HABITAT USE AND INDIVIDUAL-BASED MODELING OF BALD EAGLES IN MAINE NEAR CURRENT AND POTENTIAL WIND ENERGY FACILITIES

Blake Massey
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HABITAT USE AND INDIVIDUAL-BASED MODELING OF BALD EAGLES IN MAINE NEAR CURRENT AND POTENTIAL WIND ENERGY FACILITIES

A Dissertation Presented
by
BLAKE HAMILTON MASSEY

Submitted to the Graduate School of the University of Massachusetts Amherst in partial fulfillment of the requirements for the degree of

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HABITAT USE AND INDIVIDUAL-BASED MODELING
OF BALD EAGLES IN MAINE
NEAR CURRENT AND POTENTIAL WIND ENERGY
FACILITIES

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DEDICATION

I dedicate this work to my parents, Morris and Judy, who always encouraged me
to care about the natural world, follow my passions, and have fun on the journey.
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ABSTRACT

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Wind energy facilitates have expanded significantly in the United States over the last few decades due to technological advancements, regulatory incentives, and policies aimed at increasing renewable energy production, but poorly sited turbines may have adverse effects on local and migratory birds, bats, and other wildlife and their habitats. In the northeastern United States, Maine has become the leader in wind energy but also has the greatest density of Bald Eagles in the region. As wind energy production continues to be developed across the state and in coastal waters, research is needed to analyze and assess potential risks, including displacement, to this eagle population.

One increasingly powerful and effective tool in the assessment of ecological effects is individual-based modeling. This approach uses unique and autonomous
agents that interact with each other and their environment to simulate dynamic systems. IBMs offer a practical and flexible approach to modeling animal movement because they can accommodate landscape patterns, territoriality, and behavioral adaptations.

The objective of this project was to generate an individual-based, spatially-explicit model of breeding Bald Eagle ranging behavior in current and potential wind energy production areas. Bald Eagle movement data were collected through GPS telemetry data and used to parameterize the movement models. These models were based on underlying mechanistic and phenomenological functions and real and derived landscape variables. This model allowed eagle movement patterns to be simulated across actual landscapes and under varying development scenarios. Ultimately, this tool can help provide management decisions for landscape planning and minimize the effects of wind energy on Bald Eagles.
CONTENTS

Page

ACKNOWLEDGMENTS ................................................................. v

ABSTRACT .................................................................................. vii

LIST OF TABLES ................................................................. xi

LIST OF FIGURES ........................................................................ xv

INTRODUCTION ........................................................................ 1

CHAPTER

1. COMPARISON OF MULTI-SCALE OPTIMIZATION
   PROCEDURES FOR HABITAT SELECTION MODELING ............ 9
   1.1 Background ................................................................. 9
   1.2 Objectives ................................................................. 12
   1.3 Methods ................................................................. 12
       1.3.1 Creating Landscape Layers and Use-Absence Data .... 12
       1.3.2 Model-Fitting Procedures ................................ 16
       1.3.3 Model-Fitting Parameter Fits ......................... 19
       1.3.4 Correlation and Absolute Mean Deviation ........ 19
       1.3.5 Bias and Variance Ranges .............................. 20
   1.4 Results ................................................................. 20
   1.5 Discussion .............................................................. 24

2. BALD EAGLE HOME RANGES, BEHAVIORS, AND
   MOVEMENTS PATTERNS IN MAINE .............................. 31
   2.1 Background ............................................................... 31
   2.2 Objectives ................................................................. 32
   2.3 Methods ............................................................... 33
## LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Parameter values, their descriptions, and ranges for the landscape layers used to create the ‘true’ probability surfaces using multiple logistic regression.</td>
</tr>
<tr>
<td>1.2</td>
<td>Subset of parameter values used to create ‘true’ probability surfaces for estimating bias and variance of the model fitted parameters.</td>
</tr>
<tr>
<td>2.1</td>
<td>Summary table of landscape metrics used as covariate candidates for the Bald Eagle resource selection function models.</td>
</tr>
<tr>
<td>2.2</td>
<td>Bald Eagle trapping information and territorial data date ranges for sites in Maine.</td>
</tr>
<tr>
<td>2.3</td>
<td>Bald Eagle GPS telemetry data and utilization distribution area sizes and water body area for territorial sites in Maine.</td>
</tr>
<tr>
<td>2.4</td>
<td>Probability distribution fits assessed for the territorial distance metric, a combination of distance from the home nest and proximity to conspecific nests, of Bald Eagles in Maine.</td>
</tr>
<tr>
<td>2.5</td>
<td>Step lengths and movement kernel parameter estimates for the step types of Bald Eagles in Maine.</td>
</tr>
<tr>
<td>2.6</td>
<td>Resource selection model terms and metrics for step types with air (flight or cruise) to cruise behavior for Bald Eagles in Maine.</td>
</tr>
<tr>
<td>2.7</td>
<td>Resource selection model terms and metrics for step types with air (flight or cruise) to flight behavior for Bald Eagles in Maine.</td>
</tr>
<tr>
<td>2.8</td>
<td>Resource selection model terms and metrics for step types with air (flight or cruise) to perch behavior for Bald Eagles in Maine.</td>
</tr>
<tr>
<td>2.9</td>
<td>Resource selection model terms and metrics for step types with air (flight) to roost behavior for Bald Eagles in Maine.</td>
</tr>
</tbody>
</table>
2.10 Resource selection model terms and metrics for step types with stationary (nest or perch) to cruise behavior for Bald Eagles in Maine. ................................................................. 61

2.11 Resource selection model terms and metrics for step types with stationary (nest, perch, or roost) to flight behavior for Bald Eagles in Maine. ................................................................. 62

2.12 Resource selection model terms and metrics for step types with stationary (nest, perch, or roost) to perch behavior for Bald Eagles in Maine. ................................................................. 62

2.13 Resource selection model terms and metrics for step types with stationary (nest or perch) to roost behavior for Bald Eagles in Maine. ................................................................. 63

3.1 The model component values configured during the calibration process for the Bald Eagle IBM. ................................................................. 89

4.1 Parameter values used for a single transit turbine collision risk model by Band (2012) used to estimate a single transit collision risk for a Bald Eagle in our simulations. ................................................................. 106

C.1 Resource selection model fits for cruise-to-cruise step-type for Bald Eagles in Maine. ................................................................. 156

C.2 Resource selection model fits for cruise-to-flight step-type for Bald Eagles in Maine. ................................................................. 157

C.3 Resource selection model fits for cruise-to-perch step-type for Bald Eagles in Maine. ................................................................. 158

C.4 Resource selection model fits for flight-to-cruise step-type for Bald Eagles in Maine. ................................................................. 159

C.5 Resource selection model fits for flight-to-flight step-type for Bald Eagles in Maine. ................................................................. 160

C.6 Resource selection model fits for flight-to-perch step-type for Bald Eagles in Maine. ................................................................. 161

C.7 Resource selection model fits for flight-to-roost step-type for Bald Eagles in Maine. ................................................................. 162
C.8 Resource selection model fits for nest-to-cruise step-type for Bald Eagles in Maine. ......................................................... 162

C.9 Resource selection model fits for nest-to-flight step-type for Bald Eagles in Maine. ......................................................... 163

C.10 Resource selection model fits for nest-to-perch step-type for Bald Eagles in Maine. ......................................................... 163

C.11 Resource selection model fits for nest-to-roost step-type for Bald Eagles in Maine. ......................................................... 164

C.12 Resource selection model fits for perch-to-cruise step-type for Bald Eagles in Maine. ......................................................... 164

C.13 Resource selection model fits for perch-to-flight step-type for Bald Eagles in Maine. ......................................................... 165

C.14 Resource selection model fits for perch-to-perch step-type for Bald Eagles in Maine. ......................................................... 165

C.15 Resource selection model fits for perch-to-roost step-type for Bald Eagles in Maine. ......................................................... 166

C.16 Resource selection model fits for roost-to-flight step-type for Bald Eagles in Maine. ......................................................... 166

C.17 Resource selection model fits for roost-to-perch step-type for Bald Eagles in Maine. ......................................................... 167
LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Example of Gaussian-kernel smoothing on three raster layers to demonstrate changes in spatial scale.</td>
<td>14</td>
</tr>
<tr>
<td>1.2</td>
<td>Example of how a ‘true’ probability surface is generated based on a parameter set.</td>
<td>17</td>
</tr>
<tr>
<td>1.3</td>
<td>Procedure used to assess two model-fitting methods for multi-scale habitat selection.</td>
<td>18</td>
</tr>
<tr>
<td>1.4</td>
<td>Density and rug plot of execution times for two multi-scale optimization methods, exhaustive-search and genetic algorithm, used to fit a model with three spatial covariates.</td>
<td>21</td>
</tr>
<tr>
<td>1.5</td>
<td>Correlation between the ‘true’ probability surface and the best and worst fit model (based on AIC value) probability surfaces for each parameter set shown faceted across the σ values of the layers in the ‘true’ surface.</td>
<td>22</td>
</tr>
<tr>
<td>1.6</td>
<td>Mean absolute deviation values between the ‘true’ probability surface and the best and worst fit models (based on AIC value) probability surfaces for each parameter set shown faceted across the σ values of the layers in the ‘true’ surface.</td>
<td>23</td>
</tr>
<tr>
<td>1.7</td>
<td>Bias and variance for the fitted model σ values for the landscape layers related to the parameter values used to generate the original ‘true’ probability surface faceted by the layer’s β values.</td>
<td>25</td>
</tr>
<tr>
<td>1.8</td>
<td>Bias and variance for each of the fitted model β values for the landscape layers based on the parameter values used to generate the original ‘true’ probability surface shown faceted by the layer’s β values.</td>
<td>26</td>
</tr>
<tr>
<td>1.9</td>
<td>Bias and variance for each of the fitted model σ values for the four parameter sets used to generate a ‘true’ probability surfaces and 1000 replicates of presence-absence data.</td>
<td>27</td>
</tr>
</tbody>
</table>
1.10 Standardized bias and variance for each of the fitted model $\beta$ values for the four parameter sets used to generate a ‘true’ probability surfaces and 1000 replicates of presence-absence data. .......................... 28

2.1 Distribution of Bald Eagle trapping sites (orange circles) used in 2013–2015 in Maine. ................................................................. 35

2.2 Summer and wintering grounds and migration flight paths for the female Bald Eagle trapped at Webb Lake. .............................. 43

2.3 Migration flight paths and wintering grounds in Florida of the female Bald Eagle trapped at Webb Lake, ME. ................................. 44

2.4 Home range size and proportion of cover types within the 50% and 95% isopleths (representing the ‘core’ and ‘total’ home ranges, respectively) of utilization distributions of twelve territorial Bald Eagles in Maine. .............................................. 47

2.5 Proportion of landcover types within the 50% and 95% isopleths (representing the ‘core’ and ‘total’ home ranges, respectively) of utilization distributions of twelve territorial Bald Eagles in Maine. ....... 48

2.6 Map showing the conspecific and nest distance metric used to determine territoriality. .................................................. 49

2.7 Histogram of Bald Eagle conspecific and home nest distances. ....... 50

2.8 Proportion of diurnal Bald Eagle behavior for each sex during the breeding period based on a preliminary analysis of GPS telemetry data from Maine. .............................................. 51

2.9 The probability of behavioral state changes of diurnal Bald Eagle behavior during the breeding period based on an analysis of GPS telemetry data from Maine. ................................. 53

2.10 The probability of behavioral state changes of diurnal Bald Eagle behavior during the breeding period dependent on Julian date ....... 54

2.11 The fitted Weibull distributions (orange lines) for the step types of Bald Eagles in Maine. .................................................. 56

2.12 The fitted mixed von Mises distributions (orange lines) for the step types that had directional tendency of Bald Eagles in Maine. .............. 57
2.13 The movement kernels based on the fitted Weibull and mixed von Mises distributions for the step types of Bald Eagles in Maine. ............ 58

2.14 Maps of the resource selection probability functions for the step types analyzed for Bald Eagles in Maine. ......................... 64

2.15 Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) at Ellis Pond, Maine. .... 65

2.16 Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) at Hebron Lake, Maine. .... 66

2.17 Maps of the resource selection probability functions for the Bald Eagle territory around the nest (orange circle) at East Musquash Lake, Maine. ......................................................... 67

2.18 Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) Sandy Pond, Maine. .... 68

3.1 Overview of the Bald Eagle IBM step sequence ......................... 78

3.2 Model step types and their location change scenarios ............... 82

3.3 The cumulative distribution function of the conspecific and nest distance values of the Bald Eagles in Maine. ....................... 83

3.4 The rescaled values that relate the conspecific and nest distance values of Bald Eagles to a logistic scale parameter in the territorial kernel. ......................................................... 84

3.5 The relationship between conspecific and nest distance metrics and the territorial kernel probability surface based on a Bald Eagle's current location (located at 0 on the relative position scale) and the relative positions (higher or lower conspecific and nest distance metric values) of the surrounding cells on the landscape. .......... 84

3.6 An example of a territorial kernel generated at the Ellis Pond nest (orange circle) in Maine when a Bald Eagle (grey circle) is located 5 km southwest of the nest. .............................................. 85

3.7 An example of a territorial kernel generated at the Ellis Pond nest (orange circle) in Maine when a Bald Eagle (grey circle) is located 10 km southwest of the nest. .............................................. 86
3.8 The IBM calibration metric results showing the proportion of perching locations relative to their distance to hydrological features for the empirical data and the simulation data using the final parameterization values. ................................................. 91

3.9 The IBM calibration results showing the step path proportion of ridgeline crossings for the empirical data and the simulation data using the final parameterization values. ......................................... 92

3.10 Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at Ellis Pond, ME. ......................................................... 92

3.11 Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at Hebron Lake, ME. ............................................. 93

3.12 Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at East Musquash Lake, ME. ................................. 93

3.13 Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at Sandy Pond, ME. ................................. 94

4.1 Map of a Bald Eagle nest (orange circle) and two areas (purple polygons) of 50 m above ground good-to-outstanding wind power class conditions (National Renewable Energy Laboratory and AWS TruePower 2009) north and south of the nest on Upper Wilson Pond, Maine. ................................................................. 100

4.2 Map of a Bald Eagle nest (orange circle) and two areas (purple polygons) of 50 m above ground good-to-outstanding wind power class conditions (National Renewable Energy Laboratory and AWS TruePower 2009) north and south of the nest on West Grand Lake, Maine. ................................................................. 101

4.3 Windrose for the airport in Greenville, ME used to determine the turbine locations in the wind farm scenarios at the Upper Wilson Pond site. ................................................................. 102

4.4 Windrose for the airport in Millinocket, ME used to determine the turbine locations in the wind farm scenarios at the West Grand Lake site. ................................................................. 102
4.5 Map of the Upper Wilson Pond nest (orange circle) under four wind farm scenarios: control, no turbines; north, 15 turbines (white circles) in the northern footprint; south, 15 turbines in the southern area; north and south, 15 turbines in both the north and south (30 total turbines). The turbines are shown to scale based on a diameter of 112 m. ................................................................. 103

4.6 Map of the West Grand Lake nest (orange circle) under four wind farm scenarios: control, no turbines; north, 20 turbines (white circles) in the northern footprint; south, 20 turbines in the southern area; north and south, 20 turbines in both the north and south (40 total turbines). The turbines are shown to scale based on a diameter of 112 m. ................................................................. 104

4.7 Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the Upper Wilson Pond nest (orange circles) under four wind farm scenarios. ............... 108

4.8 Map of interpolated cruise path density for twenty simulations of Bald Eagle pairs during the breeding season around the West Grand Lake nest (orange circles) under four wind farm scenarios. ............... 109

4.9 Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the Upper Wilson Pond nest (orange circles) under four wind farm scenarios. ............... 110

4.10 Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the West Grand Lake nest (orange circles) under four wind farm scenarios. ............... 111

4.11 Simulated Bald Eagle cruise and flight transit paths through the wind farm areas near Upper Wilson Pond and West Grand Lake, ME. ............ 112

4.12 Simulated Bald Eagle cruise and flight transit paths through the wind farm turbines near Upper Wilson Pond and West Grand Lake, ME. ................................. 113

4.13 Simulated Bald Eagle flight path transits through the north and south wind farm turbines near Upper Wilson Pond and West Grand Lake, ME, showing pair-wise ANOVA results. ....................... 114

4.14 Turbine collision risk (using a 95% avoidance rate) by wind area per Bald Eagle for a breeding season under three wind farm scenarios at Upper Wilson Pond and West Grand Lake, ME. ....................... 116
4.15 Total turbine collision risk (using a 95% avoidance rate) per Bald Eagle for a breeding season under three wind farm scenarios at Upper Wilson Pond and West Grand Lake, ME. .............................................. 117

4.16 Map showing the proportion of Bald Eagle flight path transits through wind turbines under three wind farms scenarios at Upper Wilson Pond, ME. ......................................................... 118

4.17 Map showing the proportion of Bald Eagle flight path transits through wind turbines under three wind farms scenarios at West Grand Lake, ME. ........................................................... 119

B.1 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Branch Lake, ME, breeding season 2015. ..................................................... 133

B.2 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Branch Lake, ME, breeding season 2016. ..................................................... 134

B.3 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Crooked Pond, ME, breeding season 2015. ..................................................... 135

B.4 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, Ellis Pond, ME, breeding season 2015. .......... 136

B.5 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Ellis Pond, ME, breeding season 2016. ..................................................... 137
B.6 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Ellis Pond, ME, breeding season 2017.

B.7 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Eskutassis Pond, ME, breeding season 2015.

B.8 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Eskutassis Pond, ME, breeding season 2016.

B.9 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Lake Hebron, ME, breeding season 2015.

B.10 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Lake Hebron, ME, breeding season 2016.

B.11 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2015.

B.12 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2016.
B.13 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2017. .......................... 145

B.14 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2018. .......................... 146

B.15 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Penneseeawassee (Norway) Lake, ME, breeding season 2015. ....... 147

B.16 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2015. .......................... 148

B.17 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2016. .......................... 149

B.18 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2017. .......................... 150

B.19 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2018. .......................... 151
B.20 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2019. ......................................................... 152

B.21 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sheepscot Pond, ME, breeding season 2015. ......................................................... 153

B.22 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Number Three Pond, ME, breeding season 2015. ......................................................... 154

B.23 GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Upper Wilson Pond, ME, breeding season 2015. ......................................................... 155

E.1 Map of the Bald Eagle resource selection function probability surfaces by step type under the control scenario (no turbines) for the nest (orange circle) at Upper Wilson Lake, ME. ................................. 172

E.2 Map of the Bald Eagle resource selection function probability surfaces by step type under the north wind farm scenario (15 turbines) for the nest (orange circle) at Upper Wilson Lake, ME. ................................. 173

E.3 Map of the Bald Eagle resource selection function probability surfaces by step type under the south wind farm scenario (15 turbines) for the nest (orange circle) at Upper Wilson Lake, ME. ................................. 174

E.4 Map of the Bald Eagle resource selection function probability surfaces by step type under the north and south wind farm scenario (15 turbines in each area) for the nest (orange circle) at Upper Wilson Lake, ME. ................................. 175

E.5 Map of the Bald Eagle resource selection function probability surfaces by step type under the control scenario (no turbines) for the nest (orange circle) at West Grand Lake, ME. ................................. 176
E.6 Map of the Bald Eagle resource selection function probability surfaces by step type under the north wind farm scenario (20 turbines) for the nest (orange circle) at West Grand Lake, ME. ................................. 177

E.7 Map of the Bald Eagle resource selection function probability surfaces by step type under the south wind farm scenario (20 turbines) for the nest (orange circle) at West Grand Lake, ME. ................................. 178

E.8 Map of the Bald Eagle resource selection function probability surfaces by step type under the north and south wind farm scenario (20 turbines in each area) for the nest (orange circle) at West Grand Lake, ME. ................................................................. 179
INTRODUCTION

A combination of technological advancements, economic incentives, and public policies has led to growing wind energy development worldwide. Global wind energy capacity has increased approximately 25% annually over the past three decades and reached a total capacity of 837 gigawatts (GW) in 2021 (Global Wind Energy Council 2022). Wind energy has considerable overall environmental benefits compared to most fossil fuel based technologies, but poorly sited turbines may negatively affect local and migratory birds, bats, and other wildlife and their habitats (Saidur et al. 2011; Strickland et al. 2011). In the northeastern United States, Maine has become a leader in wind energy production and currently has the greatest percent (23.8%) of in-state energy production, amounting to more than twice the installed wind energy capacity (996 megawatts, MW), of the rest of New England (563 MW) combined (U.S. Department of Energy 2021). Maine has set a wind energy capacity target of at least 8,000 MW by 2030, including 300 MW from coastal waters or offshore facilities (American Wind Energy Association 2018). Maine’s wind projects are scattered in the Appalachian mountain range in the west, near the coast in the center of the state, and along the eastern border with Canada. Continued growth in the wind industry is expected due to increasingly efficient wind turbine technologies, improved electrical transmission infrastructure, and federal policies encouraging renewable energy (Fisher et al. 2010; American Wind Energy Association 2012). While it is estimated only 6-8% of Maine’s total land area has enough abundant, reliable wind to support utility-scale wind projects (Natural Resources Council of Maine 2012), one prominent ecological concern is much of the
state’s current and potential wind energy development areas overlap with known Bald Eagle (*Haliaeetus leucocephalus*) breeding territories.

Maine’s Bald Eagle population is by far the largest in New England with nesting sites concentrated at inland lakes, rivers, and along coastal and inlet habitats. The population increased from approximately 200 breeding pairs in 1999 to over 600 pairs by 2013 (C. Todd, pers. comm). In 2000, the species met the state’s recovery criteria and was removed from the state’s list of threatened and endangered species, and statewide monitoring inventories were set to continue to ensure that population goals were maintained (Todd and Matula 2008). At the national level, the USFWS estimated from aerial surveys in four of the six Eagle Management Units (including the Atlantic Flyway) that the Bald Eagle population had increased to 316,700 individuals in 2019, an increase of 4.4 times compared to the estimate in 2009 (U.S. Fish and Wildlife Service 2020). As wind energy expands in the US, modeling eagle habitat use and movements may help avoid or minimize potential negative effects of future wind energy developments for this species.

Bald eagles are protected and managed under several federal laws including the Lacey Act, Migratory Bird Treaty Act, and Bald and Golden Eagle Protection Act (BGEPA, 16 U.S.C. §§ 668–668d). The BGEPA’s primary goal is to maintain or increase populations of Bald Eagles and Golden Eagles (*Aquila chrysaetos*) and prohibits take (defined as the killing, harassment, molesting, etc.) unless authorized by the US Fish and Wildlife Service (USFWS). Wind energy developers seeking regulatory approval are advised to consult the USFWS’s Eagle Conservation Plan Guidance (ECPG; U.S. Fish and Wildlife Service 2013). Although complying with the ECPG is not a requirement, consultation with the Service may allow for the consideration of alternative development strategies and the formulation of advanced conservation practices (ACPs) to reduce adverse effects on eagle populations. The ECPG attempts to predict the direct and indirect effects of potential wind facilities.
before construction by recommending methods for monitoring eagle utilization rates, breeding productivity, and mortalities during pre-construction, installation, and operation of turbines. The ECPG also proposes methods to conduct collision risk analyses and provide compensation for potential take.

One principal focus of the ECPG is calculating eagle fatality estimates at proposed wind energy projects through collision risk models (CRM), such as the one developed by Band et al. (2007). CRMs typically use pre-construction observational survey data to record the presence, duration, and activity of species in a proposed project area. These detection rates are extrapolated to predict an annual estimate of birds that would fly through a rotor sweep zone and be struck by a turbine blade in the absence of any avoiding action. However, since most species actively avoid wind turbines, risk estimates are adjusted by a metric called avoidance rate (Band et al. 2007). Species-specific avoidance rates are typically determined by calculating the difference between pre-construction collision estimates and post-construction observed mortalities determined by standardized carcass searches under selected wind turbines (Smallwood and Thelander 2008; Péron et al. 2013).

The USFWS developed a CRM for Golden and Bald Eagles using a Bayesian analytical model to estimate potential exposure and mortalities at proposed wind energy facilities (New et al. 2015). This approach recommends biologists establish three-dimensional survey sites within the project’s proposed footprint and record the number of minutes that eagles are observed flying within these plots. These survey data are extrapolated to estimate the total annual time eagles spend within the study site and entered into a risk model to predict eagle exposure to turbines, collision probability, and fatality rates for a proposed wind facility. The USFWS originally used a study by Whitfield and Natural Research Ltd (2009) of Golden Eagle monitoring and post-construction mortality data at four wind energy projects in the United States with substantial raptor mortalities to parameterize the original
prior probability distributions and estimate eagle fatalities given exposure rates. The USFWS plans to use data from a more recent study by Bay et al. (2016) to update their prior probabilities and incorporate them into a revised version of Appendix D of the ECPG soon (New et al. 2018).

However, recent evidence suggests the exposure and probability of collisions between Golden and Bald Eagles are different, and the USFWS suggests that different priors should be used when modeling relative risk and for evaluating wind facilities (New et al. 2018). New studies by New et al. (2018) and Nasman et al. (2021) to determine Golden Eagle and Bald Eagle specific exposure rates, respectively, have focused on using Bayesian analysis to incorporate prior probabilities to estimate collision risk. Statistical analyses demonstrate that even a slight variation (<1%) in avoidance rates significantly alter estimated collisions and lead to substantial variance in risk estimates (Chamberlain et al. 2006). Additionally, in places where Bald Eagles are abundant, social behaviors and intra-specific interactions may increase their vulnerability to collisions (New et al. 2018). Such circumstances warrant situation-specific assessments of Bald Eagle risk at proposed facilities.

Although CRMs have become standard practice for pre-construction surveys and risk modeling, they have certain limitations in both accuracy and prediction ability and often assume much about bird movement and behavior (Marques et al. 2014). When the current USFWS recommended survey guidelines were applied to pre-construction Golden Eagle surveys, a post hoc analysis concluded that a single year of data provided an unreliable estimator of detections. Further, Skipper et al. (2017) suggested that even multiple years of data may be insufficient to properly capture detection rates. Likewise, a simulation study using Golden Eagle telemetry data concluded even high-effort field observation protocols (day-long surveys covering 60% of a project footprint) may result in large bias in detection probability.
and a poor approximation of actual Golden Eagle habitat use (Sur et al. 2018). These field studies demonstrate the inherent difficulty in designing efficient, practical surveys for species that change behaviors seasonally and occupy large territories. Additionally, most studies that employ observational surveys and post-construction mortality data to determine avoidance are unable to assess the underlying scale or causative factors (National Research Council 2007), a substantial weakness for relying solely on these methods to improve CRMs.

As wind energy projects have expanded nationally, policy trends and many new developments are focused on near-shore and offshore waters, especially along the northern Atlantic coast. The first commercial-scale wind farm in North America, a 30 MW offshore wind farm built near Block Island, Rhode Island, was completed in 2017 (Global Wind Energy Council 2018). The Bureau of Ocean Energy Management has over twenty active Wind Energy Areas (WEA) leases in the Atlantic Ocean north of Delaware Bay, many of which are in the environmental review process. The Biden Administration has set a national target of 30 GW of offshore wind energy capacity by 2030, including 15 GW from floating wind turbine platforms (The White House 2022). As part of Maine’s Economic Development Strategy, the state is focused on deep water turbines and is currently pursuing a one-turbine demonstration project by New England Aqua Ventus to test an 11 MW floating platform wind turbine off of Monhegan Island in the Gulf of Maine (Maine Department of Economic and Community Development 2019).

For many offshore wind farms, the risk of bird collision or displacement has been a key issue in the planning process, and concerns have led to projects being stalled or abandoned (Cook et al. 2018). Although few studies have reported birds colliding with offshore turbines, evidence suggests that significant fatalities at offshore structures can occur (e.g., Hüppop et al. 2016). Several raptor species were observed during post-construction monitoring at the Horns Rev Offshore Wind Farms in the...
North Sea off Denmark (Skov et al. 2012), and certain Bald Eagle populations frequently move between near-shore islands in the Pacific Ocean (Dooley 2009), substantiating a need to consider such species in the planning process in the United States. However, current eagle CRM models applicable to onshore facilities in the United States require post-construction mortality searches, and observing collision events or collecting carcasses in the marine environment is extremely challenging (Petersen et al. 2006). Technologies to sufficiently detect collisions at offshore wind facilities are still in development (Collier et al. 2011; Cook et al. 2018), and offshore wind facilities may require alternative methodological approaches to conduct risk assessments.

Recent studies in Europe emphasized the need for tracking studies of marine birds and suggest this type of data will be integral to studying the effects of marine renewable developments on avian populations (e.g., Masden et al. 2012; Soanes et al. 2013). These approaches can incorporate data about multiple species from previous and on-going studies. Likewise, a recent study on Petit Manan Island in Maine used automated VHF telemetry data of Common Terns (Sterna hirundo) and Arctic Terns (S. paradisaea) to assess the potential collision probability of various offshore wind development scenarios (Cranmer et al. 2017).

Moreover, there is a recognized need for ecologists and permitting agencies to advance new analytical methods that can process avian behavioral data in marine environments, especially in the context of risk assessments (Duberstein et al. 2011). The USFWS also acknowledges a need to develop alternative models that will enable more accurate predictions, especially flexible methods that directly incorporate habitat use or potential behavioral adaptations by eagles. By testing new analytical methods at onshore sites, these approaches could be adapted to environmental assessments of offshore wind energy sites. One promising technique
for being able to account for multiple factors and covariates simultaneously is a method called individual-based modeling.

Individual-based models (IBMs), also referred to as agent-based models, are composed of unique and autonomous entities that interact with each other and their environment to model dynamic systems (Railsback and Grimm 2011). This modeling approach allows for adaptive, complex behaviors and the emergence of a system’s underlying processes (DeAngelis et al. 2005). IBMs offer an effective and adaptable method to study animal movement patterns because they can accommodate varying landscape features, intra- and inter-species interactions, and behavioral modifications (McLane et al. 2011). Individual-based modeling has become an increasingly powerful and effective tool in the assessment of ecological effects (Railsback and Grimm 2011), and allows analyses that would be cost-prohibitive or impossible to do in biological systems, including the effects of wind turbine siting configurations on collision estimates of raptor species (e.g., Eichhorn et al. 2012; Schaub 2012). Such modeling efforts could enable more interdisciplinary approaches that directly integrate additional engineering, economic, and ecological data into possible development and management scenarios (Masden et al. 2012). Conservation goals, siting decisions, and mitigation efforts could be incorporated into strategic-level management frameworks for the region.

This dissertation addresses several research questions and technical challenges to determine the utility of using an IBM to model Bald Eagle habitat use and its applicability to wind energy risk assessments. Given this relatively novel research topic, this study focuses on the development of an IBM for an onshore application, but the ultimate goal is to determine the utility of eagle movement IBMs for both onshore and offshore environments. Since avoidance and scale is so critical to determining collision risk and avoidance, the first chapter addresses how an improved multi-scale optimization method may be used in habitat selection studies,
improving the ability of researchers to model avoidance behavior. The second chapter uses GPS telemetry to assess Bald Eagle home range and movement patterns for an IBM. The third chapter focuses on the development, testing, and refinement of a Bald Eagle IBM movement simulation in the R Program environment. The fourth chapter applies an IBM of Bald Eagles to a real-world landscape to conduct a risk assessment of wind farm development scenarios to demonstrate the utility of this approach for addressing potential researcher and stakeholder questions.
1.1 Background

Understanding certain ecological phenomenon, such as habitat selection, may require determining the ‘appropriate’ scale at which the process occurs (Wiens 1989). Animals select or avoid environmental features at different temporal and spatial scales. Thus, assessing how these selection patterns could be affected by humans may be critical for conservation efforts. Researchers studying wind-wildlife conflicts are particularly interested in determining the scale at which animals avoid or are displaced by wind turbines (May 2015), and insights into scale-dependent relationships between animals and their habitat may be crucial for modeling, inference, and simulation studies.

Most habitat selection studies have limited their approach to selection analyses to a single-scale framework (McGarigal et al. 2016). This single-scale approach typically uses a static distance scale (e.g., 100 m) to calculate landscape patterns and features in the habitat-selection modeling process. However, it is extremely unlikely that a species would respond to all environmental features at an identical scale, and failure to properly assess scale dependence in habitat relationships can lead to incorrect inferences (McGarigal et al. 2016). As researchers became more aware of the limitations of a single-scale approach, some studies tried to account for independent scales across covariates by optimizing the habitat selection covariates one at a time, to determine the ‘characteristic’ scale of each habitat variable and
then allowing these covariates into the model only at that specific scale. Such ‘pseudo-optimized’, multi-scale approaches consistently see improvements in their predictive power and better ecological understandings compared to a single-scale approach (e.g., Timm et al. 2016; Klaassen and Broekhuis 2018).

Yet, even these pseudo-optimized approaches are highly unlikely to find globally-optimized set of parameters. Truly optimized multi-scale selection can evaluate all covariates simultaneously across a range of scales and identify the best scale for each variable conditioned on all the other scale-dependent covariates. Studies by Guénard et al. (2010) and Latombe et al. (2014) showed the theoretical benefits and validity of using optimization procedures to find the appropriate scale for multiple covariates. In their model-fitting procedures, they used optimization algorithms to search a parameter space to find a multi-scale solution. However, in both cases, the models were limited to evaluating only two variables. Guénard et al. (2010) used a multi-scale codependence analysis (MCA) to find a scale-specific correlation metric between two variables, and Latombe et al. (2014) optimized the rate parameter for discounting functions in a pair of covariates.

In recent years, several newer methodological solutions to assess multi-scale species-habitat relationships have been proposed, such as the Bayesian latent indicator scale selection (BLISS) (Stuber et al. 2017), scale-selecting multispecies occupancy model (ssMSOM) (Frishkoff et al. 2019), least absolute shrinkage and selection operator regression (Gallo et al. 2018), multi-scale geographically weighted regression (Leong and Yue 2017), and distance weighted kernel-smoothing (Chandler and Hepinstall-Cymerman 2016). A recent review of these methods by Stuber and Gruber (2020) asserted that, compared to the others, distance weighted kernel-smoothing may be orders of magnitude more computationally intensive, a potentially significant drawback. In the study by Chandler and Hepinstall-Cymerman (2016), they used kernel smoothing on two landscape
variables, elevation and Normalized Difference Vegetation Index (NDVI), to
estimate their spatial scales and effect size on bird abundance. At each step of the
optimization procedure, the landscape layers were smoothed and the model was refit
in a maximum likelihood framework.

Our study describes and demonstrates two modifications to the kernel
smoothing multi-scale optimization approach by leveraging data manipulation and
model-fitting procedures available in new packages for the R Program (R Core
Team 2022). These packages allow for improved creation and handling of large data
sets containing complex objects, efficient generation of candidate model arrays, and
advanced model fitting and assessment tools. Some of the proposed techniques may
serve as beneficial improvements to a variety of ecological data analysis and
modeling approaches.

To demonstrate the utility of these techniques, we conducted a simulation study
to model habitat selection using a multiple logistic regression model with three
covariates representing environmental variables such as elevation, slope, or landcover
metrics or anthropogenic features such as buildings, roads, or sources of
disturbance. We varied these covariates across a range of effect sizes and spatial
scales to create ‘true’ habitat selection probability surfaces and simulated ecological
presence-absence data sets to test and evaluate two multi-scale optimization
model-fitting procedures. The first method, an exhaustive search, is a brute-force
approach that generated and evaluated models for every combination of scales
within user-provided ranges. The second method applied a genetic-algorithm
optimization from the rgenoud package to select the best-fit parameter values
(Mebane and Sekhon 2011). Genetic algorithms are powerful and flexible
optimization algorithms inspired by basic principles of biological evolution and
natural selection (Hamblin 2013). These stochastic algorithms search a parameter
space by mimicking mechanisms of evolution, including selection, crossover, and
mutation, to find the optimal solution. This approach has been used in other ecological studies such as model selection of resistance surfaces in landscape genetics analyses (Peterman 2018). Both of our approaches allow all scale-dependent variables to be assessed conditioned on the other covariates to find the globally-optimized solution. For both methods, we assessed computer processing times, parameter recovery accuracy, and bias or other significant patterns in the results.

1.2 Objectives

The goal of this study was to assess the speed and accuracy of two methods of multi-scale optimization model-fitting. These approaches make extensive use of piped workflows and list columns from the tidyverse packages (Wickham 2017). We generated a range of multiple logistic regression betas and kernel smoothing scales for three different landscapes. Each combination of parameter values constituted a ‘parameter set’ and was used to simulate a presence-absence point data set. These simulated data sets were used to test the model-fitting methods. We had four specific objectives: 1) use a range of parameter values to create functional landscape layers and simulate presence-absence location data, 2) fit the data using both an exhaustive-search and genetic-algorithm optimization procedure, 3) compare the speed and accuracy of the two methods, and 4) replicate the simulation to generate confidence intervals around the parameter estimates.

1.3 Methods

1.3.1 Creating Landscape Layers and Use-Absence Data

To conduct this analysis, we simulated landscape covariates along two ranges: spatial scales and effect sizes. The input raster data for this analysis came from two real-world layers and one simulated layer representing 30 m cells over an area of
approximately 400 km², totaling > 450 thousand cells, around Ellis Pond in Maine. The real-world data came from a USGS digital elevation model (DEM) and the Euclidean distance to the development cover class from the Designing Sustainable Landscapes (DSL) Project (McGarigal et al. 2017; U.S. Geological Survey 2017b). To reduce collinearity between these two layers, we vertically transposed the development distance layer by inverting the raster matrix column values.

We created the third layer by using the gaussMap function in the SpaDES.tools package (Chubaty and McIntire 2019) to create a raster with a random two-dimensional Gaussian distribution probability pattern with a spatial scale parameter of 200 m and a Gaussian variance parameter of 0.03. All three layers were standardized to have a continuous uniform distribution from 0 to 1. All pair-wise correlations between layers were <.001.

Each raster layer was converted into an array of spatial scales by converting the cell values into a matrix data structure and using the smoothie package to transform the values into a distance-weighted representation (Gilleland 2013). This package uses the Fourier fast transform function and convolution theorem to efficiently apply a functional transformation and recalculate each cell’s value. In this case, we applied a Gaussian kernel function to calculate a distance-weighted neighborhood mean for each cell. The function’s scale parameter, $\sigma$, controls the kernel’s bandwidth (i.e., standard deviation) in cell units. For example, a $\sigma$ of 10 would equate to a kernel bandwidth of 300 m (Figure 1.1).

To simulate the relationship between the input spatial layers and the probability of detection for a species, we used a multiple logistic regression model. This function represents the probability of obtaining a particular value of a nominal variable given a set of covariates (McDonald 2014). In this case, the probability value ranges from 0 to 1 and represents the probability of detecting a species. To allow for the function to be fit using standard regression methods, the probability value ($y$) is
Figure 1.1. Example of Gaussian-kernel smoothing on three raster layers to demonstrate changes in spatial scale. The left column, $\sigma = 0$, shows the original 30 m cell raster layers, each totaling about 400 km$^2$. The middle and right columns, $\sigma = 10$ and $\sigma = 20$, show the surfaces after smoothing (calculating distance weighted means) using Gaussian kernels with $\sigma$s of 10 and 20, equivalent to bandwidths of 300 and 600 m, respectively.
represented as an odds ratio, \(y/(1 - y)\) and converted to a natural log. In a scenario with 3 covariate layers, the multiple logistic regression model is represented as:

\[
\ln \left( \frac{y}{1 - y} \right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3
\]

In this form, the function predicts the value of \(y\) with an intercept (\(\beta_0\)) and the covariate layers values (\(x_1, x_2, \text{ and } x_3\)) with corresponding coefficients (\(\beta_1, \beta_2, \text{ and } \beta_3\)) that represent the effect size for each layer. For this simulation, we assessed the species-habitat relationships along a range of covariate effect sizes (i.e., \(\beta_s\)) and spatial scales (i.e., \(\sigma_s\)) for each covariate (Table 1.1). This equaled 216 \(\beta\) permutations and 27 \(\sigma\) permutations for a total of 5832 parameter sets.

**Table 1.1.** Parameter values, their descriptions, and ranges for the landscape layers used to create the ‘true’ probability surfaces using multiple logistic regression.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_1)</td>
<td>Layer 1 slope (effect size)</td>
<td>-3, -2, -1, 1, 2, 3</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>Layer 2 slope (effect size)</td>
<td>-3, -2, -1, 1, 2, 3</td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>Layer 3 slope (effect size)</td>
<td>-3, -2, -1, 1, 2, 3</td>
</tr>
<tr>
<td>(\sigma_1)</td>
<td>Layer 1 Gaussian kernel bandwidth</td>
<td>0, 10, 20</td>
</tr>
<tr>
<td>(\sigma_2)</td>
<td>Layer 2 Gaussian kernel bandwidth</td>
<td>0, 10, 20</td>
</tr>
<tr>
<td>(\sigma_3)</td>
<td>Layer 3 Gaussian kernel bandwidth</td>
<td>0, 10, 20</td>
</tr>
</tbody>
</table>

To ensure all three layers were equally weighted in the final probability surface, we forced the surface to have a value of .5 when: \(\beta_1 = \beta_2 = \beta_3 = .5\) by calculating the intercept (\(\beta_0\)) for each model using this formula:

\[
\beta_0 = -(\beta_1 \times .5 + \beta_2 \times .5 + \beta_3 \times .5)
\]

For each parameter set, we created a ‘true’ landscape probability surface by applying the \(\beta\) values to the covariates at the given spatial scale for each covariate.
We then randomly sampled these probability surfaces using a Bernoulli process to create an equal sample of ‘present’ (n = 200) and ‘absent’ (n = 200) locations, similar to an ecological presence-absence survey data set. The simulation and model-fitting code are detailed in Appendix A.

### 1.3.2 Model-Fitting Procedures

For each simulated data set, we compared the two model-fitting approaches’ estimates of the $\beta$ and $\sigma$ parameter values (Figure 1.2). Both methods relied on a piped workflow to pre-process the input rasters into a matrix format and run the kernel smoothing procedure for every scale. This technique allows for a computationally efficient way to generate and store each layer across a range of spatial scales for the simulation, modeling, and analysis procedures. Both model-fitting methods approaches relied on maximum likelihood estimation to determine the model coefficients ($\beta$s) but varied in how they determine the optimal combination of sigma ($\sigma$) values.

In the exhaustive-search method, we systematically generated and fit models with all possible $\sigma$ value permutations. First, we assigned an a priori range of integer values (i.e., 0 to 40) for each $\sigma$ parameter in the model and generated a set of models that encompassed the full array of $\sigma$ permutations. For example, to evaluate habitat selection models with 3 layers and 41 $\sigma$ value options for each layer, the total number of $\sigma$ permutations is 68,921 unique arrangements. For each $\sigma$ value permutation, the corresponding landscape layer covariate data were selected from the raster matrix stack and used to fit a logistic regression GLM using the presence-absence data as the response variable. For these $\sigma$ permutation model results, we evaluated fit using Akaike’s Information Criterion (AIC), and the model with the lowest AIC value was considered the optimal solution.
Figure 1.2. Example of how a ‘true’ probability surface is generated based on a parameter set. Each parameter set consists of an intercept ($\beta_0$), and betas ($\beta_1$, $\beta_2$, $\beta_3$) and sigmas ($\sigma_1$, $\sigma_2$, $\sigma_3$) for each layer. In this example, three layers (each at their respective $\sigma$) are combined in the model to generate the true ‘probability’ surface.
Figure 1.3. Procedure used to assess two model-fitting methods for multi-scale habitat selection. Models in the habitat-selection simulation are comprised of an intercept ($\beta_0$), regression coefficients ($\beta_1, \beta_2, \beta_3$), and landscape smoothing scales ($\sigma_1, \sigma_2, \sigma_3$) parameters. For each model the parameters are applied to GIS covariate data to create a ‘true’ landscape probability layer. This surface was randomly sampled for used and unused location points. These points and the original GIS data layers are used to fit a multiple logistic regression model through both an exhaustive-search method by fitting models using every possible scale combination and using a genetic algorithm model-fitting procedure.
In the second approach, we used the rgenoud package’s genetic optimization procedure to find the optimal $\sigma$ values (Mebane and Sekhon 2011). Optimization procedures for determining the best-fit solution to a multi-parameter model typically use methods such as the Nelder-Mead and BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithms that rely on derivatives that minimize (or maximize) the objective function (Nash and Varadhan 2011). However, when the function to be optimized is nonlinear or has irregularities, such as saddle-points or discontinuities, the procedure may not find the global optimum (Mebane and Sekhon 2011). As an alternative approach, optimization procedures using genetic algorithms can be used for searching integer-only parameter space and using non-derivative methods such as simulated annealing.

We used a genetic algorithm to solve the optimization by searching the $\sigma$ parameter-space (0 to 40) for the set of $\sigma$ integer values that resulted in the lowest AIC value for the GLM model. Our code used an indexed raster matrix stack to efficiently store and fit the models. By having all possible spatial-scale data readily available, we vastly reduced the processing time normally used to generate new surfaces and iteratively search the parameter space.

### 1.3.3 Model-Fitting Parameter Fits

We compared the parameter estimates between the two methods for all 5832 parameter sets. We also compared the methods’ computational speed by randomly selecting 1000 parameter sets to create presence-absence data and fit the model parameters with the two methods and clocking the processing times using the bench package (Hester 2019), a process benchmarking tool for R.

### 1.3.4 Correlation and Absolute Mean Deviation

To assess how well the estimated parameters returned probability surfaces that matched the ‘true’ probability surface, we assessed their correlation and absolute
mean deviation. The ‘true’ probability surface and model-fitted surfaces were generated from the same underlying landscape layers and are inherently correlated. To determine the extent of improvement under those conditions, we calculated the correlation and absolution mean deviation between the ‘true’ probability surface and the probability surfaces predicted by the best and worst fits of the exhaustive-search method. The genetic algorithm only produces a best-fit outcome, so it was impossible to evaluate these metrics for that method.

1.3.5 Bias and Variance Ranges

We assessed the bias and variance of $\beta$ and $\sigma$ parameter estimates on the full 5832 parameter sets to examine the global patterns of the parameters on the estimates. Additionally, we selected four representative parameter sets (Table 1.2) to run 1000 simulations of presence-absence data and fit the parameters. This allowed us to examine more explicitly how the strength of the $\beta$ and $\sigma$ values affect the accuracy and precision of parameter estimates.

<table>
<thead>
<tr>
<th>Parameter Set</th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\sigma_1$</th>
<th>$\sigma_2$</th>
<th>$\sigma_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.0</td>
<td>-2</td>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>10</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>-2.5</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>20</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1.0</td>
<td>2</td>
<td>-2</td>
<td>-2</td>
<td>20</td>
<td>20</td>
<td>10</td>
</tr>
</tbody>
</table>

1.4 Results

Both procedures returned identical parameter estimates for our 5832 parameter sets. Since the exhaustive-search method evaluated all possible $\sigma$ permutations, this method should determine the global-optimal spatial scale values for each simulation.
scenario. Therefore, this study provides evidence that genetic algorithms can also find the same optimal multi-scale model. However, the genetic algorithm’s processing time (37.1 sec ±1.7 SD) was significantly faster compared to the exhaustive-search (159.0 sec ±8.6 SD) when benchmarked (Figure 1.4).

![Figure 1.4](image). Density and rug plot of execution times for two multi-scale optimization methods, exhaustive-search and genetic algorithm, used to fit a model with three spatial covariates. We benchmarked timings for both methods by fitting randomly selecting logistic regression models 1000 times using the bench package (Hester 2019). The genetic algorithm procedure was substantially faster (37.1 sec ±1.7 SD) compared to the exhaustive search (159.0 ±8.6 SD) procedure.

For our 5832 parameter sets, the correlation and mean absolute deviation between the ‘true’ probability surface and the fitted-model results (Figures 1.5 and 1.6) showed relative improvements in these prediction metrics across all of the parameter set ranges. The best-fit models had a higher global correlation mean (0.968 ±.027 SD) compared with the worst-fit models’ global correlation mean (0.816 ± 0.068 SD). The best-fit models also had a lower absolute deviation mean (0.0427 ± 0.013 SD) relative to the worst-fit models’ global absolute deviation mean (0.0924 ± 0.024 SD) showing better estimation of the ‘true’ probability surface for all parameter sets. In both cases, the difference between the best and worst fit
models were greatest when one or more ‘true’ $\sigma$ values were 0, and the difference was reduced as one or more ‘true’ $\sigma$ values increased. Parameter sets with smaller $\sigma$ values had larger differences between the best and worst fits. As the underlying scales increase, it tends to diminish the potential differences in estimate fits.

Figure 1.5. Correlation between the ‘true’ probability surface and the best and worst fit model (based on AIC value) probability surfaces for each parameter set shown faceted across the $\sigma$ values of the layers in the ‘true’ surface.

Across the full 5832 parameter sets the bias and variance of the fitted-model parameters show the estimators are approximately unbiased. However, the weaker
Figure 1.6. Mean absolute deviation values between the ‘true’ probability surface and the best and worst fit models (based on AIC value) probability surfaces for each parameter set shown faceted across the $\sigma$ values of the layers in the ‘true’ surface.
the $\beta$, the more bias and variability in the estimated results (Figure 1.7). Similarly, when $\sigma$ approaches zero, the $\sigma$ becomes harder to estimate (Figure 1.8). Smaller $\beta$ resulted in more variance and bias in the fitted estimates. When comparing the relationship between the $\beta$ bias and variance relative to the layer’s $\sigma$ values, the $\sigma$ values had less effect on the $\beta$ variance, but smaller $\beta$s produced more variance.

From the 4 representative parameter sets, we saw that parameter sets with the weakest overall $\beta$ values had larger variances in $\sigma$ estimates (Figure 1.9). For example, parameter set 1 had overall weaker $\beta$s ($\beta_0 = 1, \beta_1 = -2, \beta_2 = 1, \beta_3 = -1$) compared to parameter set 4 ($\beta_0 = 1, \beta_1 = 2, \beta_2 = -2, \beta_3 = -2$) but identical $\sigma_2$ values (20) and $\sigma_3$ values (10), and parameter set 2 had a higher variance for both $\sigma_2$ and $\sigma_3$ estimates. Overall, we saw the $\beta$ variance was relatively small, but we did see that stronger $\sigma$ values slightly increased estimate precision (Figure 1.10).

1.5 Discussion

The main objective of this investigation was to assess two model-fitting techniques for fitting globally-optimized multi-scale ecological models. Both approaches offer advantages to traditional single ‘optimal’ scale or pseudo-optimized multi-scale methods by allowing predictor scales to be simultaneously evaluated while conditioned on other scales in the model. Our results demonstrate their applicability and suggest these techniques could be extended and implemented by the broader ecological modeling community.

The two methods had identical parameter estimate results and showed the genetic algorithm’s speed gains did not reduce parameter estimate accuracy under these conditions. Additionally, the exhaustive search would become prohibitively computationally intensive as the number of layers and candidate scales increase. For example, the study by Timm et al. (2016) fit 8 covariate layers across a range of 20 sigmas, which would require 25.6 billion scale permutations and would likely take
Figure 1.7. Bias and variance for the fitted model $\sigma$ values for the landscape layers related to the parameter values used to generate the original ‘true’ probability surface faceted by the layer’s $\beta$ values.
Figure 1.8. Bias and variance for each of the fitted model $\beta$ values for the landscape layers based on the parameter values used to generate the original ‘true’ probability surface shown faceted by the layer’s $\beta$ values.
Figure 1.9. Bias and variance for each of the fitted model $\sigma$ values for the four parameter sets used to generate a ‘true’ probability surfaces and 1000 replicates of presence-absence data.
Figure 1.10. Standardized bias and variance for each of the fitted model $\beta$ values for the four parameter sets used to generate a 'true' probability surfaces and 1000 replicates of presence-absence data.
several weeks of processing time on a typical desktop computer. Additionally, the genetic algorithm approach may allow more easy integration into other optimization coding workflows for other multi-scale variables, such as temporal scales.

We understand that by eliminating process error, our results have better model-fitting results than most real ecological data. However, both methods show relatively high accuracy and reasonable levels of precision in parameter estimates across a range of simulation conditions. The bias and variance of the fitted model results show the larger the $\beta$ values, the less bias and variability seen in the parameter fits, a pattern also seen by Chandler and Hepinstall-Cymerman (2016).

As the effect of a landscape layer approaches zero, the characteristic scale becomes increasingly difficult to estimate. Future investigations could examine whether the inclusion of environmental covariates with no predictive value would affect the outcome.

Our efforts were initially motivated to inform our habitat-selection methods in Chapter 2, and we attempted to make our code as fast and efficient as possible but recognize additional optimization could enhance performance. Most of the newer multi-scale approaches were published after the initiation of the analysis provided here, and, in many cases, the R code was not available or sufficiently documented for comparison to our methods. However, we believe our approach of pre-processing and indexing the data for analysis has potential computational and speed benefits that could apply to other analyses, and future studies could compare our approach to the newer methods, particularly the BLISS method.

In the last several years, landscape ecology has also seen a rapid increase of machine learning and artificial intelligence methods combined with complex multi-step workflows (Stupariu et al. 2021). One option to extend our method is to develop a sequential process that increases precision beyond the integer-only estimates. By sequentially refining the search space from coarser to finer levels, the
parameter estimates could be estimated to the tenth or hundredth decimal place. This would require a systematic workflow that iteratively isolates narrower parameter ranges and smooths the raster matrices along smaller gradients for each optimization step.
CHAPTER 2
BALD EAGLE HOME RANGES, BEHAVIORS, AND MOVEMENTS PATTERNS IN MAINE

2.1 Background

The USFWS Eagle Conservation Plan Guidance recognizes that a variety of uncertainties exist to adequately quantify proposed wind energy sites and conduct eagle risk assessments (U.S. Fish and Wildlife Service 2013). For example, even though collision risk and fatalities are higher for residents than for migrating raptors (Marques et al. 2014), the published and unpublished literature has few site-specific studies of the spatial extents of Bald Eagle breeding territories (U.S. Fish and Wildlife Service 2013). Such ecological knowledge gaps limit the ability to model and predict Bald Eagle utilization distributions and important eagle use areas. Therefore, researchers are constrained in making detailed landscape-level analyses of the ecological effects of proposed wind energy projects on Bald Eagle populations.

The location of Bald Eagles nest sites has been studied in Maine for many decades (Livingston et al. 2007; Todd and Matula 2008), but far less is known about how individual eagles move within their territories. Animal movements depend on a combination of factors, including internal states, motion, and navigation ability (Nathan et al. 2008). Over the last few years, methods to study animal habitat use and selection have rapidly evolved and benefited from advancements in GPS telemetry. Researchers can now collect accurate point location and movement-path data for highly-vagile, wide-ranging species (Cagnacci et al. 2010). Such standardized, high-frequency data allow enhanced approaches for quantifying,
analyzing, and modeling movements at a variety of spatial and temporal scales (Krone et al. 2009; McLane et al. 2011). Studying such movements provides a better understanding of a species spatial distribution, interspecific interactions, and habitat selection (Langrock et al. 2012).

Determining the seasonal habitat requirements for a species using GPS telemetry require assessing both their movement patterns and associated behavioral states (Roberts et al. 2017; Murgatroyd et al. 2018). As an animal moves through the landscape, it makes discrete choices at each step of what space to occupy. Using GPS telemetry data, those choices can be used to model step-selection functions (McClintock and Michelot 2018). This modeling framework generally requires two components: a resource-independent movement kernel and a resource selection function (RSF). The movement kernel represents how an animal is likely to move in the landscape in the absence of other selective factors, and the RSF gives a probabilistic function to determine what habitat an animal is likely to select given their available choices. When applied to multiple behavioral states, it is possible to generate multi-state step selection functions (Nicosia et al. 2017).

This study used GPS telemetry data and nest locations from several adult Bald Eagles in Maine to assess their spatial distributions, behavioral and movement patterns, and habitat relationships. This analysis determined the environmental covariates that best predict the suitability of habitats specifically for foraging, perching, and roosting. Ultimately, this analysis provides components for the individual-based model (IBM) in Chapter 3 to model Bald Eagle territorial ranges and predict behaviors and associated movements within these areas.

2.2 Objectives

The goals of this study were to use GPS telemetry data to characterize and model the spatial distributions, behavioral sequences, and movement patterns of
territorial Bald Eagles at inland lakes and ponds in Maine. This analysis was guided by the IBM design in Chapter 3 to provide submodel components and estimate parameters for model calibration. This analysis had five specific goals: 1) measure the size and landscape composition of home ranges during the breeding season, 2) model the spatial proximity to their own and neighboring nests, 3) model behavioral states during the breeding season, 4) use behavioral state data to fit movement kernels for each step type, and 5) model each step type with a resource selection function.

2.3 Methods

2.3.1 Data Collection

We deployed GPS-telemetry transmitters (Model CTT-1100, 100 g, solar-powered GPS-GSM units, manufactured by Cellular Tracking Technologies, Inc.) on seventeen adult Bald Eagles from 2013 to 2015 in Maine (Figure 2.1). Trapping sites at inland lake sites were selected based on nest location records for the entire state as provided by the Maine Department of Inland Fisheries and Wildlife (MDIFW). These data were used to select and confirm active nest sites based on their utility for the study and finalized through consultations with MDIFW. At these inland lake sites, nests are generally associated with super-dominant trees and negatively associated with distance to the lake shore, areas of timber harvest, and overall anthropogenic disturbance (Livingston et al. 2007). Initial efforts to deploy transmitters in the fall of 2013 and winter of 2014 resulted in two transmitters being deployed close to the Rollins wind energy facility and one transmitter being deployed adjacent to the Bull Hill facility in Penobscot County near the town of Lincoln. The primary eagle trapping efforts occurred in the summer of 2015 when fifteen transmitters were deployed across the state. We caught the eagles using floating fish snares (Jackman et al. 1993) at inland lakes and
ponds, we collected small blood samples (≈ 2 cc) to conduct DNA sex tests. All Bald Eagles were handled in accordance with the University of Massachusetts Amherst Animal Care and Use Protocol 2012-0068 and USGS Bird Banding Lab Permit 23140.

The telemetry units (<3% of body weight, per BBL standards) collected data on location (WGS84, ±18 m), elevation above sea level (±22 m), speed (±1 kts), and flight direction (±1°) and was transmitted over the Global System for Mobile Communications (GSM) network to data servers (Lanzone et al. 2012). The transmitters were programmed to determine their geographic position and adjust their duty cycle to record data every 15 minutes from one hour before sunrise to one hour after sunset. We filtered out poor-quality GPS positional data (i.e., 2D fixes or altitude above ground level of ≤0 m) which accounted for <1% of our overall data (>300,000 GPS locations). All genetic tests were conducted at Buffalo State University by Dr. Amy McMillan. We performed all GIS operations, data analysis, and model-fitting procedures in R (R Core Team 2022).

2.3.2 Home Range Estimates

We used the GPS telemetry data to delineate and characterize eagle home ranges during the territorial breeding season (15 March to 15 August). Home range analysis methods that use traditional kernel density estimators methods rely on an assumption of independent and identically distributed data. However, such assumptions are often violated by the increasingly fine-scale temporal resolution of new GPS telemetry data streams and can lead to significantly underestimated home range estimates (Fleming et al. 2015). To account for these autocorrelation problems, we used autocorrelated kernel density estimators (AKDE), which is ideally-suited for high temporal resolution data (Calabrese et al. 2016). This method is incorporated into the ctmm package for R. We calculated ‘total’ and
Figure 2.1. Distribution of Bald Eagle trapping sites (orange circles) used in 2013–2015 in Maine. Names are based on the associated water body and used for eagle identification. One individual was trapped per site, except at Onawa and Crooked where two individuals were trapped in different years.
‘core’ home ranges, using 95% and 50% isopleths of the utilization distributions, respectively, for each individual during the breeding season in order to estimate eagle territory size, and, subsequently, the proportion of vegetation classes, and open water within each territory. Additionally, we summarized the terrain ruggedness index, the terrain position index, and roughness topographic characteristics for the study population. For individuals with multiple years of data, we calculated mean values for each metric.

2.3.3 Territoriality

To assess for conspecific territoriality, we calculated how eagle locations are spatially related to their own and neighboring nests. This analysis was restricted to telemetry data recorded when field observations confirmed concurrent occupancy of neighboring nests. To account for eagles’ tendency to remain near their nests and avoid conspecific nests, we calculated two separate raster layers. First, for each study eagle (i.e., eagles with the GPS units), we calculated a raster layer with distance from their own nest. Second, within each of the study eagles’ territories, we calculated the distance from all the conspecific nests to all cells of a raster buffered 30 km around the study nest using the ‘distanceFromPoints’ function in the raster package (Hijmans 2022). For each territory, we calculated the conspecific distance value at the study nest, and we subtracted this value to the entire conspecific distance raster layer so the value would be zero at the study nest. We then added together these two raster layers to generate a new territorial distance metric raster. This metric is scaled to be zero at the individual’s home nest and increases linearly as the individual moves away from their home nest or closer to neighboring nests. This procedure accounts for the unique spatial arrangement of each nest in the study area and was calculated at each of the territories using the GPS locations of each study eagle.
Territorial distance metric values were calculated at four nests where we had sufficient GPS telemetry and nest occupancy data in 2016 to calculate the eagle locations relative to their own nest location and conspecific nest locations (Figure 2.6). By using a combined metric for both proximity to own nest and distance from other nests, we were able to fit all of the locations with a single metric (Figure 2.7). We fit the models using five statistical distributions: Exponential, Gamma, Half Normal, Pareto, and Weibull (Table 2.4), and the Gamma distribution was the best fit based on AIC.

2.3.4 Behavioral Classification and Modeling

Due to our objectives for developing an IBM in Chapter 3, we limited our behavioral classification and modeling analysis to territorial locations collected during the breeding season. During this period, eagles are central-place foragers; thus, behaviors are easily classified, and model predictions can be better compared to field observations. Data for the behavioral analysis were based on telemetry data from the breeding season with territorial behavior identified by activity centered around a discrete area on a pond or lake. The behavioral state of each GPS location was determined based on speed, above-ground level height, distance to nest, overnight roost location, and diurnal time period. Telemetry data were classified into five behavioral states: 1) cruise during high altitude flight suggestive of thermal soaring (defined by locations ≥ 200 m above ground level and a minimum speed of 5 knots); 2) flight when flying at low to mid-level altitudes with a potential of interacting with the habitat below (defined by locations ≤ 200 m above ground level with a minimum speed of 5 knots); 3) nest when at or attending the nest (defined by locations within 75 m of the nest); 4) perch occurred when there little change in altitude or horizontal location (defined by locations with speed ≤ 5 knots and step lengths of < 50 m); and 5) roost for overnight perch locations, defined by locations
within 75 m of the individual’s overnight perching site. We visually assessed these behavioral classifications with the GPS location to confirm that our categorization sufficiently classified these behavioral states.

Our behavioral state modeling was performed in a Markov-type framework that models state transitions based on observations and extrinsic and intrinsic covariates (Langrock et al. 2012). We used the momentuHMM package, which is specifically designed for the analysis of wildlife movement data and allows the assignment of observation data to behavior categories to fit a transition probability model (McClintock et al. 2012), and we included covariates of diurnal period and Julian date. Diurnal period was represented as an hour before sunrise to an hour after sunset and standardized from 0 to 1. Julian date was included to account for changes in behavior through the breeding season. Due to our small sample size, we combined males and females in the behavioral modeling analysis.

### 2.3.5 Movement Kernels

After classifying the location data into behavioral states, we quantified movement kernels for each step type. All animal movements are constrained by movement capacity (Nathan et al. 2008), and movement kernels are parametric functions that describe the probability that an animal will move a certain distance and direction, based on an individual’s current location and trajectory in the absence of other selection factors (Forester et al. 2009). If the animal being investigated has distinct behavioral states, movement kernels can be assessed for each of these states (Nicosia et al. 2017). We used the behavior-classified telemetry data to calculate the distance and angle traveled between subsequent locations for each of the step types (e.g., nest-to-flight, flight-to-perch, etc.) to derive parametric movement kernels for each step type. We fit the empirical movement data for each step type using Weibull distributions for the distance component. The Weibull
distribution has an inherently flexible shape and has been used to successfully approximate distribution of distance moved in animal movement studies (Morales et al. 2004). For step types with a directional tendency (i.e., started with flight or cruise behavior), we calculated a mixed von Mises distribution that allows for an elliptical shape for the angle component. Due to the small sample size, data for males and females were combined for all movement kernels and multi-state resource selection functions.

2.3.6 Multi-State Resource Selection Functions

Our final analysis used the behavioral data to generate multi-state step selection functions (Nicosia et al. 2017). For each of the behavioral categories, we conducted a habitat selection analysis using a conditional (a.k.a., case-controlled) logistic regression function (Fortin et al. 2005). Conditional logistic regressions require data with paired ‘available’ and ‘used’ point locations. To define ‘available’ locations, we followed Zeller et al. (2014) and used a distance-weighted kernel around each step start point location to measure covariate layers. To define ‘used’, we used the step end point locations and their corresponding landscape covariate metrics. Due to the high directional bias in some of the movement data (e.g., steps involving cruise or flight), we accounted for both distance and trajectory by using the step-type movement kernels calculated in Section 2.3.5.

Habitat covariates were based on GIS data layers gathered from the USGS, USFWS, US Forest Service, UMass Designing Sustainable Landscapes (DSL) project, and Maine Office of GIS (Table 2.1). Landscape metrics included topographic, anthropogenic, and ecological features, and were calculated as neighborhood metrics or straight-line distances (e.g., distance to water bodies). For distance to turbines, we limited the distance values to 20 km because of their limited distribution on the landscape and to better represent any effect of avoidance. To
characterize the spatial scale for the appropriate habitat covariates, we used the procedures developed in Chapter 1 to calculate each covariate at a range of spatial scales using Gaussian kernels. The covariates were assessed at sigma values of 0-100, corresponding to Gaussian kernel bandwidths of 0 to 3000 m at 30 m intervals.

The resource selection models were evaluated in step-type groups based on the starting behavior being in the air (i.e., flight or cruise) or stationary (i.e., nest, perch, or roost) and the end state of the step type (i.e., cruise, perch, flight, or roost), for a total of eight step-type groups. For each step-type group, we selected a set of candidate covariates and generated a full model (i.e., with all the covariates) and all reduced models (i.e., all possible subsets of covariates), and used these models to fit habitat selection functions in a conditional logistic framework. For each step, we calculated their start and end location and used the step-type movement kernel to determine the used vs. available habitat across all the spatial scales. All models were fit using the genetic-algorithm scale search and optimization procedure outlined in Chapter 1 to determine the optimal multi-scale solution. The candidate models were evaluated using AIC, and the models with the lowest values were retained. In cases where the best model produced flat surfaces or was not ecologically intuitive, we reduced the candidate covariate set and reran the procedure. The final set of models are resource selection functions for each of the step types and represent a set of probabilistic rules where an eagle’s choice at a given step is dependent on their behavior and the specific options in their environment at that location.

2.4 Results

For the analysis, we selected individuals with GPS location data that demonstrated territorial behavior. We confirmed from visual inspection of the data the eagle remained around individual or adjacent water bodies for an extended time
Table 2.1. Summary table of landscape metrics used as covariate candidates for the Bald Eagle resource selection function models. Sources are the University of Massachusetts - Designing Sustainable Landscapes (DSL) Project (McGarigal et al. 2017); USGS - The National Map (U.S. Geological Survey 2017b); USGS - U.S. Wind Turbine Database (Hoen et al. 2018); and National Renewable Energy Laboratory (National Renewable Energy Laboratory and AWS TruePower 2009).

<table>
<thead>
<tr>
<th>Class</th>
<th>Covariate</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landcover</td>
<td>Developed</td>
<td>Development class</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Landcover</td>
<td>Distance to Developed</td>
<td>Distance to developed class</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Landcover</td>
<td>Forest</td>
<td>Aggregated forest classes</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Landcover</td>
<td>Pasture</td>
<td>Aggregated pasture classes</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Landcover</td>
<td>Wetland</td>
<td>Aggregated wetland classes</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Landcover</td>
<td>Herb/Shrub</td>
<td>Aggregated herbaceous / shrubland classes</td>
<td>UMass - DSL</td>
</tr>
<tr>
<td>Hydrology</td>
<td>Distance to Water</td>
<td>Distance to waterbody / water area</td>
<td>USGS - National Hydrography Dataset</td>
</tr>
<tr>
<td>Wind</td>
<td>Turbines</td>
<td>Distance to wind turbines</td>
<td>USGS - United States Wind Turbine Database</td>
</tr>
<tr>
<td>Wind Resource</td>
<td>Wind Class</td>
<td>Wind class at 50 m hub height</td>
<td>NREL</td>
</tr>
<tr>
<td>Topographic</td>
<td>Elevation</td>
<td>DEM elevation</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Slope</td>
<td>DEM slope (degrees)</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Eastness</td>
<td>Eastness (radians)</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Northness</td>
<td>Northness (radians)</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Roughness</td>
<td>Difference between the maximum and minimum value of a cell and its surrounding cells</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Topographic Position Index</td>
<td>Difference between the value of a cell and the mean value of its surrounding cells</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
<tr>
<td>Topographic</td>
<td>Terrain Ruggedness Index</td>
<td>Mean of the absolute differences between the value of a cell and the value of its surrounding cells</td>
<td>USGS - NED 1/3 Arc Second</td>
</tr>
</tbody>
</table>
and returned to that area to roost. This criterion was met by twelve individuals, including seven individuals with two or more years of data (Table 2.2). Maps of the data used for the analysis are in Appendix B.

**Table 2.2.** Bald Eagle trapping information and territorial data date ranges for sites in Maine. Individuals with date ranges for territorial years had data in each year.

<table>
<thead>
<tr>
<th>Bird ID</th>
<th>Trap Site</th>
<th>County</th>
<th>Trap Date</th>
<th>Sex</th>
<th>Territorial Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Folsom</td>
<td>Folsom Pond</td>
<td>Penobscot</td>
<td>2013-09-22</td>
<td>Unknown</td>
<td></td>
</tr>
<tr>
<td>Madagascal</td>
<td>Madagascal Pond</td>
<td>Penobscot</td>
<td>2013-11-09</td>
<td>Female</td>
<td></td>
</tr>
<tr>
<td>Norway</td>
<td>Norway Lake</td>
<td>Oxford</td>
<td>2015-05-13</td>
<td>Male</td>
<td>2015</td>
</tr>
<tr>
<td>Phillips</td>
<td>Phillips Lake</td>
<td>Hancock</td>
<td>2015-05-19</td>
<td>Female</td>
<td>2015</td>
</tr>
<tr>
<td>Musquash</td>
<td>East Musquash Lake</td>
<td>Washington</td>
<td>2015-06-03</td>
<td>Female</td>
<td>2015 – 2018</td>
</tr>
<tr>
<td>Eskutassiss</td>
<td>Eskutassiss Pond</td>
<td>Penobscot</td>
<td>2015-06-03</td>
<td>Female</td>
<td>2015, 2016</td>
</tr>
<tr>
<td>Three</td>
<td>Number Three Pond</td>
<td>Penobscot</td>
<td>2015-06-04</td>
<td>Female</td>
<td>2015</td>
</tr>
<tr>
<td>Ellis</td>
<td>Ellis Pond</td>
<td>Oxford</td>
<td>2015-06-08</td>
<td>Female</td>
<td>2015 – 2017</td>
</tr>
<tr>
<td>Sheepscot</td>
<td>Sheepscot Pond</td>
<td>Waldo</td>
<td>2015-06-19</td>
<td>Female</td>
<td>2015</td>
</tr>
<tr>
<td>Sandy</td>
<td>Sandy Pond</td>
<td>Waldo</td>
<td>2015-06-18</td>
<td>Female</td>
<td>2015 – 2019</td>
</tr>
<tr>
<td>Crooked</td>
<td>Mattanawcook Pond</td>
<td>Penobscot</td>
<td>2015-06-22</td>
<td>Female</td>
<td>2015</td>
</tr>
<tr>
<td>Webb</td>
<td>Webb Pond</td>
<td>Hancock</td>
<td>2015-07-08</td>
<td>Female</td>
<td></td>
</tr>
<tr>
<td>Davis</td>
<td>Lake Onawa</td>
<td>Piscataquis</td>
<td>2015-07-17</td>
<td>Unknown</td>
<td></td>
</tr>
<tr>
<td>Hebron</td>
<td>Lake Hebron</td>
<td>Piscataquis</td>
<td>2015-07-20</td>
<td>Female</td>
<td>2015, 2016</td>
</tr>
<tr>
<td>Branch</td>
<td>Branch Lake</td>
<td>Hancock</td>
<td>2015-07-21</td>
<td>Male</td>
<td>2015, 2016</td>
</tr>
<tr>
<td>Onawa</td>
<td>Lake Onawa</td>
<td>Piscataquis</td>
<td>2015-09-13</td>
<td>Female</td>
<td></td>
</tr>
</tbody>
</table>

The eagle captured at Webb Lake made two round-trip migrations to the state of Florida during the study (Figure 2.2). This flight was consistent with other long-range migrations of eagles (Mojica et al. 2008). The eagle overwintered primarily between Orlando and Daytona Beach in Florida for both the 2015/16 and 2016/17 winter seasons (Figure 2.3).
Figure 2.2. Summer and wintering grounds and migration flight paths for the female Bald Eagle trapped at Webb Lake. These maps represent the 2015–2016 and 2016–2017 annual migrations and areas the eagle spent time during those two years. The eagle was trapped at Webb Pond, Hancock County, ME on July 8, 2015. The eagle started its southern migration on September 3, 2015, and arrived at the wintering grounds in Florida on October 18, 2015. It started the northern migration on April 6, 2016, and arrived back in Maine on May 8, 2016. It started its 2016 southern migration on August 20, 2016 and arrived in Florida on October 18, 2016. It started its northern migration on April 16, 2017 and arrived in Maine on May 14, 2017. The last GPS position was recorded on August 19, 2017.
Figure 2.3. Migration flight paths and wintering grounds in Florida of the female Bald Eagle trapped at Webb Lake, ME. These maps represent the 2015-2016 and 2016-2017 annual migrations and areas that the eagle spent time in Florida during those two seasons. The eagle arrived in the Orlando area of Florida on October 18, 2015 and started the northern migration on April 6, 2016. The following year, the eagle arrived in Florida on October 18, 2016 and started its northern migration on April 16, 2017. In both years, the eagle spent the most time in the area between Orlando and Daytona Beach.
2.4.1 Home Range Estimates

For individuals with territorial behavior, we removed portions of the data when individuals were away from their home territory for more than a day. Notably, the Musquash female made several overnight or two-night trips approximately 50 km east from her nest to a solid waste facility near Lawrence Station, New Brunswick, Canada. These trips were consistent and direct enough to indicate that visiting this site was intentional and is consistent with other studies that show Bald Eagles may routinely scavenge at landfills (Buehler 2000; DeSorbo et al. 2015). However, this behavior differed from foraging patterns in areas without artificial attractions that we were seeking to model, and, therefore, were excluded from the analysis.

We estimated the mean size for the total and core utilization distributions were 33.08 km$^2$ (16.3 – 49.8, 95% CI) and 3.64 km$^2$ (1.72 – 5.56, 95% CI), respectively (Table 2.3). The mean values for the water body areas within the total home range and core area as 4.45 km$^2$ (3.23 - 5.68, 95% CI) and 1.50 km$^2$ (1.09 - 1.90, 95% CI), respectively.

The home range results showed that the 50% and 95% utilization distribution sizes were not correlated to the number of GPS locations across years for the same individual (ANCOVA; $F(1, 11) = 0.301$, $p = 0.59$ and $F(1, 11) = 0.548$, $p = 0.48$, respectively). For individuals with multiple years of data, we used the mean values for both the number of locations and the proportion of cover type (Figure 2.4). The terrain ruggedness index, terrain position index, and roughness indexes were all lower in the core compared to total utilization distributions and are attributable to the eagles using relatively flat terrain around their nest and associated body of water compared to the uplands and ridgelines within their overall territory.

The eagles’ home ranges primarily consisted of open water and forested habitat, although the open water proportion dropped significantly and forest habitat increased between the core and total areas (Figure 2.5). Wetlands were present at
Table 2.3. Bald Eagle GPS telemetry data and utilization distribution area sizes and water body area for territorial sites in Maine. The 95% and 50% isopleths from the utilization distributions represent the ‘total’ and ‘core’ home ranges, respectively, from breeding season GPS locations.

<table>
<thead>
<tr>
<th>Eagle ID</th>
<th>Year</th>
<th>GPS Points (n)</th>
<th>95% UD Area (km²)</th>
<th>50% UD Area (km²)</th>
<th>50% UD Water-body Area (km²)</th>
<th>95% UD Water-body Area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch</td>
<td>2015</td>
<td>1637</td>
<td>23.23</td>
<td>4.52</td>
<td>11.91</td>
<td>12.53</td>
</tr>
<tr>
<td>Branch</td>
<td>2016</td>
<td>2946</td>
<td>55.03</td>
<td>5.81</td>
<td>11.91</td>
<td>12.67</td>
</tr>
<tr>
<td>Crooked</td>
<td>2015</td>
<td>879</td>
<td>16.04</td>
<td>2.94</td>
<td>5.89</td>
<td>8.85</td>
</tr>
<tr>
<td>Ellis</td>
<td>2015</td>
<td>2897</td>
<td>3.57</td>
<td>0.66</td>
<td>3.72</td>
<td>3.72</td>
</tr>
<tr>
<td>Ellis</td>
<td>2016</td>
<td>10311</td>
<td>6.83</td>
<td>0.45</td>
<td>3.72</td>
<td>3.73</td>
</tr>
<tr>
<td>Ellis</td>
<td>2017</td>
<td>2260</td>
<td>32.70</td>
<td>1.53</td>
<td>3.72</td>
<td>3.93</td>
</tr>
<tr>
<td>Eskutassis</td>
<td>2015</td>
<td>1943</td>
<td>191.11</td>
<td>23.04</td>
<td>4.23</td>
<td>25.86</td>
</tr>
<tr>
<td>Eskutassis</td>
<td>2016</td>
<td>556</td>
<td>103.83</td>
<td>7.75</td>
<td>3.58</td>
<td>7.47</td>
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<tr>
<td>Hebron</td>
<td>2015</td>
<td>676</td>
<td>22.83</td>
<td>5.50</td>
<td>2.79</td>
<td>4.24</td>
</tr>
<tr>
<td>Hebron</td>
<td>2016</td>
<td>4159</td>
<td>44.05</td>
<td>4.03</td>
<td>2.79</td>
<td>4.42</td>
</tr>
<tr>
<td>Musquash</td>
<td>2015</td>
<td>2382</td>
<td>12.15</td>
<td>1.78</td>
<td>3.31</td>
<td>4.47</td>
</tr>
<tr>
<td>Musquash</td>
<td>2016</td>
<td>6717</td>
<td>27.70</td>
<td>3.20</td>
<td>3.36</td>
<td>4.57</td>
</tr>
<tr>
<td>Musquash</td>
<td>2017</td>
<td>5309</td>
<td>26.96</td>
<td>3.43</td>
<td>3.36</td>
<td>4.56</td>
</tr>
<tr>
<td>Musquash</td>
<td>2018</td>
<td>8346</td>
<td>46.30</td>
<td>5.60</td>
<td>3.36</td>
<td>4.58</td>
</tr>
<tr>
<td>Norway</td>
<td>2015</td>
<td>6168</td>
<td>24.15</td>
<td>3.17</td>
<td>4.63</td>
<td>5.16</td>
</tr>
<tr>
<td>Phillips</td>
<td>2015</td>
<td>1581</td>
<td>7.09</td>
<td>0.63</td>
<td>3.48</td>
<td>6.45</td>
</tr>
<tr>
<td>Sandy</td>
<td>2015</td>
<td>2910</td>
<td>19.39</td>
<td>1.74</td>
<td>1.70</td>
<td>1.78</td>
</tr>
<tr>
<td>Sandy</td>
<td>2016</td>
<td>6144</td>
<td>15.08</td>
<td>1.31</td>
<td>1.70</td>
<td>1.75</td>
</tr>
<tr>
<td>Sandy</td>
<td>2017</td>
<td>3789</td>
<td>20.83</td>
<td>1.33</td>
<td>1.70</td>
<td>1.76</td>
</tr>
<tr>
<td>Sandy</td>
<td>2018</td>
<td>4333</td>
<td>32.50</td>
<td>2.37</td>
<td>1.70</td>
<td>1.77</td>
</tr>
<tr>
<td>Sandy</td>
<td>2019</td>
<td>4067</td>
<td>30.05</td>
<td>1.78</td>
<td>1.70</td>
<td>1.77</td>
</tr>
<tr>
<td>Sheepscot</td>
<td>2015</td>
<td>2356</td>
<td>13.54</td>
<td>1.69</td>
<td>1.29</td>
<td>6.25</td>
</tr>
<tr>
<td>Three</td>
<td>2015</td>
<td>3051</td>
<td>4.62</td>
<td>0.82</td>
<td>2.60</td>
<td>2.60</td>
</tr>
<tr>
<td>Wilson</td>
<td>2015</td>
<td>3289</td>
<td>14.21</td>
<td>2.39</td>
<td>9.73</td>
<td>9.74</td>
</tr>
</tbody>
</table>
Figure 2.4. Home range size and proportion of cover types within the 50% and 95% isopleths (representing the ‘core’ and ‘total’ home ranges, respectively) of utilization distributions of twelve territorial Bald Eagles in Maine.
low proportions in both core and total areas, while pasture and shrubland/herbaceous habitats were minimally represented. Developed areas were present in both but proportionally less present in the core home range areas.

**Figure 2.5.** Proportion of landcover types within the 50% and 95% isopleths (representing the ‘core’ and ‘total’ home ranges, respectively) of utilization distributions of twelve territorial Bald Eagles in Maine.

### 2.4.2 Territoriality

The results of the territorial distance metric showed the majority of eagle locations were very close to their own nest and decreased precipitously at locations farther from their own nest or closer to conspecific nests (Figure 2.7). The Gamma
distribution was the best fit probability distribution for the territorial distance metric based on AIC (Table 2.4).

Figure 2.6. Map showing the conspecific and home nest distance metric used to determine territoriality. This metric combines the distance away from their home nest and increases as they approach conspecific nests. Values start at zero at the home nest and increase linearly as they move away from their nest (orange circles) and get closer to neighboring nests (cross symbols).

2.4.3 Behavioral Classification and Modeling

Males and females spent most of their time nesting or perching (Figure 2.8). As expected, the females spent more time at the nest (39.3%) compared to the males (12.8%). Both the male and female cruise behavior were restricted to the middle of the day when the solar conditions are most conducive to thermal updrafts.
Figure 2.7. Histogram of Bald Eagle conspecific and home nest distances. Candidate probability distributions were fitted using maximum likelihood estimation and are overlaid on the empirical data. Among the candidate distributions, the Gamma distribution was selected as the best fit based on having the lowest AIC value.

Table 2.4. Probability distribution fits assessed for the territorial distance metric, a combination of distance from the home nest and proximity to conspecific nests, of Bald Eagles in Maine. The Gamma distribution had the lowest AIC value and was used for our model.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>LogLik</th>
<th>AIC</th>
<th>BIC</th>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma</td>
<td>-9693</td>
<td>19389</td>
<td>19403</td>
<td>Shape</td>
<td>0.421</td>
<td>0.0054</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Rate</td>
<td>0.236</td>
<td>0.0051</td>
</tr>
<tr>
<td>Weibull</td>
<td>-9737</td>
<td>19478</td>
<td>19492</td>
<td>Shape</td>
<td>0.553</td>
<td>0.0050</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Scale</td>
<td>1.112</td>
<td>0.0236</td>
</tr>
<tr>
<td>Pareto</td>
<td>-11108</td>
<td>22219</td>
<td>22233</td>
<td>Scale</td>
<td>0.427</td>
<td>0.0162</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Shape</td>
<td>1.240</td>
<td>0.0388</td>
</tr>
<tr>
<td>Exponential</td>
<td>-12636</td>
<td>25274</td>
<td>25280</td>
<td>Rate</td>
<td>0.560</td>
<td>0.0063</td>
</tr>
<tr>
<td>Half Normal</td>
<td>-16303</td>
<td>32607</td>
<td>32614</td>
<td>Sigma</td>
<td>3.714</td>
<td>0.0294</td>
</tr>
</tbody>
</table>
Figure 2.8. Proportion of diurnal Bald Eagle behavior for each sex during the breeding period based on a preliminary analysis of GPS telemetry data from Maine. Behavioral states are classified based on telemetry metrics (e.g., time, speed, altitude, etc.) and GIS data layers (e.g., nests, elevation, etc.).
The transition probabilities conditioned on the diurnal period showed expected behavioral patterns. Eagles typically left their roost to perch at another location in the morning (Figure 2.9). Around solar noon, cruise and flight peaked and there was a corresponding decrease in perching behavior. Nest behavior was relatively consistent with only a slight decline in the late morning. Transitions to roost behavior increased towards the end of the day. The transition probabilities conditioned on date show a decrease in transitions to cruise, flight, and nesting behaviors later in the breeding season (Figure 2.10).

2.4.4 Movement Kernels

Step types starting or ending with cruise behavior had the overall longest mean and maximum step lengths (Table 2.5), indicating we accurately classified that behavioral state. Step types including flight behavior had overall longer steps than stationary-to-stationary steps and steps that included roost behavior generally had the shortest step lengths. The fitted step-length probability distributions (Figure 2.11) showed step types that ended in cruise or flight behavior had unimodal probability distributions and the remainder had monotonically decaying shapes. For perch-to-perch step types, the eagles moved location 26% of the time.

For step types with a directional tendency (Figure 2.12), the steps that started with cruise had the strongest unidirectional angle component, but, interestingly, for cruise-to-flight and cruise-to-perch steps, the angle was in the opposite direction of the previous step. This suggests as eagles transition from cruise to other behaviors, they may be losing altitude to turn back towards their nest or territory or to get closer to something of interest. The cruise-to-cruise steps had a slight angle to the left and may be accounted for by circling upwards in thermals (Murgatroyd et al. 2018). The flight-to-flight steps had the least directional tendency, reflective of a
Figure 2.9. The probability of behavioral state changes of diurnal Bald Eagle behavior during the breeding period based on an analysis of GPS telemetry data from Maine. The date covariate is held at June 02 (median value). Behavioral states were classified based on telemetry metrics and GIS datalayers. Time is represented as the period from an hour before sunrise to an hour after sunset and standardized from 0 to 1.
Figure 2.10. The probability of behavioral state changes of diurnal Bald Eagle behavior during the breeding period dependent on Julian date. The time (daily proportion) covariate is held at 0.50 (median value). Behavioral states were classified based on telemetry metrics and GIS data layers.
Table 2.5. Step lengths and movement kernel parameter estimates for the step types of Bald Eagles in Maine. All step types that had a directional tendency (i.e., started with cruise or flight behavioral states) were fitted mixed von Mises distributions.

<table>
<thead>
<tr>
<th>Movement Step Type</th>
<th>Step Length (m)</th>
<th>Weibull</th>
<th>Mixed Von Mises</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
<td>Max</td>
</tr>
<tr>
<td>Cruise → Cruise</td>
<td>144</td>
<td>4324</td>
<td>14806</td>
</tr>
<tr>
<td>Cruise → Flight</td>
<td>88</td>
<td>4257</td>
<td>13851</td>
</tr>
<tr>
<td>Cruise → Perch</td>
<td>54</td>
<td>2706</td>
<td>11022</td>
</tr>
<tr>
<td>Flight → Cruise</td>
<td>86</td>
<td>3415</td>
<td>14529</td>
</tr>
<tr>
<td>Flight → Flight</td>
<td>42</td>
<td>3022</td>
<td>11376</td>
</tr>
<tr>
<td>Flight → Perch</td>
<td>43</td>
<td>1270</td>
<td>10160</td>
</tr>
<tr>
<td>Flight → Roost</td>
<td>43</td>
<td>617</td>
<td>2180</td>
</tr>
<tr>
<td>Nest → Cruise</td>
<td>107</td>
<td>1850</td>
<td>5006</td>
</tr>
<tr>
<td>Nest → Flight</td>
<td>61</td>
<td>1329</td>
<td>7123</td>
</tr>
<tr>
<td>Nest → Perch</td>
<td>43</td>
<td>650</td>
<td>6634</td>
</tr>
<tr>
<td>Nest → Roost</td>
<td>57</td>
<td>460</td>
<td>1871</td>
</tr>
<tr>
<td>Perch → Cruise</td>
<td>60</td>
<td>1919</td>
<td>7251</td>
</tr>
<tr>
<td>Perch → Flight</td>
<td>42</td>
<td>1280</td>
<td>9393</td>
</tr>
<tr>
<td>Perch → Perch</td>
<td>42</td>
<td>648</td>
<td>7110</td>
</tr>
<tr>
<td>Perch → Roost</td>
<td>43</td>
<td>427</td>
<td>3046</td>
</tr>
<tr>
<td>Roost → Flight</td>
<td>49</td>
<td>758</td>
<td>2748</td>
</tr>
<tr>
<td>Roost → Perch</td>
<td>45</td>
<td>660</td>
<td>3590</td>
</tr>
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</table>
Figure 2.11. The fitted Weibull distributions (orange lines) for the step types of Bald Eagles in Maine. There was insufficient data to model roost-to-cruise and cruise-to-roost step types.
meandering search behavior. We multiplied the distance and angle distributions to generate the movement kernels for all step types (Figure 2.13).

**Figure 2.12.** The fitted mixed von Mises distributions (orange lines) for the step types that had a directional tendency of Bald Eagles in Maine. Step types that started in a stationary behavior (i.e., perch, nest, and roost) did not have a directional tendency. This graph depicts the directional values on the Unit Circle, where 0 (radians) represents moving in the same direction and \( \pi \) is a step in the opposite direction of the previous step.

### 2.4.5 Multi-State Resource Selection Functions

The top ten models for each step type are in Appendix C. For conditional logistic regression models, a popular measure of goodness-of-fit is the concordance statistic (Therneau and Atkinson 2020). A concordance value of 0.5 indicates the model has no predictive ability and a value of 1 indicates perfect prediction of the outcome (Harrell et al. 1996). All of our best-fit resource selection models had a concordance value of > .71 and the majority were > .85. The best-fit resource selection models are presented in Tables 2.6 - 2.13. Each of these models had the
Figure 2.13. The movement kernels based on the fitted Weibull and mixed von Mises distributions for the step types of Bald Eagles in Maine. There was insufficient data to model roost-to-cruise and cruise-to-roost step types. Roost-to-roost steps do not occur because roost locations were always the last location of the day.
lowest AICc value of the candidate models. Wald’s Test values are the Z statistic and indicate how many standard deviations the estimated coefficients are away from 0 on a standard normal curve, and their p-values represent their statistically significant difference from zero.

**Table 2.6.** Resource selection model terms and metrics for step types with air (flight or cruise) to cruise behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cruise → Cruise</td>
<td>Tpi7</td>
<td>-0.0384</td>
<td>0.96</td>
<td>0.02</td>
<td>-1.9</td>
<td>0.06</td>
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<tr>
<td></td>
<td>Wetland100</td>
<td>11.2</td>
<td>7.3e+04</td>
<td>2.4</td>
<td>4.7</td>
<td>2.8e-06</td>
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<tr>
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<td>DistHydro</td>
<td>-0.00176</td>
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<td>0.00018</td>
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<td>0</td>
</tr>
<tr>
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<td>DistTurbine</td>
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<td>3.3e-05</td>
<td>8.8</td>
<td>0</td>
</tr>
<tr>
<td>Flight → Cruise</td>
<td>Tpi23</td>
<td>-0.0129</td>
<td>0.99</td>
<td>0.0076</td>
<td>-1.7</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>Wetland2</td>
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<td>0.41</td>
<td>0.52</td>
<td>-1.7</td>
<td>0.093</td>
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<td>0.00023</td>
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<td>1.8e-11</td>
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</table>

For the air-to-air steps, the models showed a general negative relationship with distance to hydrological features and a negative relationship with topographic positions index, as eagles may prefer thermal soaring over flat topography (Murgatroyd et al. 2018). For air-to-perch steps, eagles selected areas with a high percentage of open water with nearby wetlands and perches near open water. There was a negative relationship with nearby forested habitat, but this may be a result of the eagles preferring locations with a high percentage of water in immediate proximity of the perch site, such as spits or peninsulas, compared to sites with more limited water visibility.
Table 2.7. Resource selection model terms and metrics for step types with air (flight or cruise) to flight behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cruise → Flight</td>
<td>Roughness3</td>
<td>0.0287</td>
<td>1</td>
<td>0.0085</td>
<td>3.4</td>
<td>0.00073</td>
</tr>
<tr>
<td></td>
<td>DistHydro</td>
<td>-0.00248</td>
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<td>0</td>
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<tr>
<td></td>
<td>DistTurbine</td>
<td>0.000202</td>
<td>1</td>
<td>4.6e-05</td>
<td>4.4</td>
<td>1.1e-05</td>
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<tr>
<td>Flight → Flight</td>
<td>Eastness10</td>
<td>-1.12</td>
<td>0.33</td>
<td>0.37</td>
<td>-3.1</td>
<td>0.0022</td>
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<td></td>
<td>Roughness50</td>
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<td>0.0012</td>
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<td>0.0003</td>
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<td></td>
<td>DistTurbine</td>
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<td>7.1e-05</td>
<td>5.7</td>
<td>1.3e-08</td>
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</table>

Table 2.8. Resource selection model terms and metrics for step types with air (flight or cruise) to perch behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
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<tr>
<td>Cruise → Perch</td>
<td>Forest3</td>
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<td>0.26</td>
<td>0.84</td>
<td>-1.6</td>
<td>0.11</td>
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<tr>
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<td>OpenWater6</td>
<td>3.82</td>
<td>46</td>
<td>1.4</td>
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<td></td>
<td>ShrubHerb1</td>
<td>-3.08</td>
<td>0.046</td>
<td>2.2</td>
<td>-1.4</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>Wetland1</td>
<td>1.95</td>
<td>7</td>
<td>0.85</td>
<td>2.3</td>
<td>0.021</td>
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<tr>
<td></td>
<td>Tri5</td>
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<td>8.9e-05</td>
</tr>
<tr>
<td></td>
<td>DistHydro</td>
<td>-0.00345</td>
<td>1</td>
<td>0.00056</td>
<td>-6.1</td>
<td>9.7e-10</td>
</tr>
<tr>
<td>Flight → Perch</td>
<td>Forest10</td>
<td>-2</td>
<td>0.14</td>
<td>1.1</td>
<td>-1.9</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>OpenWater6</td>
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<td>96</td>
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<td>4.3</td>
<td>2.1e-05</td>
</tr>
<tr>
<td></td>
<td>ShrubHerb1</td>
<td>1.55</td>
<td>4.7</td>
<td>1.1</td>
<td>1.4</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Wetland1</td>
<td>1.73</td>
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<td>0.62</td>
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<tr>
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</table>
### Table 2.9. Resource selection model terms and metrics for step types with air (flight) to roost behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flight → Roost</td>
<td>Eastness5</td>
<td>13.4</td>
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<tr>
<td></td>
<td>Northness1</td>
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<td>0.22</td>
</tr>
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<td></td>
<td>DistHydro</td>
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<td>0.98</td>
<td>0.0099</td>
<td>-1.6</td>
<td>0.11</td>
</tr>
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</table>

### Table 2.10. Resource selection model terms and metrics for step types with stationary (nest or perch) to cruise behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
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<td>Nest → Cruise</td>
<td>Wetland3</td>
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<td>DistHydro</td>
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<td>0.00059</td>
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<td>Perch → Cruise</td>
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<td>DistHydro</td>
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<td>0.00036</td>
<td>-8.2</td>
<td>2.2e-16</td>
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</table>
Table 2.11. Resource selection model terms and metrics for step types with stationary (nest, perch, or roost) to flight behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coeff)</th>
<th>SE(Coeff)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nest → Flight</td>
<td>OpenWater96</td>
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<td>1.2e-06</td>
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<td></td>
<td>DistHydro</td>
<td>-0.00501</td>
<td>1</td>
<td>0.00057</td>
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<td>0</td>
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<td>Perch → Flight</td>
<td>OpenWater46</td>
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<td>1.1e+06</td>
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<td>7.3e-10</td>
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<tr>
<td></td>
<td>Tri37</td>
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<td>DistHydro</td>
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<td>0</td>
</tr>
<tr>
<td>Roost → Flight</td>
<td>Tri5</td>
<td>-1.01</td>
<td>0.36</td>
<td>0.31</td>
<td>-3.3</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 2.12. Resource selection model terms and metrics for step types with stationary (nest, perch, or roost) to perch behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coeff)</th>
<th>SE(Coeff)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nest → Perch</td>
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<td>-1.11</td>
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<td>0.45</td>
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<td>0.013</td>
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<td>OpenWater10</td>
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<td>4.3e+03</td>
<td>0.78</td>
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<td>0</td>
</tr>
<tr>
<td></td>
<td>ShrubHerb5</td>
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<td>4.8</td>
<td>-6.2</td>
<td>4.5e-10</td>
</tr>
<tr>
<td></td>
<td>Tri1</td>
<td>0.442</td>
<td>1.6</td>
<td>0.1</td>
<td>4.3</td>
<td>1.7e-05</td>
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<td>Wetland1</td>
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<td>23</td>
<td>0.6</td>
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<td>1.5e-07</td>
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<td>Forest3</td>
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<td>0</td>
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<td></td>
<td>OpenWater10</td>
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<td>1e+05</td>
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<td>23</td>
<td>0</td>
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<td>ShrubHerb7</td>
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<td>Tri1</td>
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<td>2.1e-09</td>
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<td>Wetland1</td>
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<td>0.27</td>
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<td>0</td>
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<td>Roost → Perch</td>
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<td>OpenWater10</td>
<td>16.9</td>
<td>2.1e+07</td>
<td>3.5</td>
<td>4.8</td>
<td>2e-06</td>
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</tbody>
</table>
Table 2.13. Resource selection model terms and metrics for step types with stationary (nest or perch) to roost behavior for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Step Type</th>
<th>Term</th>
<th>Coefficient</th>
<th>Exp(Coef)</th>
<th>SE(Coef)</th>
<th>Z Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nest → Roost</td>
<td>OpenWater10</td>
<td>6.94</td>
<td>1e+03</td>
<td>3.3</td>
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<td></td>
<td>Wetland1</td>
<td>5.69</td>
<td>3e+02</td>
<td>2.3</td>
<td>2.5</td>
<td>0.012</td>
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<tr>
<td>Perch → Roost</td>
<td>Northness3</td>
<td>-3.94</td>
<td>0.019</td>
<td>1.7</td>
<td>-2.3</td>
<td>0.022</td>
</tr>
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<td></td>
<td>OpenWater1</td>
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<td>-3.8</td>
<td>0.00017</td>
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<td></td>
<td>DistHydro</td>
<td>-0.0312</td>
<td>0.97</td>
<td>0.0055</td>
<td>-5.7</td>
<td>1.2e-08</td>
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</tbody>
</table>

We applied the resource selection models as resource selection probability functions (Lele 2009; Kowal et al. 2014) to the entire state of Maine (Figure 2.14), and examined the predicted surfaces at four of our study nests: Ellis Pond, Hebron Lake, East Musquash Lake, and Sandy Pond (Figures 2.15 - 2.18). Overall, the step types with only flight and cruise behavior had the broadest high probability regions. Conversely, steps that ended in roost had the sharpest gradients and the most distinct areas of high versus low probability areas.

2.5 Discussion

Capture of adult Bald Eagles in Maine had previously resulted in few successful attempts, and this study was the first to capture a significant number of free-flying adults in the state (Linda Welch, pers. comm.). Although scouting efforts to determine the territoriality of the adult eagles were done for all of the trapping sites, some of the eagles were determined to be non-breeding floaters based on their GPS location data. This is especially true with the individuals captured at Madagascal and Webb, both of which did not remain at their trap site for any length of time. Although our limited sample size precluded us from estimating the
Figure 2.14. Maps of the resource selection probability functions for the step types analyzed for Bald Eagles in Maine. The probability scale for each map is represented by A, B, or C and shown in the bottom-right corner.
Figure 2.15. Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) at Ellis Pond, Maine. The probability surfaces were clipped to a buffer of 10km around the nest for visualization purposes. The probability scale for each map is represented by A, B, or C and shown in the bottom-right corner.
Figure 2.16. Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) at Hebron Lake, Maine. The probability surfaces were clipped to a buffer of 10 km around the nest for visualization purposes. The probability scale for each map is represented by A, B, or C and shown in the bottom-right corner.
Figure 2.17. Maps of the resource selection probability functions for the Bald Eagle territory around the nest (orange circle) at East Musquash Lake, Maine. The probability surfaces were clipped to a buffer of 10 km around the nest for visualization purposes. The probability scale for each map is represented by A, B, or C and shown in the bottom-right corner.
Figure 2.18. Maps of the resource selection probability functions at the Bald Eagle territory around the nest (orange circle) Sandy Pond, Maine. The probability surfaces were clipped to a buffer of 10 km around the nest for visualization purposes. The probability scale for each map is represented by A, B, or C and shown in the bottom-right corner.
number of Maine eagles that make migration every year, we can conclude from the migrations of the Webb eagle in 2015 and 2016 that at least some of the population makes annual or regular migrations south.

Breeding adult home range sizes at inland lakes and ponds had not been collected using telemetry data in Maine before this study, and our estimates of 33.08 and 3.64 km$^2$ for total and core habitat provide an initial assessment of territorial sizes. Our estimate of core home range size was well below the mean estimated home range size of 2215 km$^2$ in a recent review by Kocina and Aagaard (2021). However, the values used in their analysis varied widely, from <1 to 22,171 km$^2$ and were compiled from a variety of methods and a variety of habitat types. Earlier estimates by Buehler (2000) of 1 km$^2$ indicate that Bald Eagle home ranges may vary widely and estimates depend on site-specific factors, data collection methods, and study designs. Our estimates are specific to Maine’s interior ponds and lakes and may not correspond to the state’s total population since many eagles nest on rivers and coastlines. The estimated home range cover types of the eagles were, as expected, primarily within forested, open-water landscapes. We also saw the utilization of anthropogenic food sources by the Musquash eagle, as observed in other eagle populations (e.g., Elliott et al. 2006; Turrin et al. 2015).

The nest and conspecific nest distance metric estimates represent a way to model territoriality, specifically central-place foraging, conspecific avoidance, and nest attentiveness. We had a limited ability to monitor neighboring nest occupancy around our study eagles and to identify explicit territorial behaviors. However, eagles can experience relatively high rates of intrusion by interspecific and conspecific intruders to their nests (Turrin and Watts 2014), and maintaining proximity to their own nest may ensure against egg or nestling depredation. The primary goal of this analysis was to generate a territorial submodel for our IBM in
Chapter 3 to constrain individual home ranges and prevent unreasonable overlap of neighboring birds in the landscape between nests.

The use of GPS transmitters provided precise spatial and temporal data to classify and model behavior states. Our model included five behaviors that represent basic, identifiable states based on expectations from natural history observations, even if it simplifies eagle behavior. However, a recent study by Bergen et al. (2022) collected immense quantities of data (> 2 million GPS telemetry points) at a very high-frequency (1-11 s) from 100 Bald Eagles and was only able to identify four behavioral states: three movement states and a perching state. Similarly, a study by Murgatroyd et al. (2018) of Verreaux’s eagle (*Aquila verreauxii*) in South Africa with equivalently high-frequency data was only able to classify four behaviors (three movement behaviors and perching) using regression analysis. Thus, given the limitations in being able to identify more discrete behavioral states, our model may be sufficient to accurately predict behaviors in the IBM in Chapter 3.

The only movement kernels we were unable to calculate were cruise-to-roost and roost-to-cruise, probably resulting from limited data. However, these step types were relatively infrequent and are unlikely to have been influential in our IBM predictions in Chapter 3.

The resource selection modeling fitting for this study was challenging because of the large number of step types that we fit in this analysis. Using the full array of landscape covariates often resulted in best-fit models that resulted in flat probability surfaces, and, therefore, we had to remove covariates from the candidate set and rerun the analysis. Given the challenges we encountered, we recommend that future efforts to analyze resource selection use the ResourceSelection package available for R (Lele et al. 2019). The final set of resource selection functions was primarily based on a set of covariates primarily related to water features, topography, forest, and wetlands. Of particular note for this study, all four air-to-air step types showed
an avoidance of wind turbines. The final resource selection functions were used for the habitat selection portion of our movement submodel in Chapter 3.
CHAPTER 3

INDIVIDUAL-BASED MODEL OF TERRITORIAL BALD EAGLE MOVEMENTS

3.1 Background

Individual-based models (IBMs) use unique and autonomous individuals that interact with each other and their environment to model dynamic systems (Railsback and Grimm 2011). Individual’s actions may be regulated by their internal states, interactions with other individuals, and their local environment. This allows for adaptive, complex behaviors and the emergence of a system’s underlying processes (DeAngelis et al. 2005). To ensure realistic behavior, each individual’s decisions are governed by fundamental principles from disciplines such as physiology, animal behavior, and landscape ecology. Since these components are just as likely to apply to new situations as to the circumstances for which the model was developed and tested, these models provide a reliable basis for biological predictions, even in situations outside current conditions (West and Caldow 2006).

As IBMs are developed, they can be improved and validated by identifying and assessing characteristic components of the simulation results in a process called pattern-oriented modeling (Wiegand et al. 2003; DeAngelis et al. 2005). Researchers can run simulations iteratively to assess and modify model structures and parameters based on emergent patterns in the output. By testing and contrasting alternative theories for individual behavior or other low-level processes, modelers can increase the rigor and comprehensiveness of the model procedure and help explain how real systems respond to external forces. These simulations may provide
hypotheses about interactions, determine the most important empirical data to collect, and allow for independent and testable predictions (Peck 2004).

IBMs offer an effective and flexible approach to animal movement ecology because they can accommodate spatial patterns, intra- and inter-species interactions, and adaptations in these systems (McLane et al. 2011). IBMs can integrate habitat selection and adaptive foraging through mechanistic and behavior-based movement rules and simulate how species are most likely to navigate their landscape (Semeniuk et al. 2012). These models help ecologists describe, analyze, and predict the movements of individuals and populations and understand how species may react to environmental changes in real-world landscapes.

Recently, IBMs were used to assess individual and population-level impacts of wind farms on raptors. In one study of Red Kites (*Milvus milvus*), an IBM was used to analyze wind turbine density and spatial configurations on population growth rates, demographic parameters (e.g., survival, dispersal), and collisions of individual kites in an artificial landscape (Schaub 2012). Another IBM study estimated the turbine collision risk of Red Kites based on movement behaviors and landscape composition (Eichhorn et al. 2012). Both simulations replicated behavioral patterns seen in observational data, but the authors suggested incorporating additional field-derived data to better inform testing and calibration of their models.

Developing customizable IBM software capable of handling interacting components, statistical models, and feedback mechanisms remains a challenge for researchers. Most early IBM research was developed in specialized software (e.g., SWARM) or shareware (e.g., NetLogo, Agentsheets) that have constraints on functionality, performance, and analysis of simulation results (Crooks and Castle 2012). Recently, methods to bridge IBM platforms with more statistically-focused software, such as the R language, have been developed and implemented as packages, including NetLogoR (Bauduin et al. 2019), RNetLogo (Thiele et al. 2012),
and nlrx (Bauduin et al. 2019). However, these packages still require a connection to NetLogo software or are dependent on the NetLogo code framework and dictionary.

This study aimed to develop a practical and efficient IBM in the R Program environment that can simulate behavioral mechanisms and habitat use patterns that Bald Eagles are most likely to employ when navigating their landscape. We used the Chapter 2 analysis results of behavioral and spatial-use patterns of territorial eagles to parameterize the IBM’s behavioral state transitions and movement models. The final IBM simulates nesting eagles that use behavior rules and environmental awareness to accomplish their goals of territorial defense, foraging, attending their young, and risk avoidance for an entire breeding season. The IBM components were calibrated using pattern-oriented modeling, and the results can be used to help predict habitat use and flight corridors around individual nests and across the landscape.

3.2 Objectives

The goal of this study was to create and evaluate a spatially-explicit IBM of breeding season Bald Eagle movement patterns. This model incorporated empirically-based Chapter 2 models to probabilistically change behavior and select the eagle’s next location at each time step in the IBM. The specific objectives of this study were: 1) develop the R code framework to run the IBM, 2) run multiple simulations over the nesting season to determine spatial habitat use patterns, 3) calibrate the simulation based on pattern-oriented modeling, and 4) run a simulation for four nests using the final model.

3.3 Methods

All individual-based modeling, simulation, and analysis were performed in the R Program (R Core Team 2022). We developed a generalized IBM simulation
framework for this study (see Appendix C) that implements the core step-sequence procedure in Railsback and Grimm (2011). Using their IBM framework, we modeled the eagle movement patterns based on the Chapter 2 results. The four critical components used in the simulation’s submodels included the Markov-type behavioral state-switching model, step-type parametric movement kernels, step-type resource selection probability functions and the conspecific and home nest metric model. After initial simulation runs, the IBM submodels were improved and validated using a pattern-oriented model calibration of the results (Railsback and Grimm 2011). Lastly, the finalized IBM was used to perform a simulation analysis of four nest sites in Maine.

3.3.1 IBM Overview

To describe the IBM model, we used the Overview, Design concepts and Details (ODD) protocol to document and describe our model as described in Grimm et al. (2006) and updated in Grimm et al. (2020). This protocol represents a systematic way to document the elements and mechanisms of an IBM, allows increased methodological understanding, more consistency among researchers, and greater reproducibility.

3.3.1.1 Purpose and Patterns

The purpose of this model and simulation is to test whether empirically-derived models of territorial Bald Eagle behavioral patterns, movement patterns, habitat selection, and locations relative to their own and conspecific nests can predict their observed phenomena of perching locations, ridgeline crossings, and approximate spatial distribution around their nests. Ultimately, this model can be used to assess the vulnerability of nesting Bald Eagles to wind energy development.
3.3.1.2 Entities, State Variables, and Scales

The entities included in this model are agents representing individual Bald Eagles, their nests, and grid cells that represent spatially-explicit landscapes in Maine. A pair of eagles, a male and female, is associated with a single nest represented by a single cell location in their territory. For the simulation, we used four nests that correspond to four known nest locations (Branch, Ellis, Sandy, and Musquash) from the Chapter 2 analysis. The landscape is represented by 30 m x 30 m raster cells, and the spatial extent is four Bald Eagle territories, each one centered on a nest and extending out a maximum radius of 45km. For our study, we wanted to confine our simulation to Maine so we clipped out Canada for Musquash and New Hampshire for the Ellis eagle territory. Each simulation ran from March 15 to August 15, and a time step occurs every 15 min from an hour before sunrise until an hour after sunset.

3.3.1.3 Process Overview and Scheduling

All individuals start a simulation run at their home territory nest site. At each time step, eagles select their next behavioral state, and, if that behavioral state requires movement, the eagle selects and moves to a new cell on the landscape (Figure 3.1). For each time step, eagles assess their current behavior and the temporal state variables (Julian date and diurnal period) to update their probabilities for each behavioral state, and then based on the behavior transition model select a new behavioral state for that step. If the selected behavior requires them to move, their next position is selected using a spatially-explicit redistribution kernel. This redistribution kernel is a combination of three components: a step-type movement kernel, a step-type dependent resource selection probability function, and a territorially kernel. The movement kernel is based on the individual’s current step type (e.g., nest-to-flight, cruise-to-perch, etc.). The resource selection
probability function accounts for local landscape features, including land cover types, topography, water bodies, and anthropogenic factors such as wind turbines. The territoriality kernel is calculated based on the spatial locations of the individual's own and neighboring nests. These three kernels are combined into a final redistribution kernel which is then used as a probability layer to select the step's end point. Individuals repeat this process of selecting a behavior and an associated step type until the simulation ends.

### 3.3.1.4 Design Concepts

**Basic principles**

Our IBM's basic principles are based on modeling eagle habitat use patterns from empirical data. We restricted the model to eagles with territorial behavior at nests to maintain a consistent set of behavioral objectives, and the eagles' behavioral states are the fundamental driver of their movements and habitat selection. Eagles regularly return to their nest and limit their movements within a limited geographic extent around their nests. We represented territoriality in the model by including the distance to their own nest and the neighboring nests in the redistribution function to reflect defensive behavior that is most common in the breeding season (Buehler 2000; Turrin and Watts 2014).

**Emergence**

The key outcomes are the spatial use patterns of the individuals around their nests. The unique environment around each nest allows for distinct spatial use patterns to emerge. The behavioral state patterns were relatively imposed by the behavior transition model and were expected to be consistent with the original empirical data because they were constrained by the current behavior, Julian date, and diurnal period covariates.
Individual-based Model
Step Process Overview

**State Variables**
- Current Behavior
- Julian Date
- Diurnal Period

**GIS Layers**
- Movement Kernel
- Resource Selection Surface
- Conspecific and Nest Distance

**Diagram Description:**
- Location
- Select Behavior
- Behavior
- Move?
- Redistribution Kernel
- New Location

**Figure 3.1.** Overview of the Bald Eagle IBM step sequence. Individuals started a simulation at their nest, and, at each time step, determined if and where they moved depending on their environment and state variables. Behaviors were selected using a behavioral state transition model with Julian date, diurnal period of the time step, and current behavior as covariates. For each movement step, a movement kernel; a resource selection probability function layer; and territorial probability surface, derived from their distance from their nest and conspecific nests, was used to generate a redistribution kernel. This redistribution kernel was used to probabilistically select their location for the end of the step. Individuals repeated this process until the simulation ended.
Adaptation

The adaptive behavior of the individual eagles was facilitated by the application of the redistribution kernels across the landscape. When a behavioral transition allowed them to move, the model generates a redistribution kernel and selects a cell with a high probability value for them to move to in that step.

Objectives

The underlying objectives of the model were based on general ecological principles of fitness. Specifically, the eagles were moving to explore their environment, find food, regularly attend their nest, and find a safe roost at night.

Prediction

The only implicit predictions were the territoriality component of the model that 1) restrained the eagles from moving unrealistic distances from their nest and 2) the requirement that eagles routinely return to their nest.

Sensing

The model assumes eagles are able to sense the external state variables of Julian date and diurnal period to select their next behavioral state and their environment to the extent of their movement kernel to select a cell during movement. Additionally, they always knew their own nest location and could return there when their behavioral state changed to nest.

Stochasticity

The model contained two main sources of stochasticity – the use of probability models for determining behavioral state changes and the selection of a destination cell from the redistribution kernel. These components were based on realistic underlying drivers but generated different behavioral sequences and movement paths in each simulation.
Observations

The observations were designed to allow a comparison between the simulation results and empirical data. The information collected from the IBM was the latitude and longitude coordinates and behavioral state for each eagle at each time step.

Learning, Interactions, and Collectives

These ODD concepts were not incorporated into the model.

3.3.1.5 Initialization

The initialization of the model began with a male and female eagle at each of the four nests sites (Hebron, Ellis, Musquash, and Sandy), and each eagle initially started in a nest behavioral state. The global parameters that controlled the model were the start and end time. The initialization was always the same in order to run and update the model under identical conditions.

3.3.1.6 Input Data

The model used the sunrise and sunset times for Bangor, Maine to derive the diurnal period for each day in the breeding season.

3.3.1.7 Submodels

At each time-step, eagles determined their behavior and location using two submodels implemented sequentially. First, the behavior submodel selected the eagle’s next behavioral state, and, secondly, if the eagle changed location, the redistribution submodel determined which cell the eagle relocated to in that step.

The behavioral submodel used the transition matrix probabilities to predict the next behavioral state using the current state, Julian date, and proportional time of the diurnal period (the portion of the daylight time between an hour before sunrise and an hour after sunset for that day) as covariates. To maintain realistic behavior we constrained the following transition probabilities. Roost behavior was limited to
not occur between > .4 and ≤ 5 during the diurnal period, which forced the eagles to leave the roost in the morning. If an eagle selected roost after noon, they remained in roost behavior at that location until the end of the day. At the last step of a day, an eagle not at their nest or a roost was forced to select nest or roost behavior. We prevented two transition types, cruise-to-roost and roost-to-cruise, because of a lack of data to properly model their movements, and we set those transition probabilities to zero.

After the next behavior was selected, the redistribution submodel was used if a location change occurred (Figure 3.2). Most step types resulted in location changes, with the exceptions being roost-to-roost and nest-to-nest. For perch-to-perch step types, a location change was determined by a Bernoulli trial \( p = .26 \) based on the Chapter 2 empirical probability value. If an eagle was away from the nest and its next selected behavior was nest, the eagle automatically relocated back to the nest in that step. For all other movements, including perch-to-perch involving relocation, we used three GIS layers to create a redistribution kernel and select a new location. First, we used the step type movement kernels using parameters for the Weibull and mixed von Mises distributions derived in Chapter 2 to generate the movement kernels. For movement kernels with a directional component, the kernel was rotated so the zero radian angle aligned with the eagle’s step direction based on their current and previous step locations. For the resource selection probability kernel, we used the step-type resource selection probability surfaces and cropped them to the bounds of the movement kernel. For step types that ended in a perch or roost behavior, we used a layer that represented only non-water cells to mask out hydrological features as potential destination cells.

To generate the territoriality kernel, we took a phenomenological approach to modeling this process by calculating kernels based on logistic functions that adjusted their shape depending on an eagle’s relative location to their own and conspecific
Figure 3.2. Model step types and their location change scenarios. Step types consist of a start and end behavior, and may result in the eagle changing locations. All steps that started or ended with cruise and flight behavior involved a change in the eagle’s location. Perch-to-perch step types had a Bernoulli trial probability \( p = .26 \) of changing locations. Steps that started with nest or roost and ended in the same behavior (e.g., nest-to-nest) always remained at the same location.
nests. Prior to running the simulation, we used the fitted Gamma distribution of
the conspecific nest distance metric values from Chapter 2 to generate a cumulative
distribution function (Figure 3.3). We then rescaled that function’s response
variable (0 to 1) to a new range between -50 and 0 (Figure 3.4). This functional
transformation allowed us to calculate these rescaled values as the eagle moved
around their territory, and we used these values as a logistic scale parameter to
generate the territorial kernels. For example, if the eagle was at locations with home
and conspecific nest distance metric values of 1, 5, or 10 that equated to values of
-22.44, -6.76, or -3.06, respectively, on the logistic scale parameter.

![Figure 3.3](image.png)

**Figure 3.3.** The cumulative distribution function of the conspecific and nest
distance values of the Bald Eagles in Maine.

This logistic scale parameter was then used to fit a logistic function centered at
0 at the eagle’s current location, and the conspecific and nest distance relative
position values (i.e., higher or lower conspecific and nest distance metric values)
around the eagle’s location were used to generate the territorial kernel’s probability
surface (Figure 3.5). This process produced kernels where the eagle was always at a
cell with a probability value of .5, and cells with lower conspecific and home nest
distances had higher probability values and cells with higher conspecific and home
nest distances had lower probability values (Figure 3.6). As the eagle moved farther
Figure 3.4. The rescaled values that relate the conspecific and nest distance values of Bald Eagles to a logistic scale parameter in the territorial kernel. From their nest, the probability gradient became larger between cells with lower and higher conspecific and home nest distances (Figure 3.7).

Figure 3.5. The relationship between conspecific and nest distance metrics and the territorial kernel probability surface based on a Bald Eagle’s current location (located at 0 on the relative position scale) and the relative positions (higher or lower conspecific and nest distance metric values) of the surrounding cells on the landscape.
Figure 3.6. An example of a territorial kernel generated at the Ellis Pond nest (orange circle) in Maine when a Bald Eagle (grey circle) is located 5 km southwest of the nest. The kernel’s probability values are fit using a logistic function where the scale parameter is based on the conspecific and nest distance metric of the eagle’s current cell. The kernel is generated so the eagle’s position always has a probability of .5, and the surrounding cells have higher or lower probability values based on their relative higher or lower conspecific and nest distance metric values.
Figure 3.7. An example of a territorial kernel generated at the Ellis Pond nest (orange circle) in Maine when a Bald Eagle (grey circle) is located 10 km southwest of the nest. The kernel’s probability values are fit using a logistic function where the scale parameter is based on the conspecific and nest distance metric of the eagle’s current cell. The kernel is generated so the eagle’s position always has a probability of .5, and the surrounding cells have higher or lower probability values based on their relative higher or lower conspecific and nest distance metric values.
To generate the final distribution kernel, we standardized each kernel to sum to 1, added weights to the three probability surfaces, and calculated the geometric mean. For the initial run, we used even weights, but we adjusted them during the calibration stage. For all redistribution kernels, we set the probability to zero at the cell the eagle currently occupied, forcing the eagle to move at least one cell away. To select the step’s final destination cell, we used the redistribution kernel’s probability values as sampling weights and used the ‘strata’ function from the sampling package (Tillé and Matei 2021) to select a set of cells (initially n = 50 but varied during calibration) and, from that set, chose the highest probability cell as the destination.

3.3.2 Pattern-Oriented Modelling and Calibration

We used pattern-oriented modeling to iteratively assess and adjust the redistribution submodel parameter values (Wiegand et al. 2003). The IBM was calibrated based on three elements representing specific spatial, behavioral, and movement patterns observed in the empirical study results. First, the proportion of flights that transected the landscape ridgelines was compared between the empirical and simulation data. Second, the distribution of perching locations’ distance to hydrological features was compared to assess how consistent model results were with known perching habitat. Lastly, we visually assessed the empirical and simulated data habitat use patterns, and, to have having matching point location counts to compare, we filtered the simulation data to only points that were the closest equivalent to the dates and times of that nest’s empirical data.

To determine the flight behavior of the individuals, we developed a state-wide GIS layer to characterize ridgelines. We found ridgelines and valleys within the spatial extent of our simulation landscapes using analysis tools from the whitebox package for R (Lindsay 2016). We found ridge areas following the general procedure outlined in Weiss (2001). First, we aggregated the USGS Digital Elevation Model
(U.S. Geological Survey 2017b) to reduce the raster resolution by a factor of five and calculated the mean value. Second, we computed how elevated or low-lying a cell is relative to its surroundings within a filter kernel of 1.5 km resulting in an index from -1 to 1, using the relative topographic position tool. Third, we reclassified cells with index values > .3 to 1, and all other cells were converted to 0. Lastly, we clumped the cells and removed any patches that had a size less than nine hectares.

To find the specific ridgelines within those ridges, we ran the 'wbt_find_ridges' tool on the aggregated DEM layer from the first step. From those results, we clipped out ridges that were within the areas determined by the original process and removed cells with less than two adjacent cells. The result of that process was converted into a vector polygon that represented the ridgelines. For calibration, we compared the proportion of step path segments that transected ridgelines between the empirical and simulation data at each of the sites.

For the second calibration metric, we calculated the distributions of perching locations’ distance to hydrological features in the empirical and simulation data to determine if the data were similarly distributed.

Finally, we assessed the habitat use patterns by subjectively comparing the habitat-use proportion locations of the empirical data to see if the simulated eagles used the landscape in a consistent pattern. We wanted to determine if the spread and configuration of these locations were spatially similar and ecologically reasonable.

### 3.4 Results

Based on our initial simulation runs, we calibrated the model by iteratively modifying two components of the model: the weights ratio of the three component kernels (i.e., resource selection, movement, and territoriality) used to calculate the
redistribution kernels, and the number of selected cells in the redistribution kernel sample for determining the final destination cell.

After an extended process of iteratively updating these two components to best reproduce our calibration metrics and spatial patterns of interest, we found a set of kernel weights and sample sizes that produced suitable results (Table 3.1). Once we finalized the component values, we reran the simulation ten times to compare the empirical and simulation results’ calibration metrics.

Table 3.1. The model component values configured during the calibration process for the Bald Eagle IBM.

<table>
<thead>
<tr>
<th>Group</th>
<th>Step Types</th>
<th>Kernel Weights(^1)</th>
<th>Sample Size(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air to Cruise</td>
<td>Flight → Cruise, Cruise → Cruise</td>
<td>3:4:1</td>
<td>25</td>
</tr>
<tr>
<td>Air to Flight</td>
<td>Cruise → Flight, Flight → Flight</td>
<td>3:2:1</td>
<td>25</td>
</tr>
<tr>
<td>Perch/Roost to Air</td>
<td>Perch → Cruise, Perch → Flight, Roost → Flight</td>
<td>3:3:2</td>
<td>25</td>
</tr>
<tr>
<td>Nest to Air</td>
<td>Nest → Cruise, Nest → Flight</td>
<td>2:3:1</td>
<td>25</td>
</tr>
<tr>
<td>Air to Stationary</td>
<td>Flight → Perch, Flight → Roost, Cruise → Perch</td>
<td>5:1:3</td>
<td>1000</td>
</tr>
<tr>
<td>Nest to Stationary</td>
<td>Nest → Perch, Nest → Roost</td>
<td>5:1:3</td>
<td>1000</td>
</tr>
<tr>
<td>Stationary to Stationary</td>
<td>Perch → Perch, Perch → Roost, Roost → Perch</td>
<td>5:2:3</td>
<td>1000</td>
</tr>
</tbody>
</table>

\(^1\) Ratio of resource selection, movement, and territorial kernel weights in the redistribution kernel.

\(^2\) Number of cells selected in redistribution kernel.
We achieved very similar results for the distributions of the perch distance to hydrological features (Figure 3.8). The empirical data distribution had a longer tail compared to the simulation data, but the general shape, especially in the values < 150 m, was suitably equivalent to meet our objectives. We fit this metric to the empirical data primarily by increasing the resource selection probability weight to a large value (5) and selecting a large sample size (1000) for the steps ending in perch and roost behavioral states.

The ridgeline crossings metric proved to be difficult to simultaneously reproduce for all four nests, but we were able to get the relative patterns within a sufficiently close range to the empirical data to be adequate for our modeling purposes (Figure 3.9). This metric was adjusted to fit the empirical data by using relatively similar kernel weights and a much smaller redistribution kernel sample size (25) for all of the step types that ended in cruise and flight behavioral states.

Lastly, we examined the density of point locations from the empirical and simulation data (Figures 3.10 – 3.13). These results show that spatial habitat use from ten simulations (representing twenty eagles) appears to emulate relatively similar spatial distributions and spreads on the landscape when compared to the empirical data from one eagle over a single year. In effect, if we had twenty years of empirical data, it would probably look like the simulation results. This suggests the model is relatively stable and consistently produces realistic results. One of the most pronounced spatial patterns was the lack of use around the turbines at the Ellis nest indicating that wind turbine avoidance was occurring in the model.

### 3.5 Discussion

Previous IBMs of eagle species have focused on the effects of anthropogenic disturbance and mortality on population trends (Ueta and Masterov 2000; Pauli et al. 2017), but limited their time steps to a single day. Our effort to develop an
Figure 3.8. The IBM calibration metric results showing the proportion of perching locations relative to their distance to hydrological features for the empirical data and the simulation data using the final parameterization values.
**Figure 3.9.** The IBM calibration results showing the step path proportion of ridgeline crossings for the empirical data and the simulation data using the final parameterization values.

**Figure 3.10.** Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at Ellis Pond, ME.
Figure 3.11. Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at Hebron Lake, ME.

Figure 3.12. Map showing the empirical and simulation point location density using the final model parameterization values for the Bald Eagle nest (orange circle) at East Musquash Lake, ME.
IBM to simulate habitat use patterns at a high-frequency step rate (15 min) required modeling of multiple behavioral states and varying step types. This greatly increased the logistical complexity of developing and coding a framework to implement a spatially-explicit IBM. Ultimately, we were able to code a sufficiently flexible framework in R to model territorial Bald Eagles and produce realistic movement patterns, including the avoidance of wind turbines. Additionally, we were able to use habitat and topographic covariates to better understand flight behavior, a recommendation within the USFWS Eagle Conservation Plan Guidance (U.S. Fish and Wildlife Service 2011).

The R language and programming framework are rapidly evolving, and sections of our code could be improved by updating some of the processes with newer workflows, data handling, and streamlining functions. For example, our code relies heavily on lists to hold complex data, including the agent data, but many of these objects could be stored in tibbles with list-columns (Wickham et al. 2019) to hold attributes and associated data, such as step data. Additionally, refactoring the code
to utilize ‘pipes’ from the magrittr package for R (Bache and Wickham 2022) to chain function calls could improve the code’s readability, flexibility, and speed.

By using a pattern-oriented modeling approach to update the IBM, we determined parameters that produced simulated habitat use patterns that approximated our observed data. However, the degree to which our patterns approximated the empirical data varied. We were able to match the perch distance to hydrological features and approximate the general habitat use pattern, but we were unable to consistently match ridgeline crossings for all four nests simultaneously using our model. In developing future IBMs, certain step types, especially ones with flight behavior, could be improved by implementing path selection functions to fit the step models. Path selection functions account for landscape covariate layers the animal traverses during steps (Zeller et al. 2016). This approach may more accurately account for some step types, and this method could enhance model accuracy and improve the calibration of the ridgeline crossings metric.

In the future, as GPS transmitters increase their accuracy, longevity, and data collection frequency, there is an opportunity to further develop this model. However, higher frequency telemetry may require different methods for determining and modeling behavioral changes because the volume of data could present problems for traditional Markov-type fitting procedures (Bergen et al. 2022). Modeling preferred perching habitat, such as super-canopy trees adjacent to shorelines (Chandler et al. 1995), could also be improved using more fine-scale habitat data such as LIDAR to identify and classify perch locations. Additionally, efforts by observational studies or collecting GPS telemetry data at adjacent nest sites could help to quantify and model territorial interactions in IBMs through more mechanistic explanations (e.g., Giuggioli et al. 2011).
As on-going eagle nest monitoring efforts locate additional nests, simulations and movement pattern predictions can be updated. This method will help determine the most significant empirical data to collect and will allow for independent and testable predictions (Peck 2004; Vander Wal and Rodgers 2012). As additional data become available, this individual-based model can be extended to other age and breeding class individuals allowing more comprehensive population risk assessments (e.g., Coss-Custard and Stillman 2008).

The development of additional model components may allow broader use of this approach to other avian species. For example, new studies focused on using external GPS-based transmitters to track seabirds could provide telemetry data with location precision enabling fine-scale location and movement data in relation to topographic factors, shifting resources, and meteorological conditions for seabirds. These types of fine-scale data may allow the development of models to predict habitat use, mortality risk, and the influence of weather conditions on the behavior of these birds in relation to the proposed offshore wind projects within the mid-Atlantic Wind Energy Areas (U.S. Geological Survey 2017a). This could better inform resource managers about recommendations to minimize the negative effects of wind energy development on a variety of bird species.
CHAPTER 4
WIND FARM DEVELOPMENT SCENARIO
ASSESSMENTS

4.1 Background

For wind energy developers assessing new sites, the USFWS Eagle Conservation Plan Guidance recommends using pre-construction monitoring to conduct collision risk analyses for eagles (U.S. Fish and Wildlife Service 2013). This collision risk model depends on the wind facility hazard footprint, the eagle exposure rate estimated by pre-construction surveys, and collision risk based on a Bayesian probability framework. This approach has been a standard for wind energy developers and the Bayesian probability distributions continue to be updated using post-construction mortality surveys (New et al. 2015), including a model specifically for Bald Eagles recently published by Nasman et al. (2021). The advantage of this model is the broad applicability and facilitation of decision-making and permitting at onshore sites. However, using this model for offshore sites is likely to be constrained by the inherent limitations of collecting the required monitoring and input parameters. Monitoring avian behavior and movements in a marine environment is challenging and typically involves costly and time-constrained boat or plane surveys or deploying automatic recording devices, such as radar or camera equipment, which can be hindered by meteorological conditions and suffer from limited detection ranges (Desholm et al. 2006; Marques et al. 2014). Furthermore, the ocean environment makes it impossible to perform mortality surveys that prevents determining accurate collision rates.
Further, studies from both onshore and offshore wind farms show that indirect disturbance may have significant adverse effects on some species. Thus, to minimize potential negative outcomes the most effective measure is appropriate siting and turbine placement (Marques et al. 2014). The additional uncertainty associated with Bald Eagle life history in novel environments may lead to potentially greater risk at certain wind farms (New et al. 2018). Therefore, new methods to determine the potential effects of proposed facilities before construction may be needed.

Individual-based modeling provides an increasingly adaptive and effective tool for assessing the effects of habitat modification on animals (Railsback and Grimm 2011). A study by Masden et al. (2012) used radar telemetry data of Common Eider (*Somateria mollissima*) at an offshore wind farm in Denmark to parameterize and simulate avoidance and movement paths of eiders around theoretical wind facilities of varying configurations, extents, and turbine spacing. A study in western Britain used IBMs of wading bird movements and foraging behavior to assess the effects of a proposed offshore wind farm (West and Caldow 2006). The results of these studies successfully predicted shorebird behavior and mortality rates at several European estuaries and increased the confidence that this type of modeling can aid policymakers regarding the management of coastal habitats and bird populations.

To determine how well the IBM developed in Chapter 3 can be used to simulate movement patterns of breeding Bald Eagles and assess displacement and mortality risk, we ran a series of simulations at two nest sites in Maine. These simulations allow spatial use and risk estimates to be calculated under both current and hypothetical, spatially-explicit wind farm development scenarios. Understanding site-specific factors can help inform policy and industry decisions to minimize the potential adverse effects of wind energy developments to adjacent breeding eagles.
4.2 Objectives

The goal of this study is to demonstrate applications of the IBM developed in Chapter 3 by simulating Bald Eagle movement patterns under spatially-explicit wind farm development scenarios at two different sites. There are two main objectives: 1) use the model developed in Chapter 3 to simulate bird flight patterns within known Bald Eagle territories under baseline conditions and three hypothetical wind farm development scenarios, and 2) use a collision-risk model to estimate predicted mortality rates under these scenarios.

4.3 Methods

4.3.1 Control and Wind Farm Scenarios

For this analysis, we selected two known Bald Eagle nest sites in Maine, Upper Wilson Pond in Piscataquis County (Figure 4.1) and West Grand Lake in Washington County (Figure 4.2). Both of these eagle nests were near areas of good-to-outstanding wind power class conditions (National Renewable Energy Laboratory and AWS TruePower 2009), which we used to represent footprints of hypothetical wind farms to conduct our simulations. To determine the location of the wind turbine locations in the spatial footprints, we used the windfarmGA package for R (Gatscha 2021). This package determines the placement of wind turbines to maximize energy output given a predefined number of turbines, rotor radius and height, and an average wind speed per wind direction. We used the USGS’s U.S. Wind Turbine Database to find mode values of turbine hub height (80 m) and rotor diameter (112 m) for Maine in the period from 2012–2018 (Hoen et al. 2018), the years for which the Chapter 2 field data were collected. For wind speed and direction data, we retrieved data from the Maine Automated Surface Observing System (ASOS) observation network (Iowa State University 2022) and used information from the Greenville and Millinocket airports to approximate conditions.
at the Wilson and Grand Lake sites, respectively (Figures 4.3 and 4.4). For both sites, we ran a genetic algorithm to determine turbine locations in the north (Wilson, n = 15; Grand Lake, n = 20) and south (Wilson, n = 15; Grand Lake, n = 20) footprints (Figures 4.6 and 4.6).

Figure 4.1. Map of a Bald Eagle nest (orange circle) and two areas (purple polygons) of 50 m above ground good-to-outstanding wind power class conditions (National Renewable Energy Laboratory and AWS TruePower 2009) north and south of the nest on Upper Wilson Pond, Maine. These two footprints were used to test IBM simulations of Bald Eagle habitat use patterns under baseline conditions (no turbines) and three hypothetical wind farm build-out scenarios: north footprint only, south footprint only, and both footprints.

4.3.2 IBM Simulations

We used the model and parameter estimates from Chapter 3 to run our IBM simulations under four conditions: 1) in the absence of wind turbines (baseline), 2)
Figure 4.2. Map of a Bald Eagle nest (orange circle) and two areas (purple polygons) of 50 m above ground good-to-outstanding wind power class conditions (National Renewable Energy Laboratory and AWS TruePower 2009) north and south of the nest on West Grand Lake, Maine. These two footprints were used to test IBM simulations of Bald Eagle habitat use patterns under baseline conditions (no turbines) and three hypothetical wind farm build-out scenarios: north footprint only, south footprint area only, and both footprints.
Figure 4.3. Windrose for the airport in Greenville, ME used to determine the turbine locations in the wind farm scenarios at the Upper Wilson Pond site.

Figure 4.4. Windrose for the airport in Millinocket, ME used to determine the turbine locations in the wind farm scenarios at the West Grand Lake site.
Figure 4.5. Map of the Upper Wilson Pond nest (orange circle) under four wind farm scenarios: control, no turbines; north, 15 turbines (white circles) in the northern footprint; south, 15 turbines in the southern area; north and south, 15 turbines in both the north and south (30 total turbines). The turbines are shown to scale based on a diameter of 112 m.
Figure 4.6. Map of the West Grand Lake nest (orange circle) under four wind farm scenarios: control, no turbines; north, 20 turbines (white circles) in the northern footprint; south, 20 turbines in the southern area; north and south, 20 turbines in both the north and south (40 total turbines). The turbines are shown to scale based on a diameter of 112 m.
turbines in the north footprint, 3) turbines in the south footprint, and 4) turbines in the north and south footprints. For each scenario’s wind turbine locations, we updated the resource selection probability functions (Appendix E). We conservatively assumed occupancy of all the neighboring Bald Eagles nests based on Maine Department of Inland Fisheries & Wildlife survey data to calculate the home and conspecific nest distance layer. At each site, we ran twenty simulation runs of two eagles for a breeding season under all four scenarios.

We used the simulation’s step location points to interpolate movement paths. Since we were interested in the altitude of the movements, we identified cruise (starting and ending in cruise behavioral state) and flight (all other movement step types) path segments. For each scenario, we compiled the cruise and flight paths to estimate distribution patterns and summarized these path data as rasters to visually assess changes in distribution patterns. We also calculated the number of cruise and flight path segments that intersected the wind farm footprints and turbines. The flight path segments are when eagles are more likely to encounter wind turbines, and we ran a pair-wise ANOVA to determine statistical differences between scenarios.

4.3.3 Collision Risk Modeling

After completing the simulations, we calculated the collision risk probability using the Band (2012) model implemented in R by Masden (2015) to determine the probability of collision for an eagle in a single transit through a rotor. To generate the parameters needed for the model (Table 4.1), we calculated the average eagle flight velocity (11.9 m/s) from our GPS telemetry data that was classified as flight behavioral state in Chapter 2, and we used the wind turbine specifications from the Vestas turbine model V112-3.3, one of the most common turbines installed in Maine between 2012 and 2018 (Hoen et al. 2018).
Table 4.1. Parameter values used for a single transit turbine collision risk model by Band (2012) used to estimate a single transit collision risk for a Bald Eagle in our simulations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Model Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>b</td>
<td>Number of blades in rotor</td>
<td>3</td>
</tr>
<tr>
<td>Ω</td>
<td>Angular velocity of rotor (radians/s)</td>
<td>1.34</td>
</tr>
<tr>
<td>c</td>
<td>Chord width of blade (varies along r)</td>
<td>.96 - 4</td>
</tr>
<tr>
<td>γ</td>
<td>Pitch angle of blade (degrees)</td>
<td>30</td>
</tr>
<tr>
<td>R</td>
<td>Total rotor radius</td>
<td>56</td>
</tr>
<tr>
<td>L</td>
<td>Length of bird (m)</td>
<td>0.9</td>
</tr>
<tr>
<td>W</td>
<td>Wingspan of bird (m)</td>
<td>2.1</td>
</tr>
<tr>
<td>β</td>
<td>Aspect ratio of bird (i.e., length/width)</td>
<td>.42</td>
</tr>
<tr>
<td>v</td>
<td>Velocity of bird though rotor (m/s)</td>
<td>11.9</td>
</tr>
<tr>
<td>α</td>
<td>$v/r\Omega$</td>
<td>0.92 - 3.94</td>
</tr>
<tr>
<td>F</td>
<td>1 for flapping birds; 2/$\pi$ for gliding birds</td>
<td>0.64</td>
</tr>
</tbody>
</table>

The model calculates the collision probability ($p$) at radius distance ($r$) from the hub and a rotor plane angle ($\varphi$; in radians, relative to vertical) of the point of passage of the bird:

$$p(r, \varphi) = \left(\frac{b\Omega}{2\pi v}\right) \left[|\pm c \sin \gamma + \alpha c \cos \gamma| + \max (L, W\alpha F)\right]$$

(4.1)

Which allows for the integration over the entire rotor area to calculate the total probability:

$$\text{Total Probability} = \left(\frac{1}{\pi R^2}\right) \int \int p(r, \varphi) r \, dr \, d\varphi$$

(4.2)

The mean value of the probability is used as the average collision risk for an eagle making a single pass through any point through the rotor. We used a conservative estimate of avoidance rate (95%) to calculate total predicted collision with turbines per eagle per breeding season.
Finally, we assessed the per turbine collision risk under the three wind farm scenarios using the interpolated flight lines and mapped the proportion of transits by a turbine to determine which turbines presented the greatest risk.

4.4 Results

The cruise and flight patterns show consistent displacement effects when wind turbines are present (Figures 4.7 – 4.10). The highest path densities did not cross through turbine arrays and shifted their use to other regions around their nest area.

We compared cruise and flight path segment transits through the wind farm areas (Figure 4.11), and turbine polygons (Figure 4.12). When turbines were present, the number of path segments through the wind farm footprint and turbines decreased. At the Wilson site under the north scenario, we saw an increase in the use of the south wind area, but, interestingly, we did not see a comparable increase in the north wind area under the south scenario. The Grand Lake site had a more consistent pattern, the use of areas without turbines always increased.

Flight path turbine transits showed a significant decrease between the control and scenarios with turbines present. The only exception was the Wilson site’s south turbines under the north and south wind farm scenario (Figure 4.13). Under this scenario, the eagle would have had displacement from both north and south but the reduction in use in the southern area may have been offset by other factors in the IBM.

Comparing collision risk per eagle for the north and south areas under the different scenarios shows that collision risk estimates always increase at a wind area when another wind farm is present on the landscape (Figure 4.14). Collectively, this indicates as the numbers and locations of wind turbines increase in the immediate area around eagle nests, the eagles may reach a saturation threshold and not be able to continue compensating to avoid these areas through displacement. In this case,
Figure 4.7. Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the Upper Wilson Pond nest (orange circles) under four wind farm scenarios. Turbines are either present (white dot) or absent (black dot) in the scenarios. The path density metric is the count of flight paths that intersect that raster cell and show the changes in movements patterns.
Figure 4.8. Map of interpolated cruise path density for twenty simulations of Bald Eagle pairs during the breeding season around the West Grand Lake nest (orange circles) under four wind farm scenarios. Turbines are either present (white dot) or absent (black dot) in the scenarios. The path density metric is the count of flight paths that intersect that raster cell and show the changes in movements patterns.
Figure 4.9. Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the Upper Wilson Pond nest (orange circles) under four wind farm scenarios. Turbines are either present (white dot) or absent (black dot) in the scenarios. The path density metric is the count of flight paths that intersect that raster cell and show the changes in movements patterns.
Figure 4.10. Map of interpolated flight path density for twenty simulations of Bald Eagle pairs during the breeding season around the West Grand Lake nest (orange circles) under four wind farm scenarios. Turbines are either present (white dot) or absent (black dot) in the scenarios. The path density metric is the count of flight paths that intersect that raster cell and show the changes in movements patterns.
Figure 4.11. Simulated Bald Eagle cruise and flight transit paths through the wind farm areas near Upper Wilson Pond and West Grand Lake, ME.
Figure 4.12. Simulated Bald Eagle cruise and flight transit paths through the wind farm turbines near Upper Wilson Pond and West Grand Lake, ME.
Figure 4.13. Simulated Bald Eagle flight path transits through the north and south wind farm turbines near Upper Wilson Pond and West Grand Lake, ME, showing pair-wise ANOVA results.
eagles may may start using wind farm areas at increasingly higher rates as turbines become more prevalent. The estimated total predicted collisions at both sites for all scenarios (Figure 4.15) indicates the highest risk occurred at Wilson Pond under the north and south scenario with 0.0611 (0.0512 - 0.0710, 95% CI) collisions per eagle per breeding season. Conversely, the lowest predicted risk was Grand Lake under the south only scenario with 0.00566 (0.0031 - 0.0082, 95% CI) collisions per eagle per breeding season.

Mapping the proportional turbine transits indicates specific turbines present a much more pronounced risk for collisions (Figures 4.16 and 4.17). At the Wilson site, two north area turbines located in the most direct path between the nest and Prong Pond (which is adjacent to Moosehead Lake) present the highest risk. In the south area only scenario, the western turbines present the greatest risk, especially the western-most turbine. For the Grand Lake site under the north scenario, the greatest turbine risk is the turbines directly in the path between West Grand Lake and Lower Oxbrook Lake. Under the south scenario, one turbine in Farm Cove had a particularly high risk.

4.5 Discussion

Our simulation results differ from data commonly collected in the field for wind farm risk exposure estimation, and we suggest this type of modeling approach is best suited to examine site-specific factors and risk under differing scenarios using collision risk estimates. Our model is based on the Chapter 3 IBM of territorial eagles at inland lake nests, and the risk scenarios should be considered within that context.

Most of the estimated flights through the turbine areas were reduced by 50% compared with the control scenario. This type of displacement has been seen in raptors in other onshore studies (Dahl et al. 2012; Dohm et al. 2019). This effect
Figure 4.14. Turbine collision risk (using a 95% avoidance rate) by wind area per Bald Eagle for a breeding season under three wind farm scenarios at Upper Wilson Pond and West Grand Lake, ME.
Figure 4.15. Total turbine collision risk (using a 95% avoidance rate) per Bald Eagle for a breeding season under three wind farm scenarios at Upper Wilson Pond and West Grand Lake, ME.
Figure 4.16. Map showing the proportion of Bald Eagle flight path transits through wind turbines under three wind farms scenarios at West Upper Wilson Pond, ME. Turbines with higher proportional rates have increased collision risk in each scenario.
Figure 4.17. Map showing the proportion of Bald Eagle flight path transits through wind turbines under three wind farms scenarios at West Grand Lake, ME. Turbines with higher proportional rates have increased collision risk in each scenario.
may be comparable to macro-avoidance (i.e., course scale avoidance), and is one reason we selected to use a low (95%) avoidance rate in the collision risk model. This IBM approach allowed us to determine risk at the individual turbine level, and found that nest proximity may be related to risk but is not the primary determinate factor. Although home range monitoring of eagles would be practically impossible using passive location point data, collision risk models could be improved using such technologies, such as cameras to position birds in 3D positional space near turbines (e.g., McClure et al. 2018).

Although our analysis only examined wind turbine presence and absence scenarios within wind farm footprints, extending the simulation to include different spatial configurations of turbines could be implemented and iterated on in a real-world consultation and review process to determine mortality risk and functional habitat loss. Identifying quantitative assessments of risk for eagles allows for compensatory mitigation options, such as lead abatement (Cochrane et al. 2015) and reduction of vehicle strikes (Lonsdorf et al. 2018).

Considering the IBM approach works to assess eagle movements in relationship to inland wind farm facilities, we believe this same approach may also be applicable to offshore facilities for assessing similar displacement effects in offshore environments, as suggested by Kelsey et al. (2018). By using the individual-based approach in combination with modern telemetry methods, such as the expanding MOTUS network, may provide data to develop and calibrate models for other species. Additional data from boat or platform-based observations could contribute to improved estimates of bird flight heights and speeds, especially in relationship to environmental conditions. Such analyses may lead to a better understanding of factors and behavioral mechanisms that affect eagles and other avian species and would allow better assessments in and around offshore wind farms. Future studies could incorporate environmental covariates to describe and predict spatial and
temporal variation in pelagic bird species spatial distributions at sea, and to help estimate macro-avoidance rates (Cook et al. 2014).

Environmental or meteorological covariate data related to movement patterns, direct collisions, and behavioral responses of eagles to wind energy facilities are sparse in Europe (Krone and Treu 2018), but the use of regional models explain behavioral patterns. Similarly, studies on habitat use, the timing of migratory and local movement patterns, potential displacement, behavioral changes, or mortality are being conducted throughout the mid-Atlantic region of the United States to determine the potential effects of off-shore wind energy on Red-throated Loons (Gavia stellata), Surf Scoters (Melanitta perspicillata), and Northern Gannets (Morus bassanus). This data is being collected to help inform siting and permitting, and help offset the adverse effect of future wind energy development in the area (Spiegel et al. 2017). An IBM approach could be used to evaluate timing and risks to the endangered northeast populations of Roseate Terns (Sterna dougallii) by proposed offshore wind energy projects (U.S. Geological Survey 2017a). Currently, collision risk models are being developed for broad-scale use for initial assessments and predicting bird collision rates with energy infrastructure along the Pacific coast (Kelsey et al. 2018) to initially quantify marine bird vulnerability (collision, displacement, and population) to potential offshore wind energy facilities.

As these developments become more advanced a more cumulative approach to assessing potential adverse effects will need to address long-term exposure to these potential hazards (Goodale and Milman 2016). Reduction of risk will help balance government and industrial goals and provide more ecologically-informed development of energy and economic benefits. Further model development could enable more interdisciplinary approaches that directly integrate engineering, economic, and ecological data in possible management scenarios (Masden et al. 2012). Resulting siting decisions, conservation goals, and mitigation efforts could be
incorporated into strategic-level adaptive management frameworks. This may reduce redundancy and expedite regulatory and permitting processes. Ultimately, researchers, conservation officials, and the wind industry can work together to both protect wildlife populations and maintain the environmental and economic benefits of wind energy resources.
APPENDIX A
MULTI-SCALE OPTIMIZATION CODE

The following R code was used to simulate an ecological presence-absence data set along a range of landscape scales and effect sizes. The data was used by two model-fitting approaches, an exhaustive search and a genetic algorithm, using a multiple logistic regression model. The 3 raster layers imported into the process were processed in advance, but the remainder of the workflow is fully functional to complete the analysis and return the model estimates. This code depends on many of the workflow operations within the tidyverse packages (Wickham et al. 2019), spatial data processing in the raster package (Hijmans 2022), and genetic algorithms from the rgenoud package (Mebane and Sekhon 2011).

```r
## Load packages -----------------------------------------------------
if(!require("pacman")) install.packages("pacman")
p_load(DescTools, dplyr, furrr, purrr, rgenoud, raster, smoothie, tidyr)

## Load Landscape Data and Smooth Rasters ----------------------------
# Load covariate rasters
covar1 <- raster("Data/covar1.tif")
covar2 <- raster("Data/covar2.tif")
covar3 <- raster("Data/covar3.tif")
names(covar1) <- "elev"
names(covar2) <- "develop"
```

123
names(covar3) <- "gauss"

opt_sigmas <- seq(0, 40, by = 1)

# Function to apply a Gaussian smoothing kernel on raster
SmoothRaster <- function(sigma = sigma, covar = covar){
  print(paste0("Starting: ", covar, ", sigma = ", sigma))
  covar <- get(covar)
  if (sigma >= 1) {
    covar_smooth <- raster(covar)  # creates blank raster
    values(covar_smooth) <- gauss2dsmooth(as.matrix(covar),
      lambda = sigma, nx = RoundTo(nrow(covar), 2),
      ny = RoundTo(ncol(covar), 2))
  } else {
    covar_smooth <- covar
  }
  names(covar_smooth) <- paste0(names(covar), sigma)
  return(covar_smooth)
}

# Create landscape covariate brick
covar_brick <- brick(c(
  tibble(sigma = opt_sigmas, covar = "covar1") %>%
  pmap(.x, SmoothRaster),
  tibble(sigma = opt_sigmas, covar = "covar2") %>%
  pmap(.x, SmoothRaster),
  tibble(sigma = opt_sigmas, covar = "covar3") %>%
  pmap(.x, SmoothRaster)))

covar_matrix <- raster::as.matrix(covar_brick)

covar_cols <- setNames(seq_len(ncol(covar_matrix)),

124
colnames(covar_matrix))
covar_names <- c(names(covar1), names(covar2), names(covar3))
rm(covar_brick)

## Create Presence-Absence Data --------------------------------------
# Set parameter values
ratio <- c(.5)
beta1 <- c(1, 2, 3)
beta2 <- c(1, 2, 3)
beta3 <- c(1, 2, 3)
sigma1 <- c(0, 10, 20)
sigma2 <- c(0, 10, 20)
sigma3 <- c(0, 10, 20)
# Create dataframe of parameter permutations
df_crossed <-
tidyr::crossing(ratio, beta1 = c(beta1, -1*beta1),
                 beta2 = c(beta2, -1*beta2), beta3 = c(beta3, -1*beta3),
                 sigma1 = sigma1, sigma2 = sigma2, sigma3 = sigma3) %>%
               mutate(sigma1 = as.numeric(sigma1),
                      sigma2 = as.numeric(sigma2),
                      sigma3 = as.numeric(sigma3))
# Calculate parameters
df_pars <- df_crossed %>%
             mutate(beta0 = -((beta1*.5 + beta2*.5 + beta3*.5) -
                            log(ratio/(1-ratio))) %>%
                           arrange(ratio, beta1, beta2, beta3, sigma1, sigma2, sigma3) %>%
mutate(number = 1:n()) %>%
dplyr::select(number, ratio, beta0, beta1, beta2, beta3, sigma1, sigma2, sigma3)

# Function to create presence-absence data using raster layers
CreatePAData <- function(sigma1 = sigma1, sigma2 = sigma2, sigma3 = sigma3, beta0 = beta0, beta1 = beta1, beta2 = beta2, beta3 = beta3){
  true_sigma1 <- covar_matrix[, covar_cols[paste0(names(covar1), sigma1)]]
  true_sigma2 <- covar_matrix[, covar_cols[paste0(names(covar2), sigma2)]]
  true_sigma3 <- covar_matrix[, covar_cols[paste0(names(covar3), sigma3)]]
  true_vec <- beta0 + (beta1 * true_sigma1) + (beta2 * true_sigma2) + (beta3 * true_sigma3)
  true_prob <- plogis(true_vec)
  pa_vec <- rbinom(length(true_prob), 1, true_prob)
  pa_all <- data.frame(cell_num = seq_len(ncell(covar1)),
                        case = pa_vec)
  pa_data <- bind_rows(
    pa_all %>% filter(case == 1) %>% sample_n(200),
    pa_all %>% filter(case == 0) %>% sample_n(200))
  print(paste0("Starting: ", paste0(names(covar1), sigma1), "/", paste0(names(covar2), sigma2), "/", paste0(names(covar3), sigma3), " (beta0 = ", signif(beta0, 2), ", beta1 = ", beta1, ", beta2 = ", beta2, ", beta3 = ", beta3, ")")
  return(pa_data)
# Populate data set

df_pa_data <- df_pars %>% sample_n(., size = 10) %>%
  mutate(pa_data = future_pmap(.l = list(sigma1, sigma2, sigma3, beta0, beta1, beta2, beta3), .f = CreatePAData, .progress = TRUE, .options = furrr_options(seed = TRUE)))

# Run Genetic Algorithm Optimization -----------------------------------
# Set sigma range
opt_sigmas <- seq(0, 40, by = 1)
# Set up parallel processing
plan(multisession)
# Function to apply optimization using indexed landscape sigma values
AICSigmaOpt <- function(sigmas, pa_data){
  cell_nums <- pa_data$cell_num
  df <- data.frame(case = pa_data$case,
                   value1 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[1], sigmas[1])]],
                   value2 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[2], sigmas[2])]],
                   value3 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[3], sigmas[3])]])
  model_logistic <- glm(case ~ value1 + value2 + value3,
                        family = binomial(link = "logit"), data = df)
  model_aic = AIC(model_logistic)
  return(model_aic)
}


# Function to wrap genetic-algorithm optimization fitting process

FitSigmaOpt <- function(number, pa_data) {
  domains = matrix(c(rep(min(opt_sigmas), 3), rep(max(opt_sigmas), 3)), ncol = 2)
  sigma3 <- sigma2 <- sigma1 <- median(opt_sigmas)
  starting_values <- c(sigma1, sigma2, sigma3)
  parms <- c(sigma1, sigma2, sigma3)
  cases <- pa_data[, "case"]
  cell_nums <- pa_data[, "cell_num"]
  opt_fit <- genoud(fn = AICSigmaOpt, nvars = 3,
                   pop.size = 10000, starting.values = starting_values,
                   optim.method = "SANN", max.generations = 2000,
                   hard.generation.limit = FALSE, wait.generations = 200,
                   P5 = 0, P6 = 0, P7 = 0, P8 = 0, BFGSburnin = 500,
                   print.level = 0, boundary.enforcement = 2,
                   pa_data = pa_data, data.type.int = TRUE, Domains = domains)
  return(opt_fit)
}

# Run genetic-algorithm optimization

df_opt_fit <- df_pa_data %>%
  mutate(opt_fit = future_map2(number, pa_data, FitSigmaOpt,
                               .progress = TRUE, .options = furrr_options(seed = TRUE)))

# Function to extract parameters from genetic-algorithm optimization

ExtractOptFit <- function(opt_fit, pa_data) {
  cell_nums <- pa_data$cell_num
  df <- data.frame(case = pa_data$case,
                   value1 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[1],
...
```r
opt_fit$par[1])
value2 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[2],
        opt_fit$par[2])]]
value3 = covar_matrix[cell_nums, covar_cols[paste0(covar_names[3],
        opt_fit$par[3])]]

opt_model_logistic <- glm(case ~ value1 + value2 + value3,
    family = binomial(link = "logit"), data = df)

opt_fit <- tibble(
    opt_model = list(opt_model_logistic),
    opt_beta0 = coef(opt_model_logistic)[1],
    opt_beta1 = coef(opt_model_logistic)[2],
    opt_beta2 = coef(opt_model_logistic)[3],
    opt_beta3 = coef(opt_model_logistic)[4],
    opt_sigma1 = opt_fit$par[1],
    opt_sigma2 = opt_fit$par[2],
    opt_sigma3 = opt_fit$par[3],
    opt_aic = AIC(opt_model_logistic))

return(opt_fit)
}

# Extract parameters and metrics
df_opt_fit_metrics <- df_opt_fit %>%
    Bind_cols(., map2_df(.$opt_fit, .$pa_data, ExtractOptFit))

# Run Exhaustive Search Optimization ---------------------------------
# Set sigma range for exhaustive-search permutations
permutations_sigmas <- c(seq(0, 40, by = 1))

# Function for exhaustive-search optimization fitting process
```
FitSigmaExhaustiveLogistic <- function(sigma1, sigma2, sigma3, pa_data){
cell_nums <- pa_data$cell_num
df <- data.frame(case = pa_data$case,
  value1 = covar_matrix[cell_nums, covar_cols[ paste0( covar_names[1], sigma1) ]],
  value2 = covar_matrix[cell_nums, covar_cols[ paste0( covar_names[2], sigma2) ]],
  value3 = covar_matrix[cell_nums, covar_cols[ paste0( covar_names[3], sigma3) ]])
model_logistic <- glm(case ~ value1 + value2 + value3,
  family = binomial(link = "logit"), data = df)
permutation_fit <- tibble(permutation_beta0 = coef(model_logistic)[1],
  permutation_beta1 = coef(model_logistic)[2],
  permutation_beta2 = coef(model_logistic)[3],
  permutation_beta3 = coef(model_logistic)[4],
  permutation_aic = AIC(model_logistic))
return(permutation_fit)
}

FitSigmaExhaustive <- function(number, pa_data){
  param_permutations <- crossing(sigma1 = permutations_sigmas,
    sigma2 = permutations_sigmas, sigma3 = permutations_sigmas) %>%
    mutate(pa_data = list(pa_data))
  permutations_fit <- param_permutations %>%
    bind_cols(., pmap_df(., FitSigmaExhaustiveLogistic)) %>%
  # Function to wrap exhaustive-search optimization fitting process

dplyr::select(-c(pa_data))
return(permutations_fit)
}

# Run exhaustive-search optimization
df_exhaustive_fit <- df_pa_data %>%
  mutate(permutations_fit = furrr::future_map2(number, pa_data,
    .f = FitSigmaExhaustive, .progress = TRUE,
    .options = furrr_options(seed = TRUE)))

# Function to extract permutations best fit
ExtractExhaustiveFit <- function(permutations_fit){
  best_fit <- permutations_fit %>% arrange(permutation_aic) %>%
    slice(1)

  permutation_best_fit <- tibble(
    permutation_best_fit = list(best_fit),
    permutation_beta0 = best_fit %>% pull(permutation_beta0),
    permutation_beta1 = best_fit %>% pull(permutation_beta1),
    permutation_beta2 = best_fit %>% pull(permutation_beta2),
    permutation_beta3 = best_fit %>% pull(permutation_beta3),
    permutation_sigma1 = best_fit %>% pull(sigma1),
    permutation_sigma2 = best_fit %>% pull(sigma2),
    permutation_sigma3 = best_fit %>% pull(sigma3),
    permutation_aic = best_fit %>% pull(permutation_aic)
  )
  return(permutation_best_fit)
}

# Extract parameters
df_exhaustive_fit_metrics <- df_exhaustive_fit %>%
  bind_cols(., map_df(.$permutations_fit, ExtractExhaustiveFit))
APPENDIX B
BALD EAGLE HOME RANGE MAPS

The following maps show the utilization distributions for each Bald Eagle used in the home range and territoriality analysis. These data were filtered to locations associated with territorial behavior. For individuals with multiple years of location data, each year is provided individually. Inset maps show the area in Maine of the location data.
Figure B.1. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Branch Lake, ME, breeding season 2015.
Figure B.2. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Branch Lake, ME, breeding season 2016.
Figure B.3. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Crooked Pond, ME, breeding season 2015.
Figure B.4. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, Ellis Pond, ME, breeding season 2015.
Figure B.5. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Ellis Pond, ME, breeding season 2016.
Figure B.6. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Ellis Pond, ME, breeding season 2017.
Figure B.7. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Eskutasssis Pond, ME, breeding season 2015.
Figure B.8. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Eskutassis Pond, ME, breeding season 2016.
Figure B.9. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Lake Hebron, ME, breeding season 2015.
Figure B.10. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Lake Hebron, ME, breeding season 2016.
Figure B.11. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2015.
Figure B.12. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2016.
Figure B.13. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2017.
Figure B.14. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at East Musquash Lake, ME, breeding season 2018.
Figure B.15. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Penroseewassee (Norway) Lake, ME, breeding season 2015.
Figure B.16. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2015.
Figure B.17. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2016.
Figure B.18. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2017.
Figure B.19. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2018.
Figure B.20. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sandy Pond, ME, breeding season 2019.
Figure B.21. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Sheepscot Pond, ME, breeding season 2015.
Figure B.22. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Number Three Pond, ME, breeding season 2015.
Figure B.23. GPS telemetry locations (purple dots), interpolated flight paths (white lines), and the 50% (yellow polygons) and 95% (red polygons) isopleths of utilization distributions, representing the ‘core’ and ‘total’ home ranges, respectively, for the Bald Eagle at Upper Wilson Pond, ME, breeding season 2015.
APPENDIX C

RESOURCE SELECTION MODEL FITS BY STEP TYPE

The following tables show the top ten models selected for the resource selection fits for each of the seventeen step types described in Chapter 2. Each of the tables show the model rank, AICc, Δ AICc, concordance, and the landscape covariates included in the model. For covariates with that included varying bandwidths, the sigma value is included as a suffix.

Table C.1. Resource selection model fits for cruise-to-cruise step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>746.10</td>
<td>0.00</td>
<td>0.79</td>
<td>-0.038<em>TPI7 + 11</em>Wetland100 + -0.0018<em>DistHydro + 0.00029</em>DistTurbine</td>
</tr>
<tr>
<td>2</td>
<td>747.72</td>
<td>1.62</td>
<td>0.78</td>
<td>11<em>Wetland100 + -0.0018</em>DistHydro + 0.00029*DistTurbine</td>
</tr>
<tr>
<td>3</td>
<td>766.92</td>
<td>20.82</td>
<td>0.76</td>
<td>-0.0078<em>TPI50 + -0.0015</em>DistHydro + 0.00026*DistTurbine</td>
</tr>
<tr>
<td>4</td>
<td>769.43</td>
<td>23.33</td>
<td>0.76</td>
<td>-0.0017<em>DistHydro + 0.00026</em>DistTurbine</td>
</tr>
<tr>
<td>5</td>
<td>824.24</td>
<td>78.14</td>
<td>0.76</td>
<td>-0.022<em>TPI50 + 9.1</em>Wetland100 + 3e-04*DistTurbine</td>
</tr>
<tr>
<td>6</td>
<td>836.23</td>
<td>90.13</td>
<td>0.74</td>
<td>-0.048<em>TPI6 + 6.2</em>Wetland100 + -0.0018*DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>838.78</td>
<td>92.68</td>
<td>0.73</td>
<td>6.2<em>Wetland100 + -0.0019</em>DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>839.66</td>
<td>93.56</td>
<td>0.73</td>
<td>-0.022<em>TPI50 + 0.00027</em>DistTurbine</td>
</tr>
<tr>
<td>9</td>
<td>842.32</td>
<td>96.22</td>
<td>0.72</td>
<td>-0.0079<em>TPI50 + -0.0016</em>DistHydro</td>
</tr>
<tr>
<td>10</td>
<td>845.47</td>
<td>99.36</td>
<td>0.74</td>
<td>-0.0018*DistHydro</td>
</tr>
</tbody>
</table>
Table C.2. Resource selection model fits for cruise-to-flight step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>352.16</td>
<td>0.00</td>
<td>0.81</td>
<td>$0.029 \times \text{Roughness3} + -0.0025 \times \text{DistHydro} + 2e-04 \times \text{DistTurbine}$</td>
</tr>
<tr>
<td>2</td>
<td>352.58</td>
<td>0.42</td>
<td>0.81</td>
<td>$-0.24 \times \text{Eastness1} + 0.027 \times \text{Roughness3} + -0.0025 \times \text{DistHydro} + 2e-04 \times \text{DistTurbine}$</td>
</tr>
<tr>
<td>3</td>
<td>364.07</td>
<td>11.90</td>
<td>0.79</td>
<td>$-0.36 \times \text{Eastness1} + -0.0023 \times \text{DistHydro} + 0.00021 \times \text{DistTurbine}$</td>
</tr>
<tr>
<td>4</td>
<td>365.88</td>
<td>13.72</td>
<td>0.78</td>
<td>$-0.0022 \times \text{DistHydro} + 0.00021 \times \text{DistTurbine}$</td>
</tr>
<tr>
<td>5</td>
<td>371.07</td>
<td>18.90</td>
<td>0.81</td>
<td>$0.03 \times \text{Roughness3} + -0.0024 \times \text{DistHydro}$</td>
</tr>
<tr>
<td>6</td>
<td>371.60</td>
<td>19.43</td>
<td>0.80</td>
<td>$-0.22 \times \text{Eastness1} + 0.028 \times \text{Roughness3} + -0.0025 \times \text{DistHydro}$</td>
</tr>
<tr>
<td>7</td>
<td>385.65</td>
<td>33.49</td>
<td>0.77</td>
<td>$-0.36 \times \text{Eastness1} + -0.0022 \times \text{DistHydro}$</td>
</tr>
<tr>
<td>8</td>
<td>387.69</td>
<td>35.53</td>
<td>0.78</td>
<td>$-0.0021 \times \text{DistHydro}$</td>
</tr>
<tr>
<td>9</td>
<td>459.84</td>
<td>107.67</td>
<td>0.69</td>
<td>$1.6 \times \text{Eastness46} + 0.0089 \times \text{Roughness3} + 0.00017 \times \text{DistTurbine}$</td>
</tr>
<tr>
<td>10</td>
<td>460.89</td>
<td>108.73</td>
<td>0.67</td>
<td>$1.7 \times \text{Eastness50} + 0.00017 \times \text{DistTurbine}$</td>
</tr>
</tbody>
</table>
Table C.3. Resource selection model fits for cruise-to-perch step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>184.03</td>
<td>0.00</td>
<td>0.92</td>
<td>-1.4<em>Forest3 + 3.8</em>OpenWater6 + -3.1<em>ShrubHerb1 + 2</em>Wetland1 + 0.2<em>TRI5 + -0.0034</em>DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>184.18</td>
<td>0.15</td>
<td>0.92</td>
<td>4.6<em>OpenWater5 + 2.6</em>Wetland1 + 0.18<em>TRI5 + -0.0036</em>DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>184.35</td>
<td>0.32</td>
<td>0.92</td>
<td>-1.1<em>Forest3 + 4.2</em>OpenWater6 + 2.2<em>Wetland1 + 0.21</em>TRI5 + -0.0036*DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>184.67</td>
<td>0.64</td>
<td>0.92</td>
<td>4.4<em>OpenWater5 + -2.4</em>ShrubHerb1 + 2.5<em>Wetland1 + 0.17</em>TRI5 + -0.0035*DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>186.46</td>
<td>2.43</td>
<td>0.92</td>
<td>-2.4<em>Forest2 + 3.1</em>OpenWater10 + -4.4<em>ShrubHerb1 + 0.18</em>TRI5 + -0.0036*DistHydro</td>
</tr>
<tr>
<td>6</td>
<td>189.27</td>
<td>5.24</td>
<td>0.93</td>
<td>-2.8<em>Forest2 + -5.3</em>ShrubHerb1 + 0.22<em>TRI4 + -0.0042</em>DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>189.62</td>
<td>5.60</td>
<td>0.92</td>
<td>-2.1<em>Forest2 + 3.5</em>OpenWater10 + 0.19<em>TRI5 + -0.0038</em>DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>189.67</td>
<td>5.64</td>
<td>0.92</td>
<td>-3.2<em>Forest2 + -5.6</em>ShrubHerb1 + -2<em>Wetland7 + 0.21</em>TRI4 + -0.0041*DistHydro</td>
</tr>
<tr>
<td>9</td>
<td>193.38</td>
<td>9.35</td>
<td>0.93</td>
<td>-2.4<em>Forest3 + 1.3</em>Wetland1 + 0.24<em>TRI4 + -0.0046</em>DistHydro</td>
</tr>
<tr>
<td>10</td>
<td>194.12</td>
<td>10.09</td>
<td>0.92</td>
<td>-2.8<em>Forest3 + 0.2</em>TRI5 + -0.0046*DistHydro</td>
</tr>
</tbody>
</table>
Table C.4. Resource selection model fits for flight-to-cruise step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>508.09</td>
<td>0.00</td>
<td>0.72</td>
<td>-0.013<em>TPI23 + -0.88</em>Wetland2 + -0.0015<em>DistHydro + 0.00025</em>DistTurbine</td>
</tr>
<tr>
<td>2</td>
<td>508.58</td>
<td>0.49</td>
<td>0.72</td>
<td>-3.1<em>Wetland46 + -0.0016</em>DistHydro + 0.00023*DistTurbine</td>
</tr>
<tr>
<td>3</td>
<td>508.85</td>
<td>0.76</td>
<td>0.73</td>
<td>-0.01<em>TPI24 + -0.0015</em>DistHydro + 0.00025*DistTurbine</td>
</tr>
<tr>
<td>4</td>
<td>508.96</td>
<td>0.87</td>
<td>0.73</td>
<td>-0.0016<em>DistHydro + 0.00024</em>DistTurbine</td>
</tr>
<tr>
<td>5</td>
<td>530.87</td>
<td>22.78</td>
<td>0.72</td>
<td>-5<em>Wetland54 + -0.0017</em>DistHydro</td>
</tr>
<tr>
<td>6</td>
<td>531.50</td>
<td>23.41</td>
<td>0.70</td>
<td>-0.0047<em>TPI50 + -5</em>Wetland52 + -0.0016*DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>534.46</td>
<td>26.37</td>
<td>0.72</td>
<td>-0.0017*DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>535.18</td>
<td>27.09</td>
<td>0.71</td>
<td>-0.0082<em>TPI23 + -0.0017</em>DistHydro</td>
</tr>
<tr>
<td>9</td>
<td>549.48</td>
<td>41.39</td>
<td>0.68</td>
<td>-0.017<em>TPI50 + -0.69</em>Wetland1 + 0.00027*DistTurbine</td>
</tr>
<tr>
<td>10</td>
<td>549.89</td>
<td>41.80</td>
<td>0.68</td>
<td>-0.016<em>TPI50 + 0.00027</em>DistTurbine</td>
</tr>
</tbody>
</table>
Table C.5. Resource selection model fits for flight-to-flight step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>299.47</td>
<td>0.00</td>
<td>0.86</td>
<td>-1.1<em>Eastness10 + 0.0066</em>Roughness50 + -0.003<em>DistHydro + 0.00041</em>DistTurbine</td>
</tr>
<tr>
<td>2</td>
<td>304.03</td>
<td>4.55</td>
<td>0.88</td>
<td>0.039<em>Roughness2 + -0.003</em>DistHydro + 4e-04*DistTurbine</td>
</tr>
<tr>
<td>3</td>
<td>308.43</td>
<td>8.96</td>
<td>0.86</td>
<td>-0.97<em>Eastness9 + -0.0028</em>DistHydro + 0.00041*DistTurbine</td>
</tr>
<tr>
<td>4</td>
<td>314.98</td>
<td>15.51</td>
<td>0.87</td>
<td>-0.0027<em>DistHydro + 0.00039</em>DistTurbine</td>
</tr>
<tr>
<td>5</td>
<td>334.83</td>
<td>35.36</td>
<td>0.83</td>
<td>-0.89<em>Eastness9 + 0.0068</em>Roughness50 + -0.0031*DistHydro</td>
</tr>
<tr>
<td>6</td>
<td>336.80</td>
<td>37.33</td>
<td>0.84</td>
<td>0.02<em>Roughness5 + -0.0031</em>DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>345.64</td>
<td>46.17</td>
<td>0.83</td>
<td>-0.74<em>Eastness8 + -0.0029</em>DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>349.86</td>
<td>50.39</td>
<td>0.84</td>
<td>-0.0028*DistHydro</td>
</tr>
<tr>
<td>9</td>
<td>451.17</td>
<td>151.70</td>
<td>0.71</td>
<td>-0.55<em>Eastness8 + -0.0037</em>Roughness16 + 0.00041*DistTurbine</td>
</tr>
<tr>
<td>10</td>
<td>452.73</td>
<td>153.26</td>
<td>0.72</td>
<td>-0.5<em>Eastness8 + 0.00041</em>DistTurbine</td>
</tr>
</tbody>
</table>
Table C.6. Resource selection model fits for flight-to-perch step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>365.98</td>
<td>0.00</td>
<td>0.95</td>
<td>-2<em>Forest10 + 4.6</em>OpenWater6 + 1.6<em>ShrubHerb1 + 1.7</em>Wetland1 + 0.072<em>TRI10 + -0.0045</em>DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>366.01</td>
<td>0.04</td>
<td>0.95</td>
<td>-2.4<em>Forest10 + 4.3</em>OpenWater6 + 1.6<em>Wetland1 + 0.077</em>TRI10 + -0.0044*DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>366.95</td>
<td>0.97</td>
<td>0.95</td>
<td>5<em>OpenWater5 + 2.2</em>ShrubHerb1 + 1.9<em>Wetland1 + 0.24</em>TRI1 + -0.0046*DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>369.28</td>
<td>3.30</td>
<td>0.95</td>
<td>5<em>OpenWater5 + 1.8</em>Wetland1 + 0.27<em>TRI1 + -0.0044</em>DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>371.04</td>
<td>5.06</td>
<td>0.95</td>
<td>-1.3<em>Forest1 + 4.1</em>OpenWater7 + 0.24<em>TRI1 + -0.0046</em>DistHydro</td>
</tr>
<tr>
<td>6</td>
<td>372.09</td>
<td>6.11</td>
<td>0.95</td>
<td>-1.2<em>Forest1 + 4.1</em>OpenWater7 + 1.1<em>ShrubHerb1 + 0.22</em>TRI1 + -0.0047*DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>374.65</td>
<td>8.67</td>
<td>0.95</td>
<td>4.7<em>OpenWater8 + 2.5</em>ShrubHerb1 + 1.3<em>Wetland1 + -0.0048</em>DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>375.76</td>
<td>9.78</td>
<td>0.95</td>
<td>-0.97<em>Forest10 + 4</em>OpenWater7 + 2.2<em>ShrubHerb1 + 1.2</em>Wetland1 + -0.0048*DistHydro</td>
</tr>
<tr>
<td>9</td>
<td>375.79</td>
<td>9.81</td>
<td>0.95</td>
<td>4.2<em>OpenWater5 + 2.1</em>ShrubHerb1 + 0.15<em>TRI1 + -0.0052</em>DistHydro</td>
</tr>
<tr>
<td>10</td>
<td>377.52</td>
<td>11.55</td>
<td>0.95</td>
<td>4.2<em>OpenWater5 + 0.17</em>TRI1 + -0.005*DistHydro</td>
</tr>
</tbody>
</table>
Table C.7. Resource selection model fits for flight-to-roost step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>14.39</td>
<td>0.00</td>
<td>0.96</td>
<td>13<em>Eastness5 + -4.5</em>Northness1 + -0.016*DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>15.79</td>
<td>1.40</td>
<td>0.91</td>
<td>4.1<em>Eastness7 + -0.0087</em>DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>15.87</td>
<td>1.48</td>
<td>0.91</td>
<td>-0.0089*DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>17.43</td>
<td>3.04</td>
<td>0.96</td>
<td>-0.83<em>Northness1 + -0.0086</em>DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>29.62</td>
<td>15.23</td>
<td>0.74</td>
<td>3.2*Eastness10</td>
</tr>
<tr>
<td>6</td>
<td>30.72</td>
<td>16.34</td>
<td>0.61</td>
<td>3<em>Eastness8 + -2.2</em>Northness10</td>
</tr>
<tr>
<td>7</td>
<td>32.31</td>
<td>17.92</td>
<td>0.61</td>
<td>-2.5*Northness10</td>
</tr>
</tbody>
</table>

Table C.8. Resource selection model fits for nest-to-cruise step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92.63</td>
<td>0.00</td>
<td>0.77</td>
<td>-3.6<em>Wetland3 + -0.0022</em>DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>93.47</td>
<td>0.84</td>
<td>0.78</td>
<td>15<em>Wetland49 + -0.0023</em>DistHydro + -0.00045*DistTurbine</td>
</tr>
<tr>
<td>3</td>
<td>95.18</td>
<td>2.55</td>
<td>0.79</td>
<td>-0.0023<em>DistHydro + -0.00027</em>DistTurbine</td>
</tr>
<tr>
<td>4</td>
<td>95.42</td>
<td>2.79</td>
<td>0.77</td>
<td>-0.0022*DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>109.07</td>
<td>16.44</td>
<td>0.82</td>
<td>-4.6*Wetland3</td>
</tr>
<tr>
<td>6</td>
<td>110.77</td>
<td>18.14</td>
<td>0.82</td>
<td>-4.2<em>Wetland3 + -1e-04</em>DistTurbine</td>
</tr>
<tr>
<td>7</td>
<td>113.90</td>
<td>21.27</td>
<td>0.61</td>
<td>-0.00021*DistTurbine</td>
</tr>
</tbody>
</table>
Table C.9. Resource selection model fits for nest-to-flight step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>152.06</td>
<td>0.00</td>
<td>0.93</td>
<td>57<em>OpenWater96 + -0.005</em>DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>172.85</td>
<td>20.78</td>
<td>0.93</td>
<td>-0.03<em>TRI50 + -0.0048</em>DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>174.78</td>
<td>22.71</td>
<td>0.90</td>
<td>-0.0053*DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>199.74</td>
<td>47.68</td>
<td>0.90</td>
<td>55<em>OpenWater70 + -0.1</em>TRI39</td>
</tr>
<tr>
<td>5</td>
<td>246.22</td>
<td>94.16</td>
<td>0.87</td>
<td>46*OpenWater60</td>
</tr>
<tr>
<td>6</td>
<td>293.65</td>
<td>141.59</td>
<td>0.84</td>
<td>-0.13*TRI24</td>
</tr>
</tbody>
</table>

Table C.10. Resource selection model fits for nest-to-perch step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>578.62</td>
<td>0.00</td>
<td>0.93</td>
<td>-1.1<em>Forest1 + 8.4</em>OpenWater10 + 3.2*Wetland1</td>
</tr>
<tr>
<td>2</td>
<td>582.85</td>
<td>4.23</td>
<td>0.93</td>
<td>9.3<em>OpenWater10 + -31</em>ShrubHerb5 + 3.7*Wetland1</td>
</tr>
<tr>
<td>3</td>
<td>593.95</td>
<td>15.33</td>
<td>0.93</td>
<td>1.6<em>Forest6 + 11</em>OpenWater10 + 3.5*Wetland1</td>
</tr>
<tr>
<td>4</td>
<td>594.78</td>
<td>16.15</td>
<td>0.93</td>
<td>9.3<em>OpenWater10 + -30</em>ShrubHerb5 + 3.1*Wetland1</td>
</tr>
<tr>
<td>5</td>
<td>602.14</td>
<td>23.52</td>
<td>0.94</td>
<td>-1.1<em>Forest1 + 6.2</em>OpenWater10 + -0.15*TRI10</td>
</tr>
<tr>
<td>6</td>
<td>607.51</td>
<td>28.88</td>
<td>0.90</td>
<td>4.6<em>Forest8 + 13</em>OpenWater10 + 3.7*Wetland1</td>
</tr>
<tr>
<td>7</td>
<td>612.45</td>
<td>33.82</td>
<td>0.94</td>
<td>6.7<em>OpenWater10 + -33</em>ShrubHerb5 + -0.15*TRI10</td>
</tr>
<tr>
<td>8</td>
<td>612.89</td>
<td>34.26</td>
<td>0.93</td>
<td>-11<em>Forest10 + -43</em>ShrubHerb5 + 2.8*Wetland1</td>
</tr>
<tr>
<td>9</td>
<td>618.48</td>
<td>39.86</td>
<td>0.91</td>
<td>9.5<em>OpenWater10 + -0.14</em>TRI10 + 3.3*Wetland1</td>
</tr>
<tr>
<td>10</td>
<td>626.34</td>
<td>47.71</td>
<td>0.93</td>
<td>-1.3<em>Forest1 + 7.3</em>OpenWater10 + -36*ShrubHerb5</td>
</tr>
</tbody>
</table>
Table C.11. Resource selection model fits for nest-to-roost step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>∆AICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.36</td>
<td>0.00</td>
<td>0.71</td>
<td>6.9<em>OpenWater10 + 5.7</em>Wetland1</td>
</tr>
<tr>
<td>2</td>
<td>27.17</td>
<td>1.82</td>
<td>0.86</td>
<td>-0.62<em>Northness1 + 7</em>OpenWater10 + 5.8*Wetland1</td>
</tr>
<tr>
<td>3</td>
<td>29.71</td>
<td>4.35</td>
<td>0.57</td>
<td>4.5*Wetland1</td>
</tr>
<tr>
<td>4</td>
<td>30.92</td>
<td>5.56</td>
<td>0.71</td>
<td>-0.83<em>Northness1 + 4.7</em>Wetland1</td>
</tr>
<tr>
<td>5</td>
<td>34.84</td>
<td>9.48</td>
<td>0.64</td>
<td>-2.9*OpenWater1</td>
</tr>
<tr>
<td>6</td>
<td>36.58</td>
<td>11.22</td>
<td>0.61</td>
<td>-0.59<em>Northness1 + -2.9</em>OpenWater1</td>
</tr>
<tr>
<td>7</td>
<td>40.65</td>
<td>15.29</td>
<td>0.64</td>
<td>1.4*Northness9</td>
</tr>
</tbody>
</table>

Table C.12. Resource selection model fits for perch-to-cruise step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
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<th>AICc</th>
<th>∆AICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>314.41</td>
<td>0.00</td>
<td>0.77</td>
<td>-23<em>Wetland100 + -0.0029</em>DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>316.05</td>
<td>1.65</td>
<td>0.78</td>
<td>-24<em>Wetland100 + -0.0029</em>DistHydro + -5.7e-5*DistTurbine</td>
</tr>
<tr>
<td>3</td>
<td>319.62</td>
<td>5.22</td>
<td>0.78</td>
<td>-0.0031*DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>321.63</td>
<td>7.22</td>
<td>0.78</td>
<td>-0.0031<em>DistHydro + -7.5e-6</em>DistTurbine</td>
</tr>
<tr>
<td>5</td>
<td>404.70</td>
<td>90.29</td>
<td>0.59</td>
<td>-33*Wetland100</td>
</tr>
<tr>
<td>6</td>
<td>404.95</td>
<td>90.54</td>
<td>0.62</td>
<td>-35<em>Wetland100 + -0.00011</em>DistTurbine</td>
</tr>
<tr>
<td>7</td>
<td>426.18</td>
<td>111.78</td>
<td>0.52</td>
<td>-1.3e-5*DistTurbine</td>
</tr>
</tbody>
</table>
### Table C.13. Resource selection model fits for perch-to-flight step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>691.92</td>
<td>0.00</td>
<td>0.91</td>
<td>14<em>OpenWater46 + -0.016</em>TRI37 + -0.004*DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>693.78</td>
<td>1.86</td>
<td>0.90</td>
<td>13<em>OpenWater43 + -0.0042</em>DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>730.90</td>
<td>38.97</td>
<td>0.91</td>
<td>-0.017<em>TRI39 + -0.0052</em>DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>733.41</td>
<td>41.48</td>
<td>0.91</td>
<td>-0.0055*DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>894.13</td>
<td>202.21</td>
<td>0.85</td>
<td>25<em>OpenWater39 + -0.058</em>TRI28</td>
</tr>
<tr>
<td>6</td>
<td>924.67</td>
<td>232.74</td>
<td>0.75</td>
<td>11*OpenWater17</td>
</tr>
<tr>
<td>7</td>
<td>1353.44</td>
<td>661.51</td>
<td>0.78</td>
<td>-0.11*TRI28</td>
</tr>
</tbody>
</table>

### Table C.14. Resource selection model fits for perch-to-perch step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2291.92</td>
<td>0.00</td>
<td>0.91</td>
<td>-3.2<em>Forest3 + 12</em>OpenWater10 + -13<em>ShrubHerb7 + 0.28</em>TRI1 + 3.5*Wetland1</td>
</tr>
<tr>
<td>2</td>
<td>2331.11</td>
<td>39.20</td>
<td>0.92</td>
<td>-2.5<em>Forest3 + 12</em>OpenWater10 + -13<em>ShrubHerb9 + 3.5</em>Wetland1</td>
</tr>
<tr>
<td>3</td>
<td>2385.04</td>
<td>93.12</td>
<td>0.91</td>
<td>13<em>OpenWater8 + -13</em>ShrubHerb10 + 0.16<em>TRI1 + 4.7</em>Wetland1</td>
</tr>
<tr>
<td>4</td>
<td>2401.28</td>
<td>109.37</td>
<td>0.91</td>
<td>13<em>OpenWater8 + -13</em>ShrubHerb10 + 4.5*Wetland1</td>
</tr>
<tr>
<td>5</td>
<td>2411.79</td>
<td>119.88</td>
<td>0.90</td>
<td>-2.2<em>Forest3 + 13</em>OpenWater10 + 3.8*Wetland1</td>
</tr>
<tr>
<td>6</td>
<td>2457.88</td>
<td>165.96</td>
<td>0.90</td>
<td>14<em>OpenWater8 + 0.15</em>TRI1 + 4.9*Wetland1</td>
</tr>
<tr>
<td>7</td>
<td>2459.53</td>
<td>167.61</td>
<td>0.91</td>
<td>-4.5<em>Forest2 + 10</em>OpenWater10 + -14<em>ShrubHerb5 + 0.26</em>TRI1</td>
</tr>
<tr>
<td>8</td>
<td>2470.87</td>
<td>178.96</td>
<td>0.90</td>
<td>14<em>OpenWater9 + 4.7</em>Wetland1</td>
</tr>
<tr>
<td>9</td>
<td>2495.38</td>
<td>203.46</td>
<td>0.91</td>
<td>-3.9<em>Forest2 + 11</em>OpenWater10 + -14*ShrubHerb5</td>
</tr>
<tr>
<td>10</td>
<td>2633.53</td>
<td>341.62</td>
<td>0.89</td>
<td>-4.1<em>Forest2 + 11</em>OpenWater10 + 0.18*TRI1</td>
</tr>
</tbody>
</table>
Table C.15. Resource selection model fits for perch-to-roost step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>60.23</td>
<td>0.00</td>
<td>0.98</td>
<td>-3.9<em>Northness3 + -5.6</em>OpenWater1 + -0.031*DistHydro</td>
</tr>
<tr>
<td>2</td>
<td>62.17</td>
<td>1.94</td>
<td>0.98</td>
<td>-4<em>Northness3 + -5.5</em>OpenWater1 + 2.2<em>Wetland10 + -0.031</em>DistHydro</td>
</tr>
<tr>
<td>3</td>
<td>67.24</td>
<td>7.02</td>
<td>0.97</td>
<td>-4.6<em>OpenWater1 + -0.026</em>DistHydro</td>
</tr>
<tr>
<td>4</td>
<td>68.75</td>
<td>8.52</td>
<td>0.97</td>
<td>-5<em>OpenWater1 + -2.9</em>Wetland6 + -0.027*DistHydro</td>
</tr>
<tr>
<td>5</td>
<td>83.73</td>
<td>23.50</td>
<td>0.95</td>
<td>-1.3<em>Northness2 + 2.7</em>Wetland1 + -0.021*DistHydro</td>
</tr>
<tr>
<td>6</td>
<td>85.12</td>
<td>24.90</td>
<td>0.96</td>
<td>2.6<em>Wetland1 + -0.02</em>DistHydro</td>
</tr>
<tr>
<td>7</td>
<td>86.43</td>
<td>26.21</td>
<td>0.95</td>
<td>-1.2<em>Northness2 + -0.023</em>DistHydro</td>
</tr>
<tr>
<td>8</td>
<td>87.52</td>
<td>27.30</td>
<td>0.96</td>
<td>-0.022*DistHydro</td>
</tr>
<tr>
<td>9</td>
<td>262.66</td>
<td>202.44</td>
<td>0.74</td>
<td>7<em>OpenWater10 + 3.7</em>Wetland1</td>
</tr>
<tr>
<td>10</td>
<td>264.53</td>
<td>204.30</td>
<td>0.74</td>
<td>-0.38<em>Northness10 + 6.9</em>OpenWater10 + 3.8*Wetland1</td>
</tr>
</tbody>
</table>

Table C.16. Resource selection model fits for roost-to-flight step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.52</td>
<td>0.00</td>
<td>0.86</td>
<td>-1*TRI5</td>
</tr>
</tbody>
</table>
Table C.17. Resource selection model fits for roost-to-perch step-type for Bald Eagles in Maine.

<table>
<thead>
<tr>
<th>Model Rank</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>Concordance</th>
<th>Full Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>85.85</td>
<td>0.00</td>
<td>0.91</td>
<td>-4.2<em>Forest1 + 17</em>OpenWater10</td>
</tr>
<tr>
<td>2</td>
<td>86.23</td>
<td>0.38</td>
<td>0.92</td>
<td>-3.5<em>Forest1 + 17</em>OpenWater10 + 1.9*Wetland1</td>
</tr>
<tr>
<td>3</td>
<td>86.57</td>
<td>0.71</td>
<td>0.92</td>
<td>-3.7<em>Forest1 + 16</em>OpenWater10 + -0.072*TRI10</td>
</tr>
<tr>
<td>4</td>
<td>86.73</td>
<td>0.88</td>
<td>0.92</td>
<td>-4.2<em>Forest1 + 16</em>OpenWater10 + -12*ShrubHerb10</td>
</tr>
<tr>
<td>5</td>
<td>86.82</td>
<td>0.97</td>
<td>0.92</td>
<td>-3.7<em>Forest1 + 16</em>OpenWater10 + -15*ShrubHerb10</td>
</tr>
<tr>
<td>6</td>
<td>87.08</td>
<td>1.23</td>
<td>0.92</td>
<td>-3.1<em>Forest1 + 17</em>OpenWater10 + -0.069<em>TRI10 + 1.8</em>Wetland1</td>
</tr>
<tr>
<td>7</td>
<td>87.42</td>
<td>1.57</td>
<td>0.93</td>
<td>-3.6<em>Forest1 + 16</em>OpenWater10 + -11*ShrubHerb10</td>
</tr>
<tr>
<td>8</td>
<td>87.76</td>
<td>1.91</td>
<td>0.93</td>
<td>-3.1<em>Forest1 + 16</em>OpenWater10 + -14*ShrubHerb10</td>
</tr>
<tr>
<td>9</td>
<td>95.09</td>
<td>9.23</td>
<td>0.94</td>
<td>18<em>OpenWater10 + -0.32</em>TRI4 + 3.6*Wetland1</td>
</tr>
<tr>
<td>10</td>
<td>96.05</td>
<td>10.20</td>
<td>0.94</td>
<td>17<em>OpenWater10 + -12</em>ShrubHerb10 + -0.31<em>TRI4 + 3.5</em>Wetland1</td>
</tr>
</tbody>
</table>
APPENDIX D

INDIVIDUAL-BASED MODELING FRAMEWORK

The following R code gives the general structure of the IBM framework used for the Bald Eagle simulations described in Chapters 3 and 4. All the functions with upper camel case names (e.g., UpdateAgentStates) were defined separately and are available upon request from the author. Additional submodels can be appended into the for loops to control for additional components (e.g., decision-making, interactions, memory, etc.).

# General function used to run an IBM simulation
RunSimulation <- function(sim = sim,
                           write = TRUE,
                           output_dir = getwd()){
  rep_intervals <- CreateReportIntervals(sim)
  sim <- UpdateAgentStates(init=TRUE, sim=sim)
  sim <- UpdateAgentStepData(init=TRUE, sim=sim)
  sim <- UpdateAgentParsData(init=TRUE, sim=sim)
  sim <- UpdateSpatial(init=TRUE, sim=sim)
  for (j in 1:length(rep_intervals)) {
    step_intervals <- CreateStepIntervals(rep_intervals[[j]])
    for (k in 1:length(step_intervals)) {
      time_steps <- CreateTimeSteps(step_intervals[[k]])
      for (m in 1:length(time_steps)) {
        step <- time_steps[[m]]
      }
    }
  }
}
alive_seq <- ReturnAliveSeq(sim)
sim$agents$all <- UpdateAgentParsData(sim$agents$all)
for (n in alive_seq) {
  agent_states <- sim$agents$all[[n]]$"states"
  step_data <- sim$agents$all[[n]]$"step_data"
  pars_data <- sim$agents$all[[n]]$"pars_data"
  # START Submodels #
  agent_states <- AgingSubModel(agent_states, step_data, step)
  step_data <- MovementSubModel(sim, agent_states, step_data, step)
  # END Submodels #
  sim$agents$all[[n]]$"step_data" <- UpdateAgentStepData(step_data)
  sim$agents$all[[n]]$"states" <- UpdateAgentStates(agent_states)
}

sim$spatial <- UpdateSpatial(sim$spatial)

sim$agents <- UpdateAgentsReport(sim, rep_intervals[[j]], step_intervals)
sim$agents <- UpdatePopReport(sim, rep_intervals[[j]], step_intervals)

WriteSimList(write = write, run = names(runs[j]), sim = sim,
             output_dir = getwd(), components = "all")
return(sim)

}
APPENDIX E

RESOURCE SELECTION MODEL FITS BY STEP TYPE FOR WIND FARM SCENARIOS

The following maps are the resource selection probability functions for the Upper Wilson Pond and West Grand Lake nest sites under the different wind turbine scenarios in Chapter 4.
Figure E.1. Map of the Bald Eagle resource selection function probability surfaces by step type under the control scenario (no turbines) for the nest (orange circle) at Upper Wilson Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.2. Map of the Bald Eagle resource selection function probability surfaces by step type under the north wind farm scenario (15 turbines) for the nest (orange circle) at Upper Wilson Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.3. Map of the Bald Eagle resource selection function probability surfaces by step type under the south wind farm scenario (15 turbines) for the nest (orange circle) at Upper Wilson Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.4. Map of the Bald Eagle resource selection function probability surfaces by step type under the north and south wind farm scenario (15 turbines in each area) for the nest (orange circle) at Upper Wilson Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.5. Map of the Bald Eagle resource selection function probability surfaces by step type under the control scenario (no turbines) for the nest (orange circle) at West Grand Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.6. Map of the Bald Eagle resource selection function probability surfaces by step type under the north wind farm scenario (20 turbines) for the nest (orange circle) at West Grand Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.7. Map of the Bald Eagle resource selection function probability surfaces by step type under the south wind farm scenario (20 turbines) for the nest (orange circle) at West Grand Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
Figure E.8. Map of the Bald Eagle resource selection function probability surfaces by step type under the north and south wind farm scenario (20 turbines in each area) for the nest (orange circle) at West Grand Lake, ME. The probability surfaces were clipped to a buffer of 15 km around the nest for visualization purposes.
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