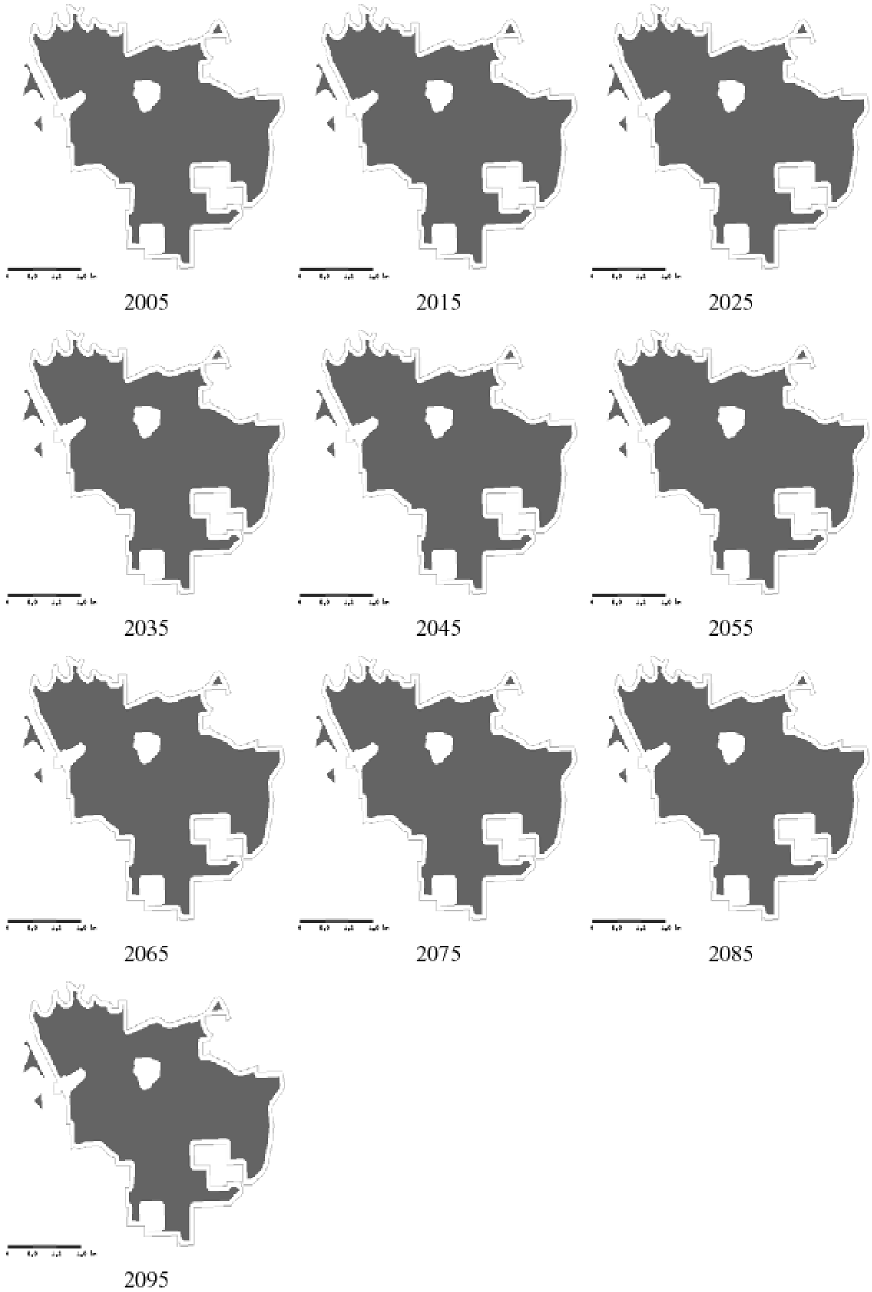
Appendix B-18. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 850 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).


2005 2015 2025 2035 2045 2055 2065 2075 2085 2095

Appendix B-19. Chronological changes in habitat patch distributions for the winter wren with a standard dispersal ecological setting at a 900 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

2035 2045 2055

2065 2075 2085

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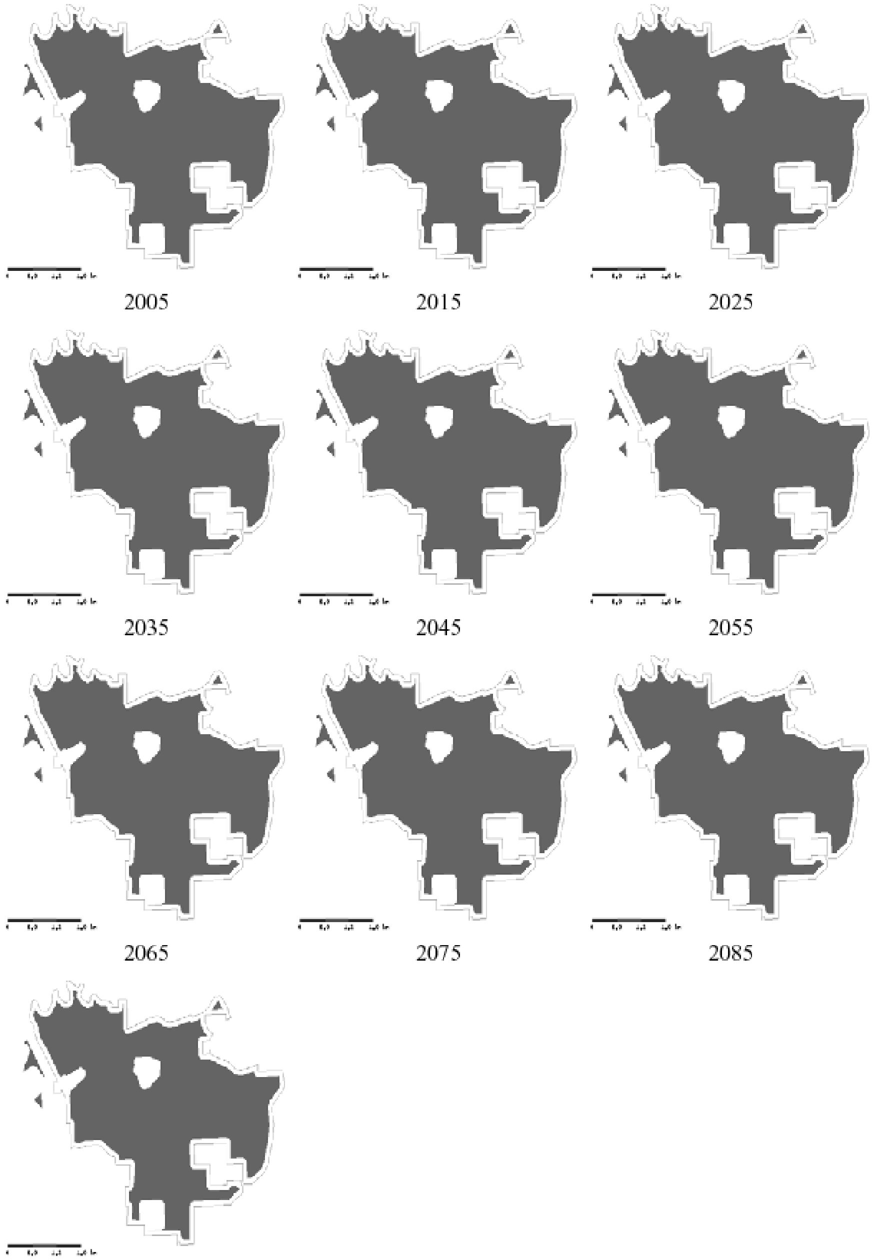
Appendix B-20. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 600 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



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2035 2045 2055

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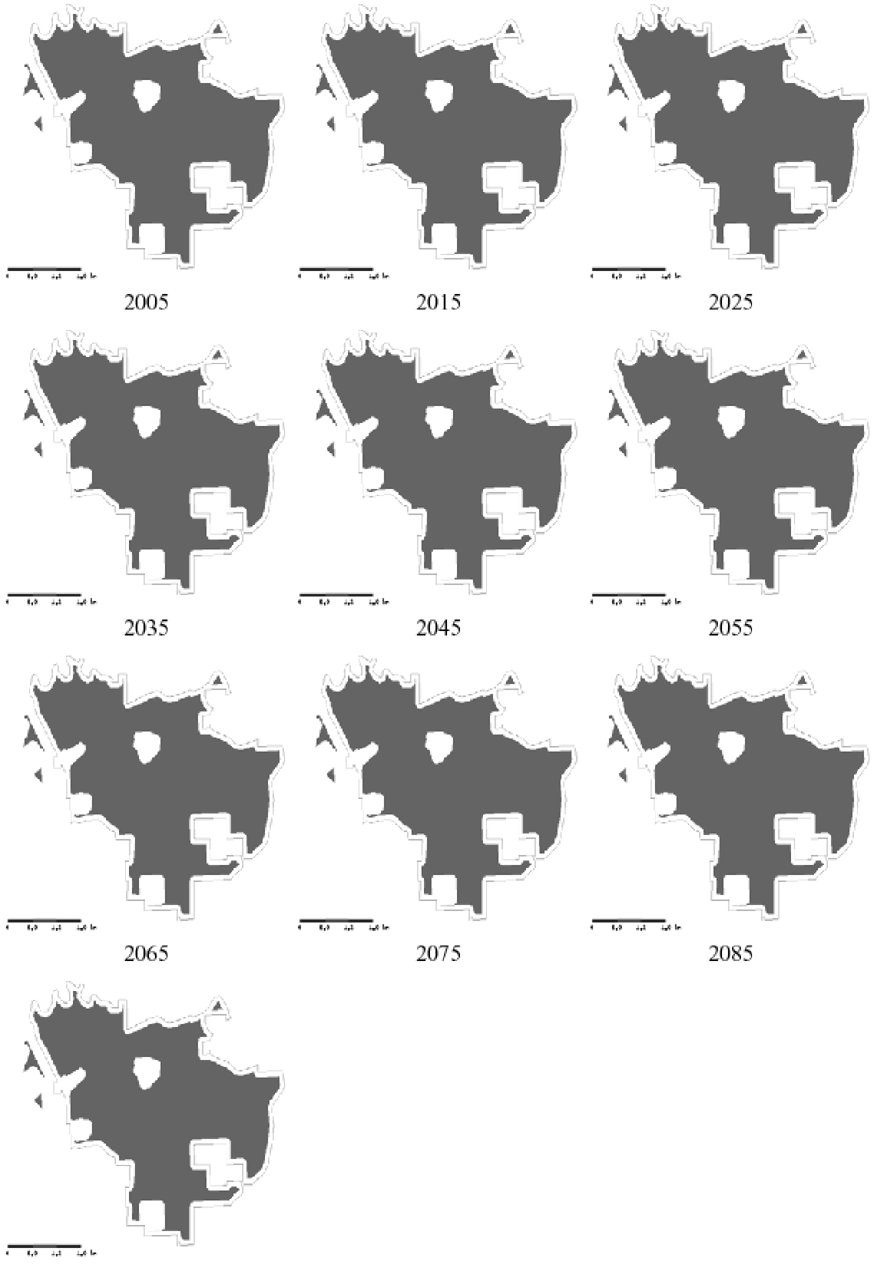
Appendix B-21. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 650 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



2005 2015 2025

2035 2045 2055

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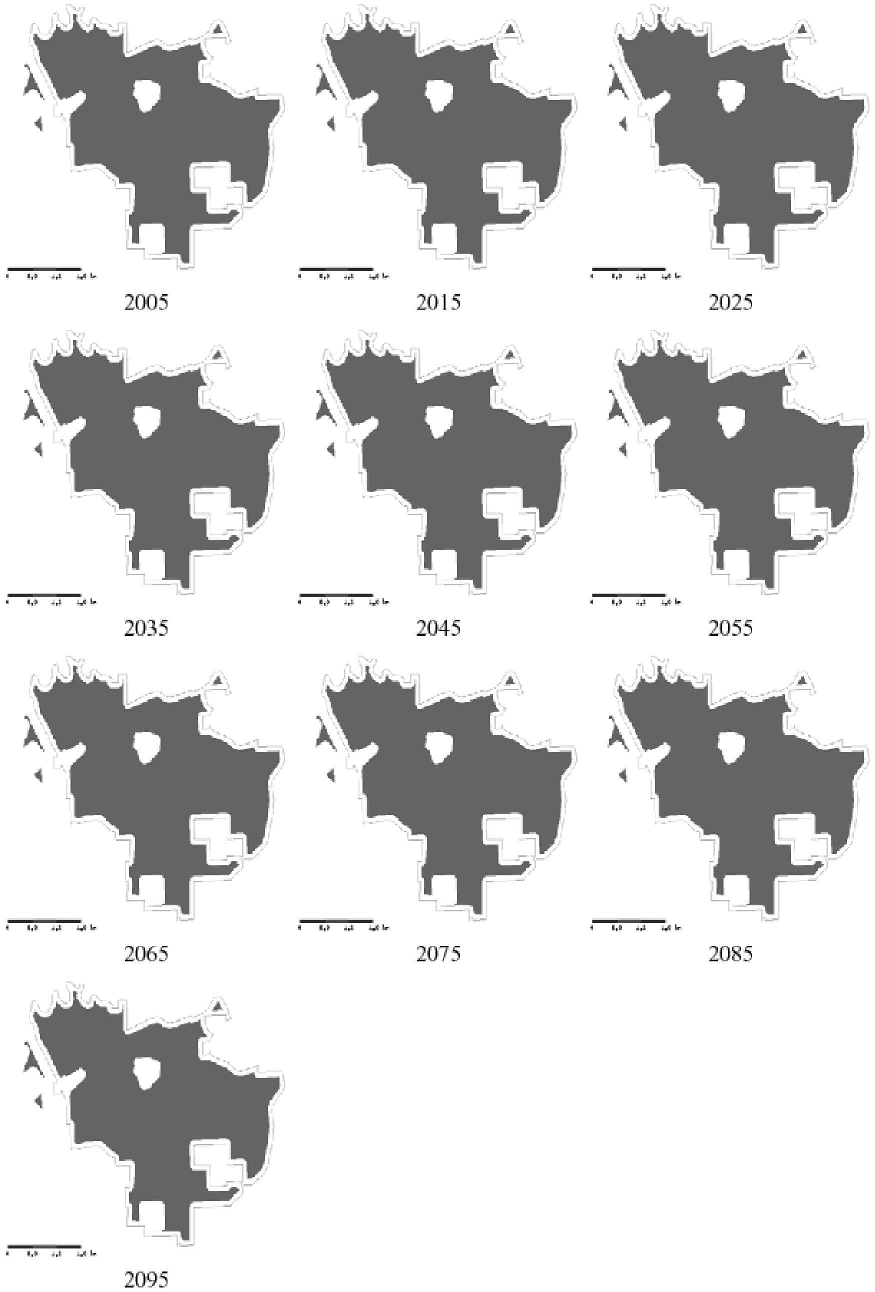
Appendix B-22. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 700 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



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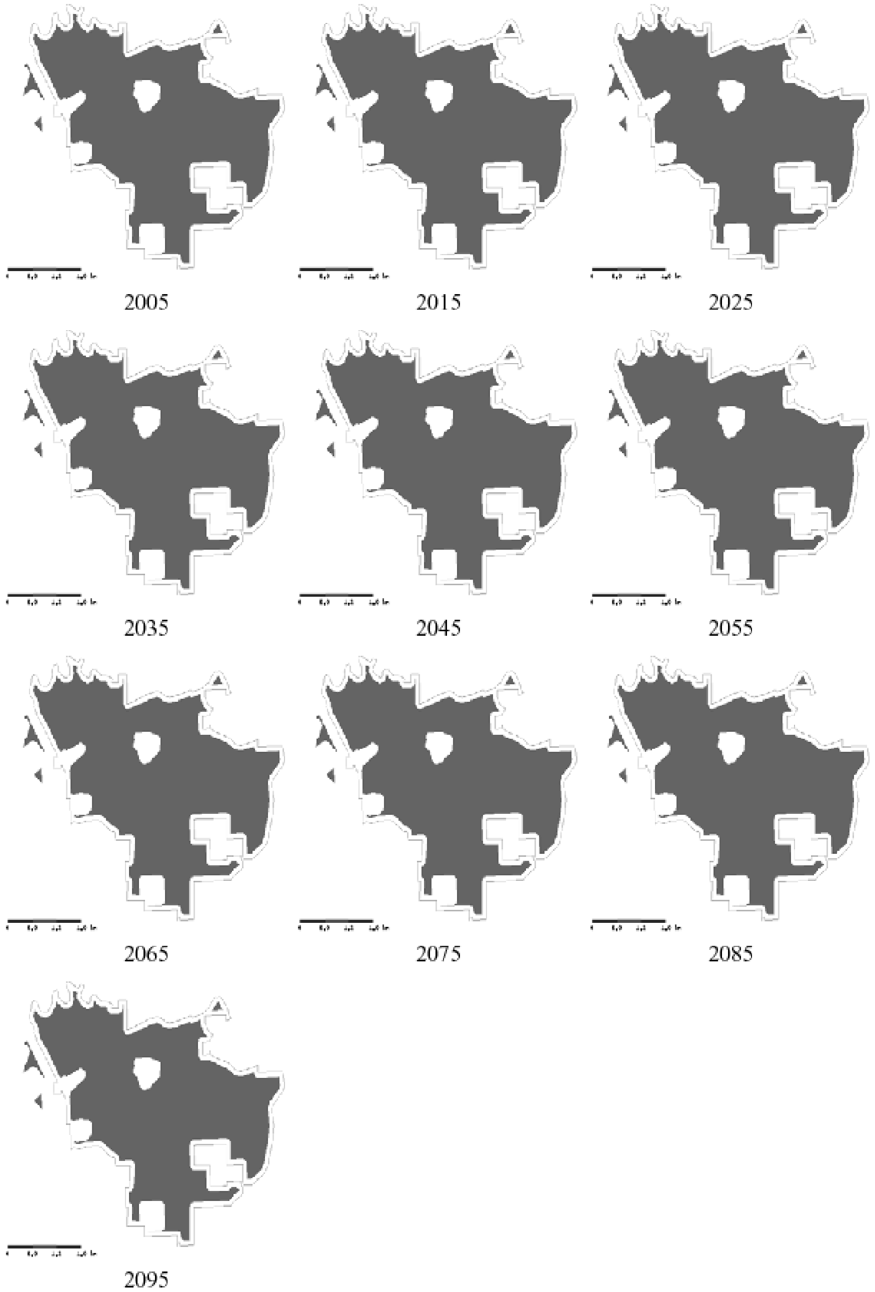
Appendix B-23. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 750 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).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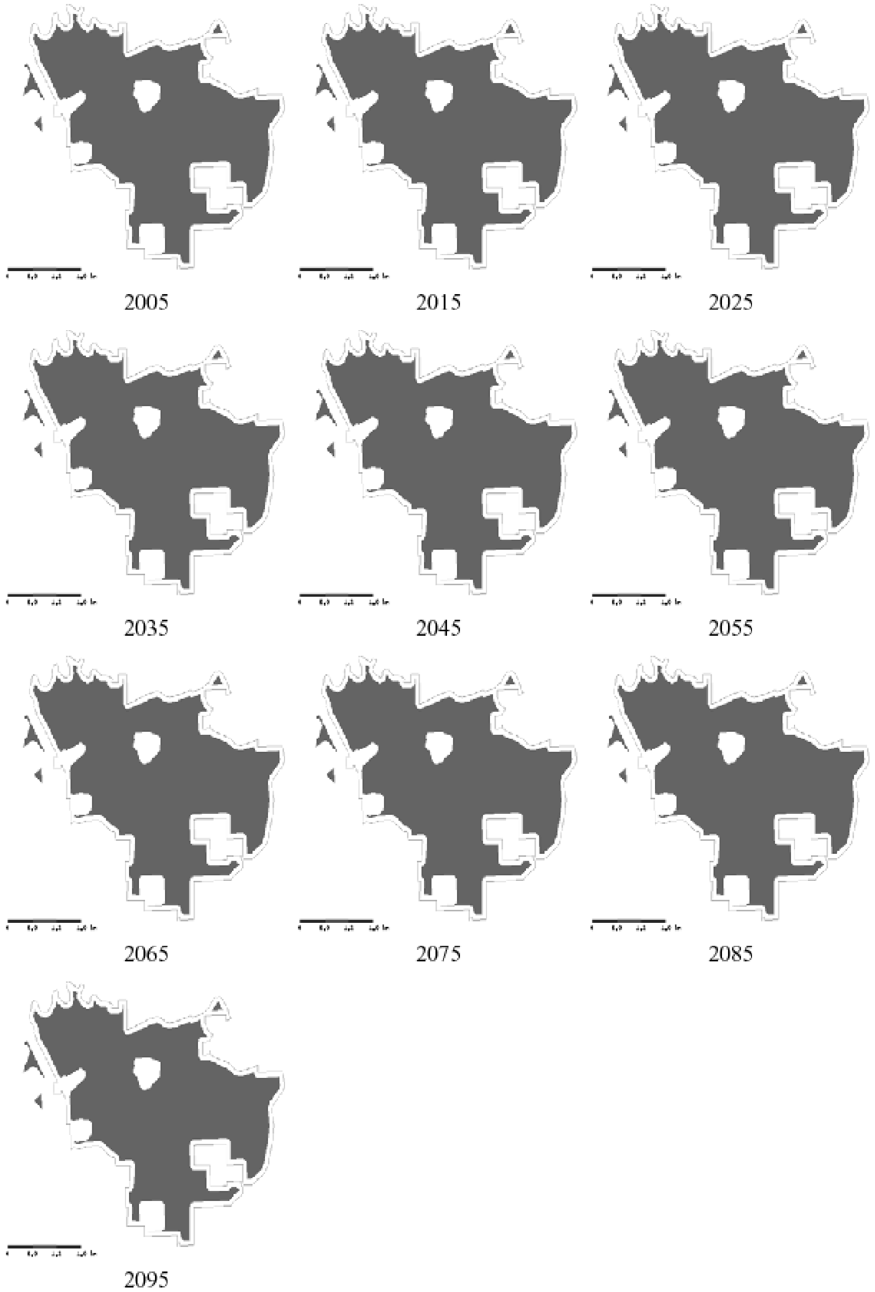
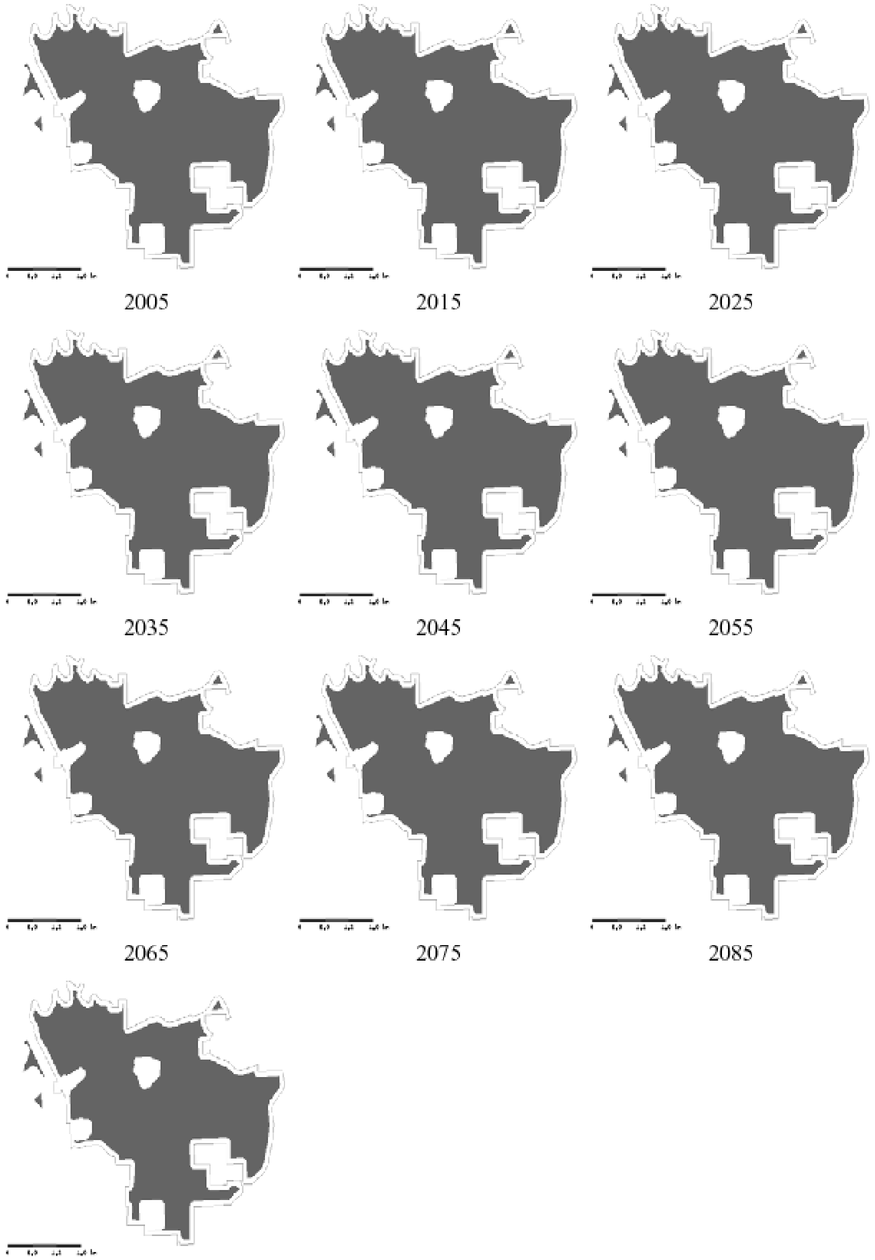
Appendix B-24. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 800 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



Appendix B-25. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 850 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).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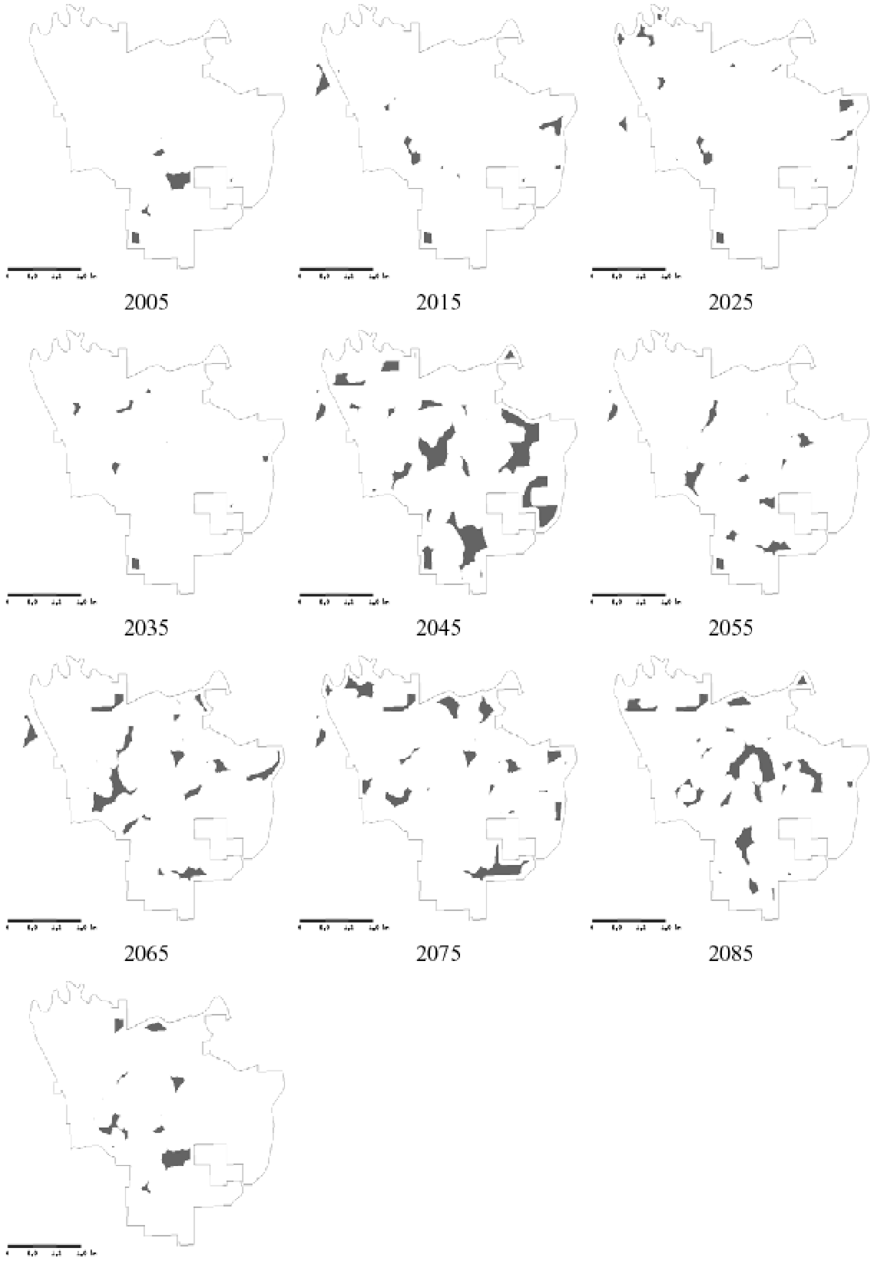
Appendix B-26. Chronological changes in habitat patch distributions for the winter wren with a short dispersal ecological setting at a 900 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



2005 2015 2025

2035 2045 2055

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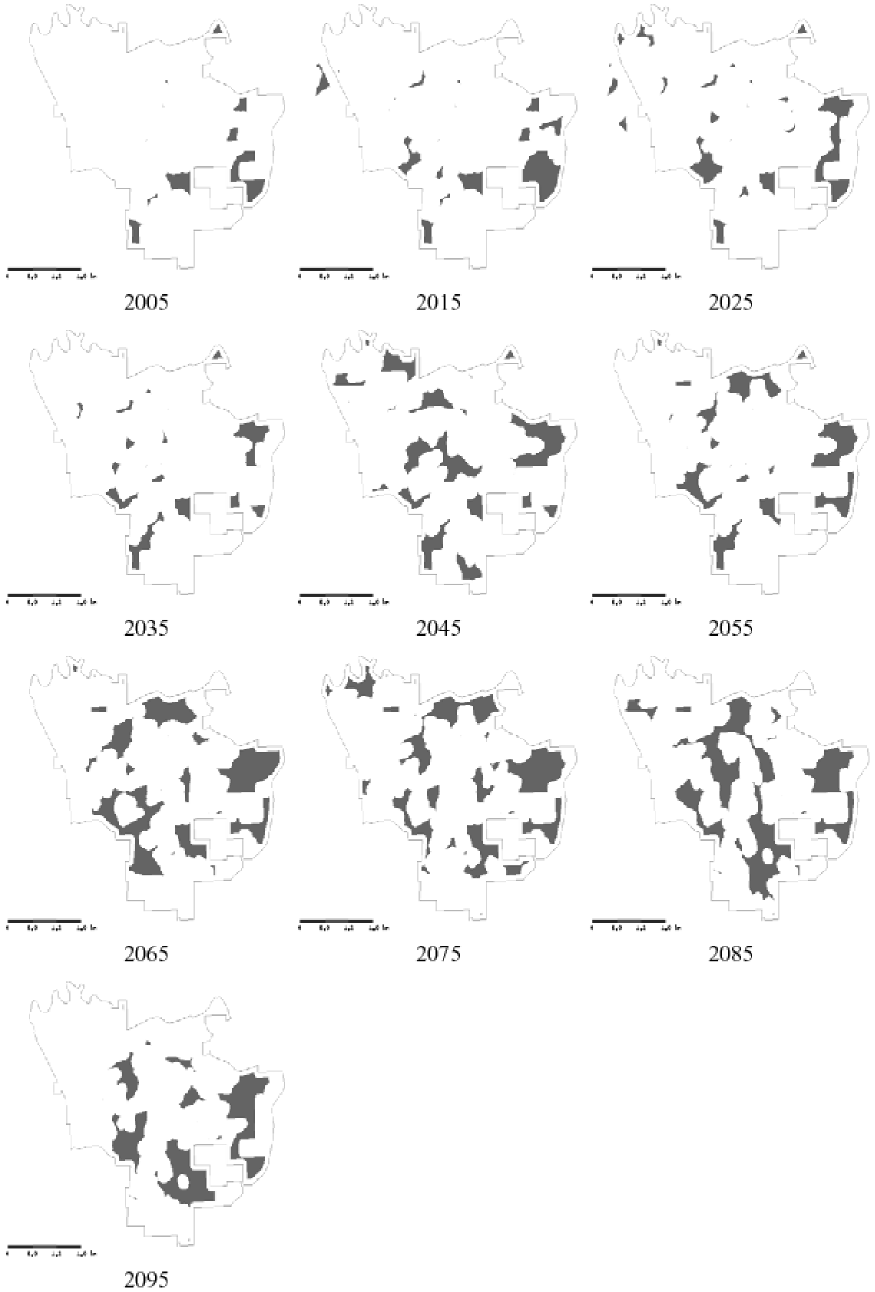
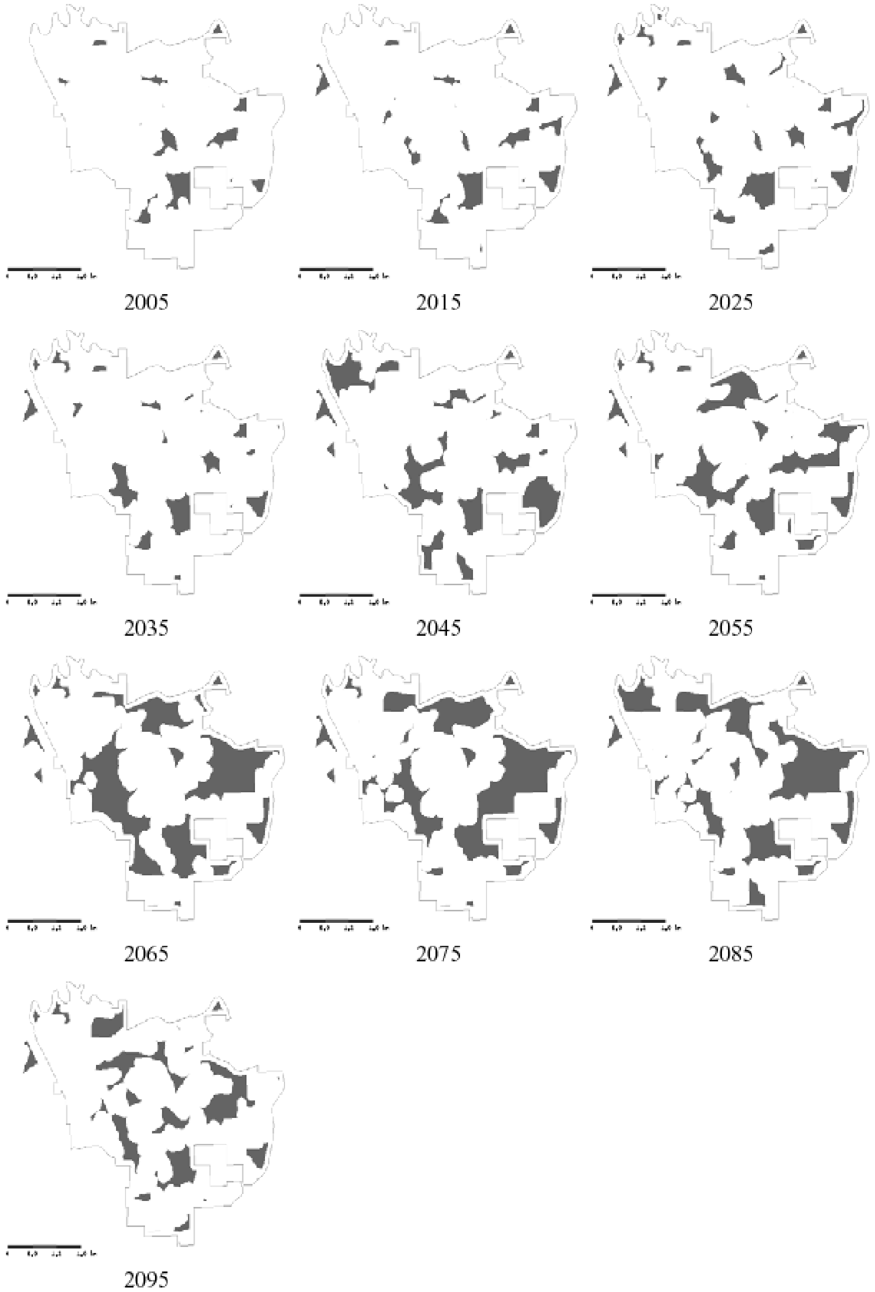
Appendix B-27. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 50 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025 2035 2045 2055 2065 2075 2085 2095

Appendix B-28. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 150 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

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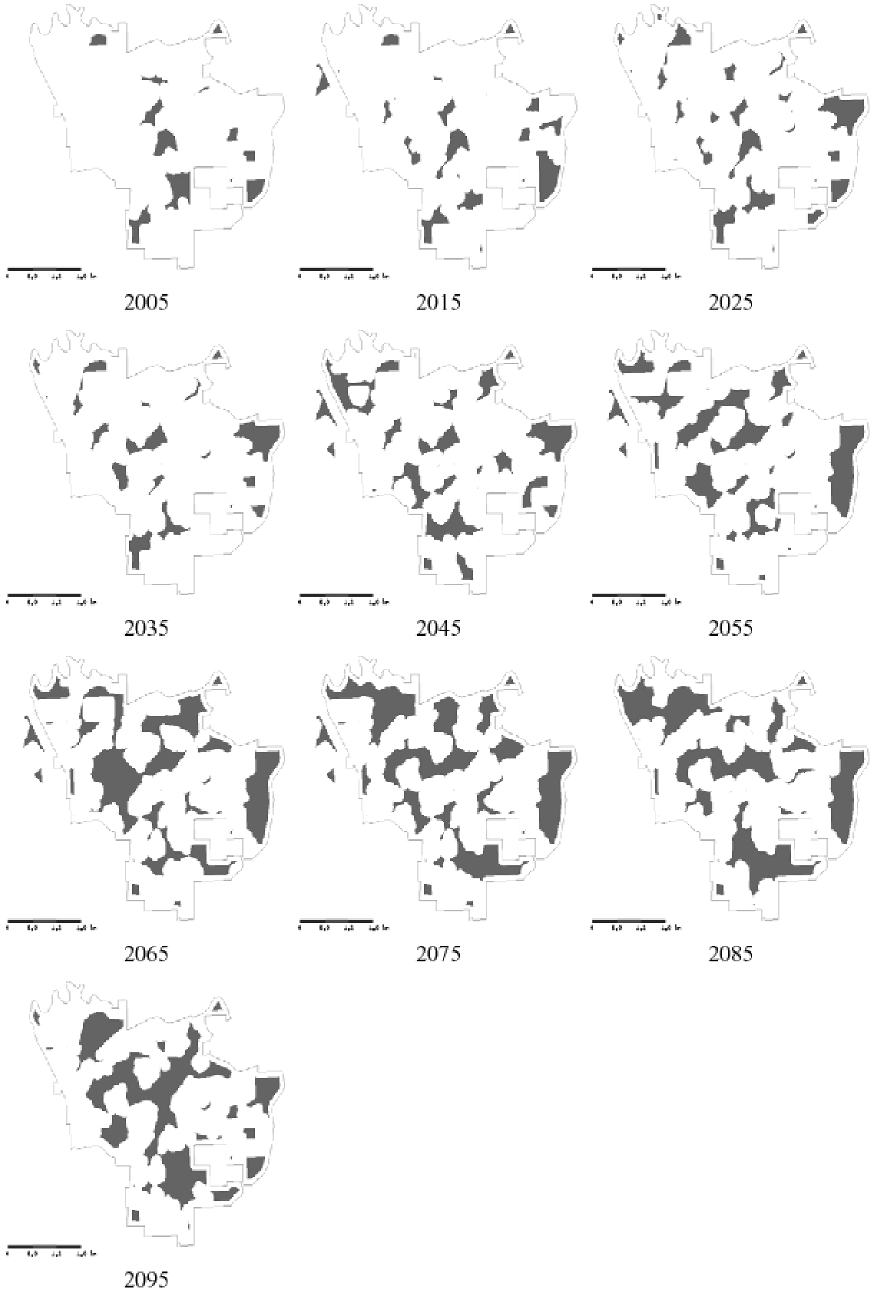
Appendix B-29. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 250 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

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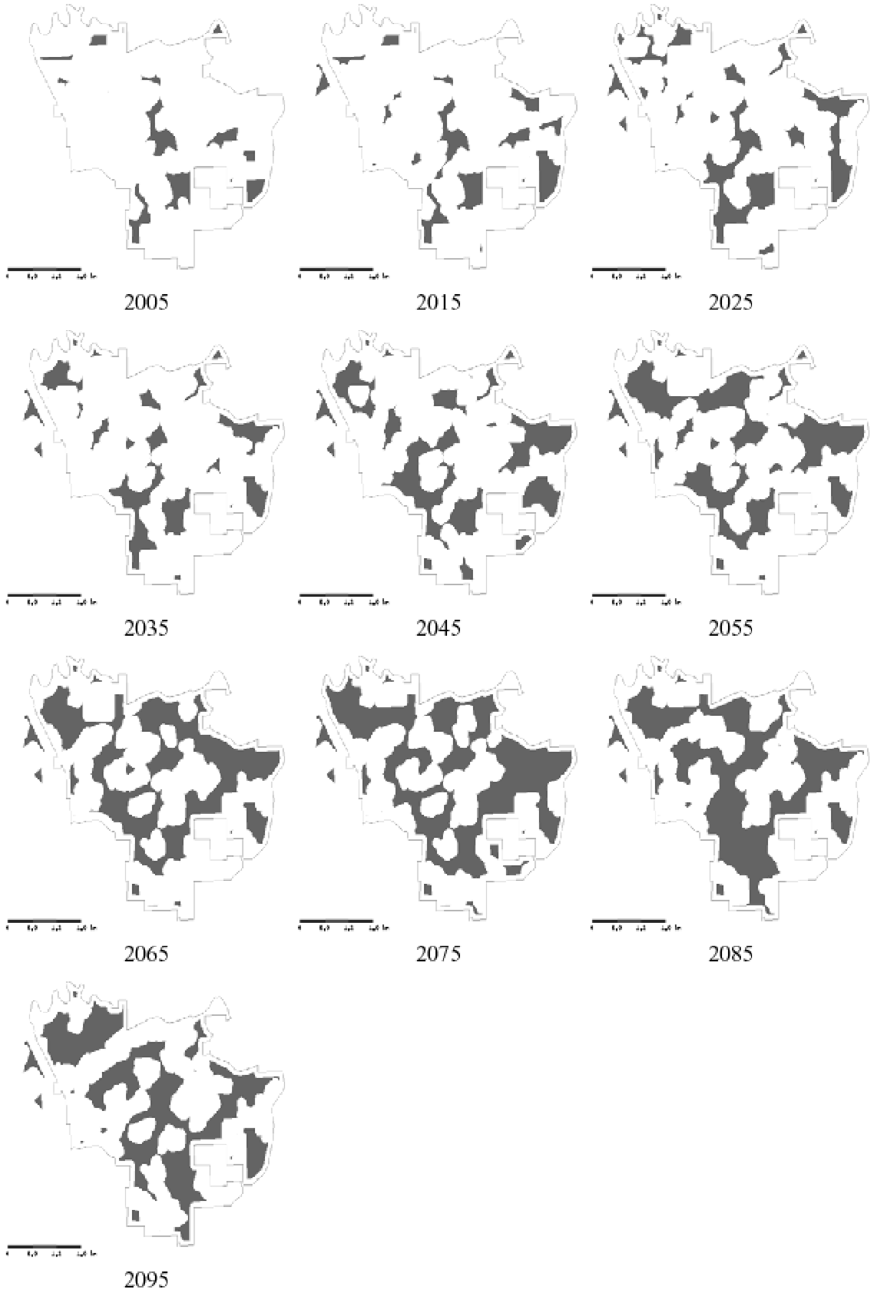
Appendix B-30. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 350 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

2035 2045 2055

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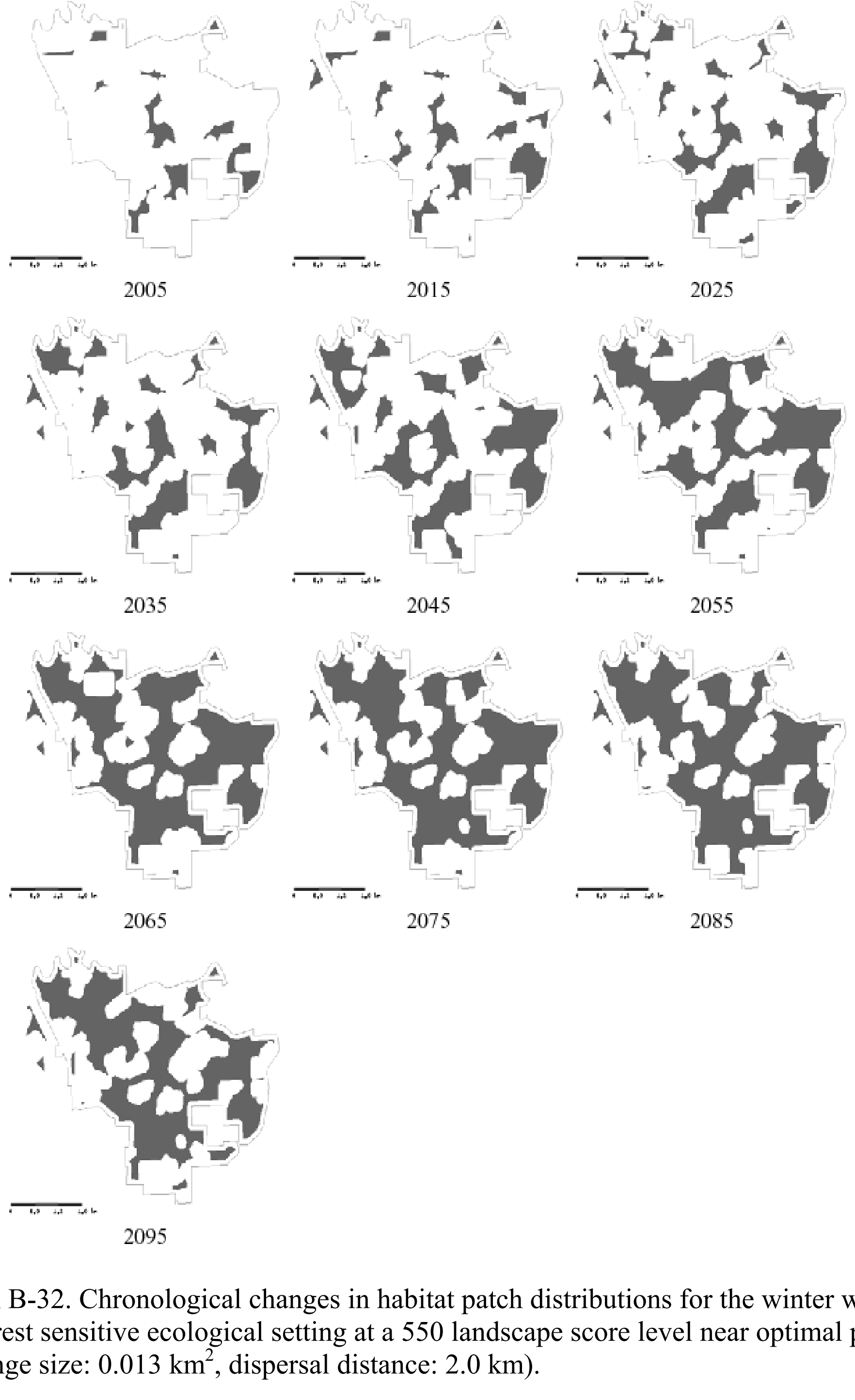
Appendix B-31. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 450 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

2035 2045 2055

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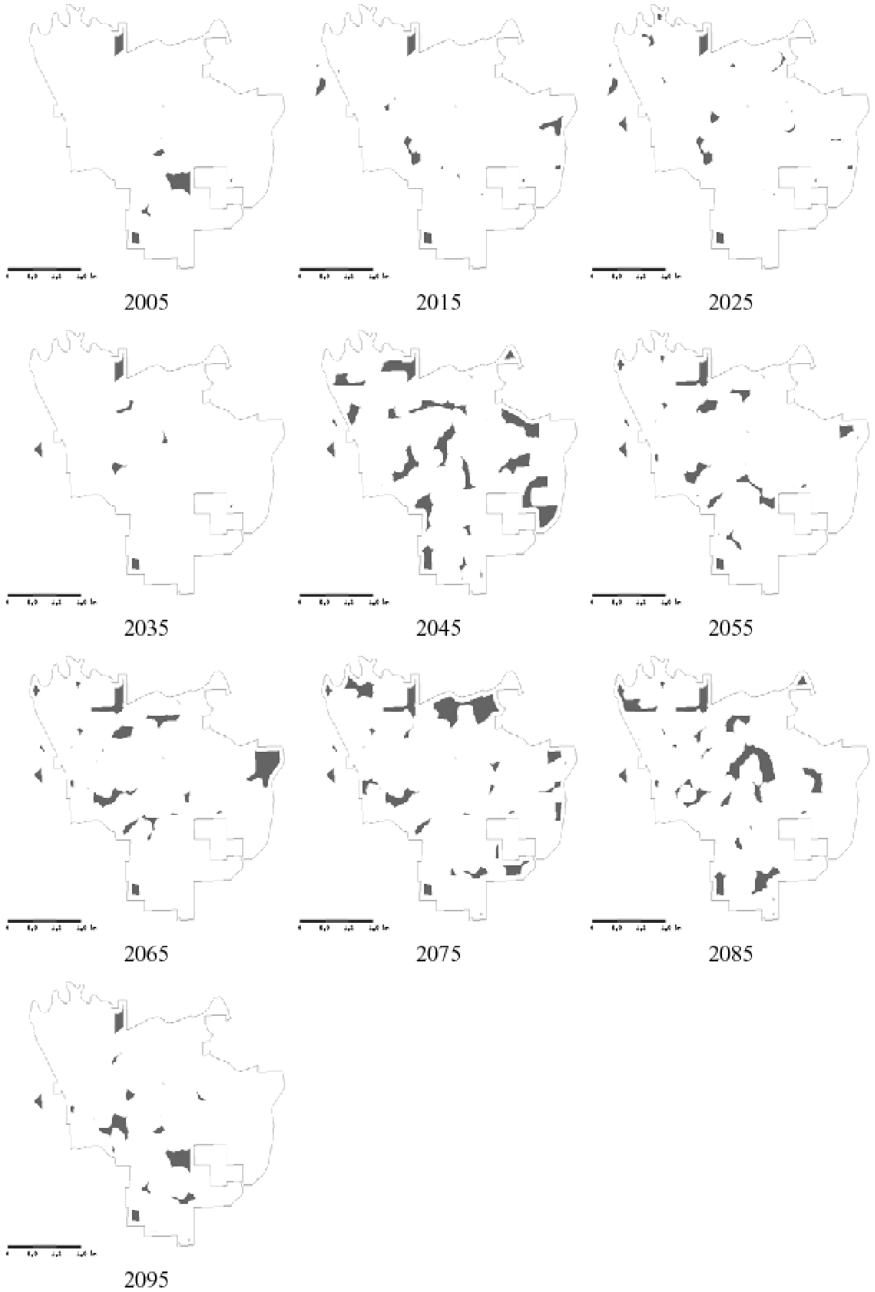
Appendix B-32. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive ecological setting at a 550 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 2.0 km).



2005 2015 2025

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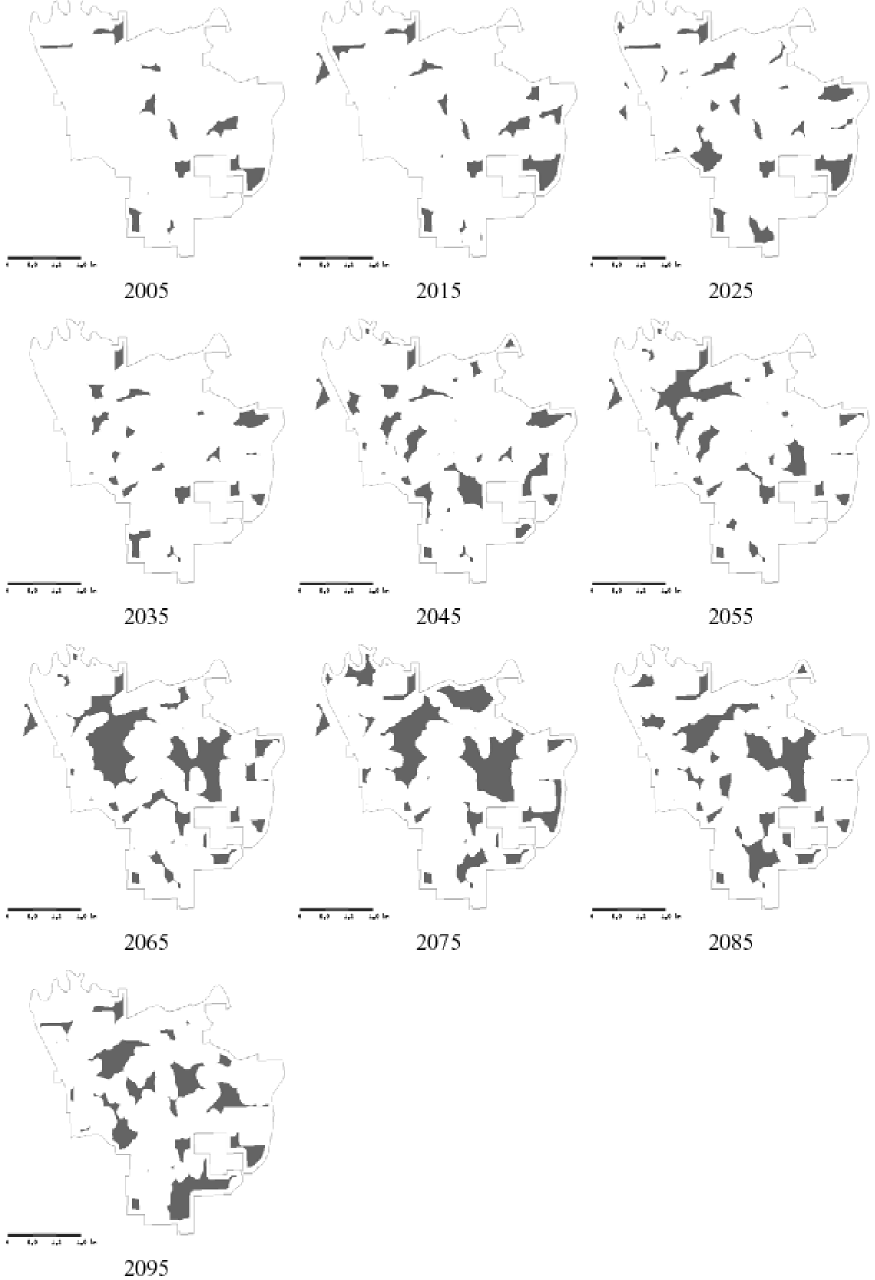
Appendix B-33. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 50 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



2005 2015 2025

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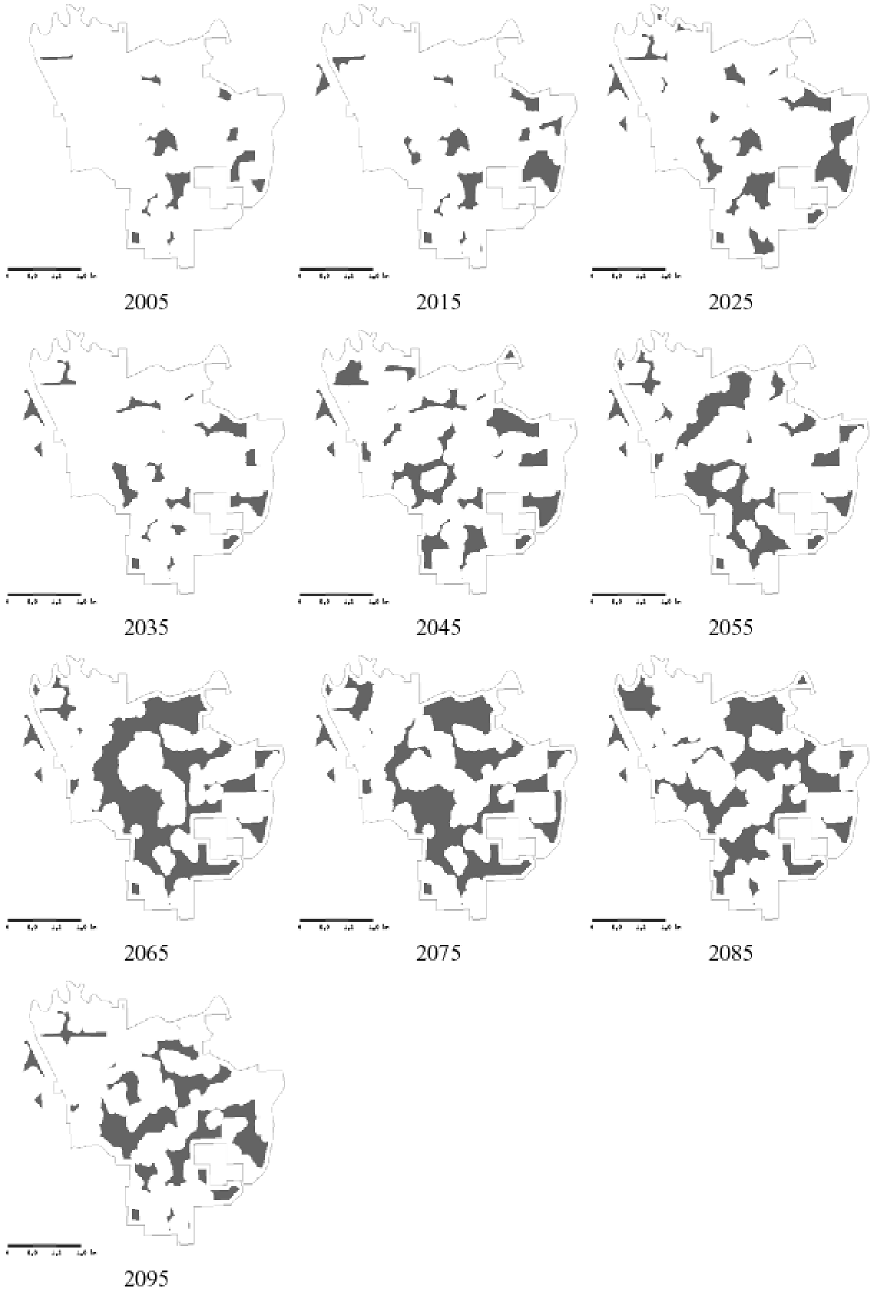
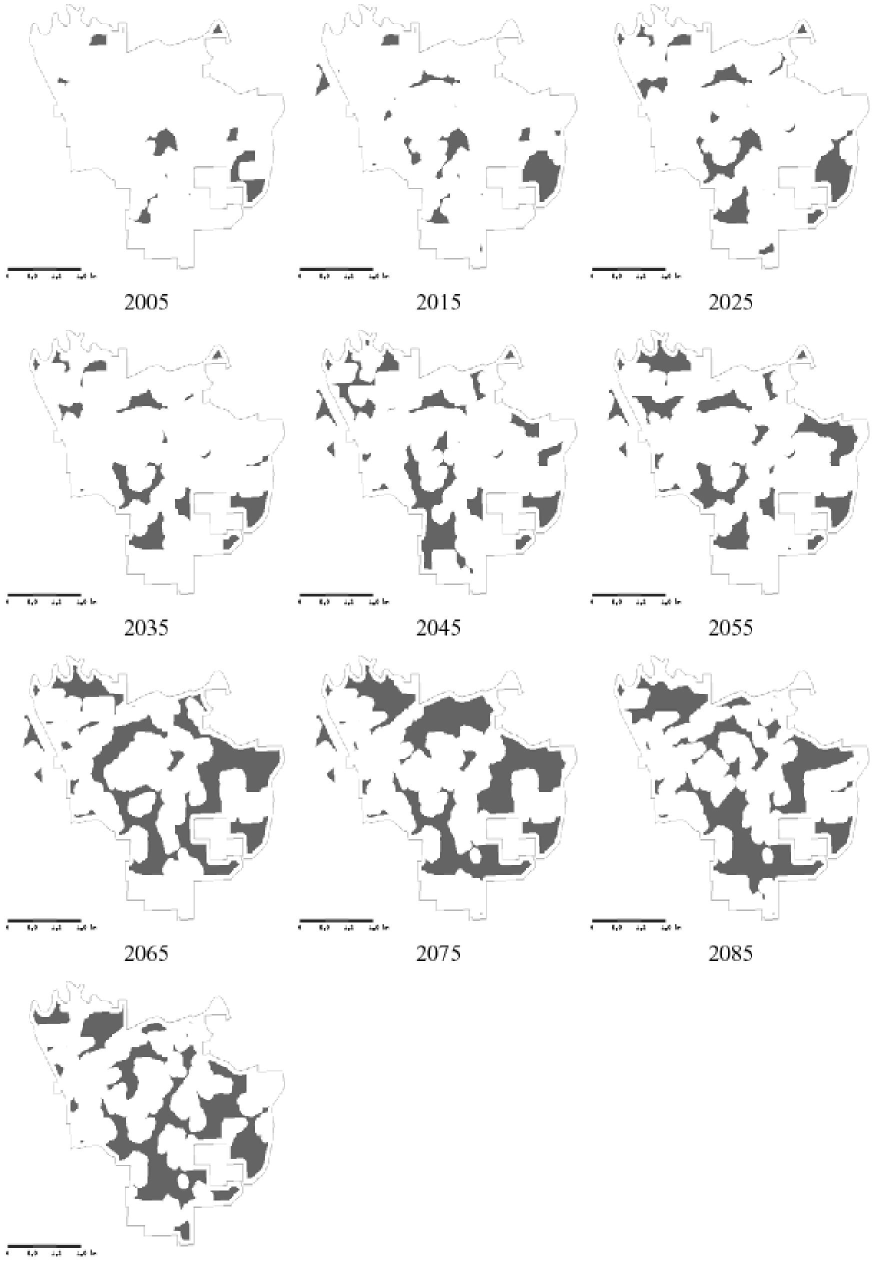
Appendix B-34. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 150 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



Appendix B-35. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 250 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).


2005 2015 2025

2035 2045 2055

2065 2075 2085

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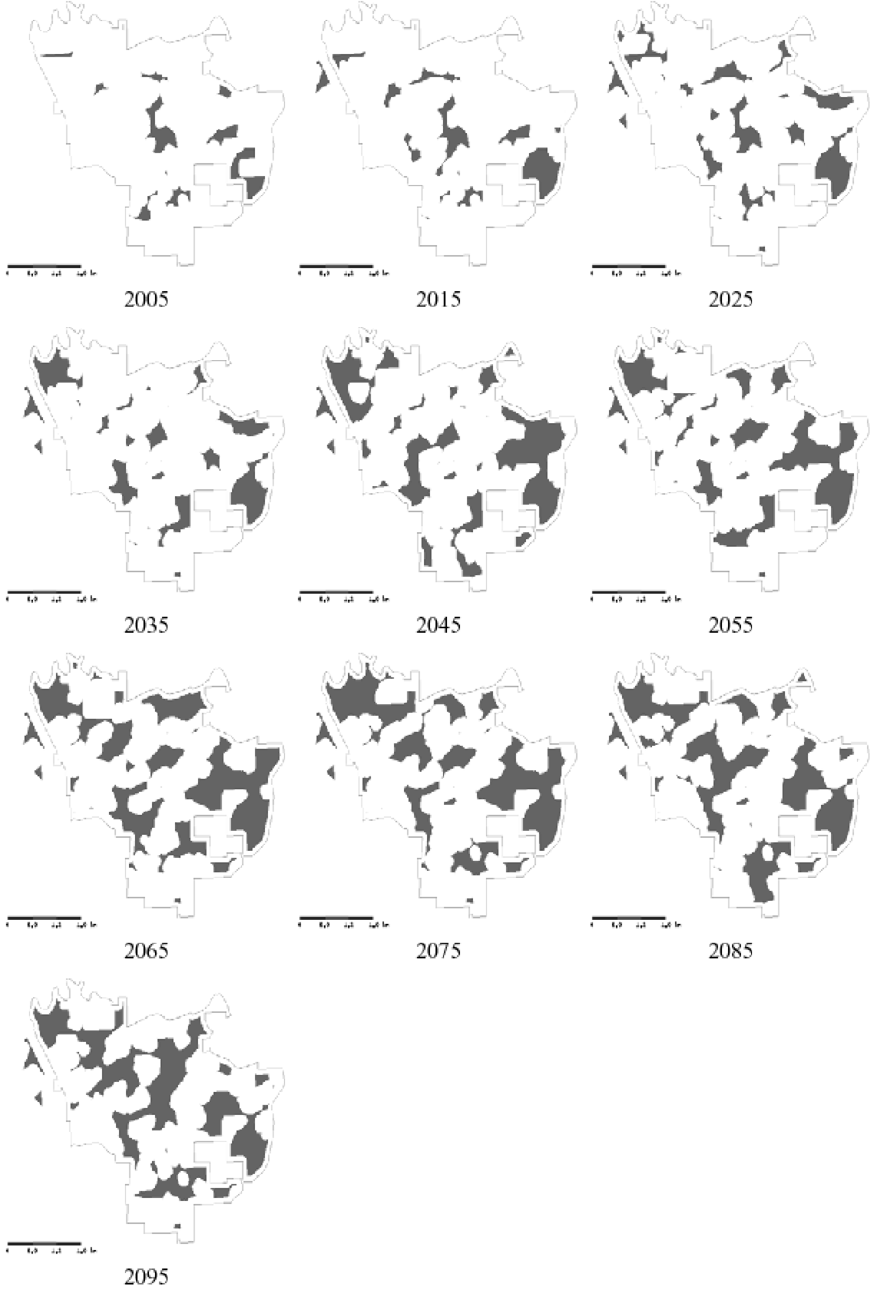
Appendix B-36. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 350 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



2005 2015 2025

2035 2045 2055

2065 2075 2085

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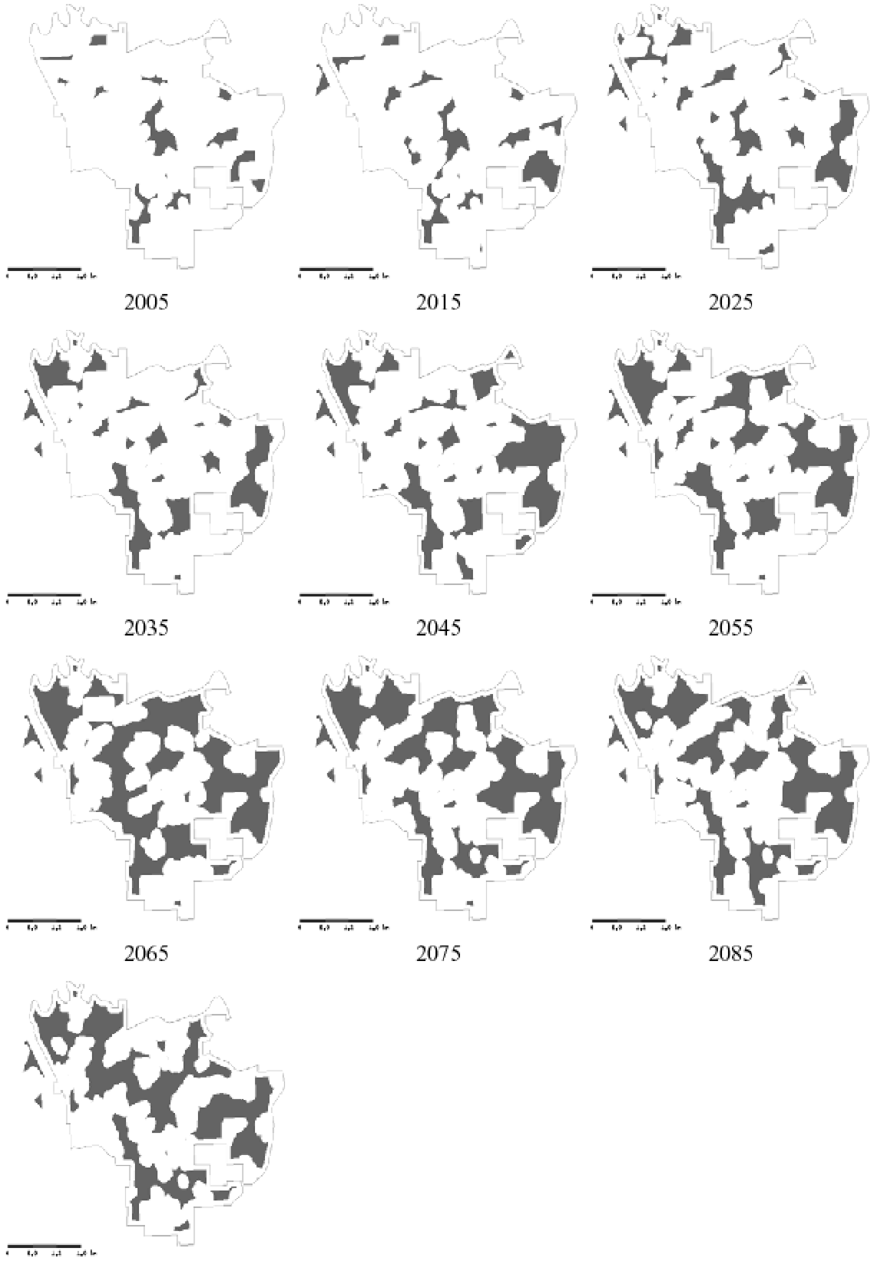
Appendix B-37. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 450 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).



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Appendix B-38. Chronological changes in habitat patch distributions for the winter wren with an old-forest sensitive and a short dispersal ecological setting at a 550 landscape score level near optimal point (home range size: 0.013 km$^2$, dispersal distance: 0.5 km).