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EXAMINING THE INFLUENCE OF LANDSCAPE ON NATURAL RESOURCE MANAGEMENT IN THE AMERICAN WEST: A GEOSPATIAL APPROACH

by

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DISSERTATION

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DEDICATION

For Catherine, whose love carries me always

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Examining the Influence of Landscape on Natural Resource Management in the American West: A Geospatial Approach

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ABSTRACT

Landscapes can influence natural resource values and management in a variety of ways. These diverse influences can be generated by biophysical or social systems, or interactions between systems. This dissertation examines the landscape determinants of natural resource values and management.

Chapter 2 examines moose habitat preferences with a spatial discrete-choice model. The study tests for spatial autocorrelation and compares the results to results from nonspatial models. The objective of this analysis is to explore the human-based and naturally occurring determinants of moose habitat selection while presenting a method and example for addressing spatial correlation between spatially positioned alternatives in a discrete-choice study. The results provide a number of insights into the seasonal habitat preferences of Alaskan moose. The significance of the estimated spatial dependence parameter suggests that accommodating spatial dependence across habitat alternatives is an important consideration in resource selection studies. Application of this modeling framework to natural resource economics is discussed.

The third chapter examines demand for forest recreation in a National Forest between 2005 and 2010 with a spatial travel cost model that accounts for landscape effects associated with an individual's home residence. Willingness to pay for access to the forest declined in real terms between 2005 and 2010. This decline is likely related to shifts in the typical mix of activities that draw visitors to the forest and changes in forest quality. The models produce significant estimated spatial dependence parameters, indicating that origin-based spatial dependence is an important consideration for recreation demand modeling.

Chapter 4 examines optimal population control of wild horses in the American West across two spatial scales. Removal and fertility control scenarios were simulated and compared in terms of economic benefits and characteristics of the optimal population and management time-paths. The benefits of removal-only management exceeded the benefits of population management using only fertility control. However, fertility control of a fixed proportion of the population increased the net benefits of removal management in some cases. The results also suggest that increasing the Bureau of Land Management resources devoted to horse gathers could substantially improve the effectiveness of fertility control management.

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Chapter 1: Introduction

1.1 Landscapes and Natural Resources

Natural resources come in many forms, ranging from extractive resources such as coal and timber to environmental service resources such as carbon storage and nutrient cycling. Natural resources are by definition formed through biophysical processes but human systems largely govern their value, use, and management. Natural resources are often located in a specific area or associated with some spatial distribution, and thus are associated with a specific natural and human landscape.

By the most common definition a landscape comprises the visible features characterizing an area of land including landforms, vegetation, and the human-built environment. Landscapes are defined more generally in this work to include the surrounding socio-economic and cultural environment as well.

Several factors indicate that the topic of this dissertation, the influence of landscape on natural resources, is ripe for research. First, this line of research is consistent with a systems-based approach to management focusing on interactions among biophysical and human processes. A systems approach permits a more holistic evaluation of resource management alternatives, including interactions and feedback loops. Second, economically efficient allocation of management resources requires an understanding of how landscape characteristics influence natural resource values and processes. This knowledge is also necessary for crafting effective conservation and utilization policies for natural resources. Third, technological change in the form of advancing capabilities of

GIS programs, increasing availability of geospatial data, and faster computer processing, continues to expand the tools available for modeling spatially heterogeneous and interconnected systems. Additional progress is still welcome in this area as estimating spatial models with discrete dependent variables remains computationally cumbersome with larger sample sizes.

There are two overarching research objectives of this dissertation. First, the studies contained within this dissertation investigate how landscape influences natural resource values, and appropriate management. The second objective is to demonstrate the application of spatial econometric models with discrete dependent variables to issues in natural resource economics.

1.2 Mechanisms of Landscape Influence

Landscapes influence the management of natural resources through a number of pathways. In-situ natural landscape features, for example, can serve as substitutes or compliments to natural resources. Alternatively, terrain and land cover may influence the accessibility of natural resources for use. Stationary human-built landscape features, such as roads, structures, and dams also influence the value and accessibility of natural resources. Another pathway through which natural resources are influenced is landscape disturbances. These include disturbances caused by human activities, such as pollution and land development, and naturally occurring disturbances including weather patterns and natural disasters. Natural resources are also influenced by the social and cultural landscape. For example, cultures with established social norms are associated with improved management of common pool natural resources (Ostrom et al., 1994). The socio-economic landscape, including resident demographics, may also influence natural resources values and the local policies that govern their use.

1.3 Empirical Models for Analyzing Landscape Effects

Empirical analysis of georeferenced data requires treatment of two spatial effects: spatial dependence and spatial heterogeneity (Anselin, 1988). Spatial dependence is related to the tendency of nearby observations to be similar. It is in some ways similar to time dependence, which arises when observations occur at similar times, except that spatial dependence is multidimensional. The second spatial effect, spatial heterogeneity, occurs when a relationship being modeled changes functionally over space. Spatial heterogeneity can be partially addressed in nonspatial econometric models by including variables that, for each observation, describe landscape membership or characteristics. Treatment of spatial dependence is more challenging and requires the use of spatial econometric models. These models assume that spatial interdependencies are generated by an underlying spatial stochastic process, a family of random variables that are well defined according to a predefined joint distribution (Anselin, 1988). Locally covariant random fields are spatial stochastic processes that assume spatial dependencies go to zero after some threshold distance between observations (Anselin, 1988).

The workhorse linear regression models of spatial econometrics include the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial autocorrelation model (SAC). Discussion of these models illustrates the structure and source of spatial dependence in spatial econometric models. The SAR model in equation 1.1 incorporates spatial dependence in the form of a spatially lagged dependent variable.

In this situation, the dependent variable at one point is space can depend on the explanatory variables associated with a different point in space. Weighting matrix $\boldsymbol{W}$ (nxn) controls the relative level of spatial dependence between two observations and dependence parameter ρ reflects the overall magnitude of dependence. Common specifications of $\boldsymbol{W}$ include inverse distance between paired observations and an indicator variable that equals one if paired observations are spatial neighbors.

$$\boldsymbol{y} = \boldsymbol{X}\beta + \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\epsilon} \tag{1.1}$$

Alternatively, the SEM model in equation 1.2 considers spatial error dependence. This form of spatial dependence occurs when error observed at one location depends on the error at nearby locations. The standard normal random variable $\mathbf{z}$ represents latent community characteristics such as social capital and culture.

$$\boldsymbol{y} = \boldsymbol{X}\beta + \boldsymbol{z}\theta + \boldsymbol{\epsilon} \tag{1.2}$$

Because z is unobserved, the vector $\boldsymbol{z}\theta$ becomes imbedded in the error term when $\boldsymbol{z}\theta$ is ignored. The SEM model assumes that the latent variable of neighborhood characteristics $\boldsymbol{z}$ follows a spatial autoregressive process so that $\boldsymbol{z} = (\mathrm{I_n} - \lambda \boldsymbol{W})^{-1}\mathrm{r}$, where $\mathrm{r} \sim \mathrm{N}(0, \mathrm{I_n})$ is a random vector of disturbances, $\boldsymbol{W}$ is the spatial weighting matrix, and λ is a scalar spatial dependence parameter.

The SAR model unifies spatial error dependence and spatial lag dependence in a single model. The typical SAR model estimates a spatial parameter and specifies a spatial weighting matrix for both the spatial error and spatial lag dependence structures.

The SAR, SEM, and SAC linear regression models serve as a departure point for the development of more complex and flexible spatial economic models such as the discrete dependent variable models used in this dissertation. Discrete dependent variable models introduce additional complexities in estimation. Specifically, discrete dependent variable spatial econometric models often do not produce a closed form solution for the likelihood function and simulation techniques are generally required for estimation (e.g. Schnier & Felthoven, 2011). However, simulation techniques are computationally burdensome and can restrict the size of a usable dataset (Billé & Arbia, 2013; Fleming, 2004). Another class of discrete dependent variable spatial econometric models produces closed form likelihood functions. Two models with closed-form likelihood functions are utilized in this dissertation to examine the influence of landscape on natural resources.

1.4 Contributions of this Dissertation

This dissertation investigates the influence of landscape characteristics on natural resources and their appropriate management with three studies from the American West. The complex interactions that occur among biophysical and human processes in a landscape over time cannot be captured in a single comprehensive model. Instead, the analyses in this dissertation extend established models of natural resource management to consider the influence of landscape. Each analysis focuses on different natural resources and mechanisms of landscape influence. The three studies, contained in Chapters 2-4, examine moose habitat selection, forest recreation demand, and wild horse population management respectively.

The analysis presented in Chapter 2 examines Alaskan moose radio collar data with spatial econometric techniques to investigate the landscape determinants of moose habitat selection. Within the random utility framework, a discrete-choice model was developed that frames habitat selection as a choice among alternative habitat patches with heterogeneous attributes. A unique habitat choice set was derived for each moose by imposing a grid over an area defined by the 50% kernel density contour of observed moose locations (i.e. core home range). Each grid cell represents a habitat alternative for the moose. Repeatedly observing moose choices among heterogeneous alternatives reveals moose preferences for landscape features. The natural landscape features specified as habitat attributes in model include slope, elevation, and forest cover. The proximity of habitat patches to human-built trails and roads is also considered as a determinant of habitat selection. Additionally, the distance between the habitat patch where the moose was last seen and alternative patches is included in the model as a habitat attribute so that observed choices are conditioned on the animal's previous location. The spatial generalized extreme value (GEV) model of discrete choice employed for estimation permits a test of spatial dependence and accommodates flexible substitution among adjacent habitat patches. Based on the literature review, this is the first discrete-choice habitat selection study to test for and accommodate spatial dependence. From a policy perspective, understanding wildlife habitat preferences helps land managers asses habitat value based on landscape characteristics. Habitat value estimates can then inform lands management policies including use regulations, conservation priorities, and development planning.

The spatial discrete-choice econometric model employed in Chapter 2 is readily applicable to a variety of environmental and natural resource economics contexts. These contexts include: 1) recreation demand modeling, 2) examining the landscape determinants of migration, and 3) valuing environmental change. With respect to recreation demand, the methods in Chapter 2 could test for and accommodate potential spatial dependence among recreation alternatives in a site-choice travel cost model. These methods could also account for spatial dependence among migration destination alternatives in a gravity model of amenity migration. Finally, there is promise for applying these methods to stated choice non-market valuation studies. Specifically, the methods in Chapter 2 could be employed to account for spatial dependencies among georeferenced environmental alternatives in a choice experiment.

Chapter 3 analyzes demand for forest recreation day trips in the front range of Colorado with a single-site travel cost model. A count-copula model is developed to test for and accommodate origin-based spatial dependence in the data[1]. Origin-based spatial dependence in recreation demand is likely related to interactions between individuals, unobserved neighborhood characteristics and diffusion effects (Sener & Bhat, 2012). Spatial heterogeneity is also addressed in the model through the inclusion of zip code income. Mean per-trip willingness to pay for access (WTPA) is estimated with 2005 and 2010 data and the welfare results are compared across years. The results indicate that WTPA for trips to Roosevelt-Arapahoe National Forest (RANF) decreased from 2005 to 2010, although the decrease is statistically insignificant in one of the presented specifications. This finding is likely related to changes in forest quality and changes in the activity-mix of visitors. The economic downturn may have also played a role, although the findings of (Loomis & Keske, 2012) suggest that the recession did not significantly influence alpine recreation expenditures in Colorado. The spatial determinants of recreation demand are an important for forest managers tasked with regulating, monitoring, and maintaining recreation resources at RANF.

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[1] As opposed to spatial dependence among recreation alternatives.

Chapter 4 develops and evaluates optimal control models of wild horse population management using non-lethal methods. The optimal population paths and net present value (NPV) benefits of fertility control and horse removal management methods are simulated over a 50-year horizon and then compared to the value of the existing management. Scenarios are also considered that combine optimal removal with fixed-proportion fertility control. Finally, scenarios are simulated that relax model gather constraints to investigate the impact of increased available resources for gather efforts. Optimal wild horse management is also examined across spatial scales to see how the optimal solution is influenced by the scope of management objectives. Specifically, separate herd-scale and state-scale models are developed that differ according to their specification of gather costs and gather constraints. The simulation results indicate that implementing long-term population strategies compared to the short-sighted policies currently in place is associated with significant economic benefits. Furthermore, the results suggest that increasing BLM gather resources could improve the effectiveness of fertility-control population management. This study adds to previous static economic analyses of Western horses (Bartholow, 2007; Garrott & Oli, 2013) and the results support policy suggestions laid out by the NRC (2013) and Garrott and Oli (2013).

The spatial econometric models applied in chapters 2 and 3 permit testing and accommodation of spatial dependencies in models with discrete dependent variables. Reviews by Fleming (2004) and Billé and Arbia (2013) discuss the estimation difficulties[2] associated with estimating discrete dependent spatial econometric models and common techniques to work around these issues. The computationally tractable

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[2] Due to the presence of multi-dimensional integrals in the likelihood function

spatial modeling techniques used in this dissertation have yet to see extensive use in the natural resource economics literature despite the inherently spatial nature of natural resource management.

Chapter 2: Flexible substitution and spatial dependence in a discrete-choice model of habitat selection

2.1 Introduction

Many decisions made by individual agents include a spatial component. Until recently, this dimension of choice had not been given full attention by researchers modeling discrete choice. Researchers since have made headway in dealing with the spatial elements of choice modeling, but the literature is still thin, in part due to difficulties with the computational burden involved in estimating spatial models of discrete choice.

Discrete-choice models are concerned with explaining the determinants of observed choices made by individuals among a number of discrete alternatives. Discrete-choice modeling has been applied to many choice contexts using both stated preference and revealed preference data. The migration decisions of American adults have been analyzed under this framework (Davies et al., 2001) as well have as the recreational choices of teenagers in the San Francisco Bay Area (Sener & Bhat, 2012). Discrete-choice models also have been applied to habitat selection in animals, the context used for the current study. All three of the discrete-choice models described above involve a spatial component, a potential complication for the estimated econometric model. This chapter accommodates spatial effects in an ecological discrete-choice model. Accounting for spatial correlation offers the potential to improve models of habitat selection that serve as valuable tools for wildlife managers.

Ecologists study animal habitat selection with individual location data such as radio telemetry data. From this data, ecologists may construct resource selection functions to investigate the relationship between the ecological characteristics at a location and the likelihood of habitat use at that location by a given animal. A variety of discrete-choice models has been utilized to investigate animal resource selection. Generally, these discrete-choice models characterize habitat selection as a choice among habitat patches in a landscape. Studying resource selection is useful for accumulating information about the habitat needs of certain organisms. Resource selection models also allow for the development of visual wildlife management tools such as habitat suitability maps.

The objective of this analysis is to present a method and example for accommodating spatial correlation in discrete-choice resource selection studies. A secondary goal is to explore the anthropogenic and naturally occurring determinants of resource selection in coastal Alaskan moose. With Kenai moose location data from 2004-2006, we estimate habitat selection preferences with a spatially explicit discrete-choice model, test for spatial autocorrelation, and compare the model with nonspatial methods. The results provide a number of insights into the seasonal habitat preferences of tracked moose and suggest that accommodating spatial dependence across habitat alternatives is an important consideration in resource selection studies.

2.2 Literature Review

This chapter is concerned with modeling locational choices made by moose as they position themselves across a heterogeneous landscape. Moose habitat choices are inherently a spatial phenomenon. Ignoring spatial effects, this type of multinomial choice is commonly modeled with the conditional logit model. A major advantage of the conditional logit model is that it provides a closed-form solution for choice probabilities. However, conditional logit models impose the strong assumptions of IID, Gumbel distributed errors and unobserved response homogeneity. Together, these restrictions imply the independence of irrelevant alternatives (IIA) property, or that the probability ratio of an individual choosing between two alternatives is independent of the availability of other possible alternatives (Hensher et al., 2005). IIA implies that all pairs of alternatives in the choice set must be equally similar or dissimilar. When choices involve a spatial dimension, spatial dependence can lead to violations of the rigid assumptions described above (see Smirnov, 2010). Spatial dependence or spatial autocorrelation occur when outcomes that occur in closer proximity tend to be similar or dissimilar. Spatial effects increasingly are being addressed in discrete-choice studies, and recent reviews by Smirnov (2010) and Billé and Arbia (2013) highlight the emerging literature on spatial discrete choice. However, many of the spatial discrete-choice specifications offered in the literature (e.g. Fleming, 2004) are not of a closed form, requiring simulation methods for model estimation. The large number of alternatives and observations associated with telemetry-based discrete-choice models pose a substantial computational burden when simulation methods are necessary for spatial-model estimation (Fleming, 2004).

2.2.1 Discrete-Choice Habitat Selection Studies

Resource selection functions are functions proportional to the probability of habitat use (Manly et al., 2002) that generally contain animal and habitat characteristics as the independent variables. Resource selection functions are valuable because they inform wildlife managers about the habitat needs of managed wildlife and the impacts of habitat change. Resource selection functions are used to manage commercial fisheries, inform endangered species debates, and understand the impacts of anthropogenic habitat change (Manly et al., 2002). One useful output from resource selection functions are habitat suitability maps, which map the probability of use to the landscape and provide a visual representation of habitat quality (D. S. Johnson et al., 2008). Furthermore, recent technological advances, including satellite tracking and land cover imagery, have increased the amount of habitat selection data available. These advancements allow development of more accurate and sophisticated resource selection studies.

Discrete-choice models are one type of resource selection function model used in wildlife management literature. A summary of prior published discrete-choice model resource selection studies is presented next.

McCracken et al. (1998) presented an early effort to analyze habitat selection with discrete-choice models using radio collar data from female black bears in the mountains of central Oregon. Beginning with the standard conditional logit model, the authors expand the specification to accommodate for sampling of choice sets, vary choice sets according to selection times, and incorporate the effects of animal characteristics (i.e., gave birth to cubs). The analysis first approximates annual home range and then analyzes selection within the home range. Yearly choice sets are constructed by sampling the unused resource units (units are one square meter) at a ratio of about three sampled units for each observed location. Model covariates include habitat type, slope, elevation, and distance to roads and streams. All variables except elevation and distance are categorical. The results prove similar to those estimated with a standard logit model.

A study by Cooper and Millspaugh (1999) used the conditional logit model to examine resource (bed site) selection by elk in South Dakota. Model covariates include canopy, slope, distance to roads, aspect (categorical), and pairwise interactions. Alternatives are defined by identifying relatively homogeneous habitat patches in the landscape. The available choices are the set of habitat patches surrounding the chosen bed site. Thus, this study accounts for changing resource availability over time as the constructed choice set changes across locations.

Manly et al. (2002) dedicated a chapter of their book to discrete-choice resource selection functions and presented two relevant examples. The first example is from Arthur et al.'s (1996) study of polar bear habitat selection. An available habitat area is constructed for each location observation (fix) based on a 200 km radius from where the animal was located three days prior. The choice set is divided into habitat types within the defined choice set. A simple iterative estimation method produces estimated selection coefficients representing selection preference for habitat types.

The second example presented in Manly et al. (2002) comes from a study by G. Golet at the U.S. Fish and Wildlife Service in Anchorage, Ala. The research examined data, with a traditional conditional logit model, on seabird foraging site selection in Prince William Sound, Alaska. The "area where the birds were observed foraging" (Manly et al., 2002, p. 156) was overlaid with a grid of 232 cells measuring 500 m by 500 m to define the choice set and alternatives. Model covariates include distance from previous location, various cell habitat characteristics, and interacted individual characteristic variables. The study finds wide heterogeneity (specialization) in the feeding patterns of individual birds. Finally, Manly et al. (2002) present an argument that in the case of large choice sets, random sampling of the choice set does not affect estimation under certain conditions.

McDonald et al. (2006) presented an overview of discrete choice models of habitat selection. Their paper includes a brief literature review of discrete-choice models in habitat selection studies, an exposition of the methods commonly used in wildlife discrete-choice models, and an example analysis with data from Northern spotted owls in California. Wildlife habitat selection data often contains data on repeated habitat choices made from one or more choice set, where only a single random sample from each choice set is available. The owl data is of this type, where choices are made with replacement. Choice sets were defined from the observed 95% utilization home ranges, and observation points are spaced 125 m apart.

Boyce (2006) explored the role of spatial scale in animal habitat selection. The study defines two dimensions of scale in resource selection studies: (a) resolution or grain and (b) domain or extent of the study area. The author notes that model design choices regarding these scale dimensions should be considered in light of what is known about the ecological processes being modeled. With regard to resolution, Boyce suggests first recognizing the scale at which the ecological process being studied occurs. Secondly, he suggests comparing the fit of empirical models of various scales. The scale of the ecological process under consideration also should guide the choice of domain. For example, to adequately characterize mule deer habitat selection, ecological variation must be characterized at the landscape scale instead of at the narrower home range scale. The author cites (D. H. Johnson, 1980) in noting that resource selection functions intended to identify habitats for direct management or for study of forage selection usually will be at the landscape or within home range scale. The study also mentions the role of scale in autocorrelation, where data at finer spatial and temporal scales tend to be more autocorrelated. A few methods for diagnosing and addressing autocorrelation in resource selection modeling are discussed briefly.

Recent discrete-choice habitat selection studies have incorporated random effects to accommodate individual animal heterogeneity and other potential violations of the IIA assumption. Thomas et al. (2006) presented a Bayesian random effects discrete-choice model to investigate population level resource selection that incorporates individual animal heterogeneity. Specifically, population-level inference is achieved using Markov chain Monte Carlo simulation techniques. The authors used radiolocation data from 76 female caribou in the Alaskan Arctic. Covariates included elevation, NDVI, and land cover type. The choice sets were created by overlaying daily population-level 99% utilization distributions from the animals being studied and then divided that area into 131 habitat cells, each 8 km^2 in area. The alternatives were defined as cells 1 through 131. Highlights from the results include significant heterogeneity in individual resource selection and that NDVI is found to have a quadratic effect on habitat selection.

Duchesne et al. (2010) also used a random parameters discrete-choice model to account for individual heterogeneity in Canadian bison. The authors tested the need for, and effectiveness of, random parameter models to deal with animal heterogeneity and IIA violations. The choice sets were constructed though a matched design (sampling)

> "… each observed location is associated with a specific set of random locations drawn within a limited spatial domain…" (Duchesne et al., 2010, p. 549).

This is the same approach used in the aforementioned study by McDonald et al. (2006).

Kneib et al. (2011) presented an example of another class of discrete-choice habitat selection models, where categorical habitat types are the alternatives. The method then is applied to songbirds in South America and brown bears in Europe. Their model incorporates individual characteristics and random effects to accommodate individual selection heterogeneity. The model also incorporates nonparametric covariates. Individual-specific random terms are included to account for multiple choices across individuals. The authors assert that their choice context is appropriate when the analysis is focused on habitat choice, but clearly it does not address animal movement. Of note, Güthlin et al. (2011) also pursued a discrete-choice model of this form to examine habitat choice in European brown bears.

Few discrete-choice models in habitat selection literature account directly for the spatial and temporal dependence inherent in high-frequency satellite telemetry data. Ramsey and Usner (2003) developed an extension to the discrete-choice model that accounts for autocorrelation. Their model includes a persistence parameter to account for the tendency of animals to stay in the same habitat over successive fixes. D. S. Johnson et al. (2008) built on the work of Christ et al. (2008) and accommodated autocorrelation in a Gaussian-process movement model. The Gaussian model outperforms the Ramsey and Usner (2003) model and a naïve discrete-choice model in analyzing simulated and example data. All of these models are based on a choice context with categorical habitat classifications as alternatives. However, they do consider movement, unlike the work of Kneib et al. (2011) and Güthlin et al. (2011).

2.2.2 Moose Habitat Selection Literature

Prior published studies have examined habitat selection in the Alaskan moose sub-species. Weixelman et al. (1998) analyzed winter habitat selection by moose in the central Kenai Peninsula of Alaska, where the data for the current study was collected. The authors found that forage selection did not vary over the winter despite variable forage availability. Snow depth and distance to escape cover also are identified as important determinants of moose habitat selection.

Maier et al. (2005) investigated the determinants of moose population density in Alaska's interior. Moose are found to concentrate in areas of moderate elevation, and near towns and rivers. The study also finds that moose respond more to environmental variables at a relatively small spatial scale (34 km^2) compared to larger spatial scales.

Numerous studies have investigated habitat selection in other moose sub-species as well. While some of these results vary, other published findings are consistent across regions and sub-species. One of these common results is that moose select habitat hierarchically at multiple spatial scales, over which selection determinants may vary (e.g. Jiang et al., 2009; Månsson et al., 2012). Variation based on seasonal (e.g. Nikula et al., 2004) and diurnal (e.g. Bjørneraas et al., 2011) temporal scales also are reported scale determinants of moose habitat selection. Elevation, a proxy for snow depth (e.g. Dussault et al., 2005; Poole & Stuart-Smith, 2006), and animal gender (e.g. Bjørneraas et al., 2012; Nikula et al., 2004) also are determinants of habitat selection in moose found across geographies and moose sub-species.

A recent research article by McLoughlin et al. (2011) estimated research selection functions for Canadian moose across seasons and land management types with a random-effects logit model. The within-home range analysis (i.e., 95% utilization distribution) found variation in resource selection across land management types and seasons. The probability of habitat use was found to decrease with distance from roads in the spring and summer and to increase with distance from roads in the winter across land management types. In the autumn, when recreational hunting occurs, the effect of roads was found to differ across land management types. Habitats near roads were found to attract and moose in areas where moose hunting was prohibited and to repel moose where hunting was allowed. The authors concluded that these behaviors were due to threats from hunting as well as from predators that use the roads.

Section 2.2 reviews the discrete choice habitat selection and moose habitat selection literatures. This chapter contributes to the former by presenting a computationally tractable method for accommodating spatial dependence that can arise based on unobserved similarities between nearby habitats. Specifically, the method allows for flexible substitution patterns compared to non-spatial methods.

2.3 Model and Methods

This analysis utilizes a variant of the generalized GEV discrete-choice model (C. R. Bhat & Guo, 2004) that offers a closed-form solution while accounting for unobserved similarities between alternative habitat patches. This approach is appropriate when the alternatives associated with a discrete-choice model are arranged spatially, as is the case with habitat selection. A few previous studies in transportation literature have utilized this specification to accommodate spatial dependence in models of human locational choices (Bekhor & Prashker, 2008; C. R. Bhat & Guo, 2004). The current chapter employs the GEV discrete-choice model to accommodate spatial dependence in a model of habitat selection.

The GEV specification allows for complex substitution patterns among habitat patch alternatives, relaxing the assumption of error independence in the conditional logit model. Specifically, the model incorporates spatial dependence between adjacent habitat patches. The utilized specification affords accommodation of complex substitution patterns in a computationally tractable model. However, this GEV approach to discrete-choice modeling also has drawbacks. Specifically, the model does account for unobserved preference heterogeneity or heteroscedasticity of the random terms among alternatives (Hunt et al., 2004). The model is theoretically inconsistent if the estimated spatial parameter (ρ) is less than zero or greater than one.

The basic setup of this study starts with imposing a digital grid over the core home range (95% kernel density contour) of moose tracked with radio collars. Then, variables describing the landscape are used to explain observed moose locations. The most common theoretical motivation for discrete-choice analysis of this kind is the random utility model (RUM). RUM assumes that the utility derived from an alternative is due to observable as well as to unobservable (random) components and that if faced with a choice between alternatives; an individual will select the alternative yielding the highest utility. In the most basic RUM model, shown in equation 2.1, the benefit that an individual moose will get from selecting a given location i is composed of an observable component (V_i) and a random, unobservable component (ε_i). The observed part is assumed to be linear in parameters.

$$U_i = V_i + \varepsilon_i \tag{2.1}$$

$$U_i = \boldsymbol{\beta}'\boldsymbol{x}_i + \varepsilon_i$$

Moose make a locational choice decision among i habitat patches ($i = 1,2, \ldots, I$). The term ω_{ij} in equation 2.2 is an indicator variable that equals one if spatial alternatives i and j are adjacent and equals zero otherwise. Thus, spatial alternative i shares an unobserved, shared utility component with $\sum_{j=1}^{I} \omega_{ij}$ other spatial units (i.e., the number of adjacent units). Unobserved correlation between units may be described using paired "nests" with dis-similarity parameter ρ. A paired nest is constructed for each of spatial unit *i's* adjacent spatial units, and the total number of paired nests equals $\sum_{i=1}^{I-1} \sum_{j=i+1}^{I} \omega_{ij}$. The allocation parameter, $\alpha_{i,ij}$, assumes an equal allocation of correlation to each nest created from the units adjacent to *i*. Sener et al. (2011) relax this assumption to create more flexible specifications of the allocation parameter. Their model accommodates correlation between nonadjacent units and correlation that is a function of independent variables. This study uses the allocation parameter specification in equation 2.2 and assumes correlation between cell i and nearby cells is allocated equally between spatial units. This is an intuitive assumption for the current moose habitat-selection application, where the observations (grid cells) are uniform.

$$\alpha_{i,ij} = \frac{\omega_{ij}}{\sum_k \omega_{ij}} \; ; \;\; \text{where } \sum_j \alpha_{i,ij} = 1 \tag{2.2}$$

Now, consider the following "G" function within the generalized extreme value (GEV) class in equation 2.3.

$$G(y_1, y_2, \dots, y_I) = \sum_{i=1}^{I-1}\sum_{j=i+1}^{I}\left[\left(\alpha_{i,ij}y_i\right)^{1/\rho} + \left(\alpha_{j,ij}y_j\right)^{1/\rho}\right]^{\rho} \tag{2.3}$$

Where: $0 < \alpha_{i,ij} < 1\ \forall\ i,j$; $0 < \rho \leq 1, y_i > 0\ \forall i$; and $\sum_j \alpha_{i,ij} = 1 \forall\ i$.

Note that these conditions imply that G is a non-negative, homogeneous degree-one function that goes to positive infinity whenever any of its arguments also go to positive infinity. Also, the *n*th cross-partial derivatives are non-negative for odd *n* and non-positive for even n because $0 < \rho < 1$ (if $\rho \neq 1$). Thus, equation 2.4 represents a cumulative extreme-value distribution.

$$F(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_I) = \exp\left\{-\sum_{i=1}^{I-1}\sum_{j=i+1}^{I}\left[\left(\alpha_{i,ij}y_i\right)^{1/\rho} + \left(\alpha_{j,ij}y_j\right)^{1/\rho}\right]^{\rho}\right\} \tag{2.4}$$

The term ε_i represents the random element of utility for spatial unit *i*. Thus, each random term ε_i has a univariate extreme value marginal CDF given by the standard Gumble distribution function:

$$F(\varepsilon_i) = \exp\left\{-\sum_{j\neq i}\alpha_{i,ij}e^{-\varepsilon_i}\right\} = \exp\{-e^{-\varepsilon_i}\} \tag{2.5}$$

The bivariate marginal CDF for two adjacent (correlated) spatial units is then given by equation 2.6.

$$H(\varepsilon_i, \varepsilon_k) = \exp\left\{\begin{matrix} -\left(1-\alpha_{i,ik}\right)e^{-\varepsilon_i} - \left(1-\alpha_{k,ik}\right)e^{-\varepsilon_k} \\ -\left[\left(\alpha_{i,ik}e^{-\varepsilon_i}\right)^{1/\rho} + \left(\alpha_{k,ik}e^{-\varepsilon_k}\right)^{1/\rho}\right]^{\rho} \end{matrix}\right\} \tag{2.6}$$

And the bivariate marginal CDF for two nonadjacent (and thus independent) spatial units is given in equation 2.7.

$$H(\varepsilon_i, \varepsilon_k) = \exp\left\{-\sum_{j\neq i}\alpha_{i,ij}e^{-\varepsilon_i} - \sum_{j\neq k}\alpha_{k,ij}e^{-\varepsilon_k}\right\} = \exp\{e^{-\varepsilon_i} - e^{-\varepsilon_k}\} \tag{2.7}$$

If the random components of utility are distributed according to the CDF above (i.e. $(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_I)$),then by the GEV postulate, the probability of choosing the i th spatial unit is shown in equation 2.8. Note that when $\rho = 1$, the model collapses to the standard conditional logit model.

$$P_i = \frac{\sum_{j \neq i} \left(\alpha_{i,ij} e^{V_i}\right)^{1/\rho} \left[\left(\alpha_{i,ij} e^{V_i}\right)^{1/\rho} + \left(\alpha_{j,ij} e^{V_j}\right)^{1/\rho}\right]^{\rho - 1}}{\sum_{k=1}^{I-1} \sum_{l=i+1}^{I} \left[\left(\alpha_{k,kl} e^{V_k}\right)^{1/\rho} + \left(\alpha_{l,kl} e^{V_l}\right)^{1/\rho}\right]^{\rho}} \tag{2.8}$$

$$= \sum_{j \neq i} \frac{\left(\alpha_{i,ij} e^{V_i}\right)^{1/\rho}}{\left(\alpha_{i,ij} e^{V_i}\right)^{1/\rho} + \left(\alpha_{j,ij} e^{V_j}\right)^{1/\rho}} \times \frac{\left[\left(\alpha_{i,ij} e^{V_i}\right)^{1/\rho} + \left(\alpha_{j,ij} e^{V_j}\right)^{1/\rho}\right]^{\rho}}{\sum_{k=1}^{I-1} \sum_{l=i+1}^{I} \left[\left(\alpha_{k,kl} e^{V_k}\right)^{1/\rho} + \left(\alpha_{l,kl} e^{V_l}\right)^{1/\rho}\right]^{\rho}}$$

$$= \sum_{j \neq i} P_{i|ij} \times P_{ij}$$

2.4 Data and Variables

This chapter analyzes moose habitat selection using a spatial discrete-choice model where the set of location alternatives available to each moose is defined by imposing a grid over a given animal’s core home range. Each cell represents a location option for the moose. Within home range, habitat selection is modeled as a function of natural and anthropological cell features.

An animal’s home range is the area where it lives and travels, and its core home range is the area it uses most intensely. Specifically, home range is commonly defined in terms of a utilization distribution, a probability density function in two dimensions. The core home range of an animal is its 50% utilization distribution contour, or the area where the moose is expected to be with 50% probability. Following the guidance of Walter, Fischer, Baruch-Mordo, and VerCauteren (2011) for large telemetry datasets, we calculate the core home range (i.e., 50% utilization distribution) with kernel density estimation using a Gaussian (bivariate normal) kernel and the plug-in estimator for bandwidth selection. Home range estimation was carried out using packages in the geospatial modeling environment software.

To describe the available location options, data was collected on the characteristics of each core home-range cell. The data collected include natural and anthropological landscape features. The elevation in meters at each cell centroid (*ELEV*) is calculated using a digital elevation map sourced from the U.S. Geological Survey’s 2011 National Elevation Dataset. The elevation data is at one arc-second resolution. The elevation data was analyzed with Arcmap10 to calculate the slope (*SLOPE*) at each cell centroid. A land cover raster with 25 m cells provides data for other variables used in the analysis. The land cover data is from the 2001 USGS National Land Cover Database (HOMER et al., 2004). The land cover data is converted into the dummy (i.e. 0/1) variable *FOR* that equals one if a habitat cell is more than 50% forested. Besides forests, dwarf scrub and shrub/scrub land cover types dominate the moose home ranges. Two measures of anthropological influence also are included in this analysis: the distance to human-built trails (*TRDIST*) and the distance to public roads (*RDDIST*). Both variables are measured from the cell centroid. The trail data was published in 2006 by the Alaska Department of Natural Resources. The road data was developed in 2010 by the Kenai

Peninsula Borough GIS Department. Of concern, the road data was created after the moose location data was collected. However, the moose locations are located generally in the national forest, away from recent road construction. This was verified for the relevant areas by comparisons with the 2001 land cover data's development layers. Definitions of the habitat characteristic variables are in Table 2.1.

The moose location data is sourced from four moose that were radio-collared by the U.S. Fish and Wildlife Service (USFS) in Alaska. All four moose reside primarily in the Chugach National Forest on the Kenai Peninsula, near the southern portion Resurrection Pass Trail. Two of the moose also travel in April to the town of Soldotna. The data is split into summer and winter samples to reflect the seasonal variation in resource availability and other determinants of habitat selection (e.g., snow cover). Summer is defined as April through September, with winter comprised of the remaining months. The radio collars transmit locations, also called fixes, every two hours. Sample statistics on the moose location data is in Table 2.2. The table includes the number of location observations used in the analysis, the percentage of time a fix was unavailable (% miss), and the relevant time period for the sample. No sample experienced a rate of failure of attempted fixes greater than 7%. The data was collected from March 2006 to November 2011.

The Resurrection Pass Trail is popular year-round with tourists and residents of the Kenai Peninsula. In the summer, there is hiking, mountain biking, and horseback riding. In the winter, there is snowmobiling, snowshoeing, dog sledding, and skiing. Two cabins in the area are open year-round, at Trout Lake and Juneau Lake. On the southern boundary of the study area is Highway 1, which connects the Kenai Peninsula to

Anchorage. The study area offers an opportunity to observe ecological and anthropological determinants of habitat selection.

This analysis focuses habitat selection within an animal's core home range and is thus at a relatively "fine" scale of hierarchal resource selection. This is consistent with research suggesting that moose select habitat at finer spatial scales (Maier et al., 2005). The statistic % used in Table 2.2 indicates that within a core home range, utilization is distributed unevenly. For example, an average of 20% of core home range habitat cells went unutilized across the eight seasonal moose samples. This suggests preference heterogeneity for within core home range habitat cells.

Resource selection studies can be biased if attempted GPS fixes are unsuccessful due to habitat characteristics (e.g. Frair et al., 2004; Nielson et al., 2009). The percentage of unsuccessful fix attempts is given by % miss in Table 2.2. Unsuccessful fix attempts are less than 1.5% of the total attempts in five of the eight seasonal moose samples. The remaining samples include 6% to 7.5% unsuccessful attempts. Nielson et al. (2009) found that if 10% or more of fixes are unsuccessful, it can cause biased results.

While most model variables are habitat-cell characteristics, one individual characteristic is included as well. The individual variable, *DIST* equals the distance from the centroid where the moose was located previously to the other cells within the animal's core home range. This variable approximates the difference in cost to the animal of relocating to nearby versus distant habitat cells.

The sample is constrained so that the *DIST* variable has a consistent interpretation across observations. Specifically, all considered location observations were preceded by another location observation within the core home range two hours prior (as scheduled). This ensures that *DIST* always equals the distance from the cell where the animal was located two hours prior.

Previous studies have uncovered seasonal variation in moose habitat selection patterns (e.g. McLoughlin et al., 2011; Nikula et al., 2004) due to changing resource availability. Separate summer and winter models are estimated to account for these seasonal differences. Winter is assumed to span October through March while summer is defined as the period from April through September.

The final model in equation 2.9 explains moose habitat choice with three naturally occurring landscape features (*SLOPE*, *ELEV*, *FOR*), two anthropogenic landscape characteristics (*RDDIST*, *TRDIST*), and a variable that conditions the choice on the animal's previous location (*DIST*).

$$V_i = \beta_1 * DIST + \beta_2 * ELEV + \beta_3 * SLOPE + \beta_4 * FOR \\ + \beta_5 * RDDIST + + \beta_6 * TRDIST \tag{2.9}$$

2.5 Results

Seasonal habitat choice models were estimated for individual moose with choice sets defined according to summer and winter core home ranges. Results from the conditional logit and GEV individual models are in Tables 2.3 and 2.4. Standard errors, calculated with the estimated Fisher information matrix, are in parenthesis. One, the estimated GEV model (627 winter), fails to converge, and two others (809 summer, 807 winter) produce negative values on the diagonal of the estimated information matrix.

These models are not considered in further analysis. Another set of seasonal models estimates habitat selection parameters using data from all four moose. The results are displayed in Table 2.5. These pooled models depict typical habitat preferences across the four moose examined in the current study.

An objective central to this analysis is to accommodate spatial dependence among alternatives in a habitat-selection discrete-choice model. The significance of spatial parameter *rho* indicates significant spatial dependence between adjacent habitat cells.

The determinants of habitat selection vary across the individual moose models. A negative and significant estimated coefficient on a given variable indicates a negative relationship between that variable and the probability of habitat selection. For example, the negative and significant estimated coefficients on *DIST* indicate that moose are less likely to select more distant habitats compared to nearby ones. The negative and significant estimated coefficients on *ELEV* indicate that Moose 809 and 627 prefer lower-elevation habitats within their core home ranges across seasons. Moose 805 prefers lower-elevation habitats during summer months. The multi-moose models indicate that when considered on aggregate, moose tend to prefer lower-elevation areas within their core home ranges across seasons.

The effect of terrain slope on habitat selection differs among the individual moose. Moose 805 prefers steeper habitats in the summer and flatter habitats in the winter. Moose 809 prefers steeper habitats within its winter home range. Moose 627 and Moose 807 also prefer flatter habitats within summer home range in the conditional logit and GEV specifications, respectively. In the multi-moose models, the insignificance of the estimated slope parameter is not surprising given the differential impact of slope on habitat selection across individual models.

TRDIST indicates that habitats further from trails are preferred during the winter months. The multi-moose model results also suggest that moose avoid trails during the winter months. In three of the winter models (809, 805 and multi-moose), moose are less likely to select habitat cells with greater than 50% forest cover based on the negative and significant estimated coefficients on *FOR*. However, none of the summer models indicate a relationship between forest cover and habitat selection.

Human disturbances also are significant determinants of habitat choice in the estimated models. The positive and significant estimated coefficient on *TRDIST* in the multi-moose models supports that when considered across individuals, our sample of moose prefers habitats nearer trails during the summer months. Results from the individual models indicate that habitats near trails were preferred by Moose 809 during winter months. In the summer, Moose 807 preferred core home-range habitat locations nearer to trails, but Moose 627 preferred habitats further from trails. Likewise, the positive and significant estimated coefficient on *RDDIST* for the winter multi-moose model suggests that moose tended to prefer core home-range cells near to roads in the summer months.

2.6 Discussion

A central implication of the model results is that spatial dependence across alternatives is an important consideration in habitat selection studies. The results of both classes of models offer insights into the habitat preferences of the four moose examined in this study.

The estimated individual moose models examine moose selection at the individual level and allow for comparison across individual results. The multi-moose models examine core home-range habitat selection in multiple moose simultaneously to consider moose choices on aggregate. These models may be useful to resource managers who are tasked with prioritizing land conservation for a given animal population or geographical area.

A majority of the estimated models indicate that moose prefer lower-elevation habitats within their core home ranges. Three of the estimated models (809, 805, and multi-moose) depict a negative relationship between densely forested habitats and moose habitat during the winter season, but forests have no impact in the summer models. This result could be related to seasonal shifts in forage availability. For example, dense forests may not provide the best forage in winter

Moose prefer winter within home-range habitats that are relatively further from trails in two of the estimated models (809, multi-moose). These findings could be related to increased predation near linear features or to avoidance of human impacts. This finding has been reported for roads but not for trails (McLoughlin et al., 2011). In the summer, Moose 807 prefers core home-range habitats that are relatively farther from trails. The

GEV model suggests Moose 627 may prefer habitats farther from trails during the summer. This result implies that trails can serve to attract or repel a given moose during the summer months. Again, these impacts are likely related to predation and/or to human interaction. For example, moose may be attracted to trails if the human impacts near trails reduce the predation risk in that area.

Likewise, two of the selection models (multi-moose, 627) indicate preference for summer within home-range habitats in relatively closer proximity to roads. As with trails, roads are linear features that can attract or repel moose depending on environmental conditions. In the study area, roads attract moose in the summer, perhaps due to reduced predation risk. Roads attracted Moose 627 in the winter months but otherwise do not have a discernible effect on habitat selection across winter models.

The multi-moose model specification imposes preference homogeneity across individual moose. While the individual model results and reported literature to not reflect preference homogeneity, increasing the number of moose in a multi-moose model captures the typical determinants of habitat selection across the moose considered. When considered across a sufficiently large sample of moose, the estimated preference parameters from the multi-moose specification could provide useful for guiding population-level habitat management and conservation strategies.

Future models may incorporate random effects and individual characteristics into aggregated GEV models to accommodate individual preference heterogeneity (e.g., Sener 2012). The disadvantage of random effects models, and the reason they are not pursued in this analysis, is the computational burden imposed by the associated simulation-based estimation with large datasets. As technology advancements reduce these constraints, random effects should be incorporated into the current study's model of habitat selection. Individual characteristics also are absent in the current model due to a lack of data, but future studies would benefit by incorporating into the model gender, age, and other individual characteristics.

This chapter utilizes a spatial discrete-choice econometric model employed in this chapter has a number of environmental and natural resource economics applications. These applications include site-choice recreation demand, amenity migration, and environmental valuation. To illustrate a recreation demand application, suppose that resource managers plan to estimate demand for recreational fishing sites positioned across the landscape with a site-choice travel cost model. The spatial GEV model would be useful for testing and accommodating spatial dependence among nearby fishing sites. The spatial dependence among sites could be weighted according to distance between nearby sites, adjacency, and shared border length. Compared to a typical travel cost study, the only additional data required to estimate a spatial travel cost model is the spatial position or extent of each fishing site. This data can then be manipulated into a neighbor weighting matrix. The GEV model's closed form solution allows for estimation both large choice sets and large number of observed choices. Furthermore, the spatial kernel density techniques in this paper could be useful for defining an angler's choice set based on reported trips.

Table 2.1 Moose Habitat Variable Descriptions

Variable	Description	Units
ELEV	Elevation at the habitat patch centroid	meters
SLOPE	Percent slope at the habitat patch centroid	degrees
FOR	Equals one if habitat is more than 50% forested and equals zero otherwise	0/1
RDDIST	Distance from the habitat patch to the nearest developed road	kilometers
TRDIST	Distance from the habitat patch to the nearest developed trail	kilometers

Table 2.2 Moose Location and Core Home Range Descriptive Statistics

	Moose 809						Moose 807					
	Winter			Summer			Winter			Summer		
Variable	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
ELEV	488.145 (155.991)	159.740	929.507	486.453 (113.655)	305.926	728.717	503.921 (116.546)	366.746	714.618	459.593 (208.585)	25.152	859.145
SLOPE	0.095 (0.075)	0.000	0.301	0.083 (0.078)	0.000	0.354	0.067 (0.046)	0.002	0.256	0.076 (0.066)	0.000	0.288
FOR	0.301 (0.460)	0	1	0.364 (0.484)	0	1	0.290 (0.458)	0	1	0.129 (0.338)	0	1
RDDIST	7.028 (3.686)	0.001	12.714	7.752 (3.128)	1.287	11.953	10.052 (2.956)	5.114	15.314	7.912 (3.067)	0.005	9.633
TRDIST	1.219 (0.760)	0.049	4.235	0.836 (0.420)	0.015	1.643	1.952 (1.986)	0.003	5.598	2.041 (1.868)	0.019	6.463
Cells	166			77			62			62		
Locations	3455			4121			1349			3528		
% used	79%			92%			97%			60%		
% miss	0.8%			1.2%			0.5%			6.1%		
Start date	2006.03.25			2006.04.01			2006.10.01			2006.04.01		
End date	2008.03.31			2007.09.29			2007.03.31			2007.08.02		

Note: Standard deviation in parentheses.

Table 2.2 (cont.) Moose Location and Core Home Range Descriptive Statistics

	Moose 805						Moose 627					
	Winter			Summer			Winter			Summer		
Variable	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
ELEV	443.459	88.030	719.895	403.989	24.996	920.453	399.593	103.702	717.355	359.273	189.863	504.820
	(183.671)			(189.428)			(132.374)			(99.801)		
SLOPE	0.073	0.001	0.247	0.059	0.000	0.264	0.118	0.000	0.382	0.089	0.000	0.185
	(0.050)			(0.063)			(0.100)			(0.054)		
FOR	0.537	0	1	0.437	0	1	0.286	0	1	0.130	0	1
	(0.500)			(0.499)			(0.455)			(0.344)		
RDDIST	8.368	0.014	13.890	7.158	0.000	9.729	5.778	0.125	9.220	5.443	0.310	8.979
	(4.625)			(3.064)			(3.433)			(3.995)		
TRDIST	1.501	0.000	5.292	1.490	0.005	6.725	1.144	0.204	3.117	0.943	0.051	2.078
	(1.605)			(2.02)			(0.622)			(0.605)		
Cells	188			87			70			23		
Locations	1426			3475			3009			1516		
% used	76%			75%			77%			83%		
% miss	0.9%			6.3%			1.0%			7.4%		
Start date	2006.10.01			2006.04.01			2007.11.29			2008.04.02		
End date	2007.03.31			2007.08.02			2008.11.14			2008.09.30		

Note: Standard errors in parentheses.

Table 2.3 Summer Individual Habitat Selection Models

	Moose 809		Moose 807		Moose 805		Moose 627	
Variable	CL	GEV$	CL	GEV	CL	GEV	CL	GEV
DIST	-9.91***	-	-11.26***	-9.93***	-10.12***	-8.94***	-12.99***	-10.98***
	(0.132)		(0.171)	(0.169)	(0.146)	(0.146)	(0.362)	(0.386)
ELEV	-3.08**	-	-7.26**	-5.78*	-3.060	-0.352	-10.35***	-12.13***
	(1.275)		(3.064)	(2.977)	(2.334)	(2.16)	(3.862)	(3.346)
SLOPE	1.060	-	-0.565	-3.12*	6.67***	5.15***	-2.51*	-1.708
	(0.858)		(1.780)	(1.782)	(1.414)	(1.289)	(1.507)	(1.305)
FOR	0.274**	-	-0.600	-0.637	-0.136	-0.066	2.706	2.452
	(0.136)		(0.378)	(0.347)	(0.183)	(0.164)	(6.96)	(2.792)
RDDIST	0.219	-	-0.157	-0.120	-0.321	-0.307	1.38**	1.70***
	(0.189)		(0.262)	(0.247)	(0.205)	(0.188)	(0.559)	(0.498)
TRDIST	-0.017	-	2.51***	1.84**	0.324	0.104	-1.133	-1.47*
	(0.300)		(0.747)	(0.744)	(0.446)	(0.418)	(0.807)	(0.699)
RHO		-		0.196*		0.329***		0.464***
				(0.112)		(0.049)		(0.062)
N	3969	-	3459	3459	3402	3402	1479	1479
K	6	-	6	7	6	7	6	7
LL	-2861	-	-1887	-1875	-2202	-2180	-530	-522
AIC	5733	-	3786	3764	4416	4374	1072	1058

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; $ = model did not converge.

Table 2.4 Winter Individual Habitat Selection Models

	Moose 809		Moose 807		Moose 805		Moose 627	
Variable	CL	GEV	CL	GEV$	CL	GEV	CL	GEV$
DIST	-9.123***	-8.15***	-9.84***	-	-7.77***	-6.70***	-9.12***	-
	(0.136)	(0.178)	(0.240)		(0.155)	(0.152)	(0.127)	
ELEV	-2.654**	-2.302**	0.163	-	-1.787	-1.662	-3.34***	-
	(0.825)	(0.751)	(2.790)		(1.888)	(1.641)	(1.168)	
SLOPE	1.26**	1.185**	-0.879	-	-3.96***	-2.54***	-0.457	-
	(0.631)	(0.555)	(1.519)		(1.121)	(0.891)	(0.746)	
FOR	-0.282***	-0.244***	-0.085	-	-0.203	-0.191*	0.006	-
	(0.076)	(0.071)	(0.214)		(0.138)	(0.114)	(0.131)	
RDDIST	-0.060	-0.047	-0.073	-	0.167	0.112	0.396*	-
	(0.097)	(0.087)	(0.292)		(0.205)	(0.178)	(0.205)	
TRDIST	0.510**	0.480**	-0.347	-	0.430	0.279	0.423	-
	(0.186)	(0.163)	(0.593)		(0.318)	(0.283)	(0.338)	
RHO		0.457***		-		0.246***		-
		(0.096)				(0.045)		
N	3388	3388	1301	-	1384	1384	2988	-
K	6	7	6	-	6	7	6	-
LL	-3254	-3269	-895	-	-1628	-1612	-2870	-
AIC	6740	6552	1802	-	3268	3238	5751	-

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1; $ = model did not converge.

Table 2.5 Pooled Habitat Selection Models

	Summer		Winter	
	CL	GEV	CL	GEV
DIST	-10.586***	-9.353***	-8.969***	-7.750***
	(0.103)	(0.108)	(0.085)	(0.084)
ELEV	-2.644***	-1.921**	-2.110***	-1.761***
	(0.795)	(0.737)	(0.524)	(0.456)
SLOPE	0.645	0.472	-0.426	-0.231
	(0.511)	(-0.461)	(0.370)	(0.322)
FOR	0.148	0.137	-0.173**	-0.137**
	(0.163)	(-0.144)	(-0.053)	(0.049)
RDDIST	0.210**	0.182*	-0.009	-0.009
	(0.103)	(0.095)	(0.059)	(0.051)
TRDIST	0.185	0.099	0.437**	0.385**
	(0.255)	(0.235)	(0.137)	(0.120)
RHO		0.449***		0.314***
		(0.033)		(0.027)
N	12309	12309	9061	9061
K	6	7	6	7
LL	-7559.1615	-7531.4905	-8696.8803	-8648.2314
AIC	15130	15077	17406	17310

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 3: A Copula Approach for Accommodating Spatial Dependence in Models of Recreation Demand

3.1 Introduction

Recreation demand is commonly modeled using travel cost approaches where demand is assumed to depend on the distance traveled to the site. The travel cost model describes a spatial process where households positioned in the landscape make decisions about which recreation sites to visit and how often. Spatial effects are common in spatially arraigned data, and spatial heterogeneity and spatial dependence are potentially important considerations for travel cost models. Spatial heterogeneity often is addressed though the inclusion of variables describing characteristics of the landscape. Testing for and accommodating spatial dependence, on the other hand, can be more difficult.

Spatial effects in recreation demand models can arise from either the spatial positioning of households or from the spatial positioning of alternative sites. This paper models recreation demand at a single site and examines potential spatial dependence based on the locations of household residence. These effects may arise through interactions among individuals or through the presence of an unobserved random field that influences recreation demand decisions.

Estimating spatial models with discrete dependent variables, such as recreational trips, presents additional challenges compared to the case of continuous, dependent variables (Billé & Arbia, 2013; Fleming, 2004; Smirnov, 2010). Copula functions offer a general approach to modeling joint discrete distributions for spatially correlated data from univariate discrete marginal distributions. The copula approach is an attractive alternative for modeling spatial dependence with count data based on its relative advantages with model flexibility, estimation, and inference (see Cameron & Trivedi, 2013 pg. 319).

This paper presents and implements a method for testing and accommodating spatial dependence in models of recreation demand based on a copula function approach. The method is applied to a travel cost model of recreation for a national forest in Colorado. Results reveal significant spatial dependence in the data and suggest that spatial dependence can be an important consideration in recreational demand models. Individual willingness to pay for access (WTPA), weighted according to sampling stratification, is estimated for 2005 and 2010. Results from both of the model specifications estimated indicate that estimated mean WTPA declined from 2005 and 2010, although the decline is not statistically significant for one specification. The underlying cause of a decline in WTPA for trips to RANF from 2005 to 2010 is likely associated with changes in economic activity, changes in the recreational activity mix of RANF visitors, and changes in forest quality over this period.

3.2 Background

3.2.1 Spatial Effects in Recreation Demand

Spatial effects often are present in data that is positioned in space, such as recreational trip data. The two major spatial effects discussed in the literature are spatial dependence, also referred to as spatial autocorrelation, and spatial heterogeneity (Anselin, 1988). Spatial heterogeneity occurs when spatial relationships or characteristics of observations vary over space. Spatial heterogeneity can be accommodated in recreational demand models though location-specific variables (Parsons, 2003; Phaneuf & Smith, 2005). Spatial dependence describes a fundamental relationship between outcomes occurring at one point in space and outcomes occurring elsewhere. The basic intuition for positive spatial dependence comes from Tobler's (1970) first law of geography: "Everything is related to everything else, but near things are more related than distant things"(p. 236). However, a major complication in accommodating spatial dependence in decision models is that most spatial interdependencies are not directly observable (Smirnov, 2010).

Spatial effects can be an important consideration when undertaking recreation demand analysis. Recreational visit observations are usually are defined geographically for both an origin location and a site location. Thus, in addition to the relationship between trip distance and demand, recreational trip data may exhibit spatial dependence between potential alternative sites or among origin locations. The former case applies to site-choice random utility models (RUM) of recreation demand. The current study examines a single-site model and focus on spatial dependence between recreational decision makers according to the location of their residence.

In the context of recreational behavior, the underlying causes of spatial dependence may include social interaction effects, unobserved location-related, or neighborhood effects, and diffusion effects (C. Bhat & Zhao, 2002; Brady & Irwin, 2011). Social interactions between individuals can influence recreational demand though recommendations, storytelling, and group recreational trips. Social interactions can cause spatial dependence if such interactions are more likely to occur between individuals who live near each other than individuals who live far apart. Regarding social interactions, Smirnov (2010) notes: "Spatial interdependencies between individuals affect their preferences, creating the phenomenon of socially influenced decision-making, so that individuals neither act fully independently, nor reach decisions jointly ” (p. 292).

Diffusion refers to the market-level processes governing the spread of technologies and ideas across society. Diffusion can cause spatially dependent demand if ideas and technologies that impact recreation preferences spread in a systematic manner across the landscape.

The final source of recreational spatial dependence is unobserved neighborhood characteristics, a broad category that refers to all of the unobserved similarities between nearby neighborhoods. Unobserved neighborhood characteristics that influence recreation demand may include traffic patterns, the presence of unobserved recreation substitutes, and social norms. Spatial dependence can result if these unobserved demand determinants are heterogeneous across the analyzed landscape and thus influence demand in a spatial manner.

Estimating models of spatial dependence with count or categorical data complicates model estimation (Fleming, 2004). Specifically, many of the solutions proposed in the literature for dealing with spatial dependence with discrete data rely on simulation or approximations for estimation and can be computationally burdensome. This paper uses a copula function and a composite likelihood function to accommodate spatial dependence among individuals in a model of recreation demand.

3.2.2 Spatial Recreation Demand Literature

Travel cost modeling captures an inherently spatial process. Individuals decide whether to travel to a given site, or to a menu of sites, from their home location.

Surprisingly, there is a relative dearth of literature examining spatial issues related to the travel cost method.

Early travel cost literature dealt with spatial limits of the model (Kerkvliet & Nowell, 1999; Smith & Kopp, 1980), finding that the nature of the recreational good is different for local versus long-distance recreationalists. This literature suggests that travel cost models, especially those based on assumptions about automobile operating costs, should focus on local recreation users (Phaneuf & Smith, 2005).

Spatial heterogeneity has long been incorporated into travel cost models using explanatory variables that describe an individual's origin location. For example, Parsons (2003) listed urban/rural distinction as one of the most commonly included variables in the single-site travel cost model. Two recently published articles explored spatial heterogeneity in models of recreation demand. The first paper (Termansen et al., 2013) estimated a RUM site choice model that includes random effects to account for preference heterogeneity and spatially explicit variables to account for spatial heterogeneity in recreation values. The estimated parameters then are utilized in mapping resource values and policy scenarios. A second paper, by Abildtrup et al. (2013), used a two-step method to explore the determinants of preference heterogeneity and the potential for endogenous spatial sorting in recreation demand. In the first step, the authors conduct a choice experiment using an actual site as the status quo alternative and hypothetical sites as other alternatives to derive estimates of individual willingness to pay (WTP) for site attributes. The second step investigates the determinants of individual WTP that are related to an individual's spatial position in the landscape. The second-stage analysis provides some support for endogenous travel distances related to parking and picnic facilities and indicates that the endogenous sorting problem described by Parsons (1991) warrants future research.

As discussed in the preceding subsection, recreational trip data may exhibit spatial dependence due to social interaction effects, diffusion, or unobserved location-related effects. However, previous studies do not examine origin-based spatial dependence in models of recreation demand. This paper models recreation demand at a national forest in Colorado with a model that accounts for spatial dependence between observations.

3.3 Theoretical Model

The present analysis uses a single-site travel cost model to estimate the willingness to pay for access (WTPA) for day trips to Roosevelt-Arapahoe National Forest in Colorado. The household production framework provides motivation for the generic travel cost problem. Households choose quantities of recreation and other goods to maximize utility subject to time and money constraints. Users of the site are arranged in the landscape heterogeneously and have different trip costs based on their distance to the site and individual characteristics. The central assumption of the travel cost model is that trip cost to a recreation site is directly related to demand for the site. All else equal, lower demand is expected from individuals who reside further away from the recreation site and thus incur higher trip costs. The travel cost method allows for construction of recreation demand curves through observation of the relationship between trip cost and trip-taking behavior. In other words, the travel cost method is roughly explained as a downward sloping demand curve with quantity of trips demanded on the horizontal axis and trip cost on the vertical axis.

Recreation demand also depends on other factors, such as the trip cost of substitute recreation sites, income, and other individual characteristics (Parsons, 2003). An expression for trip demand is in equation 3.1, where x_i is the number of trips taken by individual i. On the left side, tc_i and tc_s are individual $i's$ study site trip cost and substitute trip cost, respectively. Income is given by y_i, and z_i is a vector of individual characteristics.

$$x_i = f(tc\ ,\ tc_s\ , y_i\ , z_i) \tag{3.1}$$

Individual consumer surplus for the site, or access value, is given in equation 3.2. It is calculated as the integration of the demand curve between individual $i's$ trip cost (tc^0) and the relevant choke price (tc^*).

$$CS_i = \int_{tc^0}^{tc^*} f(tc\ ,\ tc_s\ , y_i\ , z_i) dtc \tag{3.2}$$

This is also a close approximation for on-annual WTPA as recreation demand models generally are associated with a small budget share and low income effects (Haab & McConnell, 2002).

3.4 Empirical Model

Obtaining a sufficiently large sample of site users from representative recreation surveys can be costly if users represent only a small fraction of the surveyed population. For this reason, trip data often is collected on-site so that site users can be accessed directly. The trip data used in this study was collected on-site at locations in the Roosevelt-Arapahoe National Forest. The dependent variable used in this paper is the number of visits to RANF in the past 12 months. A count model is used to estimate the demand function in equation 3.1 because it deals with this type of data. However, data collected on-site is characterized by the properties of truncation and over dispersion, which must be accounted for when selecting an estimator.

On-site data is truncated at zero because only trip-takers are observed in the sample (i.e. $x_i > 0$). Failure to account for truncation leads to inconsistent parameter estimates because truncated count data has a different conditional distribution and mean than the underlying data generating process (Cameron & Trivedi, 2013). This issue is typically addressed by normalizing the probability density function for trips by the probability of participation (i.e. $\Pr[x_i > 0]$) so that the density function of the truncated model integrates to one (Haab & McConnell, 2002).

Data collected on-site also is stratified endogenously, meaning that on-site samples are more likely to capture avid users of the site. Shaw (1988) formally defined endogenous stratification, showing that the on-site trip probability is proportional to the number of trips taken. This is stated formally in equation 3.3, where $h(j)$ is the on-site probability that a visitor took j trips, $f(j)$ is the population probability of j trips, and $E_p(x)$ is the number of expected trips in the population.

$$h(j) = \frac{j * f(j)}{E_p(x)} \tag{3.3}$$

This form also accounts for truncation because the normalization constant cancels due to endogenous stratification (Haab & McConnell, 2002).

The result in equation 3.3 can be applied easily to the Poisson distribution. The Poisson has probability density function $f(x_i \mid \boldsymbol{z}_i, \theta) = \frac{e^{-\lambda_i} \lambda_i^{x_i}}{x_i!}$ with the intensity parameter λ_i equal to the expected number of trips and the variance. Thus, equation 3.3 becomes $f(j \mid \boldsymbol{z}_i, \theta) = \frac{e^{-\lambda_i} \lambda_i^{x_i - 1}}{(x_i - 1)!}$ for the case of the endogenously stratified and truncated

Poisson. Note that this is simply the Poisson distribution with the trip count variable decreased by one.

A limitation of the endogenously stratified Poisson model used in the current study model is that the intensity parameter, parameterized as $\lambda_i = \exp(\boldsymbol{z_i \beta})$, holds the mean and variance equivalent. The negative binomial model allows for a relaxation of this constraint through estimation of a dispersion parameter. The zero truncated NB2 model accounts for truncation in the data but not for endogenous stratification. Truncated Poisson estimators with choice-based regression weights (Bowker et al., 2009; Kriesel et al., 2005) can be employed to accommodate overdispersion in on-site models, but this specification experienced convergence issues with the RANF data used in this study and can lead to biased estimates (Stynes et al., 2003).

This paper is centrally concerned with the investigation of spatial dependence in recreation demand models. Addressing spatial dependence in discrete models introduces a variety of challenges compared to the continuous dependent variable case (see Fleming, 2004). Most discrete spatial models rely on computationally intensive simulation or approximation procedures to deal with the multidimensional integrals that often appear in the likelihood functions.

3.4.1 The Copula Approach

A copula, or linking function, is used in this analysis to accommodate potential spatial dependence among observations in a model of recreation demand. Copulas are distribution functions that link multivariate distributions to their one-dimensional marginal distributions. Copulas describe a dependence relationship among random variables with pre-specified marginal distributions. The copula approach permits derivation of a parametric joint distribution for the data from individual marginal distributions using Sklar's theorem (1973). Copula models are attractive for a variety of reasons (see Cameron & Trivedi, 2013), including that they separate inference about the marginal distributions of the random variables from the dependence structure, permitting a test of spatial dependence. The copula function in equation 3.4 is a cumulative distribution function (CDF) with *n* univariate margins, where U_n is distributed standard uniformily. The parameter θ describes the correlation between the marginal distributions.

$$C_\theta(u_1, \dots, u_n) = Pr[U_1 \leq u_{1i}, \dots, U_n \leq u_n] \tag{3.4}$$

If the trip count variable X_j has CDF $F_j(.)$, then the integral transform of $F_j(X_j)$ is uniformily distributed. Thus, the n-variate distribution function $F_j(x_1, \dots, x_n)$ with univariate marginal distributions $F_1(x_1)$ ... $F_n(x_n)$ is given by:

$$\begin{aligned} \mathrm{C}_\theta(x_1, \dots, x_n) &= \Pr[X_1 \leq x_1, \dots, X_n \leq x_n] \\ &= \Pr[F_1(X_1) \leq F_1(x_1), \dots, F_n(X_n) \leq F_n(x_n)] \\ &= \Pr[\mathrm{U}_1 < F_1(x_1), \dots, \mathrm{U}_n < F_n(x_n)] \\ &= \mathrm{C}_\theta\big(F_1(x_1), \dots, F_n(x_n)\big) \end{aligned} \tag{3.5}$$

Alternatively, this can be expressed as:

$$\begin{aligned} F(x_1, \dots, x_n) &= F\big(F_1^{-1}(u_1), \dots, F_n^{-1}(u_n)\big) \\ &= \mathrm{C}_\theta(u_1, \dots, u_n) \end{aligned} \tag{3.6}$$

where $F_j^{-1}(X_j) = U_j$ and $X_j = F_j^{-1}(U_j)$. In the case of zero correlation, the joint distribution is the product of the marginal distributions.

With discrete trip count data, the CDF is a step function, and thus $X_j = F_j^{-1}(.)$ is not a unique value. This paper follows standard practice of evaluating at the minimum of the interval. The CDF $F_j(.)$ is given by the endogenously stratified Poisson distribution as described in the preceding section. The vector of demand parameters $\boldsymbol{\beta}$ then enters the empirical model through $F_j(.)$.

The functional form of the copula function itself is unknown a priori and must be chosen by the analyst. Three candidate spatial copula forms were explored for use in this analysis including the Farlie-Gumbel-Morgenstern, Generalized Gumbel, and multivariate Gaussian forms (see Sener & Bhat, 2012). The Gaussian form was selected for the copula function because the other forms lead to convergence issues in estimation. The multivariate Gaussian copula generalizes a multivariate normal dependence structure to non-normal marginals. The multivariate Gaussian copula is given in equation 3.7.

$$C_\theta(u_1,, \dots, u_n) = \Pr(U_1 < u_1, \dots, U_n < u_n) = \Phi\left(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_n)\right) \tag{3.7}$$

The function Φ is a n dimensional standard normal CDF with mean zero and a correlation matrix whose off-diagonal elements are captured in the vector θ. The term $\Phi^{-1}(.)$ represents the inverse of the univariate standard normal CDF. The spatial process in the Gaussian copula is assumed to be isotropic (i.e. $\theta_{ij} = \theta_{ij}$), and the Gaussian copula is parameterized as follows.

$$\theta_{ij} = \frac{(e^\delta)' \tilde{s}_{ij}}{1+(e^\delta)' \tilde{s}_{ij}} \tag{3.8}$$

The term $\tilde{s}_{ij}$ is a vector of variables that influence the degree of spatial dependence between observations i and j and $-1 \le \theta_{ij} \le 1$ by definition. The parameter δ is estimated. The form presented above permits usage of various spatial dependence determinants common in the literature. Depending on the construction of vector $\tilde{s}_{ij}$, spatial dependence can be based on observations being in some predefined area or "neighborhood," shared neighborhood border length of paired observational units, or inverse distance between observations. All three of these options were explored for the current model. A single neighborhood indicator variable was chosen for $\tilde{s}_{ij}$ based on model performance and the inability of the inverse distance and shared border length specifications to accommodate spatial dependence between same the ZIP code observations.

3.4.2 Estimation

Recall that the data include n observations of annual trip counts for individuals residing in geographically positioned ZIP codes. Using the Gaussian copula described in the preceding section with endogenously stratified Poisson univariate marginals, the likelihood function is given in equation 3.9, where $\boldsymbol{\Theta}$ is a vector of parameters governing recreation demand and $\mathbf{Z}$ is the observed data (Kazianka, 2013).

$$L(\boldsymbol{\Theta};\mathbf{Z}) = \sum_{j_1=0}^{1} \dots \sum_{j_n=0}^{1} (-1)^{l} C_{\theta}\left(u_{1j_1}, \dots, u_{nj_n}\right) \tag{3.9}$$

In this expression, $u_{i0} = F(z(x_i))$ is the marginal CDF; $u_{i1} = lim_{z(x)\to z(x_i)} F(z(x_i))$ is the left hand side limit of $F(z(x_i))$ for $i = 1, \dots, n$; and $l = \sum_{k=1}^{n} j_k$. Estimation of this function is not computationally tractable because it requires summing over 2^n terms in each optimization step and because copula functions can be difficult to accurately compute in high dimensions (Kazianka, 2013). Following recent literature (Kazianka & Pilz, 2010; Sener & Bhat, 2012), this paper uses a pairwise composite likelihood function to simplify the expression in equation 3.9 into a tractable form. The pairwise likelihood function given in equation 3.10 uses bivariate copulas to accommodate dependence between observational pairs. The composite approach allows the analyst to construct a pseudo-likelihood function when marginal likelihoods can be computed for subsets of the data. The resulting pseudo-likelihood function is unbiased and displays consistency and asymptotic normality under typical regularity assumptions. This analysis utilizes a pairwise marginal likelihood estimation approach, analogous to a composite likelihood with bivariate margins.

$$L^{\mathrm{CL}}(\boldsymbol{\Theta}; \mathbf{Z}) = \prod_{i,j\,\in\{1,\ldots,n\}}^{n} \sum_{j_1=0}^{1} \sum_{j_2=0}^{1} (-1)^{l} C_{\theta}\left(u_{ij_1}, u_{jj_2}\right) \tag{3.10}$$

For the Gaussian copula form utilized in this analysis, spatial dependence is accommodated through the estimated off-diagonal element of the copula correlation matrix θ. This paper estimates a single spatial dependence parameter $\hat{\theta}$ for all neighborhood pairs.

$$C_{\theta}\left(u_{i1}, u_{j1}\right) = \Phi\left(\Phi^{-1}(u_{i1}), \Phi^{-1}\left(u_{j1}\right) \mid \theta\right) \tag{3.11}$$

Substituting equation 3.11 into equation 3.10, the pairwise approach the copula function becomes

$$c_{\theta}\left(u_i, u_j\right) = \sum_{j_1=0}^{1} \sum_{j_2=0}^{1} (-1)^{l} C_{\theta}\left(u_{ij_1}, u_{jj_2}\right) \tag{3.12}$$

The non-negative weight terms ω_{ij} are indicator variables that equal one if observations i and j are spatial neighbors and equals zero otherwise. The normalizing weight terms $\mu_i$are inversely related to individual i's number of spatial neighbors. These weights allocate spatial dependence for each observation based on the number of spatial neighbors.

$$\mu_i = \frac{1}{\sum_{j \neq i} \omega_{ij}}\ , i = 1,2, \ldots n. \tag{3.13}$$

The log of the transformed likelihood function is in equation 3.14 below. Maximizing this function will yield parameter estimates for the recreation demand determinants and the spatial dependence structure.

$$\ln\left(L^{\mathrm{CL}}(\boldsymbol{\beta},\delta\ )\right)=\sum_{i=1}^{n-1}\mu_i\sum_{j=i+1}^{n}\omega_{ij}\ln C_\theta\left(u_i,u_j\right) \tag{3.14}$$

3.5 Data and Variables

This study analyzes two National Visitor Use Monitoring (NVUM) datasets collected in 2005 and 2010 at the Roosevelt-Arapahoe National Forest in Colorado. The Roosevelt-Arapahoe National Forest consists of two contiguous National Forests, Roosevelt and Arapahoe. Roosevelt-Arapahoe National Forest encompasses 1,537,543 acres (USFS, 2014b) in the foothills and mountains bordering the Front Range area of Colorado. It is the nearest National Forest to residents in Boulder, Fort Collins and Denver, and is one of the most frequently visited forest in the National Forest system with 23 million annual recreation visits (USFS, 2014a). Visitors to RANF pursue a variety of recreational activities in all seasons. Popular activities include hiking, downhill and cross country skiing, fishing, hunting, and recreational vehicle use.

The visitation data analyzed in this study is sourced from the National Visitor Use Monitoring (NVUM) program administered by the U.S. Forest Service. This program began in 2000 to produce ongoing estimates of visitation at national forests and grasslands (hereafter referred to as national forests). The program collects on-site data from visitor interviews using random, stratified sampling (English et al., 2002). Survey implementation involves stopping last-exiting vehicles at forest use sites and collecting data from the individual with the most recent birthday who is 16 years or older. The first round of data was collected at 120 national forests from 2000-2003. The second-round and third-round NVUM surveys collected information from individuals on the number of trips taken to the national forest in the past year (*TRIPS*) and the distance traveled from their residence to the interview site (*DIST*). Limited demographic information also was collected from respondents, including gender, age category, and ZIP code. Unfortunately, substitute activity and income data was collected for only a fraction of the sample and thus is not utilized in the analysis. Detailed trip expenditures and access fees also were not available for the entire sample. Respectively, the spatial distribution of annual trip observations for the 2005 and 2010 samples is depicted Figure 3.1 and Figure 3.2.

This study models demand for recreation day trips to Roosevelt-Arapahoe National Forest. Thus, the 2005 and 2010 samples are restricted to individuals taking day trips for the primary purpose of recreation. The samples also are restricted to remove outliers. Specifically, individuals reporting more than 150 annual trips, individuals who traveled more than 250 miles one-way, and vehicles with more than 10 passengers are removed from the samples. To provide a proxy for individual income, per-capita income is estimated by ZIP code for both 2005 and 2010 using tax return data[3], resulting in the variable *ZIPINC*.

Trip costs are assumed equivalent to the sum of travel costs and the opportunity cost of time. Travel costs are calculated as the product of round-trip travel distance and $0.14, the per-mile cost of personal and charitable vehicle use in 2005 and 2010, according to AAA. Treatment of the opportunity cost of time has received a great deal of attention in the literature, but no general consensus has emerged. Most studies assume

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[3] Using publically available U.S. Internal Revenue Service data from 2008, per-capita income is estimated by dividing the adjusted gross income by the estimated population. Population is estimated as the total number of dependents claimed. Due to data availability, inflation adjusted 2008 tax is used to construct *ZIPINC* for 2010. For further information, see http://www.irs.gov/uac/SOI-Tax-Stats-Individual-Income-Tax-Statistics-ZIP-Code-Data-(SOI)

that individuals substitute labor for leisure at the margin and estimate time costs as a fraction of the wage rate (Parsons, 2003). In the absence of individual income data, this study approximates time cost as one third of the wage rate[4] times travel time, assuming an average vehicle speed of 60 miles per hour.

In accordance with consumer theory, the cost of day trips to substitute national forests is expected to influence forest trip demand. As mentioned, substitute trip location was not available for the data. Spatial variables were constructed to estimate the influence of substitutes on trip demand. Substitute national forest area within a 50km radius was calculated for each ZIP code centroid to represent the relative abundance of substitutes. This variable, and similar variables calculated for different radiuses, did not provide an adequate representation of substitute trip costs in the data. Specifically, these proxy variables produced positive estimated coefficients. The distance from ZIP code centroid to the nearest substitute forest boundary similarly did not represent substitutes in the data. Substitute prices are not included in the model in the absence of a suitable proxy for substitute trip costs. A diminished role for substitute trip price in determining trip demand is expected for this study site due to the spatial position of RANF relative to its users. RANF offers a large and accessible recreation area to Front Range residents while substitute National Forests are a longer trip compared to RANF for the majority of the sample.

Welfare estimation using the NVUM data requires that welfare estimates incorporate the NVUM sampling strategy. Specifically, the number of individuals

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[4] Hourly wage is calculated as *ZIPINC* divided by hours worked, assuming 2,087 hours worked per year based on U.S. federal government standards. https://www.opm.gov/policy-data-oversight/pay-leave/pay-administration/fact-sheets/computing-hourly-rates-of-pay-using-the-2,087-hour-divisor/.

traveling in the sampled vehicle and the random stratified sampling frame must be accounted for. The following discussion describes how these issues were considered in this paper.

Recall that the demand model parameters $\boldsymbol{\beta}$ enter the empirical model through parameterization of the endogenously stratified Poisson intensity parameter λ_i. Assuming an exponential distribution for the intensity parameter[5] (i.e. $\lambda_i = \exp(\boldsymbol{z_i}\boldsymbol{\beta} + \beta_{tc}tc)$), equation 3.15 gives the annual WTPA per vehicle where $TC_i^0 = TCOST_i$ (Haab & McConnell, 2002).

$$WTPA = \int_{tc^0}^{\infty} \exp(\boldsymbol{z_i}\boldsymbol{\beta} + \beta_{tc}TCOST)\, dtc = -\frac{x_i}{\beta_{tc}} \tag{3.15}$$

Dividing by the expected number of trips[6] yields an expression for per trip WTPA in (16).

$$WTPA = -\frac{1}{\beta_{tc}} \tag{3.16}$$

This expression is converted to per-person WTPA in equation 3.17 by dividing by the number of persons in the sampled vehicle, $NUMVEH$, assuming that respondents make each trip with the same number of companions and to the same RANF site.

$$WTPA_i = {}^{-\frac{1}{\beta_{tc}}}\Big/_{NUMVEH_i} \tag{3.17}$$

Following Bowker et al. (2009), we generate the weighted average welfare by incorporating the NVUM sampling weights into welfare calculations. The weighted average measure in equation 3.18 is used in this paper for subsequent calculations of welfare.

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[5] Choke price under this assumption is infinite.

[6] $\lambda_i = E(x_i)$

$$WTPA_w = \frac{\sum_{i=1}^{N} WTPA_i * NVEXPAND_i}{\sum_{i=1}^{N} NVEXPAND_i} \tag{3.18}$$

The determinant of the degree of spatial dependence between two observations, $\tilde{s}_{ij}$, is defined as a single indicator variable that equals one if individuals i and j are spatial neighbors and equals zero otherwise. Observations are spatial neighbors if their ZIP code centroids are within 5 km or 2.5 km of each other, depending on the specification. The pairwise marginal likelihood function in equation 3.14 excludes observations for which there are no spatial neighbors. In the 5 km neighborhood specification of $\tilde{s}_{ij,}$ this results in dropping 52 and 49 observations from the 2005 and 2010 samples, respectively. In the 2.5km neighborhood specification, 74 and 78 neighborless observations are dropped from the 2005 and 2010 samples, respectively. Tables 3.1 through 3.4 provide descriptive statistics of the data for the 5 km and 2.5 km neighborhood specifications across the 2005 and 2010 samples.

3.6 Results

Spatial copula models with 5 km and 2.5 km spatial neighborhood specifications were estimated by maximizing the previously discussed pairwise marginal likelihood function for the 2005 and 2010 samples. Weighted likelihood specifications[7] also were estimated to incorporate sampling weights (Wang et al., 2004); however, these models provide an inferior model fit compared to the unweighted models, according to AIC and BIC measures. The unweighted model results thus are preferred, and instead sampling weights are instead incorporated during welfare calculation.

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[7] $Weigted\ Log\ Likelihood =$
$\sum_{i=1}^{n-1} NVEXPAND_i * \frac{n}{\sum_{i=1}^{n} NVEXPAND_i} * \mu_i \sum_{j=i+1}^{n} \omega_{ij} \ln C_\theta\left(u_i, u_j\right)$

Two specifications were estimated through pairwise marginal maximum likelihood for each model. The first is a “sparse” specification and explains trip behavior using only trip cost (*TCOST*) and the spatial dependence parameter. The second “full” specification adds gender (*FEMALE*), the number of individuals in the sampled vehicle (*NUMVEH*), and ZIP code per capita income (*ZIPINC*). Robust standard errors clustered by ZIP code are used for inference[8]. Respectively, model results for the 5 km and 2.5 km neighborhood specifications are presented in Table 3.5 and Table 3.6.

The full specification is preferred to the sparse specification across years and neighborhood specifications, according to AIC and BIC measures of fit. For this reason, the full specification is the focus of subsequent discussion and analysis.

The trip cost (*TCOST*) variable produces significant estimated coefficients at the .01 level across models. The individual variable estimated coefficients vary in significance across models, but the significant estimates are consistent in sign. In the 2010 5 km neighborhood specification, being female (*FEMALE*) is significantly associated with taking fewer trips. The 2005 5 km neighborhood model indicates that vehicles carrying more passengers are associated with taking more annual trips to RANF. As expected, individuals who live in ZIP codes of higher per-capita income (*ZIPINC*) are significantly associated with taking more recreational trips across 5 km neighborhood models and are at the .1 level of significance for the 2005 2.5 km neighborhood model .

Spatial dependence is present in recreation demand for day trips to RANF, as indicated by the significance of the estimated spatial neighborhood parameter *NEIGH*[9] at the .01 level across all estimated models. The magnitude of the spatial dependence

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[8] Obtained via the sandwich estimator

[9] δ in equation 3.8

parameter θ is consistently approximately 0.75, a sign that spatial dependence is also practically significant[10] in the model. The results suggest that spatial dependence is a potentially important determinant of recreational demand.

Individual per-trip WTPA was calculated using equation 3.18, and the results are presented in Table 3.7. Error bounds were constructed following the Krinsky-Robb procedure and using the clustered sandwich estimator variance-covariance matrix (Krinsky & Robb, 1986). In the 5 km neighborhood specification, estimated per trip WTPA decreases to $40.08 in 2010 from $43.73 in 2005 in 2010 USD. Mean individual WTP decreases even more over that time in the 2.5 km neighborhood models, from $32.04 in 2005 to $19.61 in 2010. The WTPA estimates from the 2.5km neighborhood model are higher across years, and in 2010 they are about half the size of the WTPA estimates from the 5km model. A significant change in WTPA from 2005 to 2010 is found with the 2.5 km neighborhood model, as the error bounds do not overlap.

3.7 Discussion

This paper presents and implements a method for testing and accommodating origin-based spatial dependence in models of recreation demand. Furthermore, this analysis evaluates the hypothesis that WTPA for day trips to RANF remained the same from 2005 and 2010 data. The results indicate that significant spatial dependence exists in recreation demand for trips to RANF, after controlling for trip cost and individual characteristics. The estimated models also provide some evidence that WTPA for day trips to RANF declined from 2005 to 2010.

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[10] Recall that this parameter is the estimated off-diagonal of the standard normal correlation matrix from the Gaussian copula.

The copula method used to accommodate spatial dependence in this study is straightforward, and the model can be estimated without computationally burdensome simulation techniques. The significant spatial dependence uncovered in the recreational demand model suggests that spatial dependence can play a role in recreation behavior. Accommodation of spatial dependence is a step toward incorporating a potentially important, but generally ignored, dimension of recreation demand. Spatially dependent recreation behavior is likely related to social interactions, diffusion effects, and unobserved landscape characteristics (Sener & Bhat, 2012). However, the causes and dynamics of spatial dependence are poorly understood and further research is warranted.

The welfare estimates indicate that WTPA decreased from 2005 to 2010, although the change is not significant in the 5 km neighborhood specification[11]. The most obvious reason for this decline is the sustained reduction in employment and income that accompanied the 2008 financial crisis and subsequent recession. The recreation demand models from 2005 support this possibility as they indicate that income is significantly associated with trip behavior. However, Loomis and Keske (2012) suggest that nature-based high mountain recreation in Colorado did not decline over this period in terms of visitor expenditures or total visits. Another potential explanation for reduction in WTPA from 2005 to 2010 is changes to the activity mix at RANF. Cordell (2012) found that the typical mix of recreational activities in national forests shifted substantially from 2000 to 2010, with increased participation in nature-based activities, such as wildlife viewing, and decreased participation in traditional outdoor activities, such as hunting and fishing. The results also show a decline in snowboarding participation and motorized activities

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[11] A 10 km neighborhood model also was estimated, and the results show a significant decline in WTPA from 2005 to 2010.

declined from 2005 to 2010. A shifting activity mix at RANF could be related to the decline in per-trip WTPA found in the 2.5km neighborhood model. For example, the proportion of motorized vehicle users, a costly and gear-intensive activity type, declined from 13% of the weighted sample in 2005 to 9% in 2010. Likewise, the percentage of anglers fell from 11% of the weighted sample in 2005 to 7% of the weighted sample in 2010. The 2010 weighted sample was composed of 28% hikers compared to 16% in the 2005 sample. Consistent with the national trend, the activity mix in the RANF samples shifted away from gear-intensive snow sports and toward nature-based hiking. The activity mix shift at RANF may have contributed to the decline in mean per-trip WTPA from 2005 to 2010 found in the 2.5km neighborhood model. Evolving preferences, and potential shifts in forest recreation activities need to be accounted for when crafting forest policy on maintenance, use regulations, and conservation priorities.

Other factors were also affecting forest recreation values from 2005 to 2010 including wildfires and infestation by the mountain pine beetle. Differences in weather patterns across the samples might have also had an effect on annual forest recreation value and activities across the samples.

Spatial parameters in econometric models are generally not tied to a single causation or source but instead represent the aggregation of various causes of spatial dependence. Unwinding the factors that determine spatial dependence is a challenging but promising avenue for future research. For example, wireless apps like Nextdoor could be utilized to measure social interactions between neighbors and then test whether interactions introduce spatial dependence. Furthermore, more precise information about the location of one’s home would allow for an improved specification of the determinants of spatial dependence ($\tilde{s}_{ij}$) in recreation demand.

Table 3.1 Descriptive Statistics for the 2005 Sample with 5 km Neighborhoods

Variable	Description	Mean	StDev	Min	Max	Median
COUNT	The number of respondent trips to RANF in the past 12 months	17.610	22.069	1	120	10
TCOST	Travel cost of a visit to RANF with time cost based on per-capita ZIP code income (in hundreds of 2005 USD)	0.226	0.136	0.004	0.858	0.202
FEMALE	=1 if respondent is a female and =0 otherwise	0.294	0.456	0	1	0
NUMVEH	Number of passengers in respondent's vehicle	2.315	1.151	1	8	2
ZIPINC	Average ZIP code income (in hundreds of thousands of 2005 USD)	0.357	0.160	0.119	1.623	0.315

Note: n=909

Table 3.2 Descriptive Statistics for the 2010 Sample with 5 km Neighborhoods

Variable	Description	Mean	StDev	Min	Max	Median
COUNT	The number of respondent trips to RANF in the past 12 months	17.270	22.357	1	130	9
TCOST	Travel cost of a visit to RANF with time cost based on per-capita ZIP code income (in hundreds of 2010 USD)	0.218	0.135	0.004	0.847	0.193
FEMALE	=1 if respondent is a female and =0 otherwise	0.375	0.485	0	1	0
NUMVEH	Number of passengers in respondent’s vehicle	2.564	1.391	1	9	2
ZIPINC	Average ZIP code income (in hundreds of thousands of 2010 USD)	0.363	0.139	0.111	1.432	0.328

Note: n=741

Table 3.3 Descriptive Statistics for the 2005 Sample with 2.5 km Neighborhoods

Variable	Description	Mean	StDev	Min	Max	Median
COUNT	The number of respondent trips to RANF in the past 12 months	17.880	22.425	1	120	10
TCOST	Travel cost of a visit to RANF with time cost based on per-capita ZIP code income (in hundreds of 2010 USD)	0.226	0.137	0.045	0.858	0.201
FEMALE	=1 if respondent is a female and =0 otherwise	0.293	0.455	0	1	0
NUMVEH	Number of passengers in respondent's vehicle	2.315	1.159	1	8	2
ZIPINC	Average ZIP code income (in hundreds of thousands of 2010 USD)	0.363	0.161	0.144	1.623	0.325

Note: n=864

Table 3.4 Descriptive Statistics for the 2010 Sample with 2.5 km Neighborhoods

Variable	Description	Mean	StDev	Min	Max	Median
COUNT	The number of respondent trips to RANF in the past 12 months	17.480	22.561	1	130	10
TCOST	Travel cost of a visit to RANF with time cost based on per-capita ZIP code income (in hundreds of 2010 USD)	0.214	0.133	0.004	0.847	0.187
FEMALE	=1 if respondent is a female and =0 otherwise	0.380	0.486	0	1	0
NUMVEH	Number of passengers in respondent's vehicle	2.558	1.380	1	9	2
ZIPINC	Average ZIP code income (in hundreds of thousands of 2010 USD)	0.362	0.127	0.111	0.799	0.328

Note: n=692

Table 3.5 Spatial Travel Cost Models With 5 km Neighborhoods

	2005		2010	
CONST	3.999***	3.382***	4.481***	3.279***
	(0.016)	(0.074)	(0.018)	(0.085)
TCOST	-2.075***	-1.476***	-3.416***	-1.359***
	(0.014)	(0.042)	(0.023)	(0.037)
FEMALE		-0.165		-0.865**
		(0.172)		(0.358)
NUMVEH		0.172**		0.144
		(0.082)		(0.387)
ZIPINC		0.785***		1.14***
		(0.074)		(0.036)
NEIGH	1.098***	1.098***	1.085***	1.092***
	(0.000)	(0.002)	(0.121)	(0.214)
N	886	886	721	721
K	3	6	3	6
LL	-99588	-99550	-80923	-80825
AIC	199181	199112	161852	161661
BIC	199196	199141	161866	161689

Notes: Clustered sandwich standard errors in parenthesis;
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.6 Spatial Travel Cost Models With 2.5 km Neighborhoods

	2005		2010	
CONST	3.722***	3.594***	4.406***	3.982***
	(0.001)	(0.246)	(0.006)	(0.223)
TCOST	-1.436***	-2.015***	-3.406***	-2.811***
	(0.007)	(0.066)	(0.020)	(0.158)
FEMALE		-0.253		-0.208
		(0.186)		(0.658)
NUMVEH		0.218		0.257
		(0.457)		(0.280)
ZIPINC		0.557*		-0.292
		(0.313)		(0.381)
NEIGH	1.095***	1.088***	1.098***	1.091***
	(0.037)	(0.104)	(0.000)	(0.367)
N	864	864	692	692
K	3	6	3	6
LL	-97247	-96942	-77686	-77851
AIC	194500	193896	155377	155714
BIC	194515	193924	155391	155742

Notes: Clustered sandwich standard errors in parenthesis;
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.7 Estimated Individual Per-trip WTP for Access to Roosevelt-Arapaho National Forest

	5 km neighborhood		2.5 km neighborhood	
	2005	2010	2005	2010
Mean	$43.73	$40.08	$32.04	$19.61
Range	$38.55 - $50.53	$38.73 - $46.41	$27.73 - $37.99	$18.91 - $20.34

Notes: Krinsky-Robb (1986) confidence intervals; 2010 U.S. dollars.

Figure 3.1 NVUM 2005 Day Trip Recreation Visitors to Roosevelt-Arapaho National Forest by Home Zip Code

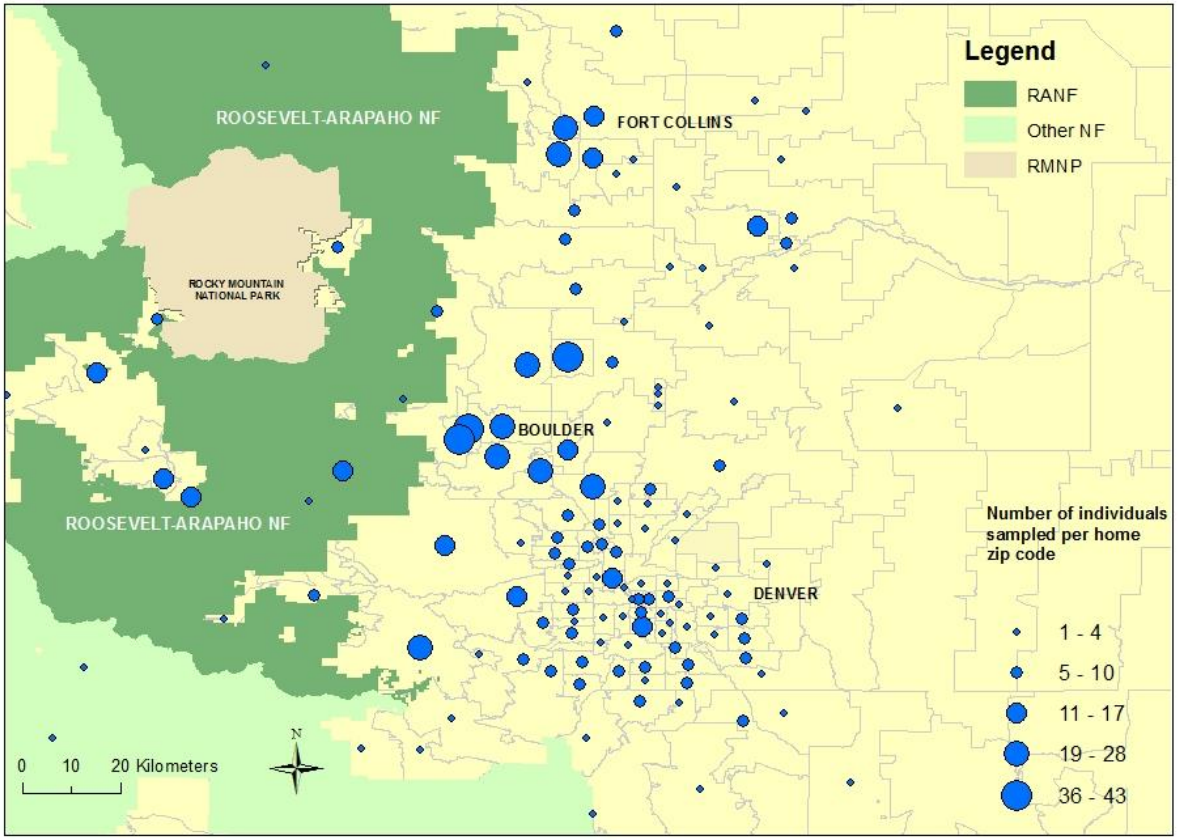
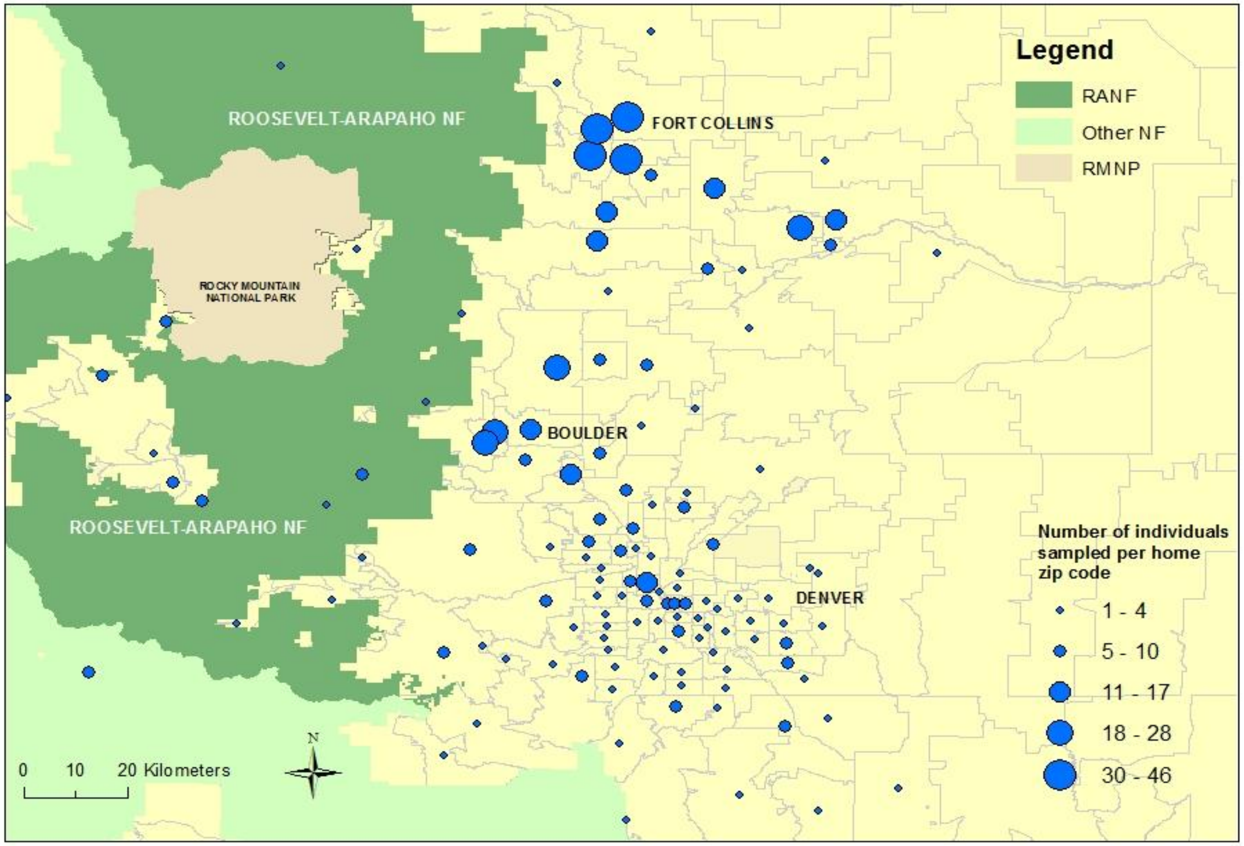


Figure 3.2 NVUM 2010 Day Trip Recreation Visitors to Roosevelt-Arapaho National Forest by Home Zip Code



Chapter 4: Optimal Population Control of Wild Horse Populations with Nonlethal Methods at Two Spatial Scales

4.1 Introduction

Wildlife populations provide a variety of amenities to society, including consumptive and nonconsumptive recreation, ecosystem regulation, and nonuse values. Wildlife populations also can impose costs on society through interference with human economic activities, degradation of habitat, and spreading of disease. Striking a balance between the costs and benefits of wildlife typically involves active population management. Population control is most commonly carried out through increased regulated hunting or trapping[12] (Rondeau, 2001). However, when species are endeared to the public, lethal population control methods can be associated with significant societal costs. In these cases, wildlife can be captured and relocated or held in captivity. Fertility-control methods also are advocated as a humane population control alternative.

This paper evaluates alternative nonlethal population control strategies for wild horse populations in the American West--an animal for which traditional population control methods are not a desirable option. The value of current management is estimated and policy simulations are carried out for optimal horse removal, fertility control, and mixed removal and fertility-control management scenarios. Additional simulations relax model constraints on horse gathering efforts to investigate the policy question of how

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[12] Bear, wolf, coyote, cougar, beaver, geese, alligator, porcupine, and deer populations are actively managed in North America.

increasing the resources available for management would influence optimal population control programs. The analysis is carried out for state-level and herd-level spatial scales.

4.2 Background

Free roaming horses are an enduring icon of the American West, but for decades an effective and sustainable management plan for wild horses has eluded land managers. Western wild horse populations are descendants of domestic animals introduced by Spanish explorers in the early 1500s. Once introduced, populations grew quickly, and by the year 1800 wild horses roamed in large herds, ranging from Texas to California (Dobie, 2005).

4.2.1 Management of Wild Horses in the Western United States

Rapid settlement of the western United States and the subsequent development of western lands led to conflicts with wild horse populations in the 1800s and 1900s. During this time, wild horses were sought out and destroyed or captured for commercial slaughter to prevent their interference with grazing and agricultural activities (Phillips, 2012). By 1971, the total U.S. population was reduced to 9,500 horses (PITT, 1985). Beginning in the mid-20th century, horse and animal welfare advocates decried the inhumane treatment of removed animals and lobbied Congress for wild horse protection. The campaign garnered public interest and media coverage, and in 1959 Congress passed legislation to prohibit the use of aircraft or motorized vehicles to hunt horses and burros on public lands (PITT, 1985). In 1971, Congress passed the Wild and Free-Roaming Horses and Burros Act, banning private horse gathers and tasking the federal Bureau of Land Management (BLM) with “protection, management and control of wild free-roaming horses and burros on public lands” (NRC, 2013). The language in the bill also guides the BLM to manage horses and burros at “the minimal feasible level” to “achieve and maintain a thriving natural ecological balance on the public lands” (NRC, 2013). These directives must be balanced with the BLM’s mandate to manage public lands for multiple uses. Without active control, horse populations often become a stress on grazing land (Pimentel et al., 2005). To prevent rangeland degradation, the BLM actively gathers wild horses and removes them from the range with the goal of keeping populations near predetermined appropriate management levels (AMLs). Adoptive homes are sought for removed horses and unadopted animals are sent to long-term holding facilities. The BLM does not support selling unwanted horses for slaughter.[13]

In recent years, unwanted horses have been accumulating at holding facilities, and the budget for caring for these animals is growing unsustainably. During the 2012 fiscal year, a full 64% of the Wild Horse and Burro Program’s $71.8 million budget was dedicated to maintaining captive horses (BLM, 2014). In 2000, by comparison, holding accounted for 46% the $19.8 million total program budget (GAO, 2008). Furthermore, Garrott and Oli (2013) estimated that the total NPV cost of caring for the horses currently in holding, if no more are added, at nearly $350 million. Under the existing management program, the authors estimate the total 2013-2030 costs of maintaining unadopted horses in captivity would total $1.1 billion.

Wildlife fertility-control methods are used with a variety of wildlife species as a means of mitigating human-wildlife conflicts (Fagerstone et al., 2010), and limited fertility-control efforts are currently undertaken by the BLM. Using static methods,

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[13] This practice was banned by law between 1988 and 2004 and currently is not advocated by BLM policy (Phillips, 2012).

Bartholow (2007) and de Seve and Boyles Griffin (2013) find significant cost savings associated with undertaking fertility control in wild horse populations. This study contributes to the literature a dynamic economic analysis of wild horse management.

4.2.2 Optimal Control of Wildlife Populations

A study by Rondeau and Conrad (2003) examined optimal management of urban deer populations in New York in a model characterized by start-up costs and linear stock-dependent marginal costs of culling. The linearity of their cost function is consistent with a “bang-bang” optimal solution, but the startup costs and stock-dependent costs violate the sufficient conditions for the bang-bang optimality described by Spence and Starrett (1975). Instead, Rondeau and Conrad (2003) found that pulsing, or letting the population rise before culling intermittingly, is the optimal solution for an urban deer population in New York. The optimality of pulsing in deer management stems from economies of scale in culling, and pulsing may be part of an optimal horse management policy if economies of scale exist in horse gathering.

4.3 Two Models of Wild Horse Population Control

This section develops optimal control models of wild horse population management. In essence, the problem is to choose a sequence of annual population control efforts to maximize over time the net benefits of a wild horse population. Two methods of population control are considered: horse removal and horse fertility control. Under current technology, both removal and fertility control generally require that herds be gathered on the range. With removal, gathered horses are transported to short-term facilities where adoptive homes are sought for the animals. Unadopted horses are shipped to long-term holding facilities. With fertility-control methods such as Porcine Zona Pellucida (PZP) injections, horses are treated immediately after they are gathered. Once treated, fertility controlled horses are released. Implementing fertility-control operations also requires additional horse population monitoring (via helicopter) compared to a horse removal program (Bartholow, 2007).

The state variable X_t is the number of horses in the horse population at the end of year t, and the horse population changes over time according to growth function $F(X_{t-1})$. Specifically, $F(X_{t-1})$ is the change in population from the end of year $t-1$ to the end of year t in the absence of population management. The choice variable Y_t is the number of horses removed or the number of horses made infertile. The marginal cost of horse gathers a given period $C_g(Y_t , X_{t-1})$ is considered a function of population size X_{t-1} and management choiceY_t. The marginal costs of transporting horses (C_{tr}), horse adoptions (C_a), and holding unadopted horses (C_h) are assumed to be constants. Adoption demand $(adopt)$ also is assumed to be constant across time.

Wild horses are associated with economic impacts beyond the costs of population management. Wild horses provide recreation benefits for wildlife watchers and nonuse values for individuals who take satisfaction in knowing that wild horses roam the western range. Horse populations also can impose economic costs through degradation of rangelands shared with wildlife species and domestic livestock. The annual net economic benefits provided by wild horses are given by the function $B(X_{t-1})$.

The discount factor ρ reflects time preference and is bound between 0 and 1 (inclusive). Wild horse managers are constrained by the number and proportion of animals that can be gathered in a given year (NRC, 2013, p. 13), and constraint parameter δ is the maximum proportion of the population that can be gathered in one period.

4.3.1 Optimal Horse Removal

The net present value of a single herd of wild horses using horse removal methods is maximized where the chosen sequence of horse gathers and removals $\{Y_0, \ldots, Y_T\}$ solves the problem in 4.1.

$$\max_{\{Y_t\}} \sum_{t=0}^{\infty} \rho^t \left[\frac{B(X_{t-1})}{\rho} - Y_t C_g(Y_t, X_{t-1}) - \gamma C_a - (Y_t - \gamma) C_h - Y_t C_{tr}\right] \quad (4.1)$$

Subject to:

$$X_t - X_{t-1} = F(X_{t-1}) - Y_t$$

$$Y_t \leq \delta X_{t-1}$$

X_{-1} is given

$$B(X_{-1}) = 0$$

Where:

$$\gamma = \begin{cases} Y_t \; if \; Y_t \leq adopt \\ adopt \; if \; Y_t > adopt \end{cases}$$

The timing of management operations in the models is as follows. Removals and fertility-control measures (Y_t) occur at the beginning of year t, when the population is size X_{t-1}. By the end of year t, the population transitions to size X_t. Periods are one year. Periods end after foals are born, and the next period begins before mating does, imposing the assumption that none of the removed or treated horses are pregnant. Also, $B(X_{t-1})$ is divided by ρ because the benefits of population X_{t-1} are realized in the previous period, where $B(X_{-1}) = 0$.

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4.3.2 Optimal Fertility Control

The marginal cost of fertility-control treatment C_f is assumed to be constant (Bartholow, 2007), as is the annual fixed cost of population monitoring m. The remaining parameters and variables are the same as for the horse removal problem. For simplicity, the model of fertility control assumes that treatment is 100% effective in making individuals infertile for one year. Furthermore, animals treated in year t impact the population transition that occurs between year $t-1$ and year t. The optimal fertility-control program is a sequence of fertility treatment choices that maximizes the problem:

$$\max_{\{Y_t\}} \sum_{t=0}^{\infty} \rho^t \left[\frac{B(X_{t-1})}{\rho} - Y_t C_g(Y_t\,, X_{t-1}) - Y_t\, C_f - C_m\right] \tag{4.2}$$

Subject to:

$$X_t - X_{t-1} = F(Y_t, X_{t-1})$$

$$Y_t \leq \delta X_{t-1}$$

X_{-1} is given

$$B(X_{-1}) = 0$$

Where:

$$C_m = \begin{cases} m\ if\ Y_t > 0 \\ 0\ if Y_t = 0 \end{cases}$$

The model assumes that the fertility-control effort controls the internal rate of horse population growth.

4.4 Model Calibration

The following section specifies parameter values and functional forms for the defined models of horse removal and fertility-control. Population management models are presented for state and herd spatial scales. The state-scale and herd-scale models consider horse populations of different sizes and differ in their treatment of gather costs. The herd-scale models are based on the Beatys Butte herd management area (HMA) in eastern Oregon. The state-scale models are constructed with data from five states with similarly sized wild horse and burro populations, Arizona, California, Oregon, Utah, and Wyoming[14], and the state-scale policy scenarios represent typical conditions in the states considered. All of the values used in the models are inflation-adjusted to 2014 dollars. The discount parameter ρ is assumed to be 0.95 to reflect a 5% discount rate.

4.4.1 Wild Horse Population Biology

Wild horse populations in the American West are growing at approximately 15-20 percent per year (NRC, 2013). Current BLM population targets (AMLs) have led to high these growth rates because the AMLs are set below levels where density affects population growth (NRC, 2013). Eberhardt and Breiwick (2012) examined population data from four horse populations in France, Argentina, and the United States. They found that the populations grew according to a theta logistic growth function with the parameter controlling the inflection point equal to two, as shown in equation 4.3.

$$F(X_{t-1}) = X_{t-1} r \left[1 - \left(\frac{X_{t-1}}{\mathrm{K}}\right)^2\right] \tag{4.3}$$

The parameter K is the carrying capacity, and r is the intrinsic growth rate. The study estimated an intrinsic growth rate (r) of 0.28 and a carrying capacity of 1,202 horses for the Beatys Butte herd in eastern Oregon. These estimates serve as parameters in the herd-scale models. In 2013, the BLM set the AML for this herd at 250 animals.

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[14] The total 2004 wild horse and burro populations in these states were as follows: AZ-2,133; CA-4,129; OR-3,085; UT-2,745; WY-4,381.

The state-scale scenarios also assume that the state horse population grows according to equation 4.3 with $r = 0.28$. Applying the theta logistic growth function at the state-scale imposes the assumption that the state horse population grows as if all horses in the state belong to the same reproducing population. The average population in the five states considered was 3,294 in 2004, the year for which other parameter estimates are available. The average ALM across the states was 2,485 in 2004. The state-scale carrying capacity is assumed to be in the same proportion to the AML as Beatys Butte herd. Thus, a carrying capacity of 12,000 is assumed for the typical five-state wild horse population.

The theta logistic growth function exhibits a few properties worth pointing out. The term $X_{t-1}r$ represents the internal increment of growth, and $X_{t-1}r\left(\frac{X_{t-1}}{K}\right)^2$ captures the density-dependent effects. As carrying capacity (K) goes to infinity, the population is unconstrained by density effects, and population growth is equal to the internal increment of growth. Conversely, as the stock approaches the carrying capacity, the theta logistic growth function goes to zero.

4.4.2 Gather Costs

Horse gathers are required for implementing horse removal and fertility-control population management methods. Available BLS cost data was used to construct stock-dependent average total cost functions for the state-scale and herd-scale scenarios. In the herd-scale scenarios, marginal costs of horse gathers decline linearly with population. Citing correspondence with BLM, an unpublished study reported that the average per-hose gather cost is \$500 in a population of 50 and is \$150 in a population of 1,000

(Arneson et al., 2002). Thus, the average total cost of gathers declines as the herd population increases. Equation 4.4 is the linear function connecting these data points and is the functional form that defines average total gather costs in the herd-scale models.

$$C_g(X_{t-1}) = 680.93 - .4839X_{t-1} \tag{4.4}$$

To account for fixed costs, the minimum cost conducting a single horse gather for the Beatys Butte herd is set to \$11,396 following Bartholow (2007) [15] . The maximum percentage of the population that can be gathered in a given period δ is set to 0.9 at the herd-level, based on previous gather data for the Beatys Butte herd[16].

Removal costs in the state-scale model are proportional to the percent of the population removed in a given year. The total 2004 horse removal costs for each state were calculated as the product of the average removal costs reported by Bartholow (2007) and the number of removals that occurred that year[17] for the five states under consideration. The percentage of the stock removed in 2004, calculated as total removals over total population, ranges from 17% in Arizona to 45% in Wyoming. The relationship between the proportion of animals removed and the total removal costs provides a basis for estimating gather costs at the state scale. Figure 4.1 depicts the relationship between the proportion of the population removed and total removal costs. The fitted linear equation connecting the data points is in equation 4.5.

$$C_g(Y_t , X_{t-1}) = 1{,}864{,}940.29\ Y_t/X_{t-1} - 165{,}913.85 \tag{4.5}$$

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[15] Bartholow estimates herd fixed removal costs of \$10,000 (2007 USD)

[16] More than 90% percent of the Beatys Butte herd was removed in 2009.

[17] Data on population size, AML, removal, and adoption are from the BLM website: http://www.blm.gov/wo/st/en/prog/whbprogram/herd_management/Data.html.

This equation implies that removing the entire state population of horses in one period costs roughly $1.7 million in 2014 USD and assumes that complete removal costs are equivalent across the five states considered. The parameter δ is assumed to be 0.5 at the state scale because no state under consideration was observed gathering more than half of its state-horse population in a single year. A minimum cost of $34,189[18] is assumed for removal operations at the state scale. Removal costs include transportation costs, and thus no additional transportation costs (C_{tr}) are included in the state-scale model. Equation 4.5 is used for state-scale fertility- control scenarios even though fertility control does not require transportation. Thus, the model may overstate gather costs for state-scale fertility control.

4.4.3 Transportation, Adoption, and Holding Costs

When wild horses are removed from the range, they are transported to holding facilities. The average transportation cost for one horse from the range to a holding facility is $243 (Arneson et al., 2002). The model assumes that all horses removed from the range are associated with this constant shipping cost.

Removed horses are made available to the public for adoption. The cost to the BLM of conducting an adoption, including advertising, equipment, facility rental, and staff travel, is approximately $1,544 (Zeigler, 2012). The standard adoption fee is $125 per animal (BLM, 2014). The number of annual wild horse adoptions averaged 170 in 2012 for the five states considered, and the state-scale model assumes $\gamma = 170$. The

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[18] Assumes that three herds must be managed to initiate state-level management. Equivalent to $30,000 in 2007 USD.

Beatys Butte herd's proportional population share of Oregon adoptions in 2012 was 68, and $\gamma = 68$ in the herd-scale model.

Unadopted animals are sent to long-term holding facilities. Garrott and Oli (2013) estimated that the annual maintenance cost per horse in holding was $1,074 (2012 USD) and that the average life expectancy of animals entering holding is 15 years. Assuming a 5% discount rate, the present-value cost of holding a horse for 15 years (C_a) is $11,865.

4.4.4 Fertility Control Application

Fertility-control management can reduce population growth rates. A recent National Research Council report states that fertility-control agents have:

> ". . . the potential to reduce population growth rates and hence the number of animals added to the national population each year" (NRC, 2013, p 13).

The population transition function for the fertility-control management scenarios is shown in equation (4.6). The form of equation 4.6 assumes that the percent of a horse population not fertility treated (f_t) is proportional to the growth rate following fertility control. Alternatively, this form could be interpreted as having a reproducing population of ($X_{t-1} - Y_t$) animals that exert density effects on growth consistent with a population of X_{t-1} animals.

$$X_t - X_{t-1} = X_{t-1} r \left[f_t - \left(\frac{X_t}{K}\right)^2 \right] \tag{4.6}$$

Where:

$$f_t = 1 - \frac{Y_t}{X_{t-1}}$$

Undertaking fertility control in wild horse populations requires additional population monitoring efforts compared to management with horse removal. Based on the previous estimates, the marginal cost of fertility-control application (C_f) is \$244, and the annual cost of fertility monitoring (m) is \$5,698 (Bartholow, 2007).

4.4.5 Net Benefits Function

Wild horse populations are associated with significant benefits and costs. Wild horses provide existence benefits to wild horse supporters and recreation benefits to wildlife enthusiasts. When populations go unmanaged, wild horses can damage rangeland shared with other wildlife and domestic livestock. Pimentel et al. (2005) estimated that U.S. populations of wild horses and burros cause \$5 million in forage losses annually. Bastian et al. (1999) found that the marginal opportunity costs of additional horses on the range in excess of target population levels in Wyoming is \$2,695 per horse. At levels well beyond the AML, marginal damage rises to approximately \$3,546. This analysis follows Rondeau and Conrad (2003) in assuming that total net benefits can be represented by a Gompertz function where:

$$B(X) = \begin{cases} 0 & \text{if } X = 0 \\ a\,X\,Ln\left({}^{b}/_{X}\right) & \text{if } X > 0 \end{cases} \tag{4.7}$$

The AML set by the BLM is assumed to be the population level $\bar{X}$ that corresponds with the maximum of $B(X)$. The Gompertz is a single, peaked function, and thus $B_x(\bar{X}) = 0$, $B_x(X) > 0\ for\ X < \bar{X}$ and $B_x(X) < 0\ for\ X > \bar{X}$. The marginal damage caused by an additional wild horse at high population levels is approximately \$3,546 (Bastian et al., 1999). Assuming that this is the value of marginal damage at carrying capacity, then $B_x(K) = -3{,}546$. Parameters a and b then can be solved for by considering this equation together with the equation at the maximum. In the state-level model, parameters a and b are equal to 2,251.83 and 6,754.93, respectively. The resulting function implies that a population of 10 horses produces $147,000 total net benefits annually, a population at the five-state average AML (2,485) produces $5.6 million in net benefits, and a herd at the five-state average carrying capacity (12,000) produces annual net benefits of negative $15.5 million. In the herd-scale model, parameter a equals 2,258.07, and parameter b equals 679.57. This function implies that the Beatys Butte herd is associated with annual net benefits of $95,000, $565,000, and negative $1.5 million when the population is at 10, at the AML (250), and at K (1,200) respectively.

4.5 Results

This section presents simulated optimal management programs based on the previously specified models and parameters. The 50-year net present value of management scenarios was calculated under the status quo and under various optimal population management regimes. A 50-year time horizon is used to compare scenarios. A long-term planning horizon is appropriate for this context because the public will manage wild horses for the foreseeable future.

4.5.1 Valuation of Current Management

The value of the existing horse management was estimated to establish a baseline. Historical horse gather and removal data from the BLM provides the basis for constructing baseline scenarios[19]. A horse gather at the Beatys Butte herd management

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[19] Data is not available on the limited fertility control efforts undertaken by the BLM so the baseline scenarios focus on removals.

area in 2009 removed 379 animals, more than 90% of the estimated population[20]. This was the only horse gather at Beatys Butte from 2009 to 2013. The herd-scale baseline management scenarios assumed a five-year management cycle where 80% of the population is removed in the first year and then no removals occur for the next four years. The NPV of this management program over a 50-year management horizon is -$12 million.

Management actions from 2005 to the present were evaluated at the state-scale to construct current state-management scenarios. Each of the five states considered undertook some removal efforts each year, although the intensity of removal efforts sometimes varied substantially from year to year. A spike in removals is common following a few years of lower intensity management. Additionally, horse stocks in the states remained relatively constant from 2004-2013. The state-scale baseline management scenario assumed a variable five-year management cycle based on removing fixed proportions of the population. In the first year of the cycle, 45% of the population is removed, followed by 25% in the second and third years, and 15% for the final two years of the cycle. The estimated NPV of state-level wild horse management under current policies is -$45.8 million over a 50-year time horizon.

4.5.2 Solving the Dynamic Optimization Problem

The existence of an analytical solution to the horse population control problem is unlikely because the objective function is linear in the control variable, nonmonotone in the state variable, has a nonlinear law of motion for the stock, and marginal costs

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[20] Comparison of the gather data to the population data suggests the population was underestimated.

decrease as stock increases (Rondeau & Conrad, 2003). Instead, this analysis seeks analytical insights through simulations.

The solution to the problem in (4.1) is produced by solving Bellman equation 4.8 subject to the constraints from before and the terminal condition $V(T+1,\ X_t)=0$ where $T$is the finite time horizon.

$$V(t,\ X_{t-1}) = \max_{\{Y_t\}}\left\{\rho^t\left[\frac{B(X_{t-1})}{\rho} - Y_tC_r(Y_t\ ,X_{t-1}) - adoptC_a - (Y_t - adopt)C_h - Y_tC_{tr}\right]\right\} + (\ \rho^{t+1}V(t+1,\ X_t) \tag{4.8}$$

The function $V(t,X)$ is the maximum achievable NPV benefits starting at time t with stock level X and given action Y. All subsequent actions are assumed to be taken optimally, given the action taken in the current period. Bellman equation 4.9 is the equivalent for fertility-control population management.

$$V(t,\ X_{t-1}) = \max_{\{Y_t\}}\left\{\rho^t\left[\frac{B(X_{t-1})}{\rho} - Y_tC_r(Y_t\ ,X_{t-1}) - Y_tC_f - C_m\right]\right\} + \rho^{t+1}V(t+1,\ X_t) \tag{4.9}$$

The Bellman equations were solved in the computer program MATLAB with a backward recursion algorithm that starts at the terminal period and works back to the initial period. Terminal period T is set to 70 years so that the realization of the terminal condition is not taken into account in the optimal management simulations. Robustness checks with longer horizon models suggest that the solutions are stationary. To facilitate dynamic programming of the solution, the problems were discretized through rounding of the state variable to the nearest integer before each value calculation[21].

The state-scale and herd-scale scenarios were simulated deterministically with a 50-year planning horizon for the horse removal and fertility management models. Results from the four scenarios, including the optimal removal and population over time, and the present value of the management regime, are presented in Table 4.2.

4.5.3 Horse Removal Simulations

In the state-scale scenario, the optimal horse removal program yielded $13.8 million in NPV benefits over a 50-year period. During that time, the mean annual horse removal was 318 animals with a standard deviation of 273.5. Also, the minimum number of horses removed in a given year was 186 animals, and the maximum was 1,644. The optimal path for the horse population over the 50-year period is shown in Figure 4.2. The starting population level is the five-state horse population average for 2004. The optimal removal strategy is to decrease the population to below 1,000 animals in the first five years and then begin a three-year pulsing cycle where the population fluctuates between 828 and 894 and removals range between 186 and 312. Pulsing exploits economies of scale in horse gather costs by increasing removal effort in a given period after allowing the population to grow previously.

The herd-scale horse removal scenario produced $4 million in net benefits over the 50-year horizon. The mean number of horses removed over this period was 66, with a standard deviation of 48.5. The maximum number of horses removed in a given year was

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[21] In the state-level model, discretization also involved grouping the horses into six-horse units to limit the dimensionality of the linear programming problem.

400, and the minimum was 56. The optimal horse population path for this scenario is shown in Figure 4.3. The initial population is 532 based on the 2013 estimated population for the Beatys Butte herd. In the first few years, the population drops steeply due to a high number of initial removals. When the population reaches approximately 250, the herd AML, the path flattens out. This is likely related to the fact that the benefits function is maximized at the AML, and population reduction beyond the AML represents a tradeoff between reduced management costs and foregone population benefits. By year 17, the population reaches a steady state of 208 animals, and management remains constant at 56 removals for the balance of the periods.

4.5.4 Horse Fertility Control Simulations

Deterministic simulations were run next for the herd-scale and the state-scale scenarios with fertility-control management. When used as the only population control method, fertility control produced -\$4.7 million in NPV benefits at the state scale over the 50-year horizon. The state-scale optimal management program averaged 3,863 horses treated annually, with a standard deviation of 273.5. The minimum number of horses treated in a given year was 1,644 while the maximum was 4,236. The optimal 50-year population path is displayed in Figure 4.4. The path traces an S-curve, with population growing quickly from the initial population level and then slowly approaching the steady state of 8,478 animals.

At the herd-scale, the NPV of the optimal fertility-control program was -\$2.8 million over a 50-year horizon. The optimal fertility-control program averaged 377 animals treated annually, with a standard deviation of 33.5. The minimum number of horses treated was 349, and the maximum was 408. The optimal population path associated with this scenario is shown in Figure 4.5. The population decreases gradually from the initial value to a steady-state population of 392 animals over the first 35 years of the program.

4.5.5 Horse Removal with Fixed Proportion Fertility Control

The previous two subsections indicate that management with optimal horse removal produces larger NPV benefits than does management with optimal fertility control across spatial scales. This result is related to the relatively large number of horse gathers required to implement optimal fertility control. Fertility control alone does not appear to be a preferred optimal management alternative, but fertility control may benefit management if used in tandem with horse removal. This section develops and evaluates a model of optimal horse removal with annual fertility control of a fixed proportion of the population. The optimal removal program with fixed-proportion fertility control is a sequence of removal choices that maximizes problem 4.10, where ε_f is the percentage of the stock fertility controlled annually.

$$\max_{\{Y_t\}} \sum_{t=0}^{\infty} \rho^t \left[\begin{matrix} \frac{B(X_{t-1})}{\rho} - (Y_t + \varepsilon_f X_{t-1}) C_g\left(Y_t + \varepsilon_f X_{t-1}\, , X_{t-1}\right) - \gamma C_a \\ -(Y_t - \gamma) C_h - Y_t C_{tr} - \varepsilon_f X_{t-1} C_f - C_m \end{matrix} \right] \tag{4.10}$$

Subject to:

$X_t - X_{t-1} = F\left(X_{t-1}, \varepsilon_f\right) - Y_t$

$Y_t \leq \delta X_{t-1}$

X_{-1} is given

$B(X_{-1}) = 0$

Where:

$$\gamma = \begin{cases} Y_t \; if \; Y_t \leq adopt \\ adopt \; if \; Y_t > adopt \end{cases}$$

$$C_m = \begin{cases} m \; if \; Y_t > 0 \\ 0 \; if Y_t = 0 \end{cases}$$

The population change from one period to the next under this hybrid management system is given in equation 4.11. The total number of horses gathered in period t equals $\mathrm{Y_t} + \mathrm{\varepsilon_f X_{t-1}}$.

$$X_t - X_{t-1} = X_{t-1} r \left[\left(1 - \varepsilon_f\right) - \left(\frac{X_t}{K}\right)^2 \right] - Y_t \tag{4.11}$$

The Bellman equation in 4.9 was solved with backwards recursion assuming a 70-year horizon and subject to the constraints from before and the terminal condition $V(T + 1, X_t) = 0$.

$$V(t, X_{t-1}) = \max_{\{Y_t\}} \left\{ \rho^t \left[\begin{matrix} \frac{B(X_{t-1})}{\rho} - (Y_t + \varepsilon X_{t-1}) C_g (Y_t + \varepsilon X_{t-1}, X_{t-1}) - \gamma C_a \\ -(Y_t - \gamma) C_h - Y_t C_{tr} - \varepsilon X_{t-1} C_f - C_m \end{matrix} \right] \right\} + \rho^{t+1} V(t + 1, X_t) \tag{4.9}$$

Four management scenarios that differed according to their assumed value of ε were simulated for a 50-year management horizon for the herd-scale and state-scale models. Table 4.3 contains characteristics of the optimal management and population paths. In the state-scale scenarios, fixed fertility control led to larger steady-state populations and higher NPV benefits compared to removal alone. The scenario with 20% percent annual fertility control of the stock yielded \$17.7 million in NPV benefits, the highest of the fixed fertility-control scenarios and nearly \$4 million more than in the removal-only scenario. Additionally, the 20% fixed fertility-control scenario sustained an optimal steady-state population more than 200 animals larger than the steady state population in the removal-only scenario. The state-scale fixed fertility optimal population paths are shown in Figures 4.6a to 4.6d. The increased fixed fertility-control effort is associated with longer approach paths to the optimal steady-state population level and less extreme shifts in management.

In the herd-level simulations, fixed-proportion fertility control led to lower NPV benefits with similar steady-state populations compared to horse removal alone. The optimal population paths under this scenario are in Figures 4.7a to 4.7d. The optimal herd-scale removal program under fixed-proportion fertility control involves pulsing, where managers limit population management in some periods to exploit the economies of scale in horse gathering in subsequent periods.

4.5.6 State-scale Population Management Without Gather Constraints

The state-scale management scenarios considered so far assume that no more than 50% of a state's horse population can be gathered in a single period (i.e. $\delta = 0.5$). This assumption is consistent with recent BLM management efforts in the states considered but may be the result of BLM resource limitations rather than physical constraints. This section presents simulations that relax the gather constraint, consistent with increased available resources for gathers. The optimal 50-year population paths for horse management with $\delta = 1$ are shown in Figures 4.8 through 4.10. Characteristics of the optimal population and management paths with $\delta = 1$ are in Table 4.4. The horse removal only and horse removal with a 20% fixed fertility-control management scenario simulations both produced higher NPV benefits compared to their constrained counterpart. The population paths in the unconstrained models also approach the steady state more quickly.

The fertility control problem showed the most dramatic change from the constrained scenario to the unconstrained scenario. The NPV benefits increase from -\$4.7 million in the constrained case to \$63.7 million in the unconstrained case. The steady-state population is also 70% lower with unconstrained fertility control. The optimal population path with unconstrained fertility control, shown in Figure 4.9, reduces the population in the first 20 years before entering the pulsing cycle. One complete cycle lasts eight periods and includes seven periods of intense fertility control (>98%) and one period of moderate fertility control (66%), which allows the population to increase.

The 50-year NPV benefits of fertility control increase dramatically when horse gathers are unconstrained. However, the optimal management program with unconstrained fertility control requires that nearly all of the animals in a given state be gathered in six of every seven years and may not be feasible regardless of available resources.

Additional simulations were run to evaluate fertility-control management benefits when$0.5 < \delta < 1$. The NPV benefits of state-scale fertility control increase from -\$2 million when $\delta = 0.65$ to \$12.3 million when $\delta = 0.7$. Fertility-control NPV benefits rise to \$25.7 million and \$38.2 million when the gather constraint δ equals 0.75 and 0.8, respectively. Together these results suggest that fertility control is preferred to all other management programs considered when more than75% of the state horse population can be treated in each period.

4.6 Discussion

The 50-year NPV benefits of optimally chosen management programs are greater than the estimated NPV benefits of current management across models and scenarios. The NPV benefit values for the simulated scenarios are summarized in Table 4.5. In the state-scale model, the NPV benefits of state-scale optimal horse removal exceed the benefits of the current management program by $60 million, a large figure compared to the NPV estimates calculated for the other management scenarios. The most noticeable difference in the optimal vs. the status quo removal programs is that the optimal programs call for a sharp reduction in the early periods. Thus, the model of optimal control developed in this paper supports recent calls for immediate and high intensity management actions (Garrott & Oli, 2013; NRC, 2013). More broadly, the results suggest that a strategic, long-term approach to population management can substantially increase the societal value of wild horses compared to current management.

This chapter developed and analyzed optimal control models of wild horse population management with nonlethal methods. The simulation results reveal a number of management implications. Optimal fertility control is associated with larger steady-state populations compared to optimal horse removals. However, optimal fertility control leads to lower NPV benefits compared to removals. This pattern is consistent across the state-scale and herd-scale simulations. These results suggest that fertility control alone is not a tenable strategy for managing wild horse populations.

The optimal steady-state population levels in the most scenarios were below current levels. The exception occurs when the state-scale fertility-control models are gather constrained. This suggests that optimal management often involves reducing populations first.

A program of fixed-proportion fertility control with optimally chosen removals increases the NPV benefits compared to removal alone in the state-scale scenarios and decreases the NPV benefits compared to removal alone in the herd-level scenarios. NPV benefits in the state-scale analysis were highest with constant fertility control of approximately 20%.

Without gather constraints, state-scale management with fertility control yields the highest NPV benefits across the considered scenarios. However, unconstrained fertility control requires a large share of the population to be treated each year. The NPV benefits of state-scale fertility control are the largest of any state-scale management program considered when at least 75% of the population can be gathered annually. From a policy perspective, this result suggests that enhancing the BLM's ability to conduct large-scale gathers could improve the effectiveness of fertility-control efforts and increase the economic benefits provided by wild horse populations over time. Optimal fertility-control efforts require substantially more gathers annually compared to optimal removal. However, the costs of additional gathers are outweighed by the benefits of foregone adoption and holding costs.

For two reasons, the analysis might overstate costs in the fertility-control scenarios. First, the model assumes that fertility treatment lasts for only one year where in reality PZP and similar treatments can last for more than two years (Bartholow, 2007). Second, in the state-level scenarios, the costs of removals are used as a proxy for the cost of horse gathers, so that transportation costs are included even though with fertility control no transportation is necessary. Despite these issues, unconstrained fertility control yields the highest NPV of any policy considered.

Future dynamic analysis of wild horse management might explore a scenario where removal and fertility-control efforts are chosen simultaneously with the objective of maximizing NPV benefits.

Table 4.1 Parameters Values Used in the Optimal Control Models

Parameter	Description	State-scale	Herd-scale
X_{-1}	Number of horses at start of analysis	3,294	532
K	Carrying capacity	12,000	1202
r	Intrinsic growth rate of horse populations	0.28	0.28
C_{tr}	Average shipping costs for one horse from range to holding facility	\$242.99	\$242.99
C_a	Net cost of administering an adoption	\$1,415.12	\$1,415.12
$adopt$	Annual adoption demand for wild horses	170	68
C_h	NPV cost of holding horse for 15 years	\$11,865	\$11,865
C_f	Fertility control cost per horse	\$243.88	\$243.88
m	Population monitoring cost of fertility control effort	\$5,698.15	\$17,094.44
ρ	Discount factor	0.95	0.95

Table 4.2 Solution Characteristics for Optimal Horse Removal and Fertility Control

	State Scale		Herd Scale	
	Removal	Fertility Control	Removal	Fertility Control
Optimal management				
mean	318.1	3,863.3	66.0	377.4
stdev	273.5	706.4	48.5	33.5
min	186	1,644	56	349
max	1,626	4,236	400	477
steady state	186-312	4,236	56	349
Optimal population				
initial	3,294	3,294	532	532
mean	985.1	7,752.7	222.8	421.3
stdev	438.6	1,400.4	46.7	36.7
min	828	3,294	208	392
max	3294	8,478	532	532
steady state	828-894	8,478	208	392
Benefits				
50-year NPV	$13.8 million	-$4.7 million	$4.0 million	$2.8 million

Note: Multiple steady-state values represent the range of a pulsing cycle.

Table 4.3 Solution Characteristics for Optimal Horse Removal by Percentage of Population Fertility Controlled Annually

	State Scale				Herd Scale			
	10%	15%	20%	25%	10%	15%	20%	25%
Optimal management								
mean	333.8	317.6	337.4	375.0	58.6	55.1	50.4	45.5
stdev	226.8	214.0	186.5	161.8	52.0	50.7	49.8	50.1
min	228	228	246	252	0	0	0	0
max	1,314	1,152	984	816	361	340	319	304
steady state	228-282	228	246	252	0-68	0-67	0-65	0-68
Optimal population								
initial	3,294	3,294	3,294	3,294	532	532	532	532
mean	1,174.6	1,170.5	1,352.7	1,571.6	216.3	211.6	205.8	191.1
stdev	446.7	503.4	516.8	566.9	53.3	56.0	59.6	63.7
min	1,020	978	1,122	1,230	172	159	161	153
max	3,294	3,294	3,294	3,294	532	532	532	532
steady state	1,020-1,044	978	1,122	1,230	172-224	174-214	161-207	153-184
Benefits								
50-year NPV	$15.9 million	$16.9 million	$17.7 million	$17.1 million	$3.7 million	$3.6 million	$3.5 million	$3.4 million

Table 4.4 Solution Characteristics for State-scale Management without Gather Constraints

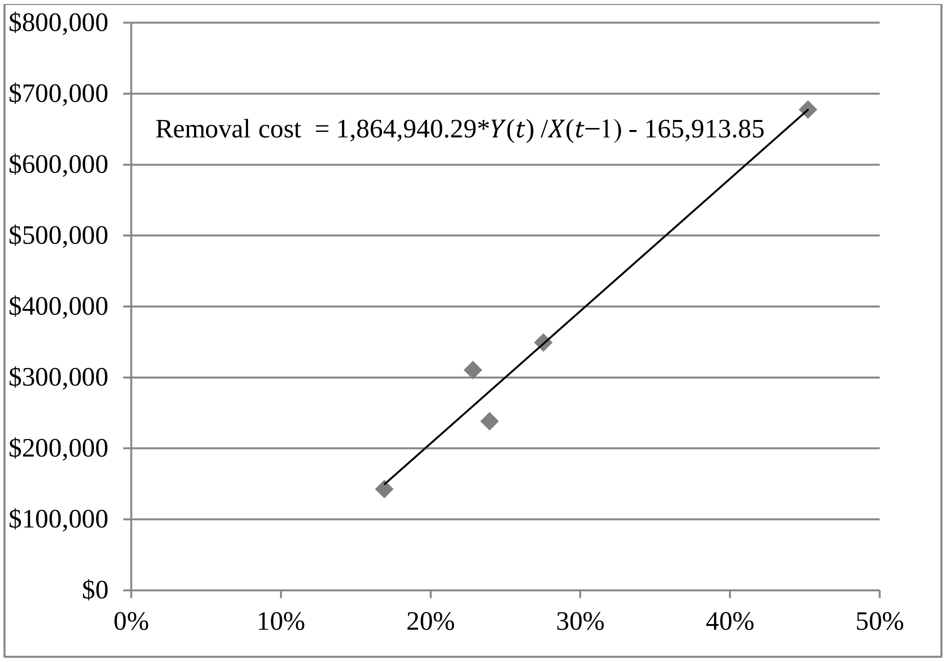
	Removal	Fertility control	Removal with 20% fertility control
Optimal management			
mean	298.3	2,557.3	298.6
stdev	433.0	340.8	337.7
min	186	1,608	180
max	3,276	3,294	2,616
steady state	216-312	1,608-2,586	246
Optimal population			
initial	3,294	3,294	3,294
mean	912.4	2,630.5	1,167.9
stdev	341.2	220.0	305.4
min	828	2,424	1,068
max	3,294	3,294	3,294
steady state	828-870	2,424-2,622	1,122
Benefits			
50-year NPV	$18.3 million	$63.7 million	$25.1 million

Table 4.5 Net Present Value of 50-year Management Scenarios

	Removal	Fertility control	Fertility control with $\delta = .75$
<u>State level</u>			
Status quo			
50-year NPV	-$45.8	-	-
Optimal			
50-year NPV	$13.8	-$4.7	$25.7
<u>Herd level</u>			
Status quo			
50-year NPV	-$12.0	-	-
Optimal			
50-year NPV	$4.0	$2.8	-

Note: In millions of 2014 U.S. dollars

Figure 4.1 State Removal Costs and the Proportion of Stock Removed, 2004



Note: AZ, 17%; CA, 24%; OR, 28%; UT, 23%; WY, 45%.; In 2004 USD.

Figure 4.2 Optimal Horse Population over Time: Horse Removal, State-scale

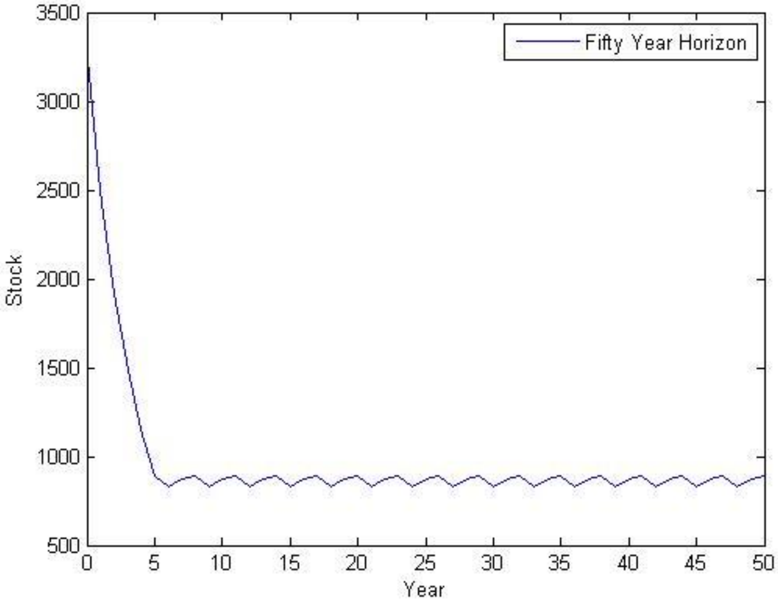


Figure 4.3 Optimal Horse Population over Time: Horse Removal, Herd-scale

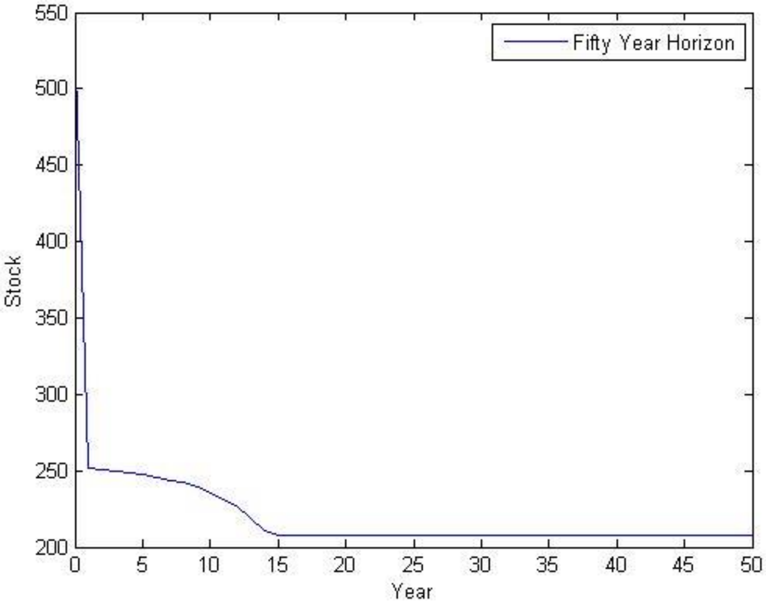


Figure 4.4 Optimal Horse Population over Time: Fertility Control, State-scale

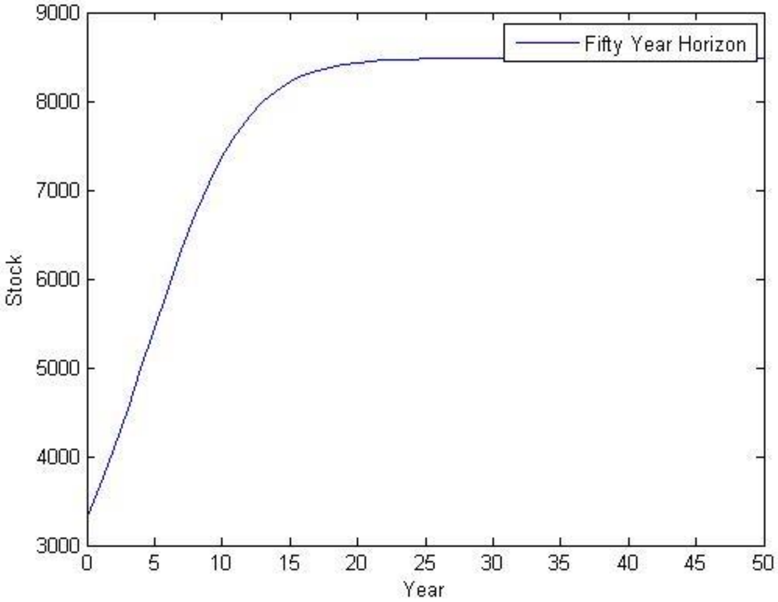


Figure 4.5   Optimal Horse Population over Time: Fertility Control, Herd-scale

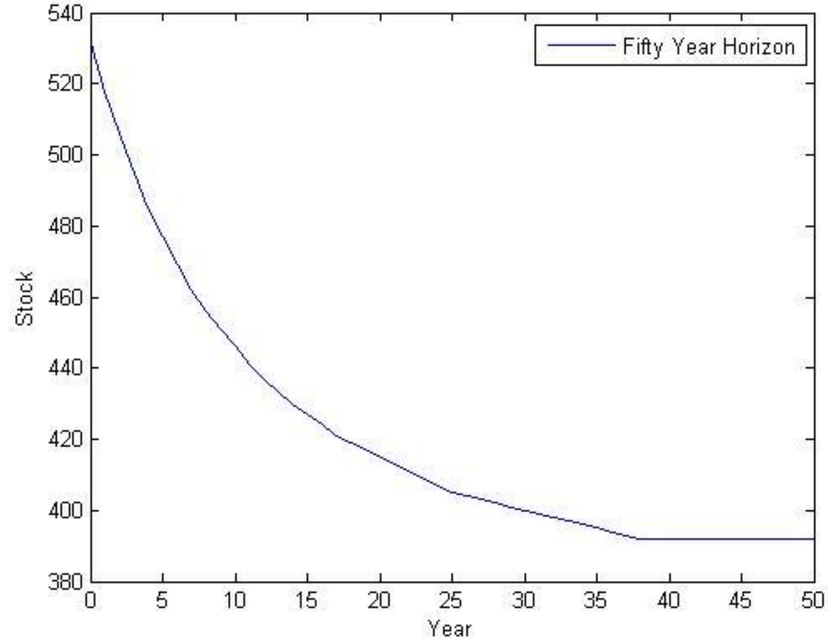


Figure 4.6a   Optimal Horse Population over Time: Horse Removal with Fertility Control of 10% of Population, State-scale

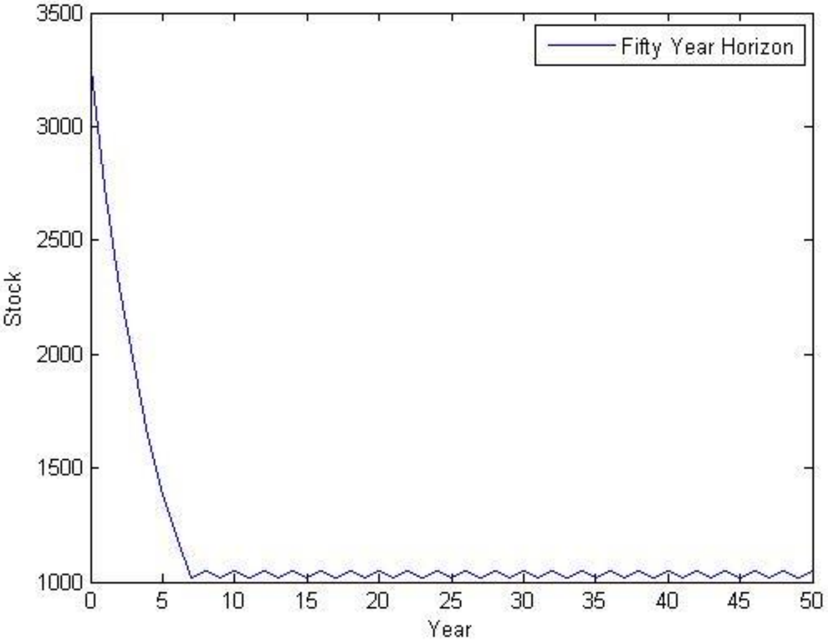


Figure 4.6b Optimal Horse Population over Time: Horse Removal with Fertility Control of 15% of Population, State-scale

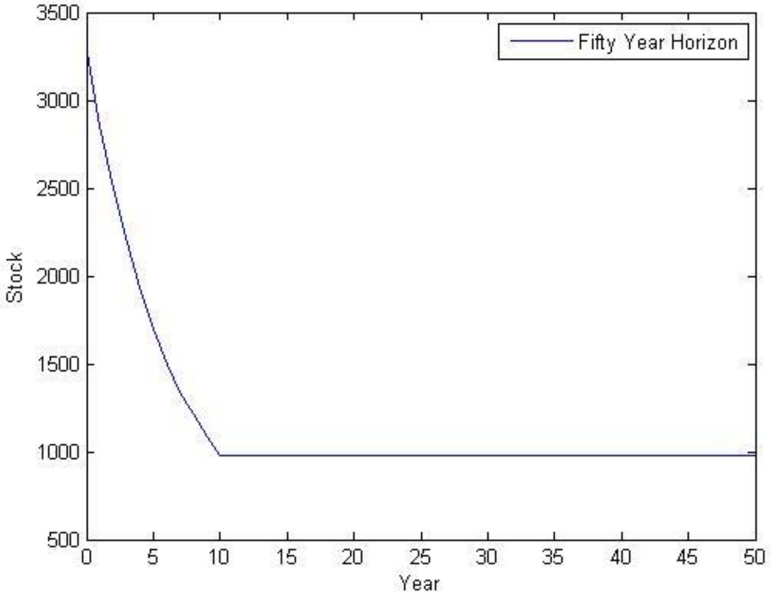


Figure 4.6c Optimal Horse Population over Time: Horse Removal with Fertility Control of 20% of Population, State-scale

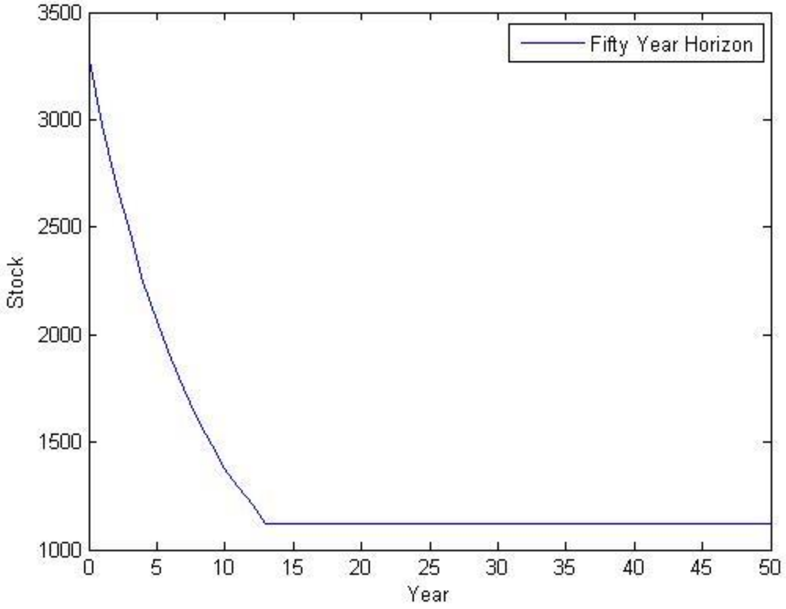


Figure 4.6d Optimal Horse Population over Time: Horse Removal with Fertility Control of 25% of Population, State-scale

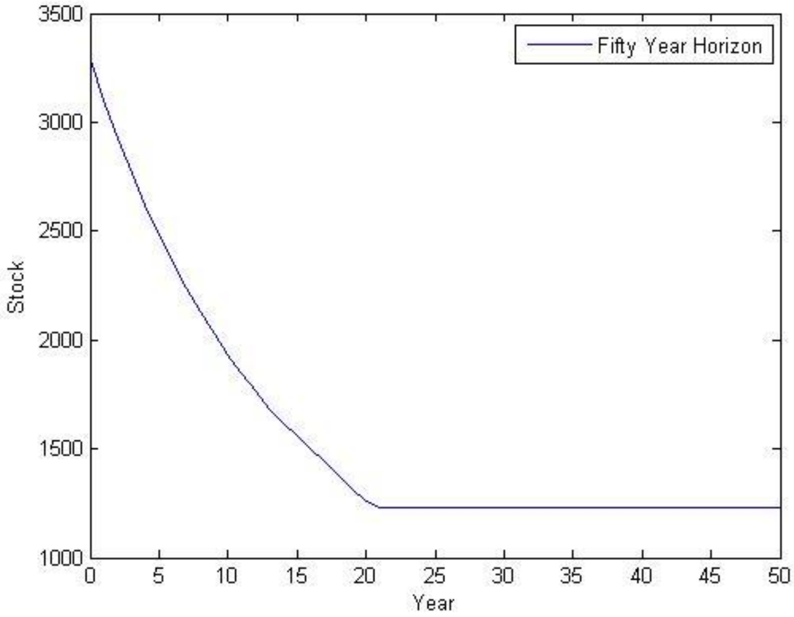


Figure 4.7a Optimal Horse Population over Time: Horse Removal with Fertility Control of 10% of Population, Herd-scale

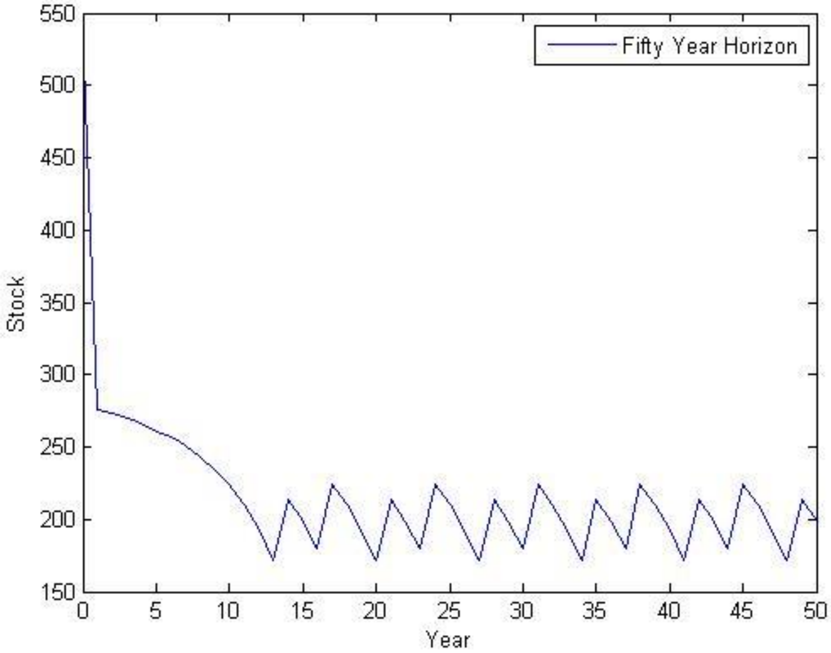


Figure 4.7b Optimal Horse Population over Time: Horse Removal with Fertility Control of 15% of Population, Herd-scale

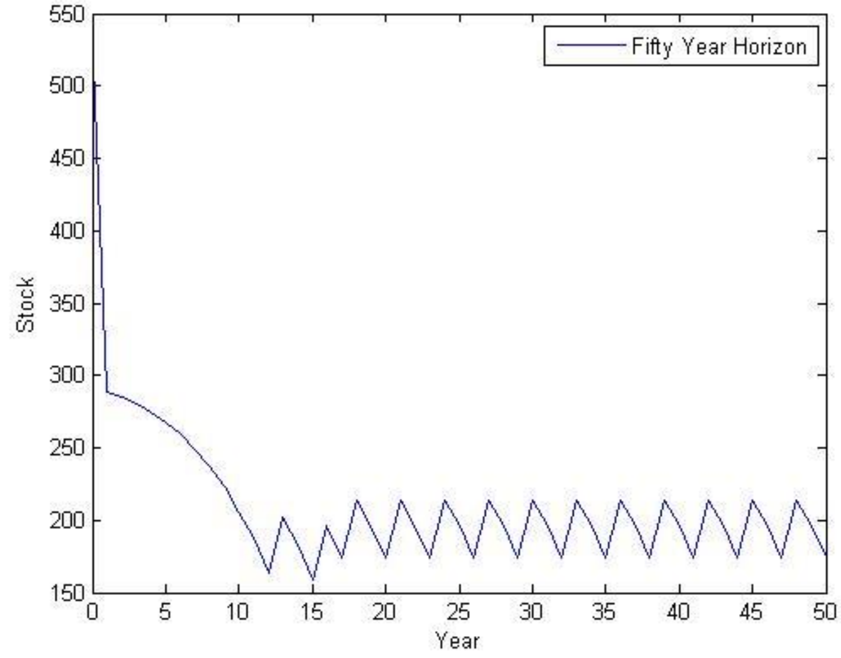


Figure 4.7c Optimal Horse Population over Time: Horse Removal with Fertility Control of 20% of Population, Herd-scale

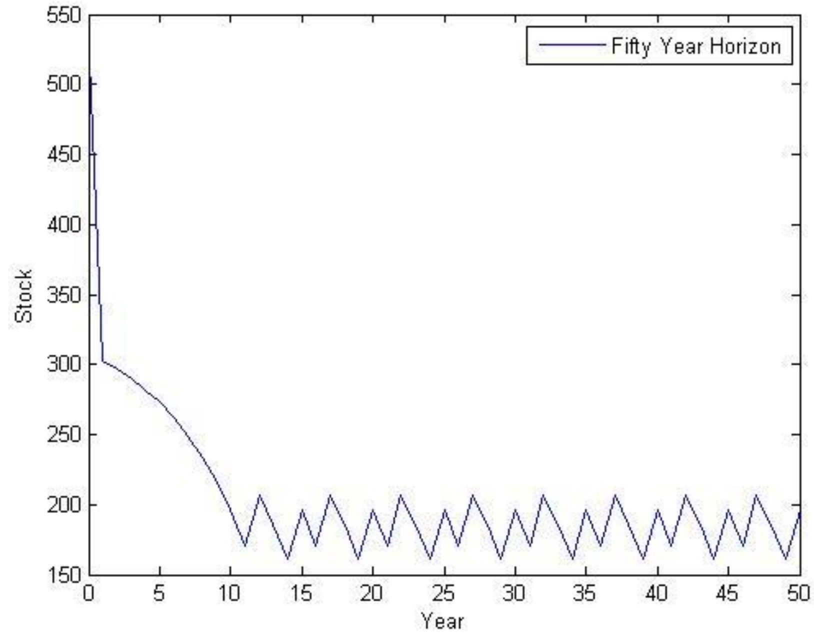


Figure 4.7d Optimal Horse Population over Time: Horse Removal with Fertility Control of 25% of Population, Herd-scale

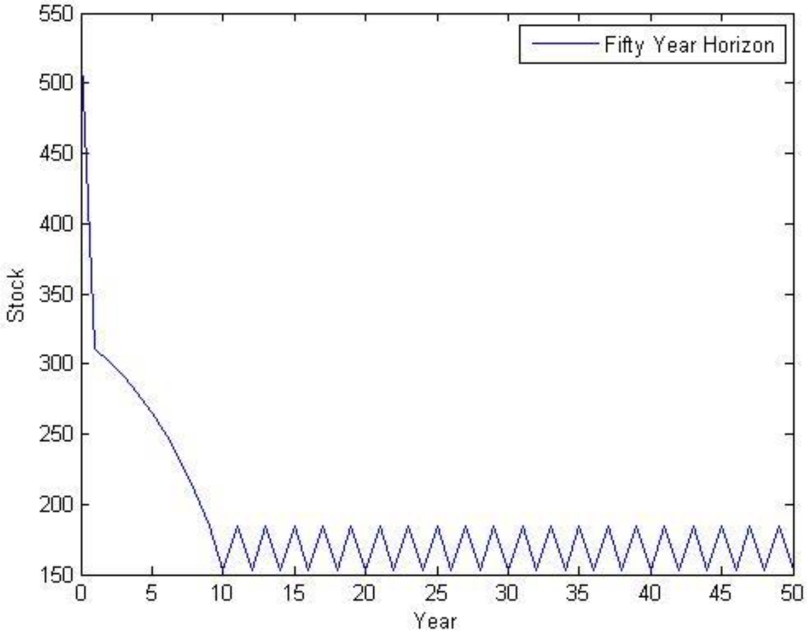


Figure 4.8 Optimal Horse Population over Time: Unconstrained Horse Removal (δ=1), State-scale

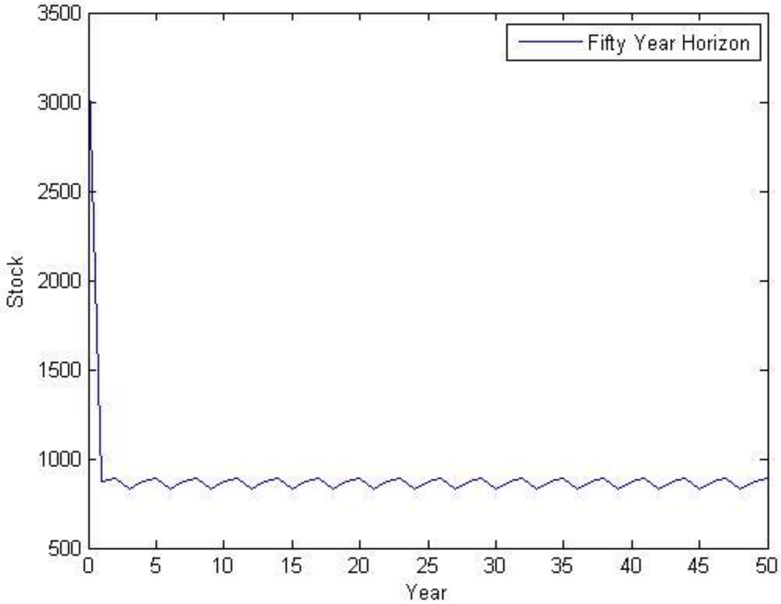


Figure 4.9 Optimal Horse Population over Time: Unconstrained Horse Fertility Control (δ=1), State-scale

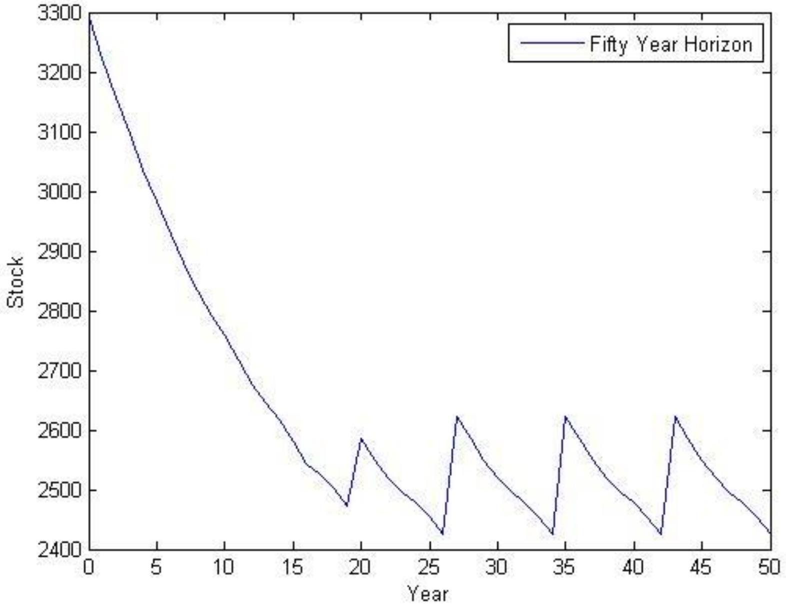
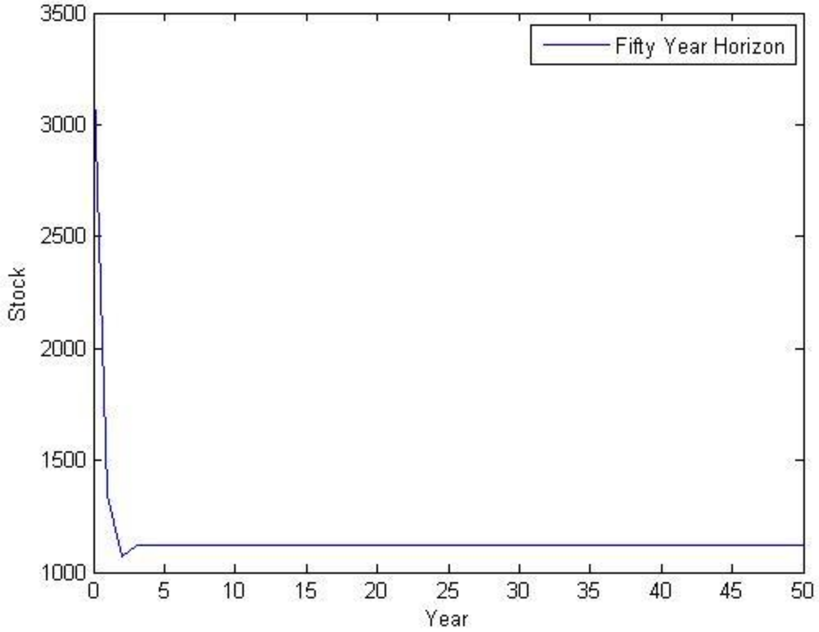


Figure 4.10 Optimal Horse Population over Time: Unconstrained Horse Removal (δ=1) with Fertility Control of 20% of Population, State-scale



Chapter 5: Concluding Remarks

5.1 Dissertation Summary

This dissertation presented three studies that each explore the role of landscape in determining natural resource values and management. The first two studies also apply computationally tractable spatial econometric models for analysis of discrete dependent variables.

The first study examined moose habitat selection in a heterogeneous landscape with a discrete choice model. The data was analyzed using a variant of the generalized GEV model with an allocation parameter to nest correlation between adjacent habitat patches. This approach is novel to habitat selection literature and allows for complex substitution patterns among habitat-patch alternatives. Model results provide a number of insights into the seasonal habitat preferences of tracked moose, including the influence of natural and human-built landscape features. The significance of the spatial parameter in the estimated models suggests that spatial dependence is an important consideration for discrete-choice habitat studies. Furthermore, this study demonstrates the generalized GEV model's ability to test and accommodate spatial dependence in a large dataset. These properties are valuable to spatial econometricians, and the generalized GEV model appears like an appropriate general model for analyzing other situations where choice alternatives are arranged spatially.

The second study analyzed demand for forest recreation in Colorado with a spatial travel cost model. The analysis focused on two objectives. First, mean per-trip WTPA was estimated and compared across samples from 2005 to 2010. The decline in estimated WTPA over this period is explained jointly by the economic recession and a shift towards nature-based activity participation ,and away from motorized and other gear intensive activities. Second, the study developed and applied a spatial travel cost model to investigate the landscape determinants of recreation demand. Spatial dependence can result from interactions among individuals in the same landscape or through the presence of an unobserved random field that influences recreation demand through some spatial stochastic process. The spatial model utilized a copula, or linking function to permit spatial dependence among observations. Model results revealed significant spatial dependence among recreational-demand decisions, suggesting that spatial dependence is an important consideration in models of recreation demand.

The horses ranging on public lands in the American West are managed to control the benefits and costs they produce for society. The third and final study in this dissertation utilized optimal control models and simulation techniques to analyze non-lethal wild horse population management at two spatial scales. Results from policy simulations produced a number of findings that are relevant to management. First, optimally chosen scenarios yielded significantly larger estimated NPV benefits than the current management scenario across management types and spatial scales. This finding stresses the importance of undertaking strategic management actions that consider future costs and benefits. Second, the NPV benefits of management with optimal removal were greater than with optimal fertility control. In the state-scale scenarios, fertility control of a fixed proportion of the population increased the value of optimal removal management. At the state-scale, fertility control became the optimal strategy when 75% or more of the population could be gathered annually.

5.2 Future Research

The models and findings produced by this dissertation invite future research efforts to examine the influence of landscape factors on natural resource values and management.

The spatial econometric models utilized in this study have seen sparse application in the natural resource economics field despite their advantages in estimation and spatial inference. There are a number of potential applications for these models related to examining landscape-natural resource effects. For example, the generalized GEV model could be used to accommodate dependence among recreational sites in a site-choice travel cost model. Alternatively, the generalized GEV model is appropriate for analyzing models of residential choice, where location alternatives are spatially correlated. Similarly, the copula model from chapter two is appropriate for testing and analyzing origin-based spatial dependence in discrete dependent variable models.

Future research might also improve upon the presented studies. Incorporating individual characteristics into the habitat selection model is one obvious potential improvement that would provide useful information to wildlife managers. In the recreation demand analysis, a comparison of the fitted values produced by spatial and nonspatial models could facilitate a comparison of model fit. Thus, generating model predictions that incorporate spatial effects is another area for future research. Finally, future optimal control studies of wildlife might consider incorporating two or more management decisions so that optimal ‘hybrid’ management programs may be developed. Finally, stochastic state transitions might be incorporated in the optimal wildlife control model to reflect the random nature of fertility treatment effectiveness.

Appendix: MATLAB and R codes

Generalized GEV Habitat Selection Regression (R): Section 2.5

```
###############################################################################
#--------------------------------------------------------------------------------
# Generalized GEV Habitat Selection Model
# collared moose location data
# Data required: (both identified by id)
# moose location data - "m809w6_250_loc.csv"
# Land features data - "allcov_250.csv"
# Core home range raster - "m809w6_250r.tif"
# Code written by Robert Fonner
# -------------------------------------------------------------------------------
##############################################################################

setwd("")
# Read in available_habitat.txt
features <- read.csv("allcov_250.csv", header=T, sep=",")
names(features)

# Create Dummys for cover type variables
features$scrub_dum <- as.numeric(features$pct_scrub >= 50)
features$for_dum <- as.numeric(features$pct_for >= 50)

# Number of cells in study area
n.cells <- length(features$id)
n.cells
```

```
# elev in km
features$elevationkm <- features$dem/1000

# Read in gps_locations.txt
locations <- read.csv("m809w6_250_loc.csv", header=T, sep=",")
locations$id[locations$id==0] <- NA #NA non-identified fixes

# Number of fix attempts
fix.attempts <- length(locations$id)

# Deviate variables from their mean
features$elevationkm <- features$dem/1000
features$slope1 <- features$slope - mean(features$slope)
features$elevationkm1 <- (features$elevationkm - mean(features$elevationkm))
features$wat_dist1 <- (features$wat_dist - mean(features$wat_dist))
features$rd_dist1 <- (features$rd_dist - mean(features$rd_dist))
features$tr_dist1 <- (features$tr_dist - mean(features$tr_dist))

# Matrices of habitat data
distance <- as.matrix(dist(cbind(features$xpts, features$ypts)))
slope <- matrix(features$slope1, nrow=n.cells, ncol=n.cells, byrow=T)
elevation <- matrix(features$elevationkm1, nrow=n.cells, ncol=n.cells, byrow=T)
cosaspect <- matrix(features$cosaspect, nrow=n.cells, ncol=n.cells, byrow=T)
pct_for<- matrix(features$pct_for, nrow=n.cells, ncol=n.cells, byrow=T)
pct_scrub<- matrix(features$pct_scrub, nrow=n.cells, ncol=n.cells, byrow=T)
```

```
scrub_dum<- matrix(features$scrub_dum, nrow=n.cells, ncol=n.cells, byrow=T)

for_dum<- matrix(features$for_dum, nrow=n.cells, ncol=n.cells, byrow=T)

wat_dist<- matrix(features$wat_dist1, nrow=n.cells, ncol=n.cells, byrow=T)

rd_dist<- matrix(features$rd_dist1, nrow=n.cells, ncol=n.cells, byrow=T)

tr_dist<- matrix(features$tr_dist1, nrow=n.cells, ncol=n.cells, byrow=T)

lnwat_dist <- matrix(log(features$wat_dist1+1e-50), nrow=n.cells, ncol=n.cells,
        byrow=T)


#'Load homerange raster and identify adjacent cells

r <-raster("m809w6_250r.tif")

# SpatialPointsDataFrame from raster

sp.points <- rasterToPoints(r, spatial = TRUE) #raster to point conversion

# Distance based neighbors (with only 4 neighbors)

dnb <- dnearneigh(sp.points, d1 = 0, d2 = 251)  # d2 =251 because the cell size is 250

list.w <- nb2listw (dnb,zero.policy=TRUE) # list alpha mat

weight.mat <- as(listw2mat(list.w),"sparseMatrix") # this is the alpha matrix

alpha.mat <- weight.mat

alpha.vec <- sapply(list.w$weights,unique)

alphaj <- matrix(alpha.vec, nrow=n.cells, ncol=n.cells, byrow=T)


#Lag variable

locations$Lag <- rep(1, times=fix.attempts)

for(i in 2:fix.attempts){

  if(is.na(locations$id[i-1]) == T) locations$Lag[i] <- locations$Lag[i-1] + 1

}


# Detected (Yes = 1; No = 0)

detected <- as.numeric(!is.na(locations$id))
```

```
locations <-locations[detected==1,] #drop unidentified

fix.num <-length(locations$id)

#####################################################################################

#=========================================================================

# Habitat Selection Model

# Conditional Logit Likelihood

CL <- function( a ){

  # Matrix of movement probabilities (based on Discrete Choice Function)

  EXP = exp(a[1]*distance +a[2]*elevation +a[3]*slope + a[4]*for_dum +a[5]*rd_dist +
          a[6]*tr_dist)

  sumEXP = matrix(apply(EXP, 1, sum), nrow=n.cells, ncol=n.cells, byrow=F)

  D <- EXP / sumEXP

  dimnames(D) <- dimnames(distance)

  prob = rep(NA, times=fix.num)

  for(i in 2:fix.num){

    # If 2 consecutive scheduled GPS fixes were successful

    if(locations$Lag[i]<12){

      prob[i] <- D[rownames(features[features$id == locations$id[i-1],]),

                   rownames(features[features$id == locations$id[i],])]

    }

  }

  -sum(log(prob), na.rm=T)

}


# Maximize likelihood to obtain starting values

out1.optim <- optim( theta <- rep(-.1,times=6), CL, hessian=TRUE, method="BFGS" ,
control=list(maxit=5000, trace=2))

cl_pars <- out1.optim$par
```

```
startv <- c(cl_pars,.5)


#Generalized GEV likelihood
mat.num <-
  function(r, c, alphaj, exb, alpha.mat, rho){
    a <- (alphaj[r, c] * exb[r, c])^(1/rho) *
      ((alphaj[r, c] * exb[r, c])^(1/rho) + (alpha.mat[c, ] * exb[r, ])^(1/rho))^(rho-1)
    return(sum(a[alpha.mat[c, ] != 0]))
  }
mat.num.vec <- Vectorize(mat.num, vectorize.args = c('r', 'c'))
mat.den <-
  function(r, c, alphaj, exb, alpha.mat, rho){
    a <-
      ((alphaj[r, c] * exb[r, c])^(1/rho) + (alpha.mat[c, ] * exb[r, ])^(1/rho))^(rho)
    a[1:c] <- 0
    return(sum(a[alpha.mat[c, ] != 0]))
  }
mat.den.vec <- Vectorize(mat.den, vectorize.args = c('r', 'c'))


SCL <- function( par ){
  a <- par[1:k]
  rho <- par[k+1]
  EXP <- exp(a[1]*distance +a[2]*elevation +a[3]*slope + a[4]*for_dum +a[5]*rd_dist +
          a[6]*tr_dist)
   P.num <-
    outer(1:n.cells,1:n.cells, FUN = mat.num.vec, alphaj = alphaj, exb = EXP,
          rho = rho, alpha.mat = alpha.mat)
  P.den <-
```

```
    outer(1:n.cells,1:n.cells, FUN = mat.den.vec, alphaj = alphaj, exb = EXP,
          rho = rho, alpha.mat = alpha.mat)
  P.denSum <- matrix(rowSums(P.den), nrow = n.cells, ncol = n.cells, byrow = FALSE)
  D <- P.num / P.denSum
  dimnames(D) <- dimnames(distance)
  prob <- rep(NA, times = fix.num)
 for(i in 2:fix.num){
  if(locations$Lag[i]<12){
     #Grabs rows from D corresponding to the ith cell features and the i-1th fix.
      prob[i] <- D[rownames(features[features$id == locations$id[i - 1], ]),
                   rownames(features[features$id == locations$id[i], ])]
    }
  }
  return(-sum(log(prob), na.rm=T))
}

#Optimization with box constraints
k <- length(rsf_pars)
upperb<-c(rep(1000,times=k),.9998)
lowerb<-c(rep(-1000,times=k),.0001)

out1.optim <- optim( theta <- startv, SCL, method="L-BFGS-B" ,
                    lower=lowerb,upper=upperb, control=list(trace=2), hessian=TRUE)
summary(out1.optim)

#Print Results
theta <- out1.optim$par
```

```
k <- length(theta)

LL <- -out1.optim$value

AIC <- 2*k - 2*LL

n <- nrow(locations)

vcm <- solve(out1.optim$hessian)

#Robust SE

SCLns <- function( par ){

  a <- par[1:k]

  rho <- par[k+1]

  EXP <- exp(a[1]*distance +a[2]*elevation +a[3]*slope + a[4]*for_dum +a[5]*rd_dist +
          a[6]*tr_dist)

   P.num <-

    outer(1:n.cells,1:n.cells, FUN = mat.num.vec, alphaj = alphaj, exb = EXP,

          rho = rho, alpha.mat = alpha.mat)

  P.den <-

    outer(1:n.cells,1:n.cells, FUN = mat.den.vec, alphaj = alphaj, exb = EXP,

          rho = rho, alpha.mat = alpha.mat)

  P.denSum <- matrix(rowSums(P.den), nrow = n.cells, ncol = n.cells, byrow = FALSE)

  D <- P.num / P.denSum

  dimnames(D) <- dimnames(distance)

  prob <- rep(NA, times = fix.num)

 for(i in 2:fix.num){

  if(locations$Lag[i]<12){

      prob[i] <- D[rownames(features[features$id == locations$id[i - 1], ]),

                   rownames(features[features$id == locations$id[i], ])]

    }

  }

  return(-log(prob))
```

```
}

jacob <- jacobian(SLCns, theta ,method="Richardson" )

jacob <- na.omit(jacob)

bread <- vcm

meat <- t(jacob)%*%jacob

sandwich <- bread%*%meat%*%bread

robse <- sqrt(diag(sandwich))

t <- theta/robse

pval <- 2*(1-pt(abs(t),df=n-k))

results <- cbind(theta,robse,t,pval)

colnames(results)<-c("theta","robse","t","p")

rownames(results)<-c("b_dist", "b_elev", "b_slope", "b_fordum" ,"b_rddist",
        "tr_dist","rho")

print(results,digits=3)

# ------------------------------    End    ------------------------------------------------------

# =====================================================================

#####################################################################################
```

Generalized GEV Habitat Selection Regression (R): Section 3.6

```
#############################################################################
#------------------------------------------------------------------------------------------
#  NVUM recreational day-trip data from Roosevelt-Arapahoe National Forest
# Data required: (all identified by ZIPCODE)
# 2010 NVUM data - "NVUM_RANF_10_dayrec.csv"
# IRS tax and income data by zip code - "IRS_zip_08.csv"
# Zip code centroid coordinates –“ zip_04.csv”
# Code written by Robert Fonner
# -----------------------------------------------------------------------------------------
############################################################################
setwd("")

#load programs
library(sp)
library(mnormt)
library(Newbold & Massey)
library(numDeriv)
library(car)
library(sandwich)

#set seed for random number generation
set.seed(123)

#Read  in data
NVUM_RoosArap <- read.csv("NVUM_RANF_10_dayrec.csv", header=T, sep
```

```
NVUM_RoosArap <- NVUM_RoosArap[order(NVUM_RoosArap$ZIPCODE),]
# IRS Zipcode income for  08
zip_dat08 <- read.csv("", header=T, sep=",")
#Zip code centroids
zip_04 <- read.csv("", header=T, sep=",")
zip_04 <- subset(zip_04,select=c(latitude,longitude,ZIPCODE))
zip_dat <- merge(zip_04,zip_dat08, by="ZIPCODE") NVUM_RoosArap <-
        merge(NVUM_RoosArap,zip_dat, by="ZIPCODE")
#weights
nvexpand <- NVUM_RoosArap$NVEXPAND
#Inflate from 2008 to 2010 USD
zipinc <- NVUM_RoosArap$agi/NVUM_RoosArap$exemptions/1000*1.012787
tdist <- NVUM_RoosArap$TRAVEL_DISTANCE
#Travel cost
transpcost <- 2*(tdist*.14)
timecost2 <- 2*((1/60)*tdist*(zipinc*1000/2087*(1/3))) #2087hrs/year
tcost <- transpcost + timecost
#Trips
count <- NVUM_RoosArap$NV_VISITS_12MONTHS
count1 <- count -1
numveh <- NVUM_RoosArap$PEOPLE_IN_VEHICLE
female <- as.numeric(NVUM_RoosArap$PERSON1_SEX == "F")
ZIPCODE <- as.numeric(as.character(NVUM_RoosArap$ZIPCODE))
lat <- NVUM_RoosArap$latitude
long <- NVUM_RoosArap$longitude
data <- as.data.frame(cbind(tcost,count,female,zipinc,ZIPCODE,count1,lat,long,numveh,
        tdist, nvexpand))
data <- na.omit(data)
```

```
data <- data[data$count>0&data$tdist<250&data$count<150& data$ZIPCODE>60035 &
        data$numveh<10,] # Trim sample
#Drop neighbor-less observations
coord <- cbind(data$long,data$lat)
Wdis<- spDists(coord,coord,longlat=TRUE)
thresh <- ifelse(Wdis <= 2.5,1,0) # no correlation after 5 km
diag(thresh) <-0
data <- data[apply(thresh, 1, sum)>1,]
###########################################################################
#==============================================================
'*** Distcrete spatial copula***'

#Distance matrix nxn in meters
coords <- cbind(data$long,data$lat)
Wdist<- spDists(coords,coords,longlat=TRUE)
Winvdist <- ifelse(Wdist==0,0,1/Wdist)

#Omega threshold distance weights
omega.mat <- ifelse(Wdist <= 2.5,1,0) # no correlation after 2.5 km
diag(omega.mat) <-0
#omega.mat <- Matrix(omega.mat, sparse= TRUE)

#Mu standardizing weights
neigh.sum <- apply(omega.mat, 1, sum)
length(neigh.sum[neigh.sum==0])
neigh.sum[neigh.sum==0] <- 1 #avoid Inf values by dividing zeros by ones
mu.mat <- omega.mat/matrix(neigh.sum, nrow(data), nrow(data), byrow=F)
```

```
#Shared zip matrix (neighbor) component of vector S
Wneigh <- ifelse(Wdist <= 2.5,1,0)
diag(Wneigh) <-0
#Scaling
data$tcost <- data$tcost/100
data$pcturb <- data$pcturb/100
data$zipinc <- data$zipinc/100
#canned poisson
canpoisson <- glm(count1~tcost+female+numveh+zipinc, family = "poisson", data=data)
startv <- c(coefficients(canpoisson),1)

'Gaussian Copula Likelihood'
gauscop <-
  function(r,c,exb, y, theta, omega.mat){
    gcop <- 0
    if(omega.mat[r,c]!=0){
      varcov <- matrix(c(1,theta[r,c],theta[c,r],1),2,2) ### depends on parameterization

      qnorm.c1 <- ifelse(ppois(y[c],exb[c])==1,qnorm(1-1e-7, mean=0,
sd=1),qnorm(ppois(y[c],exb[c]), mean=0, sd=1))

      qnorm.r1 <- ifelse(ppois(y[r],exb[r])==1,qnorm(1-1e-7, mean=0,
sd=1),qnorm(ppois(y[r],exb[r]), mean=0, sd=1))

      qnorm.c0 = ifelse(y[c]>0,qnorm(ppois((y[c]-1),exb[c]), mean=0, sd=1),qnorm(1e-50,
mean=0, sd=1))
      if(qnorm.c0==Inf) qnorm.c0 <- qnorm(1-1e-7), mean=0, sd=1)
```

```
      qnorm.r0 = ifelse(y[r]>0,qnorm(ppois((y[r]-1),exb[r] ), mean=0, sd=1),qnorm(1e-50,
mean=0, sd=1))

      if(qnorm.r0==Inf) qnorm.r0 <- qnorm(1-1e-7), mean=0, sd=1)


      phi.11 <- pmnorm(c(qnorm.r1,qnorm.c0), mean=c(0,0),varcov)

      phi.00 <- pmnorm(c(qnorm.r0,qnorm.c0), mean=c(0,0),varcov)

      phi.01 <- pmnorm(c(qnorm.r0,qnorm.c1), mean=c(0,0),varcov)

      phi.10 <- pmnorm(c(qnorm.r1,qnorm.c0), mean=c(0,0),varcov)


      gcop <- sum(c(phi.11,-phi.10,phi.00,-phi.01), na.rm=TRUE)

    }

    return(gcop)

  }

gauscop.vec <- Vectorize(gauscop, vectorize.args = c('r', 'c'))


x<-length(startv)

GAUSCOPULA <- function( par ){

  a <- par[1:x]

  sig <- par[(x+1)]  #:(k+2)

  theta.num <-  exp(sig[1])*Wneigh

  theta <- theta.num/(1+theta.num)

  EXB <- exp(a[1] + a[2]*data$tcost +a[3]*data$female + a[4]*data$numveh +
          a[5]*data$zipinc)


  copula.mat <- outer(1:n,1:n, FUN = gauscop.vec, exb = EXB, y = data$count1,
          theta=theta, omega.mat=omega.mat)

  copula.mat <- ifelse(copula.mat < 0,0,copula.mat)

  LL.mat <- mu.mat * omega.mat * log(copula.mat+1e-50)
```

```
  return(-sum(LL.mat, na.rm=T))

}

out1.optim <- optim( params <- startv, GAUSCOPULA, hessian=TRUE,
          control=list(maxit=2000))

out1.optim$converge

theta <- out1.optim$par

theta

LL <- -out1.optim$value

k <- length(theta)

AIC <- 2*k - 2*LL

hessian <- out1.optim$hessian

vcm <- solve(hessian)

#Standard errors

setheta <- sqrt(diag(solve(hessian)))

setheta


#Robust Clustered Standard Errors

#Input for jacobian

x<-length(startv)

GAUSCOPULAns <- function( par ){

  a <- par[1:x]

  sig <- par[(x+1)]  #:(k+2)

  theta.num <-  exp(Roheim et al.)*Wneigh

  theta <- theta.num/(1+theta.num)

  EXB <- exp(a[1] + a[2]*data$tcost +a[3]*data$female + a[4]*data$children
          +a[5]*data$zipinc)
```

```
  copula.mat <- outer(1:n,1:n, FUN = gauscop.vec, exb = EXB, y = data$count1,
          theta=theta, omega.mat=omega.mat)

  copula.mat <- ifelse(copula.mat < 0,0,copula.mat)

  LL.mat <- mu.mat * omega.mat * log(copula.mat+1e-50)

  return(-apply(LL.mat,1,sum))

}


jacob <- jacobian(GAUSCOPULAns, theta ,method="Richardson" )

jacob <- na.omit(jacob)

bread <- vcm

meat <- t(jacob)%*%jacob

sandwich <- bread%*%meat%*%bread

robse <- sqrt(diag(sandwich))

#clustered

m <- length(unique(data$ZIPCODE))

u <- jacob

u.clust <- matrix(NA,nrow=m,ncol=k)

for(j in 1:k){

u.clust[,j] <- tapply(u[,j],data$ZIPCODE,sum)

}

cl.vcov <- vcm %*% ((m/ (m-1)) * t(u.clust) %*% (u.clust)) %*%  vcm

clstse <- sqrt(diag(cl.vcov))

clstse

t <- theta/clstse #setheta

t

pval <- 2*(1-pt(abs(t),df=n-k))

pval
```

```
############################################################################
#=============================================================
‘***Store regression results in csv file***’


ses <- paste("(",clstse,")", sep="")
ts <- c(t[1],"",t[2],"",t[3],"",t[4],"",t[5],"",t[6],"",rep("", times=4))
pvals <- c(pval[1],"",pval[2],"",pval[3],"", pval[4],"",pval[5],"",pval[6],"",  rep("",
times=4))


thetap <- round(theta, digits=3)
thetastar <- rep(NA, times=k)
for(i in 1:k){
  if(pval[i] > .01) thetastar[i] <- thetap[i]
  if(pval[i] <=.01) thetastar[i] <- paste(thetap[i],"***",sep="")
  if(pval[i] <=.05 & pval[i] > .01) thetastar[i] <- paste(thetap[i],"**",sep="")
  if(pval[i] <= .1 & pval[i] > .05) thetastar[i] <- paste(thetap[i],"*",sep="")
}
thetastarp <-
        c(thetastar[1],ses[1],thetastar[2],ses[2],thetastar[3],ses[3],thetastar[4],ses[4],thetas
        tar[5],ses[5],thetastar[6],ses[6],n,k,LL,AIC)
results <- cbind(thetastarp,ts,pvals)
colnames(results)<-c("theta","t","pval")
rownames(results)<-c("CONST", "", "TCOST2" , "", "d_NEIGH","" ,"FEMALE","",
        "NUMVEH","" ,"ZIPINC",  "N", "K", "LL", "AIC")
print(results,digits=3)


write.csv(results, file = "C:/Users/Robert
        Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop_2.5km_TC_20
        10.csv", row.names = TRUE)
```

```
write.csv(cl.vcov, file = "C:/Users/Robert
          Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop__2.5km_clstvc
          m_2010.csv", row.names = F)

write.csv(theta, file = "C:/Users/Robert
          Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop_2.5km_theta_2
          010.csv", row.names = F)

write.csv(startv, file = "C:/Users/Robert
          Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop_2.5km_startv_
          2010.csv", row.names = F)

#######################################################################

#==============================================================

'*** Krinsky Robb CIs ***'

theta  <- as.matrix(read.csv("C:/Users/Robert
          Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop_2.5km_theta_2
          010.csv", sep="," , header = T))

vcm  <- as.matrix(read.csv("C:/Users/Robert
          Fonner/Documents/UNM/Recreation_choice/results/RA_gauscop__2.5km_clstvc
          m_2010.csv.csv", sep="," , header = T))

#Welfare measure

wtpa <- exp(theta[1] + theta[2]*data$tcost +theta[3]*data$female
          +theta[4]*data$numveh + theta[5]*data$zipinc)/-theta[2]

wtpa.visit <- -1/theta[2]

CS.i <- sum( wtpa.visit/data$numveh*data$nvexpand)/sum(data$nvexpand)*100

#Mean CS

CS.i

#Krinsky Robb CIs per person per trip value

Cpr = chol(vcm[1:(k-1),1:(k-1)])

B <- matrix(theta[1:(k-1)])

Nsim <- 10000

siglevel <- .05

simCS <- matrix(NA,nrow=Nsim, ncol=1)

for( i in 1:Nsim){
```

```
  x <- matrix(rnorm(k-1))
  Z <- B + Cpr%*%x
  CS.i <- -1/Z[2]/data$numveh*data$nvexpand
  CS.weight <- sum(CS.i)/sum(data$nvexpand) #sum.nvexpand
  simCS[i] <- CS.weight
}
simCS <- simCS[order(simCS)]
#Lower Bound
lowbnd <- simCS[Nsim*siglevel+1]
lowbnd*100
#Upper Bound
Upbnd <- simCS[Nsim*(1-siglevel)-1]
Upbnd*100
```

Solving for Benefit Function Parameters: Section 4.4.4

```
%State-scale
syms a b
S = solve(a*(log(b)-log(12000)-1)== -3545.81, a*(log(b)-log(2484)-1)== 0)
```

Wild Horse Dynamic Simulations(MATLAB): Section 4.5

```
% Code written by Robert Fonner

%STATUS QUO NPV

% statusquo.csv - 50-year population and removals under status quo

cd('Results')
statusquo = csvread('statusquo.csv', 1, 0);
X_sqs = statusquo(:,1); %Status quo population, state-level
Y_sqs = statusquo(:,2); %Status quo removal, state-level
X_sqh = statusquo(:,3); %Status quo population, herd-level
Y_sqh= statusquo(:,4); %Status quo removal, herd-level

%Run the code below after defining reward matrix (f) for state
t = 1:50;
NPV50_state = zeros(50,1);
for i = 1:50
NPV50_state(i) = f(round(X_sqs(i)/hu)+1,round(Y_sqs(i)/hu)+1)/(1+.05)^t(i);
end
sum(NPV50_state)

%Run the code below after defining reward matrix (f) for herd
t = 1:50;
NPV50_herd = zeros(50,1);
for i = 1:50
NPV50_herd(i) = f(X_sqh(i)+1,Y_sqh(i)+1)/(1+.05)^t(i);
end
sum(NPV50_herd)


%HORSE REMOVAL

%State level parameters%
hu = 6; %horse units
x0 =  3295; % initial population
Cad = hu*(1543.77-128.65); % costs of adoption minus adoption fee
gamma = 170/hu; %adoption demand
holdcost =  hu*1105.34; % annual maintenance cost for horses in holding
```

```
holdyr = (0:14)'; %  avg 15 years in holding
SC = 34188.88; %start-up costs
K = 12000/hu; %carrying capacity
X = (0:K)'; % vector of states
n = length(X); % number of states
Y = (0:K)'; % vector of actions
m = length(Y); % number of actions
rho = 0.95; % discount factor
r = .28; % internal rate of growth
alpha = .5; %percent of horses that can be rounded up in one period
Coc = hu*2694.818127; % marginal opportunity cost of range use after AML
AML = 2485;
Xhu = hu*X;
%Benefits - Gompertz fnc.
B = 2251.8312*Xhu.*log(6754.9303./Xhu);
B(1) = 0;
B = repmat(B,1,m);
%Benefits - constant marginal decline after AML
%B =   - max(Coc*(Xhu-AML),0);
%B(1) = 0;
%B = repmat(B,1,m);

% Cost of removal - state
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = 1864940.29*Y(i)./X - 165913.85;
Cr(1864940.29*Y(i)./X - 165913.85<SC,i) = SC;
end

Cht = holdcost*rho.^holdyr;
Chi = sum(Cht);
Ch = zeros(m,n);
for i=1:m;
Ch(:,i) = Chi*max(Y(i)-gamma,0);
end

%adoption cost
Ca = zeros(m,n);
for i=1:m;
Ca(:,i) = Cad * min(gamma,Y(i));
end

%Reward matrix
f = B/rho - Cr - Ca - Ch; %
for i=1:m;
f(Y(i)>alpha*X,i) = -inf;
```

```
end
%f(X<100,:) = -inf; % if population can be smaller than 500 then pulsing

%Transition matrix
g= zeros(m,n);
for i=1:m
j = max(0,round((hu*X + hu*X*r.*(1-(X/K).^2)-hu*Y(i))/hu))+1;
j = min(j,K+1);
g(:,i) = j;
end

%Optimization
T = 70; % model horizon
model.reward = f;
model.transfunc = g;
model.horizon = T;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);

%Analysis of optimal solution
s1 = round(x0/hu+1); nyrs = 50;
xfpath = ddpsimul(pstar,s1,nyrs);
figure(3)
plot((0:nyrs)',6*X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath)*hu)
std(X(xfpath)*hu)
min(X(xfpath)*hu)
max(X(xfpath)*hu)


% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
mean(Y(yfpath)*hu)
min(Y(yfpath)*hu)
max(Y(yfpath)*hu)
std(Y(yfpath)*hu)

%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
```

```
NPV(i) = f(X(xfpath(i)),Y(yfpath(i)))/(1+.05)^time(i);
end
sum(NPV)

figure(1); plot(X,Y(yf));
xlabel('Stock'); ylabel('Optimal Fertility Control');
figure(2); plot(X,vf);
xlabel('Stock'); ylabel('Optimal Value');

%Herd level parameters%
x0 =  532; % initial population
Cf = 243.88; % marginal cost of fertility control
Cad = 1543.77-128.65; % costs of adoption minus adoption fee
Cshp = 242.99; % average shipping costs
gamma = 68; %adoption demand
holdcost =  1105.34; % annual maintenance cost for horses in holding
holdyr = (0:14)'; %  avg 15 years in holding
SC = 17094.44; %start-up costs
K = 1202; %carrying capacity
X = (0:K)'; % vector of states
n = length(X); % number of states
Y = (0:K)'; % vector of actions
m = length(Y); % number of actions
rho = 0.95; % discount rate
r = .28; % internal rate of growth
alpha = .9; %percent of horses that can be rounded up in one period
Coc = 2694.818127; % marginal opportunity cost of range use at K
AML = 250;
%Benefits - Gompertz fnc.
B = 2258.073*X.*log(679.570./X);
B(1) = 0;
B = repmat(B,1,m);
%Benefits - constant marginal decline after AML
%B =  - max(Coc*(X-AML),0);
%B(1) = 0;
%B = repmat(B,1,m);

% marginal cost of roundup - herd
Cri = -.4839*X+680.93;
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = Y(i)*Cri;
Cr(Y(i)*Cri<11396.29,i) = 11396.29;
end

%Holding cost
```

```
Cht = zeros(length(holdyr),1);
for i=1:length(holdyr)
Cht(i) = holdcost*rho^holdyr(i) ;
end
Chi = sum(Cht);

Ch = zeros(m,n);
for i=1:m;
Ch(:,i) = Chi*max(Y(i)-gamma,0);
end

%adoption cost
Ca = zeros(m,n);
for i=1:m
Ca(:,i) = Cad * min(gamma,Y(i));
end

%shipping cost
Csh = zeros(n,m);
for i=1:m
Csh(:,i) = Cshp*Y(i);
end

%Reward matrix
f = B/rho - Cr - Ca - Ch - Csh;
for i=1:m;
f(Y(i)>alpha*X,i) = -inf;
end
%f(X<45,:) = -inf; % over 50 just mrap to min allowed

%Transition matrix
g= zeros(m,n);
for i=1:m
j = max(0,round((X + X*r.*(1-(X/K).^2)-Y(i))))+1;
j = min(j,K+1);
g(:,i) = j;
end

%Optimization
T=70
model.reward = f;
model.transfunc = g;
model.horizon = T;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);
```

```
%Analysis of optimal solution
x0 = 532+1; nyrs = 50;
xfpath = ddpsimul(pstar,x0,nyrs);
figure(3)
plot((0:nyrs)',X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath))
std(X(xfpath))
min(X(xfpath))
max(X(xfpath))


% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
mean(Y(yfpath))
std(Y(yfpath))
min(Y(yfpath))
max(Y(yfpath))


%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
NPV(i) = f(X(xfpath(i)),Y(yfpath(i)))/(1+.05)^time(i);
end
sum(NPV)




%HORSE FERTILITY CONTROL%

%State level parameters%


hu = 6; %horse units
x0 =  3295; % initial population
Cf = hu*243.88; % marginal cost of fertility control
SC = 34188.88; %start-up costs
K = 12000/hu; %carrying capacity
X = (0:K)'; % vector of states
n = length(X); % number of states
```

```
Y = (0:K)'; % vector of actions
m = length(Y); % number of actions
rho = 0.95; % discount factor
r = .28; % internal rate of growth
alpha = .5; %percent of horses that can be rounded up in one period
Coc = hu*2694.818127; % marginal opportunity cost of range use at K
AML = 2485/hu;
Xhu = hu*X;
%Benefits - Gompertz fnc.
B = 2251.8312*Xhu.*log(6754.9303./Xhu);
B(1) = 0;
B = repmat(B,1,m);
Cm = repmat(3*5698.14,m,n); %monitoring costs
Cm(:,1) = 0;

% Cost of removal - state
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = 1864940.29*Y(i)./X - 165913.85;
Cr(1864940.29*Y(i)./X - 165913.85<SC,i) = SC;
end

%fertility control cost
Cfert = zeros(n,m);
for i=1:m
Cfert(:,i) = Cf*Y(i);
end

%Reward matrix
f = B/rho - Cr - Cfert - Cm; %
for i=1:m;
f(Y(i)>alpha*X,i) = -inf;
end

%Transition matrix
g = zeros(n,m);
for i=1:m
j = max(0,round((hu*X+hu*X*r.*( (1-Y(i)./X) -(X/K).^2 ))/hu)) + 1;
j = min(j,K+1);
g(:,i) = j;
end

%Optimization
T = 70;
model.reward = f;
model.transfunc = g;
```

```
model.horizon = T;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);

%Analysis of optimal solution
s1 = round(x0/hu+1); nyrs = 50; %round(x0/hu+1)
xfpath = ddpsimul(pstar,s1,nyrs);
figure(3)
plot((0:nyrs)',hu*X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath)*hu)
std(X(xfpath)*hu)
min(X(xfpath)*hu)
max(X(xfpath)*hu)


% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
mean(Y(yfpath)*hu)
std(Y(yfpath)*hu)
min(Y(yfpath)*hu)
max(Y(yfpath)*hu)


%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
NPV(i) = f(X(xfpath(i)),Y(yfpath(i)))/(1+.05)^time(i);
end
sum(NPV)

figure(1); plot(X,Y(yf));
xlabel('Stock'); ylabel('Optimal Fertility Control');
figure(2); plot(X,vf);
xlabel('Stock'); ylabel('Optimal Value');


%Herd level parameters%
x0 =  532; % initial population
Cf = 243.88; % marginal cost of fertility control
gamma = 68; %adoption demand
```

```
SC = 17094.44; %start-up costs
K = 1202; %carrying capacity
X = (0:K)'; % vector of states
n = length(X); % number of states
Y = (0:K)'; % vector of actions
m = length(Y); % number of actions
rho = 0.95; % discount rate
r = .28; % internal rate of growth
alpha = .9; %percent of horses that can be rounded up in one period
Coc = 2694.818127; % marginal opportunity cost of range use at K
AML = 250; % Appropriate management level set by BLM
Cm = repmat(5698.14,m,n); %monitoring costs
Cm(:,1) = 0;

%Benefits - Gompertz fnc.
B = 2258.073*X.*log(679.570./X);
B(1) = 0;
B = repmat(B,1,m);
%Benefits - constant marginal decline after AML
%B =  - max(Coc*(X-AML),0);
%B(1) = 0;
%B = repmat(B,1,m);

% marginal cost of roundup - herd
Cri = -.4839*X+680.93;
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = Y(i)*Cri;
Cr(Y(i)*Cri<11396.29,i) = 11396.29;
end

%fertility control cost
Cfert = zeros(n,m);
for i=1:m
Cfert(:,i) = Cf*Y(i);
end

%Reward matrix
f = B/rho - Cr - Cfert-Cm;
for i=1:m;
f(Y(i)>alpha*X,i) = -inf;
end
%f(X<45,:) = -inf; % over 50 just mrap to min allowed

%Transition matrix
g = zeros(n,m);
```

```
for i=1:m
j = max(0,round(X+X*r.*( (1-Y(i)./X) -(X/K).^2 ))) + 1;
j = min(j,K+1);
g(:,i) = j;
end

%Optimization with ddpsolve package
% For discrete state and action variable case
T = 70
model.reward = f;
model.transfunc = g;
model.horizon = T;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);

%Analysis of optimal solution
s1 = 532+1; nyrs = 50;
xfpath = ddpsimul(pstar,s1,nyrs,yf);
figure(3)
plot((0:nyrs)',X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath))
std(X(xfpath))
min(X(xfpath))
max(X(xfpath))

% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
mean(Y(yfpath))
std(Y(yfpath))
min(Y(yfpath))
max(Y(yfpath))

%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
NPV(i) = f(X(xfpath(i)),Y(yfpath(i)))/(1+.05)^time(i);
end
sum(NPV)
```

```
%HYBRID MANAGEMENT%


%State level parameters%
hu = 6; %horse units
x0 =  3295; % initial population
Cad = hu*(1543.77-128.65); % costs of adoption minus adoption fee
gamma = 170/hu; %adoption demand
holdcost =  hu*1105.34; % annual maintenance cost for horses in holding
holdyr = (0:14)'; %  avg 15 years in holding
Cf = hu*243.88; % marginal cost of fertility control
SC = 34188.88; %start-up costs
K = 12000/hu; %carrying capacity
X = (0:K)'; % vector of states
n = length(X); % number of states
Y = (0:K)'; % vector of actions
pctfert = .2; %percent of horses treated
Q = round(X*pctfert); %number of horses treated
Cfert = repmat(Q*Cf,1,m); % Fertility costs
m = length(Y); % number of actions
rho = 0.95; % discount factor
r = .28; % internal rate of growth
alpha = 1; % percent of horses that can be rounded up in one period
Cm = repmat(3*5698.14,m,n); %monitoring costs - 3 herds
Cm(:,1) = 0;
Coc = hu*2694.818127; % marginal opportunity cost of range use after AML
AML = 2485;
Xhu = hu*X;
%Benefits - Gompertz fnc.
B = 2251.8312*Xhu.*log(6754.9303./Xhu);
B(1) = 0;
B = repmat(B,1,m);

% Cost of removal - state
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = 1864940.29*(Y(i)+Q)./X - 165913.85;
Cr(1864940.29*(Y(i)+Q)./X - 165913.85<SC,i) = SC;
end

Cht = holdcost*rho.^holdyr;
Chi = sum(Cht);
Ch = zeros(m,n);
for i=1:m;
Ch(:,i) = Chi*max(Y(i)-gamma,0);
end
```

```
%adoption cost
Ca = zeros(m,n);
for i=1:m;
Ca(:,i) = Cad * min(gamma,Y(i));
end

%Reward matrix
f = B/rho - Cr - Ca - Ch - Cm - Cfert;
for i=1:m;
f((Y(i)+Q)>alpha*X,i) = -inf;
end

%Transition matrix
g= zeros(m,n);
for i=1:m
j = max(0,round((hu*X + hu*X*r.*((1 - pctfert)-(X/K).^2)-hu*Y(i))/hu))+1;
j = min(j,K+1);
g(:,i) = j;
end

%Optimization
T = 70; % model horizon
model.reward = f;
model.transfunc = g;
model.horizon = T;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);

%Analysis of optimal solution
s1 = round(x0/hu+1); nyrs = 50;
xfpath = ddpsimul(pstar,s1,nyrs);
figure(3)
plot((0:nyrs)',hu*X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath)*hu)
std(X(xfpath)*hu)
min(X(xfpath)*hu)
max(X(xfpath)*hu)

% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
```

```
mean(Y(yfpath)*hu)
std(Y(yfpath)*hu)
min(Y(yfpath)*hu)
max(Y(yfpath)*hu)

%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
NPV(i) = f(X(xfpath(i)),Y(yfpath(i)))/(1+.05)^time(i);
end
sum(NPV)

figure(1); plot(X,Y(yf));
xlabel('Stock'); ylabel('Optimal Fertility Control');
figure(2); plot(X,vf);
xlabel('Stock'); ylabel('Optimal Value');

%Herd level parameters%
x0 =  532; % initial population
Cf = 243.88; % marginal cost of fertility control
Cad = 1543.77-128.65; % costs of adoption minus adoption fee
Cshp = 242.99; % average shipping costs
gamma = 68; %adoption demand
holdcost =  1105.34; % annual maintenance cost for horses in holding
holdyr = (0:14)'; %  avg 15 years in holding
Cf = hu*243.88; % marginal cost of fertility control
SC = 17094.44; %start-up costs
K = 1202; %carrying capacity ASSUMPTION
X = (0:K)'; % vector of states
n = length(X); % number of states
Y = (0:K)'; % vector of actions
Cm = repmat(5698.14,m,n); %monitoring costs
Cm(:,1) = 0;
pctfert = .25; %percent of horses treated
Q = round(X*pctfert); %number of horses treated
Cfert = repmat(Q*Cf,1,m); % Fertility costs
m = length(Y); % number of actions
rho = 0.95; % discount rate
r = .28; % internal rate of growth
alpha = .9; %percent of horses that can be rounded up in one period
Coc = 2694.818127; % marginal opportunity cost of range use at K
AML = 250;
%Benefits - Gompertz fnc.
B = 2258.073*X.*log(679.570./X);
B(1) = 0;
B = repmat(B,1,m);
```

```
% marginal cost of roundup - herd
Cri = -.4839*X+680.93;
Cr = zeros(n,m);
for i=2:m
Cr(:,i) = (Q+Y(i)).*Cri;
Cr((Q+Y(i)).*Cri<11396.29,i) = 11396.29;
end

%Holding cost
Cht = zeros(length(holdyr),1);
for i=1:length(holdyr)
Cht(i) = holdcost*rho^holdyr(i) ;
end
Chi = sum(Cht);

Ch = zeros(m,n);
for i=1:m;
Ch(:,i) = Chi*max(Y(i)-gamma,0);
end

%adoption cost
Ca = zeros(m,n);
for i=1:m
Ca(:,i) = Cad * min(gamma,Y(i));
end

%shipping cost
Csh = zeros(n,m);
for i=1:m
Csh(:,i) = Cshp*Y(i);
end

%Reward matrix
f = B/rho - Cr - Ca - Ch - Csh - Cfert - Cm;
for i=1:m;
f((Q+Y(i))>alpha*X,i) = -inf;
end
%f(X<45,:) = -inf; % over 50 just mrap to min allowed

%Transition matrix
g= zeros(m,n);
for i=1:m
j = max(0,round(X + X*r.*((1 - pctfert)-((X/K).^2))-Y(i)))+1;
j = min(j,K+1);
g(:,i) = j;
```

```
end

%Optimization
model.reward = f;
model.transfunc = g;
model.horizon = 70;
model.discount = rho;

[vf,yf,pstar] = ddpsolve(model);

%Analysis of optimal solution
x0 = round(x0+1); nyrs = 50;
xfpath = ddpsimul(pstar,x0,nyrs);
figure(3)
plot((0:nyrs)',X(xfpath));
legend('Fifty Year Horizon');
xlabel('Year'); ylabel('Stock');
mean(X(xfpath))
std(X(xfpath))
min(X(xfpath))
max(X(xfpath))


% Compute horse removal path over 50 year horizon
yfpath = zeros(nyrs,1);
   for i=1:nyrs
   yfpath(i) = yf(xfpath(i),i);
   end
mean(Y(yfpath))
std(Y(yfpath))
min(Y(yfpath))
max(Y(yfpath))


%NPV - 50 year horizon
time = 1:nyrs;
for i = 1:nyrs
NPV(i) = f(xfpath(i),yfpath(i))/(1+.05)^time(i);
end
sum(NPV)
```

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