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Spatial and Spatial-Temporal Analysis of Grizzly Bear Movement Patterns as Related to Underlying Landscapes Across Multiple Scales

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SPATIAL AND SPATIAL-TEMPORAL ANALYSIS OF GRIZZLY BEAR MOVEMENT PATTERNS AS RELATED TO UNDERLYING LANDSCAPES ACROSS MULTIPLE SCALES

by

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DISSERTATION
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in partial fulfillment of the requirements for
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2010

ABSTRACT

Studying the movements of grizzly bears (*Ursus arctos*) in Alberta is imperative for scientifically informed management practices. To properly balance industry requirements with conservation imperatives, it is necessary to understand the spatial and spatial-temporal movement patterns of grizzly bears as they relate to underlying landscape properties. As part of the Foothills Research Institute Grizzly Bear Research Program, this dissertation explored both fine and large-scale movement patterns generated from global positioning system (GPS) radiotelemetry data.

Between 1999 and 2005, grizzly bears were captured and radio-collared across western Alberta. The temporal resolution of GPS data collection had a large impact on the amount of information available for analysis. A significant decrease in available information was demonstrated as time between locations increased. The presence of serial autocorrelation indicated the presence of prolonged movement behavior in fine-scale vector structures. The ability to identify internal vector clusters dramatically decreased as temporal resolution decreased.

The relationship between level of human activity and grizzly bear movement rate across multiple spatial and temporal scales was studied in detail. Resulting movement patterns of grizzly bears were found to be intrinsically linked to both internal and external factors. Overall, grizzly bears residing in mountain environments were found to have significantly slower movement rates and smaller home ranges sizes when compared to grizzly bears residing in foothills environments. Temporally, movement rates also varied significantly according to season, month, and time of day. These findings have significance for modeling efforts which attempt to replicate grizzly bear spatial and temporal movement patterns across Albertan landscapes.

The use of time sequence graphs aided in differentiating between different types of movement behaviors and allowed for the quantification and assessment of consecutive vector data. Results emphasized that slow movement clusters occurred more often and for longer periods of time when compared to fast travel segments. While some movement-habitat relationships were identified, results were highly individual by bear. Overall models tended to respond the best when working with mountain bears over foothills bears. Results further suggested that vector-based movements should be separated according to type (slow versus fast) for future modeling efforts.

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ACF	Autocorrelation Function
BMA	Bear Management Area
COY	Cubs of the Year
CRW	Correlated Random Walk
CSR	Complete Spatial Randomness
DEM	Digital Elevation Model
DFA	Discriminant Function Analysis
DOP	Dilution of Precision
FRI	Foothills Research Institute
FY	Females with Yearlings
GIS	Geographic Information Systems
GPS	Global Positioning Radiotelemetry
KDE	Kernel Density Estimation
LCP	Least-cost Path
LSCV	Least Squares Cross Validation
LZM	Linkage Zone Models
MCP	Minimum Convex Polygon
MLR	Multiple Linear Regression
MOST	Moving Object Spatiotemporal
PACF	Partial Autocorrelation Function
PPA	Point Pattern Analysis
RSF	Resource Selection Function
SSF	Step Selection Function
VIF	Variance Inflator Function
VRM	Vector Ruggedness Measure

CHAPTER 1 – INTRODUCTION

1.1 Context

In western Canada, the grizzly bear (*Ursus arctos*) is currently at risk from expanding industrial, residential and recreational developments (Ross 2002). Nationally, the grizzly bear is listed as a species of special concern (COSEWIC 2002). Because grizzly bears demonstrate a lack of resilience to anthropogenic disturbance (Weaver et al. 1996, Carroll et al. 2001, Gibeau et al. 2001, Garshelis et al. 2005), they are often used as a focal species for conservation whose presence and persistence is considered an excellent indicator of ecosystem integrity (Noss et al. 1996, NESERC 2000, Carroll et al. 2001). This is especially relevant for grizzly bears in Alberta where the continual loss and fragmentation of critical habitat due to increased human development is threatening the long-term viability of the population (Rosenberg et al. 1997, Beier and Noss 1998, Gibeau 2000, Gibeau et al. 2002, Nielsen et al. 2004a, Nielsen 2005). Overall, declining grizzly bear populations are predicated by low population densities due to large area requirements, low reproductive rates, limited dispersal ability, and human-bear mortalities (Carroll et al. 2001). In 2000, the total grizzly bear population on provincial lands in Alberta was estimated to be approximately 840 bears (Kansas 2002). By 2003, the estimated number of grizzly bears in Alberta had dropped to 500 individuals or less (Stenhouse et al. 2003). Due to the recognition of current population declines, Alberta's Endangered Species Conservation Committee has recently listed the grizzly bear as 'under review for threatened status' (ESCC 2005, Garshelis et al. 2005).

Imperative to wildlife conservation is understanding the relationship between wildlife and habitat (Nams et al. 2006). Since 1999, now the Foothills Research Institute (FRI), formerly the Foothills Model Forest Grizzly Bear Research Project (FMFGBRP), has conducted research to provide land-use managers with the information and tools needed to ensure the long-term conservation of grizzly bear populations in Alberta, Canada (NESERC 2000). As with the conservation of any species, understanding grizzly bear behavior at multiple spatial and temporal scales is paramount for informed management practices. Global Positioning Systems (GPS) radiotelemetry data and Geographic Information Systems (GIS) have become important conservation and management tools. Over the past 10 years, the FRI has developed detailed models that predict and describe habitat preference, security areas, and mortality risk locations (Gibeau et al. 2001, Nielsen et al. 2002, 2003, Nielsen et al. 2004a, Nielsen et al. 2004b, Nielsen et al. 2004c, Linke et al. 2005, Munro et al. 2006, Nielsen et al. 2006). However, spatially explicit models which focus on quantifying grizzly bear movement behavior have remained underdeveloped and limited in scope (Schwab 2003, Hunter 2007, Berland et al. 2008).

The detailed study of movement patterns is necessary to provide information regarding general space-use, basic habitat interactions, dispersal characteristics, and population distributions. Historically, the quantification of grizzly bear movements had been predominantly ignored or modeled because reliable GPS telemetry data did not exist (Boone and Hunter 1996). Within the past decade, improvements to GPS radiocollar technology has improved our ability to monitor movements and collect exceptionally large and detailed data sets for individual animals (Frair et al. 2004, Dettki and Ericsson 2006). Further, new analytical approaches and statistical methods have been developed to handle GPS telemetry data sets with improved quality and quantity (Johnson et al. 2002, Nielsen 2005, Dettki and Ericsson 2006, Horne et al. 2007, Hunter 2007).

Spatial data analysis has grown rapidly in the fields of geography, wildlife biology and landscape ecology (Bailey and Gatrell 1995, Fortin and Dale 2005). One of the primary challenges confronting research involving spatial data analysis stems from the complex interaction between space and time (Wagner and Fortin 2005). Broadly defined, spatial data analysis is the quantitative study of phenomena (spatial data events) that are physically referenced in space (and further in time), often with an emphasis on spatial arrangement or pattern (Bailey and Gatrell 1995). It has been recognized that quantitative methods are needed to link spatial patterns and ecological processes at various spatial and temporal scales (Turner et al. 2001, Fortin and Dale 2005). For grizzly bears, this link has largely been explored through the utilization of habitat-use or resource selection models (Nielsen et al. 2002, Nielsen 2005).

Spatial data analysis typically employs statistics and models to infer information about the spatial processes generating the pattern of observations or population in question (Liebhold and Gurevitch 2002). In an effort to make these generalizations, researchers often group data events with similar properties (defined either spatially or temporally) and attempt to characterize and understand the resulting spatial pattern. For example, a spatial or temporal cluster of grizzly bear GPS data locations may indicate preference for a specific habitat type. Beyond the basic consideration of spatial pattern, is the complex consideration of process. Often, a spatial pattern results from more than one process (Liebhold and Gurevitch 2002, Wiegand and Moloney 2004, Fortin and Dale 2005, Wagner and Fortin 2005). That is, it might be more than simply habitat type creating a cluster of GPS radiotelemetry locations. External influences could include individual bear social interactions or human-bear encounters. As such, the relationship between pattern and process remains a challenging and important area of research (Turner et al. 2001). Emergent technologies and analytic tools are making it possible to better integrate the concepts of pattern with process (Chetkiewicz et al. 2006).

Grizzly bear GPS radiotelemetry data is an example of a spatial point pattern. 'Real life' spatial patterns often result from both first-order and second-order effects (Bailey and Gatrell 1995, Fortin and Dale 2005). From a statistical perspective, an observed spatial point pattern is the realization of spatial stochastic process (Gatrell et al. 1996). First-order statistics, such as kernel density estimation are often employed to describe the intensity of a point pattern where the expected value (mean or average) varies over space (Gatrell et al. 1996). Second-order statistics, such as bivariate K-functions are used to describe the internal structure of a point pattern (Wiegand and Moloney 2004). Where first-order approaches describe large-scale (global) variation in intensity, second-order approaches summarize point-to-point distances and detect local patterns across difference scales (Wiegand and Moloney 2004). While these approaches are capable of detecting various types of clusters in the data, they might not determine the underlying stochastic process generating the clusters (Fotheringham et al. 2000). They are often further limited by the scale at which they can be applied and are susceptible to boundary edge effects (Gatrell et al. 1996, Wiegand and Moloney 2004). Furthermore, typical point pattern analysis (PPA) methods lack the ability to deal with consecutive data points as required by GPS telemetry data.

The development of spatial movement models is largely reliant on the acquisition of GPS radiotelemetry data. In fact, without the use of GPS data, the ability to model, predict and further understand the movement characteristics of grizzly bears would remain limited in scope. A movement pattern, created from consecutive GPS point and vector data, requires an additional suite of analytical procedures. Movement paths of individual animals reflect behavioral responses to environmental properties and may serve to identify changes to movement processes (Johnson et al. 2002). Based on preliminary explorations (Schwab 2003), grizzly bear movements are not uniformly distributed across the landscape and violate the typical model assumption of constant movement behavior (Morales and Ellner 2002, Johnson et al. 2006). As such, grizzly bear spatial movement patterns can be characterized as a spatially heterogeneous process that is nonstationary. When a grizzly bear changes its behavior, it is proposed that the mathematical properties of movement steps and therefore vector characteristics could change accordingly (Martin et al. 2008). For example, step lengths may be significantly shorter while an individual forages as opposed to when the individual moves to a new feeding location. Empirically-based measures such as step length distributions can help to describe the stochasticity of the velocity or movement rate for an individual (Tischendorf 1997). It has been suggested that to further understand this problem, researchers should study the spatial structure of the entire trajectory to identify patterns in the movement path (Martin et al. 2008). Unfortunately, making the leap from static recorded GPS locations to a continuous behavior, such as movement, remains burdened by many data assumptions.

In the past, explorations of grizzly bear movements were limited to simple large-scale descriptions such as home range size, annual distance travelled, and daily movement rate. With the recent advancement in GPS data collection techniques, larger, more detailed data sets provide a new opportunity to accurately separate movement strategies into behavioral categories (Johnson et al. 2002, Fortin et al. 2005, Frair et al. 2005, Dettki and Ericsson 2006, Coulon et al. 2008). Movement behavior is a highly variable process that is specific to individual grizzly bears and difficult to generalize across populations (Schwab 2003, Nielsen 2005, Stenhouse et al. 2005, Hunter 2007). Ironically, population-level inferences are often the focus of telemetry-based studies (Aarts et al. 2008). The understanding of movement is required to help know when individuals are active, how fast they move, what physical areas they move through, and how much they vary in these traits. The use of individual empirical-based models may capture environmental relationships which further shape our understanding of population distributions (Aarts et al. 2008). As such, researchers are often interested in the physical location of an individual in relation to supplementary data sources. For example, low gradient riparian areas are highly selected for by grizzly bears as preferred habitat (McLellan and Hovey 2001a). Unfortunately, river bottoms and valleys have also been identified as a primary sink (attractive habitat coupled with high risk of mortality) (Nielsen et al. 2006). A few studies exist which have quantitatively examined the movements of large carnivores (Amstrup et al. 2000, Amstrup et al.

2001, Austin et al. 2004, Collins et al. 2005), however, none of these are specific to grizzly bears in Alberta. Individually-based models and empirical assessments are still needed to identify key variables that influence the movement of grizzly bears across Albertan landscapes.

Further, there exists a significant lack of understanding of how grizzly bear movements are distributed in space and time. To properly understand grizzly bear movement as a behavioral process, it is important to first empirically identify the relevant spatial and temporal scales at which movement occurs (Johnson et al. 2002, Fortin and Dale 2005, Hunter 2007). For example, grizzly bears shift their behaviors seasonally as food availability changes spatially and temporally (Nielsen et al. 2002, Mueller et al. 2004). Individuals further modify their movement behaviors in response to reproductive strategies and social interactions during specific times of the year (Dahle and Swenson 2003b, 2003a, Stenhouse et al. 2005). Finally, the classifications of movements are often subject to researcher interpretation. These movements can be simultaneously interpreted across multiple spatial or temporal scales. For example, spatial classifications include long-range dispersal, daily movement within home ranges, or localized foraging movements. Temporal scales of movement can be examined annually, seasonally, daily, or hourly depending on the purpose of analysis.

In addition to spatial and temporal considerations, grizzly bears are thought to exhibit different types of movement (Hunter 2007). As grizzly bears utilize the entire landscape (habitat and non-habitat) and respond to gradients of habitat quality, it is often assumed that GPS-based spatial movement patterns will reflect information regarding individual-landscape interactions. The most common approach is to separate movements into two general behaviors where foraging movements are characterized by slow, sinuous vectors and traveling movements are characterized by fast, straight vectors (Zollner and Lima 2005, Nams 2006a). The identification of movement oriented locations, for instance, may aid in the identification of important corridors (Schwab

2003). In comparison, non-movement locations can help to identify locally important habitat patches (Hunter 2007). The ability to identify local spatial and temporal variability within an entire movement trajectory requires exceptionally fine-scale data sets (Hunter 2007). Further, critical to understanding such detailed behavioral characteristics are appropriate methods for quantifying and analyzing the movements of individual animals (Franke et al. 2004, Horne et al. 2007). As a first step, empirical results provided by GPS-based studies can strengthen the basic understanding of overall movement characteristics. Subsequently, by linking vector-based consecutive data structures with supplementary data layers, information can be extracted regarding the underlying process generating the resulting spatial movement pattern. Finally, combining empirically-generated results with modeling efforts could improve movement analyses which attempt to replicate animal behavior across complex landscapes (Ager et al. 2003).

1.2 Research Objectives

The primary goal of this research is to analyze both the spatial and spatial-temporal movement patterns of grizzly bears in western Alberta, Canada. More specifically, I intend to characterize the movement behavior of grizzly bears as it pertains to underlying landscape characteristics and related levels of human activity. To accomplish this goal, I focus largely on the role of GPS radiotelemetry data to 1) quantify grizzly bear movement rates, and 2) examine the relationship between grizzly bear spatial response and underlying landscape structure. The dissertation is heavily weighted on empirically-based assessments. Associated with the overall purpose of this research are a series of relevant questions.

- Why is it important to understand grizzly bear movement?
- How should movement data be spatially represented?
- At what spatial and temporal scales should movement be addressed?

- Is it possible to discriminate between slow and fast movement types for grizzly bears using GPS radiotelemetry data?
- How do underlying landscape properties influence grizzly bear movement rates and patterns?
- How does understanding more about movement help management make conservation decisions?

The next chapter in this dissertation (Chapter 2) will provide an extensive summary of previous research studies and techniques quantifying spatial and temporal movement patterns with specific reference to grizzly bears. First, a detailed review of grizzly bear spatial and temporal landscape and habitat interactions is conducted. Following this, pattern-based and process-based approaches to modeling animal movement are reviewed. Specifically, I focus on approaches and models that deal with the consecutive nature of GPS radiotelemetry data. The chapter then discusses data challenges when dealing with GPS radiotelemetry data including locational error, autocorrelation, and vector uncertainty. Finally, regions of analysis by chapter are outlined and available supplementary data layers are reviewed.

The following chapters (Chapters 3 – 6) in this dissertation are intended to address the four separate but related research objectives listed below.

1. To examine the spatial and spatial-temporal relationship between GPS radiotelemetry capture rate and resulting vector characteristics as indicated primarily by movement rate (Chapter 3).
2. To quantify and compare large-scale GPS radiotelemetry grizzly bear movement rate and home range size as related to population subgroup characteristics, spatial location, and temporal scale (Chapter 4).

3. To examine the relationship between grizzly bear home range size and underlying landscape characteristics (Chapter 5).
4. To differentiate between movement behaviors and relate individual fine-scale grizzly bear movements to underlying landscape properties (Chapter 6).

Lastly, Chapter 7 will summarize the major findings of the dissertation in order of chapter development. Emphasis will be placed on significant research contributions to grizzly bear movement ecology, along with recommendations to improve modeling efforts which attempt to replicate grizzly bear movement patterns across large-scale landscapes. Future research directions will be discussed with reference to localized management and conservation practices.

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CHAPTER 2 – UNDERSTANDING THE SPATIAL AND TEMPORAL MOVEMENT PATTERNS OF GRIZZLY BEARS

2.1 Introduction

Current global positioning systems (GPS) based-studies have allowed for considerable research advances in the fields of conservation biology and wildlife management specific to large ranging species (DeCesare et al. 2005). The majority of previous studies based on large GPS radiotelemetry data sets often adopt descriptive statistics (e.g. average daily movement rate or movement orientation) (Amstrup et al. 2000, Amstrup et al. 2001, Maehr et al. 2002, Ager et al. 2003) or pattern-based approaches (e.g. home range delineation) (McLoughlin et al. 2000, Collins et al. 2005) where general inferences are made regarding the underlying process. For example, clusters of data points are often utilized to determine habitat use or selection. Unfortunately, working with radiotelemetry data is not a spatial panacea. While the use of GPS radiotelemetry data can strengthen the development of reliable landscape-level models, such as those required by grizzly bear conservation, many challenges remain when linking process-based models with the behavioral characteristics of a species (Schick et al. 2008).

2.2 Grizzly Bear Spatial and Temporal Landscape Interactions

Grizzly bear distributions and their use of habitats have been well documented within Alberta (Hamer et al. 1991, Gibeau et al. 2001, Gibeau et al. 2002, Nielsen et al. 2002, Chruszcz et al. 2003, Nielsen et al. 2003, Mueller et al. 2004, Nielsen et al. 2004a, Nielsen et al. 2004c, Garshelis et al. 2005, Linke et al. 2005, Stenhouse et al. 2005, Munro et al. 2006, Nielsen et al. 2006, Pengelly and Hamer 2006). Since 1999, extensive resource selection function (RSF) models have been developed detailing the habitat-use of grizzly bears in west-central Alberta (Nielsen et al. 2002, 2003, Nielsen et al. 2004a, Nielsen 2005). Despite individual variability in resource selection (Nielsen et al. 2002), grizzly bears are largely habitat generalists (Noss et al. 1996, Ross 2002) consuming a variety of plant and animal species to satisfy their nutritional requirements (Munro et al. 2006). The process of acquiring resources and the behavioral response of movement are intricately linked and differentiating between the two can be difficult. As such, it is vital to consider bear behavior as related to habitat selection and activity patterns when examining movements across landscapes.

Grizzly Bear Habitat Interactions

The habitat selection and diet of grizzly bears in Alberta is diverse and varies both spatially and temporally (Nielsen 2005, Munro et al. 2006). Though grizzly bears are adaptable, seasonal influence on plant phenology is a significant factor influencing habitat selection (McLellan and Hovey 2001a). Generally, grizzly bears hibernate from late October or early November until mid April. To account for seasonal variability in food availability, bear activities are usually classified into 3 separate seasons occurring between April 1st and October 15th (Nielsen 2005). The first season, hypophagia or den emergence, occurs from mid-April to June 14th. The second season, early hyperphagia or pre-berry, occurs from June 15th to August 14th. The third season, late hyperphagia or berry, occurs from August 15th to denning (mid/late October).

During the spring months after den emergence (hypophagia), Nielsen et al. (2002) found bears to select for areas of high greenness (regions of high vegetation productivity), streamside and alpine habitats. Bears were generally found to avoid non-vegetated areas and young regenerating forests (Nielsen et al. 2002). Diets primarily consisted of sweet vetch (*Hedysarum*) digging, other roots, grasses, and some ungulate matter (Munro et al. 2006). In addition, bears selected intermediate-aged clearcuts that were more complex in shape during hypophagia (Nielsen et al. 2004a). During the summer (early hyperphagia) and autumn (late hyperphagia) months, bears were found to select for high greenness, streamside, alpine, young and old cutblocks, herbaceous areas, open forests and shrub-wetland habitats, while avoiding regenerating burn sites and non-vegetated classes (Nielsen et al. 2002). Summer diets were generally dominated by green vegetation such as grasses, forbs, and horsetails, while autumn diets consisted primarily of buffalo berry (*Shepherdia canadensis*) and mountain blueberry and huckleberry (*Vaccinium* spp.) (Munro et al. 2006). Results further indicated that bears avoided moderate density levels of access during the summer and autumn months. Elevation and hillshade appeared not to affect grizzly bear distributions (Nielsen et al. 2002). Prior to denning in the fall, grizzly bears returned to root digging as the primary food source (Munro et al. 2006).

Only one study currently exists which examined the diets of grizzly bears according to landscape type or physical location (Munro et al. 2006). Munro et al. (2006) stratified individuals into mountain or foothills based on home range location. Mountain bears were defined as having ≥ 80% of their home range fall within mountain landscapes (> 1,700 m elevation threshold). The remaining home ranges were classified as foothills bears. Slight changes for both diet and consumption period were reported when comparing mountain bears with foothills bears. Munro et al. (2006) reported a reduction of ungulate matter in the diets of mountain bears when compared to foothills bears. Additionally, mountain bears were found to have higher root content in their diet (Munro et al. 2006). Temporally, insect foraging began 1 month earlier in the foothills when compared to the mountains. Fruit consumption (e.g. berries) began earlier and lasted longer in the foothills when compared to mountain bears.

Grizzly bear response to human development and activities have also been documented in Alberta (Gibeau et al. 2002, Chruszcz et al. 2003, Linke et al. 2005, Berland et al. 2008, Roever et al. 2008a, 2008b). Human development features include roads, forestry clearcuts, and industrial resource extraction features such as seismic lines, all of which impact grizzly bear habitat selection and therefore movement patterns. Research has indicated that grizzly bears respond to road development at different spatial and temporal scales (Roever et al. 2008a, 2008b). In some cases, roads create potential barriers to grizzly bear movement within the mountain parks and the eastern slopes regions (Gibeau et al. 2002, Proctor et al. 2005). Alternatively, roads also support the growth of herbaceous vegetation selected by grizzly bears in the spring and early summer (Roever et al. 2008a, 2008b). Chruszcz et al. (2003) examined grizzly bear spatial response to roads, road crossing behavior, and habitat and temporal patterns of cross-road movements. Two overall trends emerged: 1) high-volume roads were generally avoided, and 2) movement decisions relative to roads were related to habitat quality. Overall results highlighted that grizzly bears were found closer to low-volume than to high-volume roads (Gibeau et al. 2002, Chruszcz et al. 2003). However, when analyzed according to sex, females were found further from paved roads than males suggesting females to be more cautious than males (Gibeau et al. 2002). More specifically, males were more likely to exploit high quality habitat near roads when it was night and hiding cover was present (Gibeau et al. 2002). This was further supported by Chruszcz et al. (2003) which found grizzly bears utilized high quality valley-bottom habitat adjacent to low-volume roads. Overall, the probability of road crossings was found to increase when more vegetation was present emphasizing the need for security (Chruszcz et al. 2003). None of the above studies provided information regarding movement rates surrounding roads or in regards to road crossings.

Information regarding grizzly bear use of clearcuts has recently been reexamined. Past studies have largely promoted the argument that grizzly bears avoided clearcut features within home ranges (McLellan and Hovey 2001a). More recently, grizzly bears have been observed using clearcuts in forestry dominated landscapes (Nielsen et al. 2004a, Nielsen et al. 2004c). In these studies, the use of clearcuts in Alberta was found to be highest during mid-summer and lowest during late-summer (Nielsen et al. 2004c). Individual GPS locations were consistently located closer to clearcut edges than clearcut centers (Nielsen et al. 2004a). More specifically, clear-cut interiors were avoided while higher perimeter-to-edge ratio clearcuts were selected

(Nielsen et al. 2004a). This may suggest a preference for hiding cover proximity or transition between cover types (Gibeau et al. 2002, Nielsen et al. 2004a). Lastly, clearcut habitats were found to be utilized more than expected during the twilight and nocturnal times of day (Nielsen et al. 2004a). This may suggest that bears prefer to use open areas under the cover of night.

Results concerning seismic lines are somewhat confounding. When examining whether grizzly bear landscape use is affected by seismic cutlines and the resulting landscape structure, Linke et al. (2005) found no direct relationship between the proportion of seismic cutlines and population-level landscape use. However, the study found that while the grizzly bear population did not respond to seismic cutline densities, the population did respond to the habitat structure created by seismic line presence (Linke et al. 2005). For example, bears appeared to use areas more when landscape patches were larger. Unfortunately, no specific conclusions could be made regarding any direct relationship between seismic lines and grizzly bear populations.

Grizzly Bear Movements

Efforts to quantify movement rates for grizzly bears in the past have focused on comparisons of fidelity (White and Garrott 1990), home range size (Gibeau et al. 2001, Dahle and Swenson 2003a, 2003b, Berland et al. 2008), natal dispersal (Boone and Hunter 1996, McLellan and Hovey 2001b), daily movement rate (Gibeau et al. 2001), and genetic connectivity (Proctor 2003, Proctor et al. 2005). Of the previous approaches listed, home range size is the most common and widely used surrogate for wildlife movement. Home range is generally defined as the area traversed by an individual grizzly bear for normal activities (White and Garrott 1990). Typically, home range analysis is employed to assess both the extent of habitat use for a landscape, as well as the change in area or space over time. Further, home range-based analysis can be used to test the impacts of human activities on animal movements by measuring a significant shift to mean or central area of use (Worton 1987).

Mean annual home range sizes for grizzly bears from previous studies are summarized in Table 2-1. A description of home range types can be found on pages 26 to 28. A direct comparison was difficult as methods and data varied among studies. In all cases, the mean annual home ranges for males are significantly larger than those of females. Studies demonstrated that home range sizes also varied according to body mass, food availability, dispersal, and reproductive strategy (Dahle and Swenson 2003a, 2003b, Collins et al. 2005). A recently conducted study employed home range comparisons as a surrogate for seasonal movements and change to spatial patterns (Berland et al. 2008). Home ranges were found to be the largest during early hyperphagia indicating high amounts of related movement. Early hyperphagia is concurrent with the season when male-female associations occur (Stenhouse et al. 2005). Another study reported movements (indicated by home range size) to increase during mating season for both male and female bears (Dahle and Swenson 2003b). While home range size provides a quantitative description of area utilization and large range movements (Austin et al. 2004), it fails to provide an understanding of movements occurring at finer spatial and temporal scales (Rettie and Messier 2001). To do this, movements must be assessed using vector-based movement rates.

Table 2-1. Mean annual home ranges for female and male grizzly bears as reported by previous studies. Home range types include minimum convex polygons (MCP) and kernel density estimation (KDE) outlines.

Study	Location	Mean home range size (km^2)	Home range type
(Mace and Waller 1997)	Montana, US	M: 768, F: 125	KDE
(Dahle and Swenson 2003a)	Scandinavia	M: 944, F: 249	95% MCP
(McLellan and Hovey 2001b)	BC, Canada & Montana, US	M: 668, F: 253	MCP

To my knowledge, only a few studies currently exist which provide a detailed assessment of vector-based movement rates for grizzly bears in Alberta (Gibeau et al. 2001, Stenhouse et al. 2005, Hunter 2007, Cattet et al. 2008). The most common measure of movement is daily movement rate typically expressed as the mean distance over a 24-hr period. Gibeau et al. (2001) reported female grizzly bears (*n* = 16) in the central Canadian Rocky Mountain regions to have a mean daily movement distance of 3.4 km (range 0.2 – 16.3 km) or an average movement rate of 0.14 km/h. Results showed no differences between day versus night movements, but found substantial differences to movement patterns when human activity was factored in (Gibeau et al. 2001). An additional study reported daily movement distances for adult female grizzlies to range from 3.0 km to 6.4 km (0.13 km/h to 0.27 km/h) (Berland et al. 2008). Often, the quantification of movement rate isn't the primary focus of the study and as such, detailed information regarding grizzly bear movement rates is limited.

In 2005, two studies were published that assessed the movement rates of grizzly bears in relation to road crossings (Waller and Servheen 2005) and female-male associations (Stenhouse et al. 2005). The first study, conducted in Montana, found that reported movement distances and movement rates were significantly greater when bears crossed highways compared to not crossing highways (Waller and Servheen 2005). Data associated with a highway crossing recorded a mean movement rate that was 573 m/h or 0.57 km/h significantly faster than other hourly movement rates. Mean 24-hr movement rates surrounding a road crossing were 0.7 km/h faster when compared to the normal 24-hr movement rate. The non-crossing movement rates were not reported for comparison. The second study, conducted in Alberta, reported mean rates of movement for both male and female bears to be significantly higher surrounding a mating event (Stenhouse et al. 2005). More specifically, movement rate was found to increase for both the approach and departure when compared to the actual association. When analyzed by sex, males had a faster rate of movement prior to and after a mating event than females (Stenhouse et al. 2005).

Andrew Hunter (2007) conducted a comparison of movement velocities for one individual grizzly bear using 2005 GPS radiotelemetry data locations. Hunter (2007) identified the average movement rate for an adult male bear (G098) as 5.2 m/min or 0.31 km/h. Results further identified a movement behavior threshold of 6.5 m/min or 0.39 km/h with a 95% confidence interval (LB: 5.5 m/min; UB: 7.7 m/min) (Hunter 2007). Movements occurring below this threshold were considered foraging, while movements above 0.39 km/h were considered locomotion. Hunter (2007) then assessed the relationship between both foraging locations and locomotion locations with underlying landscape properties using a habitat selection model. Foraging-based movements were positively associated with water, edge features, leaf area index, and crown closure, while negatively associated with slope aspect and net radiation. Results suggested that locomotion movements were positively associated with water, leaf area index, and barren lands. To summarize, individual male G098 preferred to travel through cooler areas, closer to water features, and through barren landscapes with green vegetation present (Hunter 2007). Of particular interest, the locomotion model highlighted a clear preference for movement along river and stream networks. The model presented here was limited to one individual. Further, separating movement and foraging data was not conclusive with significant overlap occurring between the two (e.g. water and barren). For example, when examining the locomotion versus foraging home range areas it appeared that the resulting spaces were nearly 100 percent overlapped (Hunter 2007). When using a two-process model to separate movement from foraging, it is inevitable that some events will be misassigned and attributed to the wrong process. Yet, the approach of partitioning an animal's trajectory data into different types of behavior may significantly improve modeling results (Hunter 2007).

Lastly, Cattet et al. (2008) analyzed the movement rates of radiocollared bears following a capture event to determine if capture and handling had any long-term effects on mobility. It was reasoned that if mobility was reduced for an extended period of time, then an individual's ability to acquire resources would also be reduced. Model results suggested that movement rate varied as a function of sex and reproductive class, month, the interaction between month and day of month, and the number of days following capture (Cattet et al. 2008). Overall, the study found grizzly bear movement rates to be significantly reduced (57% below normal) following a capture event. Reduced movement rates lasted from the day of capture up to 6 weeks before returning to mean levels (Cattet et al. 2008). The study further found movement rates to peak at 28 days (SE = 4.3 days) post-capture. These results have large implications when working with GPS radiotelemetry data to assess movement rates as this dissertation does. Results suggest that data may need to be discarded prior to analysis.

2.3 Movement Strategies for Assessing Consecutive Data (Pattern and Process Models)

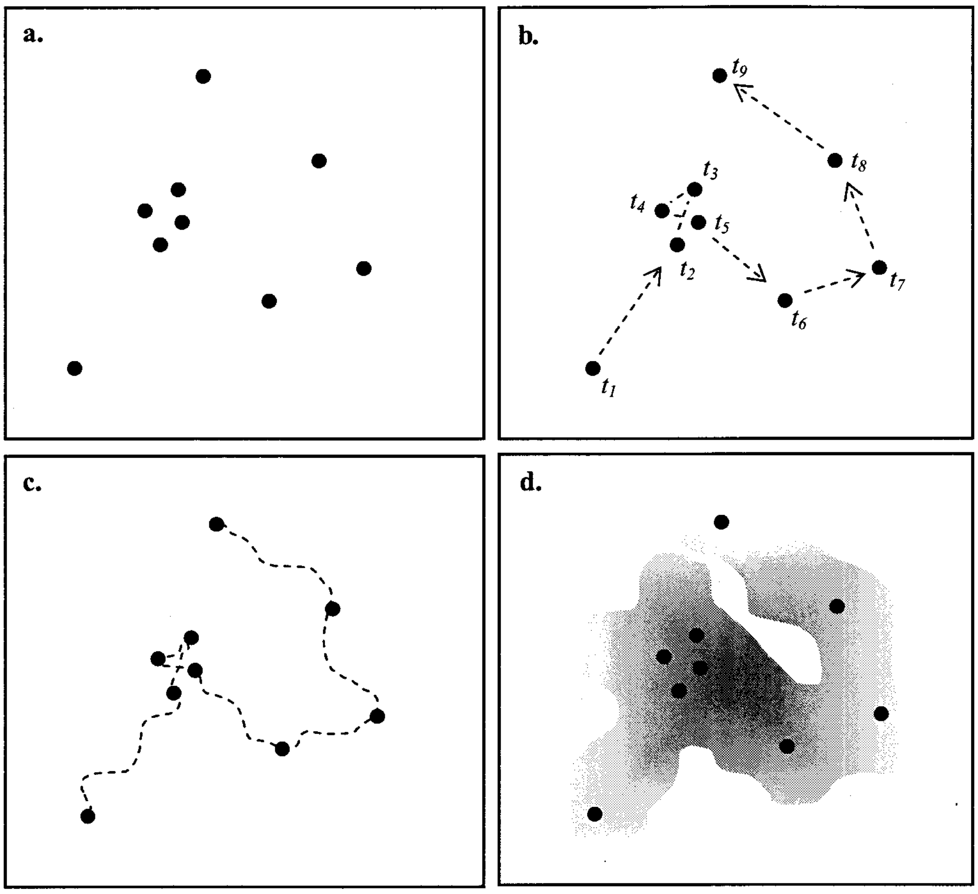
Relationships between movement patterns and processes have received increased attention over the last decade (Tischendorf 1997, With et al. 1999, Zollner and Lima 1999, Johnson et al. 2002, Chetkiewicz et al. 2006, Schick et al. 2008). Movement pattern refers to the spatial composition and configuration of the data itself (Chetkiewicz et al. 2006). Much more complicated is the concept of movement process. Process refers to the way grizzly bears interact within or spatially respond to landscapes, subsequently creating movement patterns (Chetkiewicz et al. 2006). Process-based approaches focus predominantly on inferring how individual-environment interaction influences movement behavior (Schick et al. 2008). It is suggested that progress in movement ecology requires a merging of the two approaches. First, a solid understanding of the movement data is required. Then, approaches which integrate data with behaviorally-based movement models are required.

To understand spatial and temporal movement patterns specific to grizzly bear populations within Alberta, it is important to understand and address individual grizzly bear movements within and across heterogeneous landscapes (Ager et al. 2003). When dealing with large GPS radiotelemetry data sets, one must first understand how spatial movement patterns should be conceptualized. That is, how should we define movement and represent movement in space given a GPS spatial point data set? Second, how should spatial movement patterns be analyzed and what methods are available for linking movement patterns to underlying process? Lastly, can we differentiate between movement behaviors? The following section endeavors to address these questions by reviewing all pertinent movement literature using grizzly bear spatial response as examples where possible.

Pattern-based Approaches

The complexity with which wildlife interact within their environment generates intricate movement patterns (Jonsen et al. 2003). These movements can be accurately mapped as point, vector, or grid-based representations (Figure 2-1). The term movement is used here to describe the process by which individuals are displaced (change in spatial location) in space and time (Turchin 1998, Nathan et al. 2008). As an individual moves through space, a path can be recorded reflecting its past and present positions and its attributes (Wentz et al. 2003). Once understood in these theoretical terms, spatial patterns emerge which reflect real-world processes. When dealing with GPS radiotelemetry data, it is important to first understand movement empirically prior to any model development (Turchin 1998). GPS radiotelemetry data sets can empirically be approached in two primary ways: 1) as individual data locations demonstrating points in space and time (Figure 2-1a), or 2) as vector data representation linking consecutive points across space and time (Figure 2-1b).

Figure 2-1. Diagram of: a) spatial point data, b) vector-based representation of spatial point data, c) least-cost path representation showing simulated movement between known locations, and d) kernel density interpolation of movement based on spatial point data.



Spatial point data typically represent static locations in two-dimensional *x, y* space where each location is characterized by an attribute or measure of the phenomenon being studied. For example, Figure 2-1a may represent the physical locations of individual grizzly bear denning sites in west-central Alberta. With typical point data sets, the main purpose of analysis is to determine whether or not observed events exhibit any systematic pattern or departure from Complete Spatial Randomness (CSR) (Boots and Getis 1988, Bailey and Gatrell 1995). This analytical approach is termed Point Pattern Analysis (PPA). The presence of clustered or dispersed patterns can be recognized using CSR as a null model providing an effective summary of spatial interaction or dependence (Boots and Getis 1988). In the case of GPS radiotelemetry data representing one unique grizzly bear, points that are grouped in space may indicate feeding or selection behavior for a preferred resource patch. As a corollary, GPS locations that exhibit dispersion or regularity may represent searching or travel movement across landscapes. Departure from CSR as a null model is often visually apparent *a priori* (Gatrell et al. 1996). Finally, the use of CSR techniques assumes that the occurrence or position of any point remains independent of the position of any other point (Wiegand and Moloney 2004). This is not the case with moving point data as will be discussed later in this chapter.

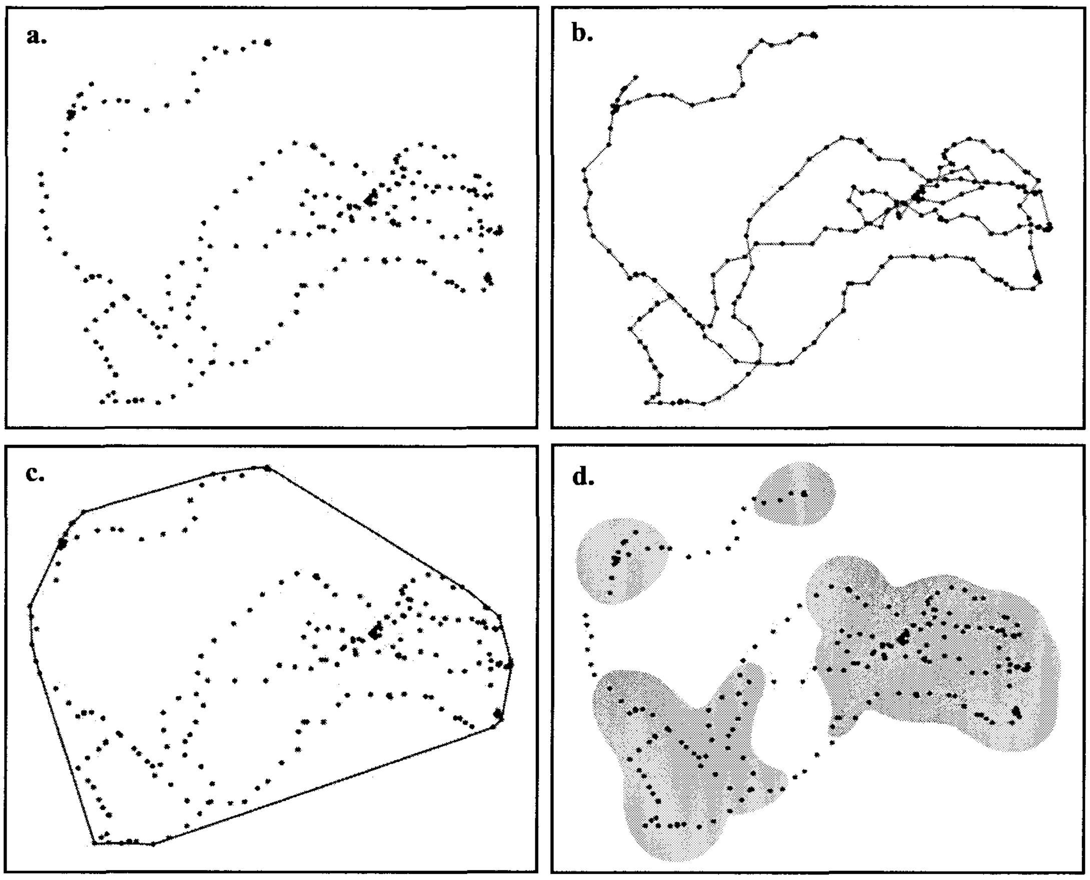
While Figure 2-1a provides information regarding discrete locations, the relationship between individual events, and information regarding event distribution across space, it fails to acknowledge the consecutive nature of moving point data as demonstrated in Figure 2-1b. Now consider an individual grizzly bear moving across two-dimensional space, point events are now recorded intervals represented by physical locations (x, y) with the addition of time (t). Here, the added element of time transforms a spatial point pattern characterized by individual events to a spatial 'movement' pattern characterized by points (recorded intervals) and linkages between consecutive points. Further, as time (t) is recorded sequentially, ($t_1, t_2, t_3 \ldots t_n$), points can be linked in space providing additional information regarding distance and direction. Thus, the spatial movement pattern described by recorded locations from t_1 to t_9 can further be defined as a path or movement trajectory (sequence of consecutive points) containing a series of moves or path segments (Turchin 1998).

Path segments provide quantitative information on time duration, path length, path direction, path velocity, and overall tortuosity between recorded locations. These metrics provide quantitative insight and can be used to parameterize movement rules for the spatially explicit process-based models described in the following section (Turchin 1998, Chetkiewicz et al. 2006).

For grizzly bears, movement is a continuous process. The data in Figure 2-1b provides information regarding geographical locations for t_1 and t_2; however, travel between these points may be convoluted and depends on many unknowns such as individual bear behavior. While visually represented as straight-line connections (Figure 2-1b), for grizzly bears, the analysis of vector plots is typically unrealistic when dealing with data sets where locations are collected across large temporal intervals (e.g. 4-hr separations). As such, empirical methods or pattern-based approaches remain limited in application, restricted primarily to the description of movement rates and delineation of home ranges (Turchin 1998, Amstrup et al. 2000, Amstrup et al. 2001, Rettie and Messier 2001).

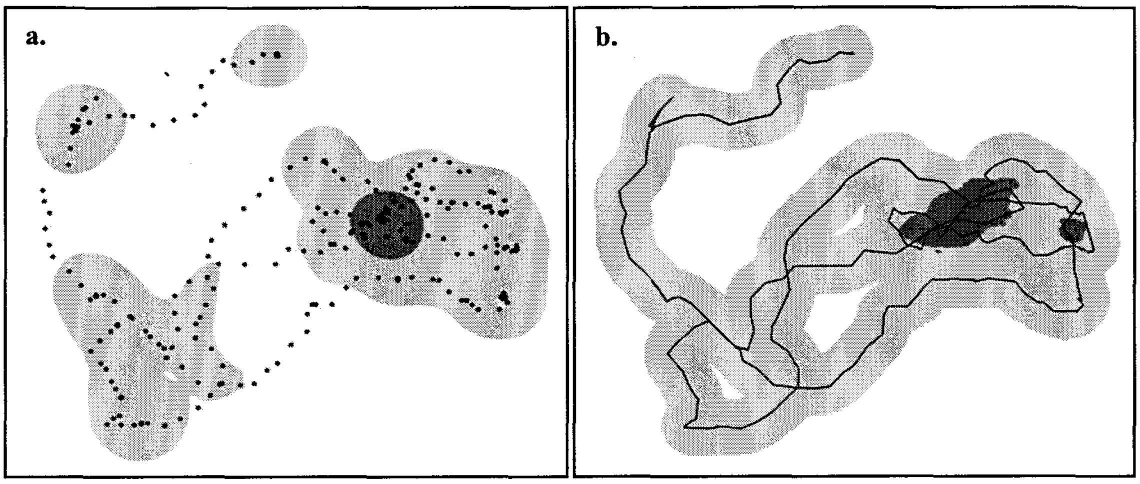
The two most common home range estimators include minimum convex polygon and kernel density estimation home ranges. Minimum convex polygon (MCP) home range delineation is a non-statistical polygon method of estimating spatial usage (Ostro et al. 1999). This approach simply describes the outer limits of each animals movements by connecting the peripheral locations (Worton 1987) (see Figure 2-2c). It has been realized that the use of MCP often overestimates an individual's home range. For example, MCP can include large areas of land which are never visited by the individual, in some cases due to geographic constraint (Worton 1987). They further provide no detailed information regarding internal intensity or usage (Worton 1987).

Figure 2-2. Diagram from bear G216 highlighting: a) GPS radiotelemetry point data set, b) vector-based movement pattern, c) minimum convex polygon home range, and d) kernel density estimation highlighting 95% contour outline.



Kernel density estimation (KDE) is currently the home range technique most widely accepted and applied by wildlife biologist and ecologists (Worton 1987, Kernohan et al. 1998, Matthiopoulos 2003a). Kernel density estimation is a nonparametric approach resulting in a continuous intensity surface which varies across the individual's distribution (Mace and Waller 1997, Berland et al. 2008). KDEs characterize the relative intensity of space use in the form of a probability density function. The most basic use of kernel density estimation is to employ the 95% outline as the home range descriptor and ignore the internal information (Figure 2-2d).

Figure 2-3. Diagram from bear G216 highlighting: a) a GPS radiotelemetry point data set with 50% and 95% kernel outlines, and b) a GPS vector data set with 50% and 95% kernel outlines, generated in ArcView 3.2 with the default ad hoc smoothing parameter.



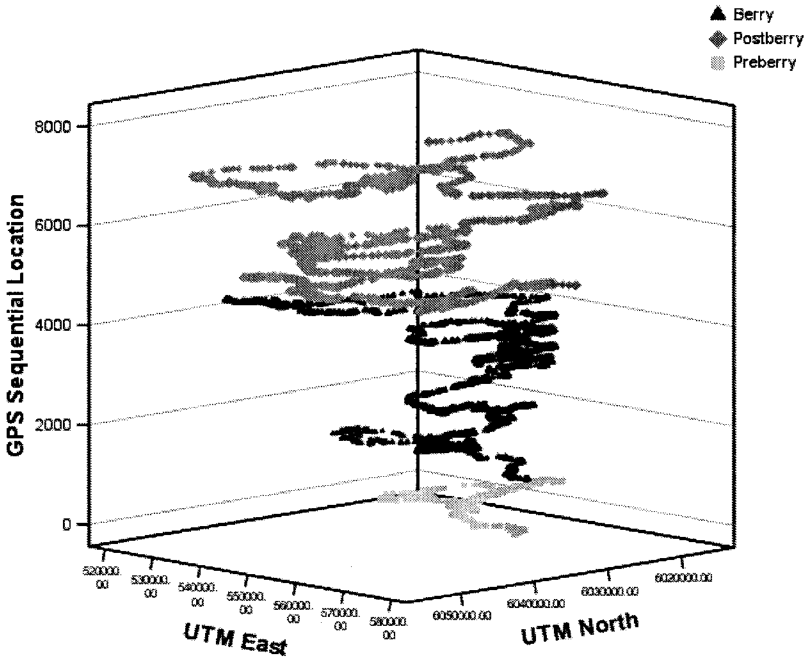
Resulting kernel surfaces can additionally be used to identify 'hot spots' or regions of high usage by an individual or population (Matthiopoulos 2003a). By generating internal contours, such as 50% probability outlines, core areas within an individual's home range can be identified (Figure 2-3a). Hot spots or core areas can then be characterized by extracting underlying landscape properties to determine which factors affect the distribution (or movement) of the study species (Matthiopoulos 2003a).

As animal movements occur in network space as a series of trajectories or paths, it may be more reasonable to create network-based kernel density estimators. The above example (Figure 2-3) compares a point-based kernel home range and a vector-based kernel home range. Both kernel home ranges in this example were generated using the Animal Movement Extension in ArcView 3.2 (Hooge et al. 1999). The above network or vector-based kernel representation (Figure 2-3b) preserved the linear spatial pattern resulting from movement paths when compared to the point-based kernel home range (Figure 2-3a). The resulting vector-based 95% kernel outline is similar in appearance and shape to a standard distance-based or path buffer. In the above example, the resulting outer kernel could be used to identify travel-based movements while the 50% vector-based core area contour would identify foraging-specific movements. If a study is interested in examining home range movement patterns or movement patterns related to landscape properties, it might be more appropriate to choose a vector-based approach like the example above. The only example similar to this approach in the current literature is the Brownian Bridge model presented by Horne et al. (2007).

When dealing with continuous data, there may not be a biologically obvious way to classify or characterize an individual's movement path. Few approaches exist which retain the consecutive nature of GPS data. These vector-based analytical approaches include three dimensional space-time prisms, moving object spatio-temporal data models (MOST), and graph theory models. Of these, space-time prisms are the most easily applied to GPS telemetry data. Hagerstrand (1970) used space-time continuum modeling to conceptualize and diagram where individuals came from and where they were bound at different points in space and time (Baer and Butler 2000). Space-time prisms were employed as conceptual tools for understanding variations in location and mobility (Hagerstrand 1970). A movement path, in Hagerstrand terminology, simply reflects the trajectory of an individual over space and time (Baer and Butler 2000). The potential path area is defined as the interior of the prism which houses all locations in space and time that the individual can occupy (Miller 2005). Baer and Butler (2000) suggest that because grizzly bears have trajectories in space and time, their paths can be modeled in this fashion (Figure 2-4).

The space-time prism can be a useful tool for understanding how the location and mobility of grizzly bears vary over space and time (Baer and Butler 2000). When applied to individual grizzly bears, the approach can provide additional detail regarding internal clustering and spatial patterns within annual home ranges (Figure 2-4). Within the space-time prism, horizontal distance represents geographical dispersion of the individual while vertical distance represents elapsed time. Change from a wide to narrow horizontal distance would indicate a change in behavior. For example, wide horizontal distance suggests large amounts of traveling while a narrow horizontal distance indicates a localized phenomenon, such as feeding (Baer and Butler 2000). The space-time prism technique is exploratory in nature. The approach further offers an alternative to standard boxplots and quantitative summaries as mobility patterns are represented graphically (Baer and Butler 2000). Unfortunately, its large-scale utility is limited. While potentially taking home range explorations to a new level, Miller (2005) states that rigorous analytical and statistical measurement of space-time prisms do not yet exist.

Figure 2-4. Example of a 3D space-time prism for individual grizzly bear G203 showing the potential path area (PPA) as season (preberry, berry and postberry) changes. The space-time prism path begins at the bottom of the graph, progressing upward as sequential GPS locations are added. The vertical spread represents the temporal duration of radiocollar data. The horizontal spread represents the spatial PPA or home range of the individual bear during a given time frame.



Process-based Approaches

This section of the chapter focuses specifically on movement models and approaches for dealing with consecutive data points such as GPS radiotelemetry data. In most cases, movement models examine how patterns in the data correspond with patterns in the environment (Schick et al. 2008). Strategies for analyzing movements range from the simple to the complex and have been applied at varying spatial and temporal scales (Turchin 1998, Chetkiewicz et al. 2006). Organizing movement models into a cohesive and logical progression is difficult. There appear to be multiple paradigms concerning movement ecology (Turchin 1998, Chetkiewicz et al. 2006, Holyoak et al. 2008, Nathan et al. 2008, Schick et al. 2008).

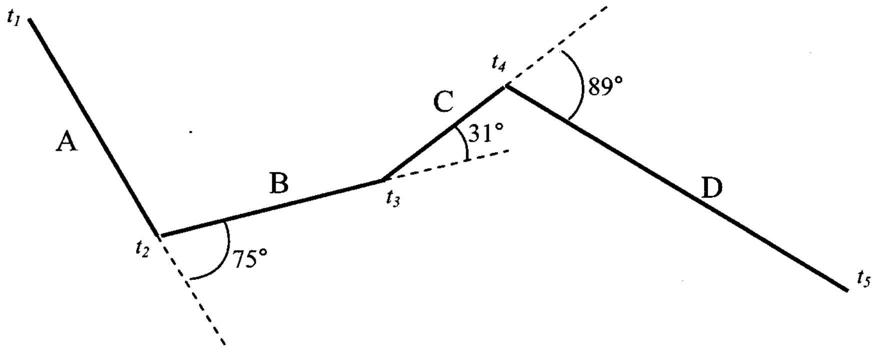
Approaches to understanding and modeling GPS-based movements have previously been classified as: vector versus raster-based approaches (Tischendorf 1997), empirical versus simulation-based movement models (Turchin 1998), Eulerian versus Lagrangian approaches (Turchin 1998), and most recently, non-inferential versus inferential movement models (Schick et al. 2008). Choosing an appropriate classification scheme is difficult given the overlapping nature of the above dichotomies. To reiterate, because this research focuses on previously collected GPS radiotelemetry data, the movement models reviewed here are largely empirically vector-based approaches with specific focus on individual-landscape interactions. The subsequent process-based models are reviewed in a logical progression by which animal movements can be summarized, quantified and then modeled.

As previously mentioned, one of the most recent movement papers suggested that process-based models can theoretically be classified into non-inferential and inferential movement models (Schick et al. 2008). Non-inferential refers to statistical-based approaches which focus on the interaction between individuals and their environment (Schick et al. 2008). Examples of non-inferential vector-based models include fractal analysis, random walk, correlated random walk and step selection function models. These empirically-based approaches characterize movement paths primarily based on their pattern using step length, turning angle, velocity, and fractal dimension (Chetkiewicz et al. 2006). Small-scale simulations are often employed to highlight significant patterns in the data. Further these approaches tend to be popular in large part because of the inherent ability to relate patterns in movement data to patterns in the environment (Schick et al. 2008). More complex approaches include first-time passage models (Frair et al. 2005) and Levy flight approaches (Marell et al. 2002). More recently, researchers have further developed empirically-based models termed multi-behavior or two-process models to distinguish between types of movements, such as foraging or dispersal (Johnson et al. 2002, 2006, Hunter 2007, Schick et al. 2008). Finally, a time series segmentation approach that focuses on vector movement strategies is reviewed (Dettki and Ericsson 2006, Barraquand and Benhamou 2008). These latter technologies and new analytical tools are making it possible to better integrate landscape patterns with behavioral processes (Chetkiewicz et al. 2006).

Inferential movement models address both the state of the moving individual and its response to the state of the map over which it moves (Schick et al. 2008). Small-scale examples of inferential movement models include Hidden Markov models (Franke et al. 2004), and state-space models (Jonsen et al. 2003, Flemming et al. 2006, Barraquand and Benhamou 2008). In these examples animal movements are often simulated over computer generated heterogeneous landscapes. They are computationally intensive and have yet to be applied to large collections of radiotelemetry data as required by grizzly bear research. Instead, this review will focus on large-scale inferential models used to simulate movements across landscapes which include cost-distance models (Adriaensen et al. 2003) and grid-based diffusion models (Blackwell 1997, Horne et al. 2007). Simulation approaches are typically used to identify movement processes over large landscapes where movement data are unavailable, incomplete, or contain substantial error. However, two recent studies have emerged which combine the vector properties of GPS radiotelemetry locations with large-scale GIS grid-based movement models (Graves et al. 2007, Horne et al. 2007).

Moving point data is typically modeled or simulated in one of two ways: 1) as a vector-based model approximating movement paths between patches or known locations (Figure 2-1b and Figure 2-1c), or 2) as a continuous grid-based or density surface demonstrating movement as related to underling landscape surfaces (Figure 2-1d). The majority of empirical vector-based models quantify the patterns as presented by movement pathways (Figure 2-5).

Figure 2-5. Example of vector segment calculations for distance (km), movement rate (km/h), and deviation angle (deg) or turning angle parameters where distance for vector segment A is the straight line distance between t_1 and t_2. Movement rate is calculated by dividing the distance for vector segment A by the time difference between t_1 and t_2. Lastly, deviation angle is the bearing in degrees that the following vector segment (B) deviates from the bearing of vector segment (A) preceding it.



The most straightforward of these is vector distance or step length, turning angle, and movement rate. Resulting movement parameters (small step lengths versus long step lengths) are then compared to specific landscape features. For grizzly bears, long step lengths and small turning angle coupled with high movement rates may indicate directed travel through undesirable habitat (Graves et al. 2007). Understanding these basic parameters of movement for a particular species is an important first step to more complex movement analyses. Further, these basic metrics can be used to parameterize movement rules for spatially explicit models such as those described below (Chetkiewicz et al. 2006).

Approaches which focus on simulating vector-based movements most commonly employ fractal analyses (Crist et al. 1992, Bascompte and Vila 1997, Phillips et al. 2004), random walk models (Schippers et al. 1996, Turchin 1996), correlated random walk models (Kareiva and Shigesada 1983, Bergman et al. 2000, Austin et al. 2004), or step selection functions (Fortin et al. 2005). In all cases, movement length, turning angle and velocity distributions are considered to be indicators of complex behavioral processes (Bartumeus and Levin 2008).

The most straightforward indices, such as net squared displacement, path tortuosity or complexity, and fractal dimension are fairly intuitive (Turchin 1998, Bergman et al. 2000, Wentz et al. 2003, Whittington et al. 2004). They are commonly employed to summarize movement behavior in relation to habitat quality or habitat complexity based on whether the movement path or trajectory is classified as straight or convoluted (Bascompte and Vila 1997, Whittington et al. 2004). For example, path tortuosity or fractal dimension would be influenced by behavioral aspects such as foraging intensity or navigation ability (Whittington et al. 2004, Nams 2005). The attractiveness of using a measure like fractal dimension is that it can be compared across different populations or subgroups by testing for significant differences in the degree of complexity. However, as fractal dimension is an overall summary measure, internal variations related to landscape heterogeneity can be missed (Nams 2005). A more powerful and detailed approach describes individual movements as random walks or correlated random walks (Turchin 1996).

Applying random walks directly to movement data take process-based analyses to the next level. First, an individual (vector movement pattern) is described as a sequence of probabilistic discrete steps expressing its walk under homogeneous or null conditions. Movement is typically broken down into two components: move length and turning angle between successive moves (Tischendorf 1997). The accumulation of these measurements creates a frequency distribution for total step length and turning angle. The step length distribution describes the stochasticity (shape) of the velocity of the moving individual and the convolution of the movement path is expressed by the step angle distribution. To create a random walk model, turning angles and length units are randomly drawn from a continuous uniform distribution (Fortin and Dale 2005) often creating a highly tortuous and circular path (Whittington et al. 2004). The raw movement data are then compared to the simulated random walk model to highlight significant behavioral trends of the species under question.

In reality, individual movements fall somewhere between random walk and directed walks (Tischendorf 1997). By constraining movement between known locations and concentrating movement direction by assuming a non-uniform distribution of turning angles, a correlated random-walk (CRW) model can be generated. CRW models have been quite successful in exploring and simulating the biological or behavioral response of an individual to their habitat (Bergman et al. 2000). For example, straight-line paths often represent large contiguous patches of habitat while highly sinuous paths represent convoluted routes through fragmented and patchy landscapes. Length and direction of the movement steps determine the grain of the simulated organism's response to the landscape (Tischendorf and Fahrig 2000). CRW movement paths are usually characterized by some degree of directional persistence or net direction bias where smaller turning angles are more probable than larger turning angles (correlated move directions) (Turchin 1998, Bartumeus and Levin 2008). While random walk models assume there is no autocorrelation present in sequential step lengths or turning angles, CRW models predict the next step will equal that of the previous step demonstrating a high directional persistence and low path tortuosity (Whittington et al. 2004). CRW models typically can be used to examine first-order autocorrelation for movement length and direction (Fortin and Dale 2005). For example, positive correlation in sequential turn direction can indicate area-restricted habitat searches (Turchin 1998).

The advantage of CRW approaches is that behavioral changes, such as foraging or directed walks, can be analyzed with respect to expected net displacement to test the appropriateness of the model (Turchin 1998, Fortin and Dale 2005). According to Bergman et al. (2000), comparing the observed and predicted displacements can produce three possible outcomes: 1) data can correspond to model predictions indicating directed random movement, or 2) the model may overpredict displacement indicating preference for an area, or 3) the model may underpredict displacement indicating avoidance of an area. Resulting correlated random walk patterns behave like linear movement at very small scales and like random Brownian movement at very large scales (Turchin 1996).

Individual-based models provide an opportunity to identify key variables that influence the movement of animals through space (Boone and Hunter 1996). Further, the results are often used to create movement models which aim to incorporate movement behavior (Jerde and Visscher 2005). According to Turchin (1998), the above approaches provide more descriptive statistics that are useful for summarizing organism dynamics but lack the spatial explicitness to describe large-scale movement patterns. Movement pathways which span long time periods are likely to contain complexities that are difficult to compare directly to a random walk model or correlated random walk model (Jonsen et al. 2003). For example, a CRW model can fail to describe movement across larger scales due to changes in individual movement behavior (Morales and Ellner 2002). This transferability is important for grizzly bear research which requires movement models to be applied across large landscapes. Finally, the major assumption of the CRW model is that move lengths (and by extension movement rate) and turning angles are not autocorrelated (Austin et al. 2004). This type of autocorrelation (evident in fine-scale grizzly bear data, see Chapter 3) is the primary reason for rejecting the use of CRW models (Turchin 1998). An extension of random walk models more applicable to current grizzly bear research are least-cost path models or linkage zone models.

More recently, extrinsic biases to animal movements have been evaluated using step selection function (SSF) models (Fortin et al. 2005, Coulon et al. 2008). Similar to a CRW model, random steps are generated from distributions of length and turning angles observed from many individuals. The observed and random steps are then contrasted using a conditional logistic regression similar to that found in a resource selection function (RSF) models (Nielsen et al. 2002). Resulting steps with a higher SSF score will have increased odds of being chosen by the animal (Fortin et al. 2005). The approach is novel because it employs vector steps (segments separating successive locations) rather than location or areal data (Coulon et al. 2008). The utilization of vector-based steps results in an understanding of the landscape characteristics the path will encounter between known points. However, no studies have yet attempted to distinguish between types of movement using this approach. For example, while results presented by Coulon et al. (2008) state that movements do not occur randomly in space and that distance to roads had the largest effect on roe deer movements, the study was unable to state whether individuals moved faster or slower relative to certain features. Despite the various limitations, these type of models serve as learning tools to assess how movement behavior varies from random (Johnson et al. 2006).

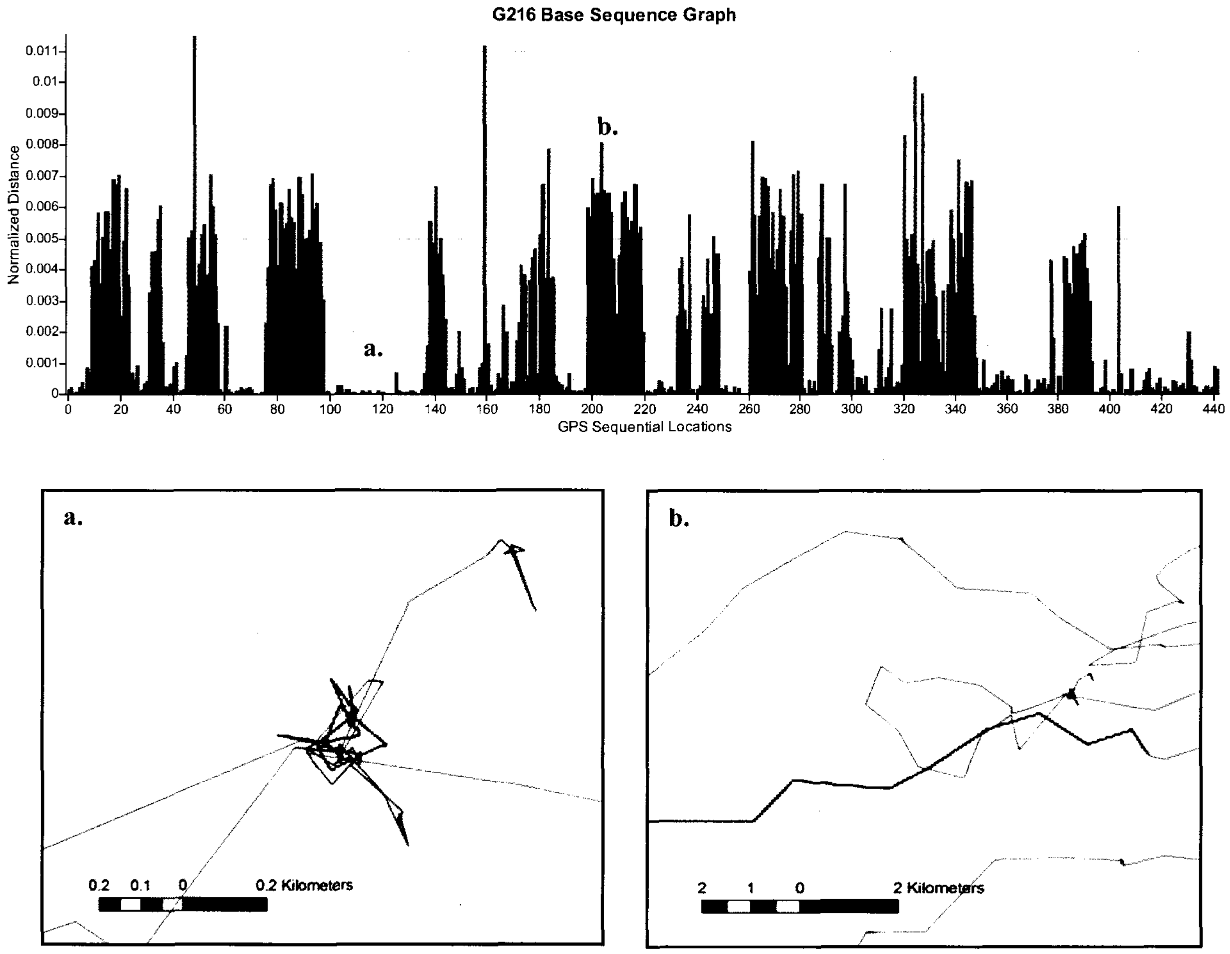
Somewhere between pattern and process-based approaches falls the empirical assessment of distinguishing between types of movement behavior. Movement studies require nonlinear methods because animal behaviors or changes between behavioral states are inherently nonlinear (Jonsen et al. 2003). Both two-process curve fitting behavior models (Johnson et al. 2002, Hunter 2007) and time-series models (Dettki and Ericsson 2006) are capable of describing such nonlinearities. These efforts focus primarily on using GPS-based vector movement rates to establish scalar or discrete types of movement. For example, by partitioning grizzly bear movement into fast movement or locomotion movement and foraging or specialized movement it is possible to account for more variation in model parameters (Hunter 2007). Activity levels are assumed to follow a bimodal frequency distribution where slow movement behaviors (resting, sleeping, prolonged foraging) are close to zero and active behaviors (travelling) are relatively high in comparison (Gervasi et al. 2006).

Recently, studies have employed a non-linear two-process curve fitting model to differentiate types of movement behavior (Johnson et al. 2002, 2006, Hunter 2007). This technique fits a nonlinear concave function to the log transformed frequency distribution of movement velocities. Major inflections or natural breaks along the curve provide a method to differentiate or identify a threshold between movement types or processes. More frequent slow movements occur on the steep phase of the function while fast movements occur on the tail (less steep portion) of the function (Johnson et al. 2006). Studies using this approach assume that small, slow and large, fast movements correspond to within (foraging) and between habitat patch (travel) movement behaviors. Unfortunately, establishing a dichotomy between movement types is a complicated generalization of real movement behaviors. For example, an individual may travel to a new place and forage along the way (Nams 2005). This is quite often the case for grizzly bears. In such cases, a three-process model identifying foraging, searching and traveling behavior would be needed (Johnson et al. 2002, Hunter 2007). However, previous attempts to identify a third-scale of movement were not successful by either study. Further, while able to identify distinct scales of movement, this approach does not retain the consecutive nature of the data. Continuous path data that provides information regarding animal behavior along that path is needed (Hunter 2007).

Direct observation of an individual's movement path may be the most powerful method for quantifying movement patterns (Horne et al. 2007). A time series is a collection of observations made sequentially in time. While commonly used in economic forecasting or stock market analysis (Chatfield 1980), the approach has recently been applied to GPS radiotelemetry data sets (Dettki and Ericsson 2006). Records of animal movement are rarely continuous and a typical data set consists of time-ordered sequences of coordinate pairs separated by known time intervals (Matthiopoulos 2003b). When observations are taken at predetermined intervals (typically equally spaced), the time series is said to be discrete (Chatfield 1980). A time series graph can be used to visualize descriptive measures as well as highlight internal patterns in the data such as sequential temporal clusters related to speed, distance or some other quantitative characteristic of the data in question (Dettki and Ericsson 2006). Further, using time series analysis provides an opportunity to assess serial or temporal autocorrelation in the vector data structure (Chatfield 1980).

In the below example, a time series graph has been generated for an individual male grizzly bear (Figure 2-6). The resulting graph structure visualizes the complete movement trajectory using normalized distance to describe vector characteristics. Low normalized distances occurring below < 1.0 mean standard deviations were coded as short movement vectors (Figure 2-6a). All remaining vectors were coded as fast movement vectors (Figure 2-6b). Further, sequential clusters with similar values were highlighted to demonstrate consecutive vectors with related speeds. Both visually and through the use of basic table analysis it is possible to identify internal vector clusters within the time sequence graph. By partitioning the data into foraging and travel vectors, future modeling efforts can account for more of the variation found within movement data structures (Dettki and Ericsson 2006). Lastly, by directly linking the graph structure to raw data in a GIS environment, individual grizzly bear movement patterns can be compared visually and quantitatively to underlying landscape properties.

Figure 2-6. Example of a time series sequence graph for male G216 with a normalized distance threshold < 1.0 standard deviation below the mean normalized distance demonstrating the separation of a) slow movements, and b) fast movements with related spatial vector patterns.



Slow movement vector pattern

Fast movement vector pattern

Large-scale grid-based movement models have been developed where knowledge about landscape features and individual movements can be combined in a spatial context (Tischendorf 1997). For grizzly bears, the development of GIS cost-based models for movement simulations across larger landscapes have received considerable attention (Boone and Hunter 1996, Walker and Craighead 1997, Clevenger et al. 2002, Larkin et al. 2004, Kindall and Manen 2005, Graves et al. 2007). These models generally take the form of either least-cost path (LCP) models or linkage zone (LZM) models. The most common approach is to create underlying spatially explicit habitat models to identify movement corridors or linkage zones across large landscapes (Clevenger et al. 2002, Singleton et al. 2004). Both models rely on underlying grid surfaces to simulate the most likely pathway or movement zone for moving individuals to travel from a start location to a destination. Permeability or cost surfaces are generated by classifying available habitat into categories reflecting the resistance value to movement (Boone and Hunter 1996, Larkin et al. 2004). Higher values equate increased resistance while lower values are intended to promote movement across the landscape. Resulting movement routes (vector or grid-based) reflect the most suitable habitat and fewest surmountable barriers (Larkin et al. 2004, Kindall and Manen 2005). When used in a GIS environment, least-cost path models can facilitate the identification of barriers and corridors important to animal movement (Clevenger et al. 2002). However, these models are primarily landscape driven and while useful for assessing potential movement patterns, cost-distance approaches often lack sensitivity testing and validation against empirical data (Boone and Hunter 1996, Driezen et al. 2007). Larkin et al. (2004) admit their use of least-cost path analysis is subjective at best.

More recently, Graves et al. (2007) combined vector-based GPS movements with GIS techniques to identify primary habitat and functional corridors for brown bears in Alaska. This approach used movement path characteristics (path density, speed and angular deviation), rather than vegetation and landscape structure, to determine functional travel corridors (Graves et al. 2007). It was assumed that movement paths in primary habitat would be dense, slow, and sinuous as grizzly bears search for food or rest. The study further assumed movements to be constrained, linear and faster in landscapes with fragmentation or fewer resources indicating a travel corridor

(Graves et al. 2007). Movement parameters were transferred to grid-based landscape surfaces and reclassified into either primary habitat patches or highly functional bear corridors depending on cell value. Results reported the best discrimination between classes when locations were sampled at 6-h intervals using a search radius of 1,000 m and a cell size of 500 m. The approach as presented is useful for identifying large-scale landscape functionality as used by GPS-collared bears in the study region (Graves et al. 2007). It was suggested that for fine-scale location data a smaller cell size and search radius would be needed. There was no report of movement rate characteristics in this paper.

One of the most interesting papers related to analyzing animal movements with specific reference to bears was recently published by Horne et al. (2007). The authors developed a Brownian bridge movement model for estimating the expected movement path of an animal between consecutive data points. A Brownian bridge is a continuous-time stochastic model of movement in which the probability of being in an area is based on the time, distance, and mobility between successive pairs of locations (Horne et al. 2007). The approach is akin to modeling an animal's utilization distribution for a period of observations (Horne et al. 2007). The resulting Brownian home range (similar to its kernel counterpart) highlighted multiple centers of activity as well as likely "connections" via pathways between the areas of frequent use. It was reported that this is likely a result of the models mechanistic basis which estimates the home range by modeling the animal's expected movement path (Horne et al. 2007). Movement path uncertainty is directly incorporated via the mobility parameter and the measurable location error. While a sophisticated new approach for analyzing an individual's home range with emphasis on movement, the approach did not differentiate between types of behaviors. For example, a similar approach could be reached using a vector-based kernel estimator to identify a movement home range. According to Horne et al. (2007) incorporating estimates for different behaviors could more accurately depict animal movements.

As this chapter has reviewed, most pattern-based analyses employ a data driven approach which aim to make inferences about underlying processes. For example, empirically-based measures provide a simplified understanding of the behavioral process generating a resulting movement pattern. In movement simulations, long displacements and nearly straight paths are assumed to represent highly permeable patches while short displacements and convoluted or tortuous paths indicate low permeability patches or search behaviors (Boone and Hunter 1996). Often, these approaches are too specific in their application thus limiting transferability (Barraquand and Benhamou 2008). An additional problem is that no two studies can effectively employ the same set of assumptions. Due to the inherent uncertainty in model frameworks, comparisons across studies become difficult (Table 2-2).

Table 2-2. Summary of movement model approaches with emphasis on GPS moving point data.

	Empirical Assessment		**Simulation Models**
	GPS Point Data	GPS Vector Moving Data	Continuous Movement Data
1st Order Approaches (Global, Pattern)	Quadrat, nearest neighbor, minimum convex polygons, kernel density analysis	Net displacement, tortuosity, fractal dimension, space-time prisms, network KDEs	GIS-based corridor models, linkage zone models, least-cost path models
2nd Order Approaches (Local, Process)	Ripley's *K*, O-ring statistic, Moran's I_i, Getis	RW, CRW, SSF, two-process behavior models, time series models	Diffusion, state-space models, combined vector-grid GIS models
	Non-inferential	→	**Inferential**

Moving point data or spatial movement patterns require additional analytical techniques beyond those currently offered by point pattern analysis. These include both measures and techniques which acknowledge consecutive data structures and the inherent temporal component of GPS data. More specifically, a process-based model driven by empirical data will provide an opportunity to test model sensitivity to changing parameters and resulting patterns of vector-based movement representation. Extensive telemetry data sets further provide researchers with an opportunity to explore the nature of consecutive vector data. These approaches step beyond the simpler exploration of movement patterns and begin to integrate the underlying process. Only a few of the previously reviewed approaches examined actual changes in movement rate or velocity. Further, maintaining the integrity of consecutive movement data is rare and not often considered or incorporated. Yet, two studies promote the importance of this approach through the use of time series analysis (Dettki and Ericsson 2006, Barraquand and Benhamou 2008).

2.4 GPS Data Challenges

GPS Data Uncertainty

Working with GPS radiotelemetry data introduces issues regarding spatial (positional), temporal and attribute (characteristic) error. Despite significant improvements to the technology, error remains inherent in animal movement data (Frair et al. 2004). Two primary types of error can bias analyses and results based on GPS locations: spatial location error and missed location fixes (Frair et al. 2004, Lewis et al. 2007). Studies have shown that steep slopes, slope orientation, dense forest canopy, collar brand, and animal behavior (collar position) can all contribute to a reduction in GPS data acquisition and location accuracy (Frair et al. 2004, Gau et al. 2004, DeCesare et al. 2005, Sundell et al. 2006, Heard et al. 2007). Studies have further explored the influence of measurement error on habitat selection (Rettie and McLoughlin 1999, Frair et al. 2004, Lewis et al. 2007) and movement parameters (Jerde and Visscher 2005, Ganskopp and Johnson 2007).

GPS radiotelemetry data is much more accurate today than it was previously. Prior to selective availability, Mace and Waller (1997) reported an average error of 150 m. Since 2000, most studies report stationary GPS locations to be accurate to within approximately 30 m. However, when dealing with moving point data mean error values have been reported to range from 14.3 m (Lewis et al. 2007) up to 55.0 m (Hunter 2007). Lewis et al. (2007) recorded a mean location error of 14.3 m however this result varied substantially within different habitat groups. Hunter (2007) calculated an average estimated horizontal error of 55.0 m ranging from 17.7 m to 329.3 m.

Large amounts of location error or spatial inaccuracy can result in the misclassification of habitats or bias estimates of movement paths. Habitat classification accuracy is dependent on the amount of location error and the degree of landscape heterogeneity (Frair et al. 2004). Spatial inaccuracies are further influenced by habitat type and amount of habitat cover. For example, one study documented a positive trend between increasing canopy closure and GPS error (DeCesare et al. 2005). Specifically, error distances (up to 8 m from the true path) were found to be larger and more variable under high canopy closure forests. It has been suggested that buffering individual points will help to capture portions of habitat type missed by location error (Rettie and McLoughlin 1999). However, the use of buffers will also contribute habitats that potentially did not influence resulting animal behaviors (Frair et al. 2004).

The second type of error inherent in GPS radiotelemetry data is missed fix acquisitions directly resulting in missing data points. According to Friar et al. (2004) this problem has largely been ignored. Even slight underrepresentation will have significant effects on ecological models (Heard et al. 2007). Missed fixes can result in large time gaps making it difficult to get detailed movement paths. Gaps in time sequence often result from collar failure or failure of the collar to acquire satellite signals in mountainous terrain or dense canopy cover (Lewis et al. 2007). For example, Heard et al. (2007) found that as canopy cover increased the probability of obtaining a fix decreased. Further, closed conifer and deciduous forest types reported large negative effects on the probability of acquiring a GPS location (Frair et al. 2004). Heard et al. (2007) also reported an interaction effect between collar orientation and canopy cover. Therefore, it can logically be assumed that GPS locations will be underestimated in areas with dense forest or high canopy cover – especially when grizzly bears are resting there and collars may not be upright. However, if an individual is resting for significant amount of time in high canopy cover, the pattern should still be identifiable.

Collar brand, type, and year of construction will further contribute to both fix acquisition rate and spatial accuracy (Frair et al. 2004, DeCesare et al. 2005). Previous work by Friar et al. (2004) tested 3 different collar types and found the Televilt brand radiocollar to have a lower probability of acquiring GPS radiotelemetry locations than ATS or Lotek collars. Overall, mean rates of successful location attempts ranged from 68% to 98% depending on collar brand (Frair et al. 2004). Another study recorded GPS Lotek collar fix rate for 10 individual black bears ranging from 89% to 96% (Lewis et al. 2007). Of note, moving fix rate was only 7.3% lower than the fix rate recorded for stationary test collars (Lewis et al. 2007). Lastly, a previous study of Televilt Simplex collars recorded a mean success rate of 65% (Gau et al. 2004). It's important to note that direct comparisons between studies are not realistic given they were conducted in different study regions with different years of data. The construction and functionality of radiocollars today has evolved considerably over earlier models circa 1999 – 2001 (G. Stenhouse, personal communication).

When screening location data, there is a trade-off between data accuracy and data reduction. To reduce data error, studies often initiate a GPS Dilution of Precision (DOP) cut-off threshold. Lower GPS DOP values result from a widely dispersed satellite array yielding a higher level of positional accuracy (Ganskopp and Johnson 2007, Lewis et al. 2007). As DOP is related to location error, it has been suggested that locations with a high DOP (greater than 6) be removed from the data sets (Ganskopp and Johnson 2007, Lewis et al. 2007). Of course, by removing data to reduce location error, the decreased number of data points itself may add other bias in the resulting GPS data set.

In effort to better understand the quality of GPS radiocollar data used in this dissertation, I conducted a simple comparison of both mean DOP value and the proportion of location fixes. Collar performance (grouped by collar type – T. Simplex, ATS or T. Tellus) was compared for all bears across all years by assessing GPS fix success rate. Overall GPS fix success was calculated as:

$$\frac{(\text{scheduled fixes per day} \times \text{total \# of days})}{\text{\# of actual fixes recorded}} \qquad \text{(Equation 2.1)}$$

For all collar types, capture success rate ($F_{6,143} = 2.81$, $P = 0.013$) and DOP ($\chi^2 = 33.403$, df = 6, $P < 0.001$) were significantly different across years. More specifically, 1999 recorded the highest mean capture success rate (mean = 0.70, SE = 0.04), while 2003 (mean = 3.63, SE = 0.09) and 2005 (mean = 3.56, SE = 0.16) recorded the lowest or best DOP scores. Overall, capture success rates when grouped by collar type were found to be moderate, recording on average between 51% and 62% of total scheduled GPS events (Table 2-3). Capture success rate ($\chi^2 = 8.96$, df = 2, $P = 0.011$) and DOP ($\chi^2 = 78.12$, df = 2, $P < 0.001$) were significantly different for each collar type.

Table 2-3. Success rate and average dilution of precision (DOP) score by collar type (n = 150) from 1999 to 2005.

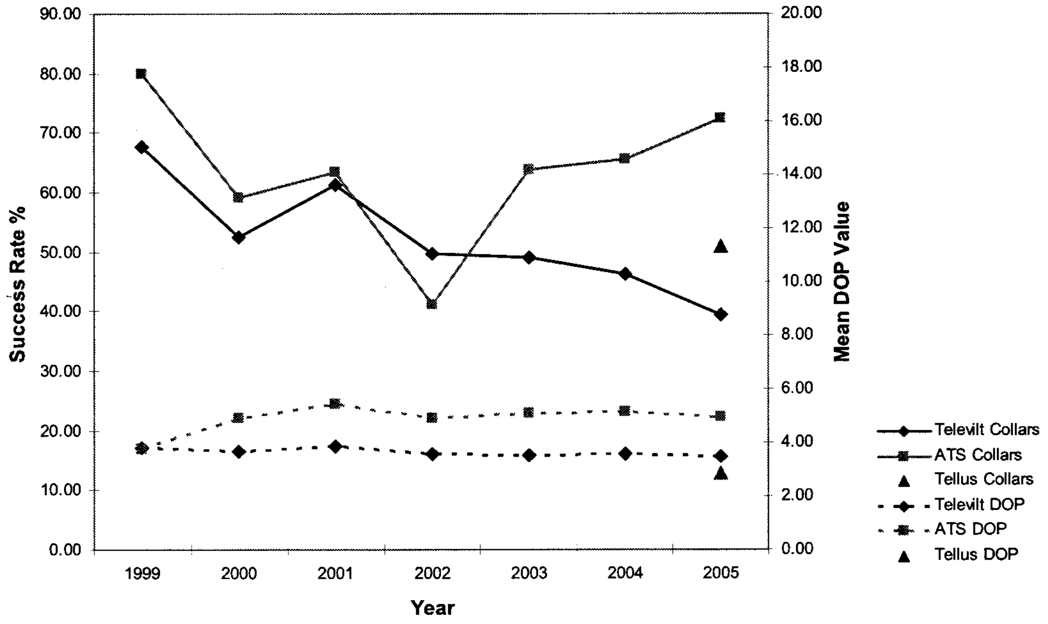
Collar type	**1999**			**2000**			**2001**			**2002**		
	n	Success %	Mean DOP	*n*	Success %	Mean DOP	*n*	Success %	Mean DOP	*n*	Success %	Mean DOP
T. Simplex	9	67.6	3.79	12	52.6	3.69	14	61.2	3.84	15	49.6	3.55
ATS	2	79.9	3.78	7	59.2	4.91	5	63.5	5.43	4	41.2	4.89
T. Tellus	-	-	-	-	-	-	-	-	-	-	-	-

Collar type	**2003**			**2004**			**2005**			**Overall Mean**		
	n	Success %	Mean DOP	*n*	Success %	Mean DOP	*n*	Success %	Mean DOP	***n***	**Success %**	**Mean DOP**
T. Simplex	27	49.2	3.52	24	46.3	3.57	11	39.4	3.5	**112**	**50.7**	**3.61**
ATS	2	63.9	5.11	3	65.6	5.15	5	72.4	4.95	**28**	**62.2**	**4.97**
T. Tellus	-	-	-	-	-	-	10	51	2.86	**10**	**51.3**	**2.93**

ATS collars were found to capture approximately 10% more data locations ($P = 0.027$) than Televilt Simplex or Televilt Tellus brand collars. However, ATS collars were also found on average to have higher DOP values (Figure 2-7). This result suggests that while ATS collars successfully retrieve more GPS radiotelemetry location, the quality of the data was generally worse. Televilt Tellus collars ($n = 10$), after 1 year of deployment were found to have the best or lowest mean DOP (mean = 2.93, SE = 0.11, $P < 0.001$). No direct correlation between DOP and capture success rate was found. It is important to note that complexities of data capture related to habitat type were not analyzed as part of this study.

Results from various studies have found that habitat selection bias via GPS-based animal locations can result in type II errors and therefore bias model parameters or coefficients (Frair et al. 2004). Statistical corrections for GPS bias require knowledge of both the canopy cover and the behavior of the individual animal (Heard et al. 2007). Estimating correction factors is difficult at best, especially when dealing with large landscapes and populations. Results from a Monte Carlo simulation demonstrated that estimates of turning angle and step length are accurate only when the distance between two locations is large relative to the measurement error (Jerde and Visscher 2005). However, results from one study found that uncorrected data exhibited remarkable accuracy for estimating distance between adjacent coordinates of moving GPS collars (Ganskopp and Johnson 2007). The study states that distance error measurements (overestimates and underestimates) will likely compensate for one another over time equaling zero as long as movement segments exceed normal position error (Ganskopp and Johnson 2007). According to Johnson et al. (2002), using movement rate or velocity, as opposed to distance, will help to standardize variation in sampling interval due to occasional missed fixes and slight differences in acquisition time, as well as differences in collar scheduling.

Figure 2-7. Average success rate and dilution of precision (DOP) score by collar type (*n* = 150) from 1999 to 2005.



Temporal and Spatial Autocorrelation

Another fundamental consideration of moving point data is the presence of spatial (geographical) and temporal (serial) autocorrelation between locations. The presence of spatial autocorrelation and time to independence or temporal autocorrelation has particular implications for studies based on GPS radiotelemetry data (Rooney et al. 1998). The primary premise when working with GPS radiotelemetry data is that locations must be statistically independent to achieve valid results (Otis and White 1999). For example, methods for estimating home range or utilization distributions assume the locational observations to be independent (Worton 1987). Autocorrelation is a measure of whether closer events are more likely to have similar magnitudes (Fortin and Payette 2002). Simply described, if autocorrelation is high then the ability to predict an individuals position based on its last position is also high (Rooney et al. 1998). Because a movement path or trajectory is modeled as a continuous, stationary, stochastic process, it is by definition an autocorrelation function (Otis and White 1999). Therefore, moving data descriptions such as distance or movement rate will be correlated and thus are not considered statistically independent. This lack of spatial and temporal independence has typically been viewed as a problem in ecological studies (Liebhold and Gurevitch 2002).

In geographic research, spatial autocorrelation is more commonly addressed in research studies when compared to temporal autocorrelation (Christman 2007). Positive spatial autocorrelation refers to nearby locations of GPS observations which have a similar magnitude than those randomly placed in the study area (Dale et al. 2002, Fortin and Payette 2002). As a corollary, negative spatial autocorrelation exists when nearby events are dissimilar. Understanding the degree of spatial association or autocorrelation in the data, allows the researcher to determine the level of spatial dependence. If observations are clustered then estimates may be overly precise and biased as the values are not stochastically independent from one another (Legendre 1993, Flahaut et al. 2003). It is generally considered that ignoring autocorrelation results in misleading conclusions including an increase in type I errors (i.e. tests are declared significant when they are not) (Fortin and Payette 2002, Diniz-Filho et al. 2003, Martin et al. 2008). For example, the presence of positive autocorrelation will lead to the underestimates of standard errors thereby producing a false increase in model precision (Legendre 1993, Aarts et al. 2008).

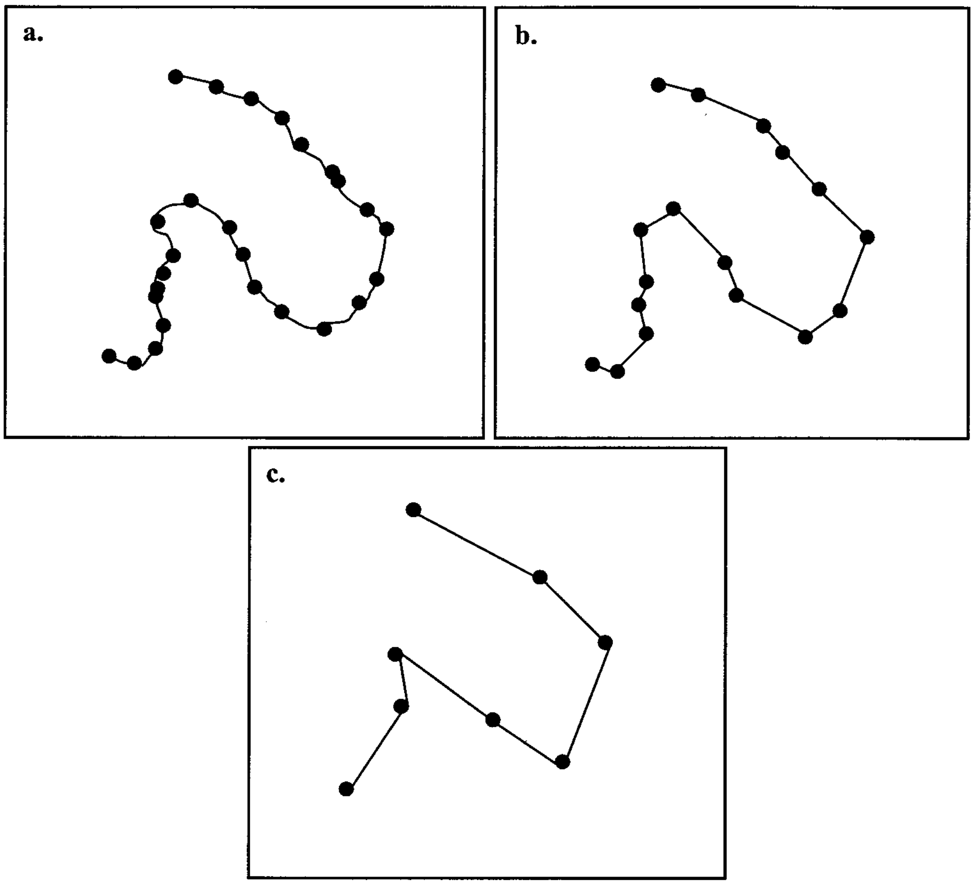
Previous studies have suggested that spatial autocorrelation in the data be avoided or minimized. The most common practice is to employ a random sampling regime in an attempt to ensure that consecutive GPS locations are independent of each other (Rooney et al. 1998, Liebhold and Gurevitch 2002). For example, in effort to eliminate autocorrelation associated with telemetry data, Dahle and Swenson (2003b) excluded GPS locations < 100 hours for individual bears while Chruszcz et al. (2003) excluded locations < 10 hours for individual bears. Efforts for dealing with spatially autocorrelated data specifically in bear research vary considerably, if addressed or mentioned at all.

Methods employed to quantitatively assess the amount of spatial autocorrelation in a data set can be classified as either global measures or local measures. Global measures quantify spatial autocorrelation by computing a single value for the entire data set (Boots 2002). Local measures quantify variations in spatial autocorrelation within the data set or study region. The most commonly employed global indices include Moran's I and Geary's c. Both approaches assume stationarity, meaning that the underlying process should have roughly the same parameter values (mean and variance) for the entire study region (Wagner and Fortin 2005). They further assume that the spatial autocorrelation value at different spatial distances or lags is also similar over the entire study region (Wagner and Fortin 2005). Often, ecological processes (movement) are nonstationary resulting in the mean and variance of a variable changing across a study region. In such cases, local indices of spatial autocorrelation are used. These include local Moran's I_i and local Getis G_i for example. Local spatial statistics are used to detect clusters of either high or low spatial autocorrelation values.

Due to the automation of GPS collection, moving point data are further characterized by temporal or serial autocorrelation between successive locations (Martin et al. 2008). Defined, serial autocorrelation is the phenomenon where the position of an individual at time $t + \Delta t$ is not independent of its position at time t. The most straight forward method of assessing temporal autocorrelation is to calculate the time to independence using rate of movement (Rooney et al. 1998). Time to independence is most commonly achieved by subsampling the data set until autocorrelation in the data is eliminated (Fortin and Dale 2005). In most cases, the resulting subsampled data set is then used for all future statistical analysis. There is usually no way *a priori* to determine what the time to independence will be. Approaches such as time series analysis can be used to characterize the autocorrelation properties of vector movement segments using parameters such as step length, turning angle, or velocity.

Some studies state that autocorrelation between GPS radiotelemetry locations is not entirely undesirable as it contains relevant information regarding movement patterns and behavioral characteristics (Cushman et al. 2005, Martin et al. 2008). Due to the consecutive nature of GPS location data, the resulting data sets are often characterized by short intervals between successive locations. Points closer together in space and time have higher levels of autocorrelation (Figure 2-8a). As moving data is increasingly subsampled to remove autocorrelation in the data (Figure 2-8c), resulting movement patterns will be significantly underestimated (Rooney et al. 1998). By subsampling, the quality of data and usefulness may be severely compromised (Ostro et al. 1999).

Figure 2-8. Diagram showing a) example of detailed movement data with high degree of spatial autocorrelation, b) example of current spatial moving data set, and c) example of generalized movement data with reduced levels of spatial autocorrelation between GPS locations (after Turchin 1998).



One potential solution to this problem would be to study the internal spatial structure of the movement trajectory to identify patterns of non-stationarity prior to data resampling (Martin et al. 2008). For example, when a grizzly bear changes its behavior during the monitoring period, the mathematical properties of the steps may change accordingly (slow versus fast). This type of non-stationarity in bear behavior results in varying levels autocorrelation across the total length of the movement trajectory (Figure 2-8a). By subsampling the data and breaking down the total trajectory important information and trends in movement behavior may be lost (Figure 2-8c). The inclusion of autocorrelated data in GPS-based studies can provide added knowledge regarding animal movement patterns and resulting movement models (Martin et al. 2008). It has further been suggested that an adequate sample size may be more important than achieving independence between points (Seaman et al. 1999).

Vector Data Uncertainty

A major concern when working with moving point data is that GPS radiotelemetry is only sampled at discrete moments in time. In addition to location error, researchers must also consider vector uncertainty. Interpolating a path or trajectory between known points has been approached in a variety of ways (Shi and Liu 2000, Wentz et al. 2003, Miller 2005, Pfoser et al. 2005). Two primary concerns regarding movement path creation are 1) the individual doesn't follow a directed line between two points, and 2) our inability to observe the movement pathway continuously. Advances are being made on both fronts. There are a few GIS-based studies dedicated to moving objects and assessing the uncertainty associated with positional accuracy (Wentz et al. 2003, Miller 2005).

The most standard approach to dealing with vector uncertainty when working with vector-based movement data (Figure 2-9a) is to use error bands or distance-based buffers (Figure 2-9b). For example, a distance buffer is intended to represent the potential area over which an individual may have ranged between locations (Johnson et al. 2002). This approach is further used to counter the potential location bias associated with collar failure. The buffer is typically superimposed on the landscape and the underlying landscape properties are extracted for assessment. Often vector-based buffers are employed when the successive locations are separated by large time periods and the potential for error increases. One study, Johnson et al. (2002), employed circular buffers (based on the distance of each vector segment) between successive locations greater than 3 hours apart (Figure 2-9c). As demonstrated below, as the vector distance increases, the resulting circular buffer is also increased to account for additional uncertainty between known points. A more realistic interpretation of an error buffer for moving point data is the directional error ellipse (Shi and Liu 2000, Miller 2005).

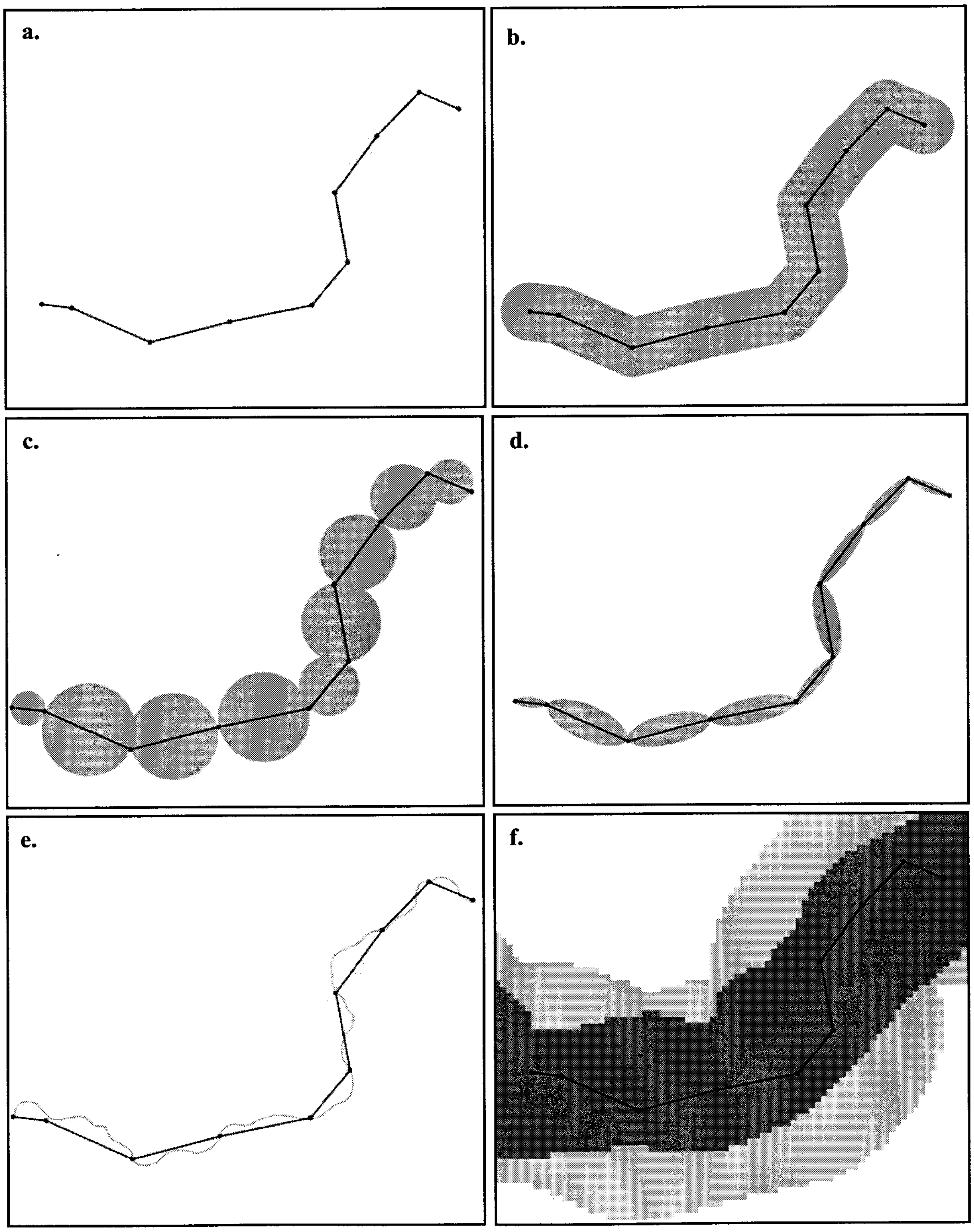
To accommodate mobile objects, Miller (2005) proposed a moving object spatiotemporal (MOST) model to estimate movement possibilities between two sample locations. The MOST data model represents the area within which movement can occur as a lens-shaped region or ellipse between the two sample locations (Figure 2-9d). This ellipse or lens demonstrates the uncertainty at a point in time over a given time interval between the two known events (Miller 2005). The ellipse region is intended to represent the maximum possible travel extent for each individual vector segment. Similar to the circle buffer approach, as the vector distance between known locations increases the corresponding ellipse will also increase in size. While an interesting framework for dealing with moving vector data, the approach has yet to be transferred to a working GIS environment. Further, an alternative consideration is that as an individual moves further, faster, and more directed distances, the uncertainty associated with vector placement will decrease. The result is that the error buffer would be smaller in width rather than larger.

Other approaches include using a least-cost path approach or constrained random walk approach (Figure 2-9e) to model the missing data between two known points in a modeling environment (Wentz et al. 2003). The former involves relating movement to underlying landscape properties and the latter incorporates direction change and altering speed of travel between known locations. Both approaches require large amounts of extremely fine-scale data for validation. Further, the parameters governing the resulting movement paths are species specific and difficult to transfer due to individual movement behaviors. For example, Wentz et al. (2003) discovered that a standard Euclidean straight-line model performed better for one species of monkey, while the constrained random walk performed better for the other species of monkey. Regardless, path interpolations were found to represent reasonable approximations of missing movement patterns (Wentz et al. 2003).

A more applicable buffer choice would be a probability density function created for each individual line segment (Shi and Liu 2000, Pfoser et al. 2005). This technique would create similar results to a point-based kernel density estimator. A resulting vector-based density surface will result in higher probabilities at the vector location and lower probability values as distance from the vector location increases (Figure 2-9f). Resulting kernel movement bands will vary depending on the smoothing value and cell size used. The approach has the ability to add variability to commonly used stationary buffers. It further has the ability to be applied over large landscapes with limited computational difficulty.

Geographic movement parameters such as resulting vectors and related movement rates (velocity) are always measured with inherent error and limited precision in reality (Miller 2005). One critical question suggested by Miller (2005) is, how does error and uncertainty propagate through inferred entities (e.g. movement representation) and relationships (movement paths over landscapes)? The representation of moving point data as a space-time path is currently poorly validated in landscape ecology and wildlife biology. Due to computational limitations, the approaches reviewed here provide more of a visual representation of movement than an actual reflection of real-world movement. The appropriate choice for movement research depends largely on the scale of analysis and the questions being asked.

Figure 2-9. Conceptual diagrams highlighting different approaches to dealing with vector uncertainty: a) GPS point and vector data set, b) standard vector buffer, c) vector circle buffer based on distance, d) directional ellipse or lens buffer, e) least-cost path or correlated random walk approach, and f) vector-based kernel density estimation.

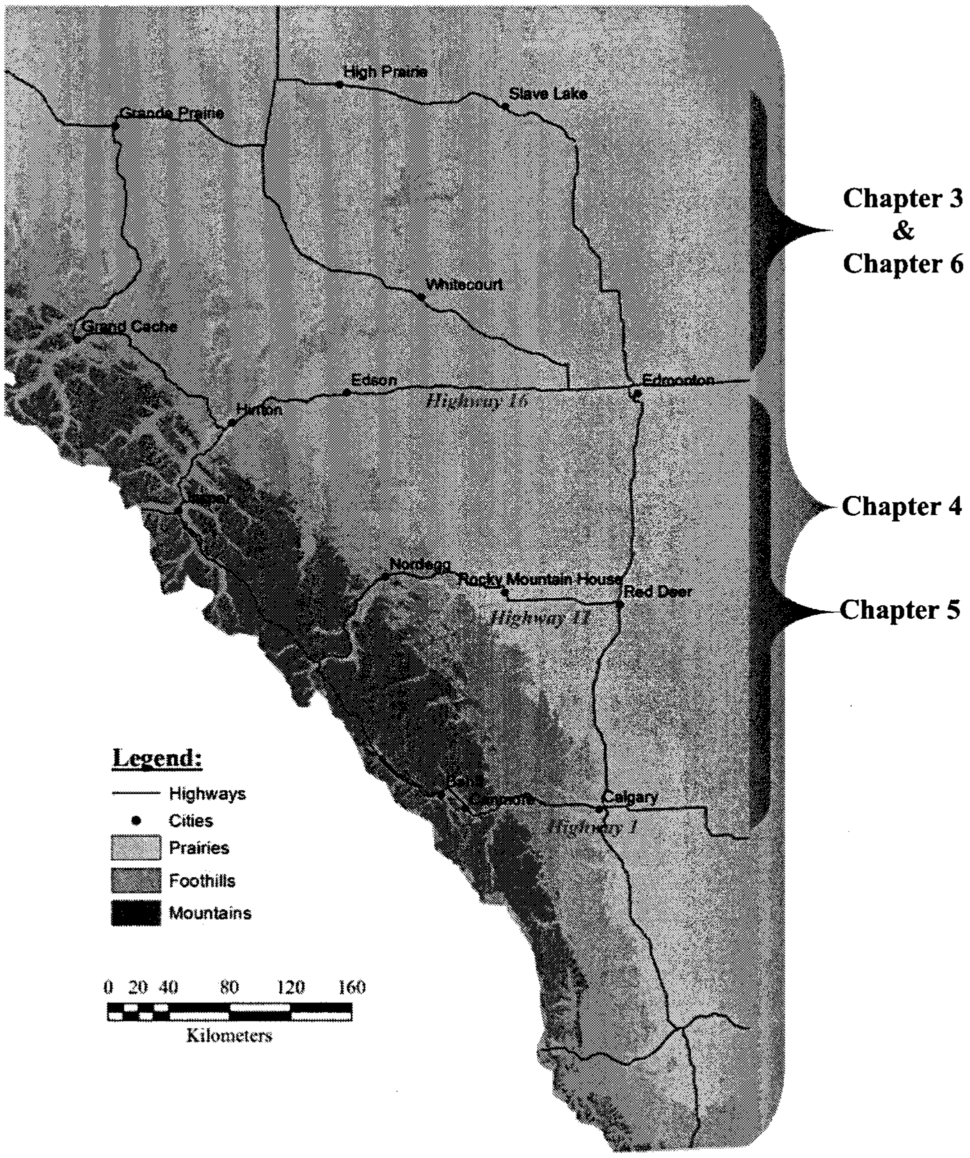


2.5 *Linking GPS Data with Supplementary Data*

GPS telemetry data alone doesn't inform researchers which types of landscape elements are being used and which are being avoided. To truly understand how grizzly bears exist within landscapes, it is important to study the interaction between landscape properties and grizzly bear spatial response. Very few examples exist which examine the relationship between vector-based movement rate and landscape properties. As such, there is no clear understanding of how to approach this question. As reviewed, various options exist although few appear to work with large amounts of GPS radiotelemetry data over large landscapes.

Supplementary data commonly used to describe grizzly bear occurrence include land cover or vegetation classification maps (Franklin et al. 2001, McDermid 2005), vegetation indices such as greenness or canopy cover, elevation or terrain ruggedness, distance to riparian areas, distance to forest edge, distance to roads or road density, and more recently, resource selection function maps (Nielsen et al. 2002). As this research project and related grizzly bear GPS radiotelemetry data encompass a large portion of Alberta (Figure 2-10), the following chapters are in part reliant on the large-scale remote sensing products created by the FRI mapping team. Mapping products produced and supplied by the FRI will be reviewed here in detail and then utilized within subsequent chapters as needed. Figure 2-10 highlights the specific research areas according to chapter. Chapter 3 and Chapter 6 both focus on a small region north of Highway 16. Chapter 4 encompasses the entire front range of the Rockies from the south to the northwest corner of the map. Lastly, Chapter 5 focuses on the main west-central portion of Alberta ranging from Highway 1 in the south to Highway 16 in the north.

Figure 2-10. West-central Alberta, Canada study region showing major highways with mountains (dark grey), foothills (medium grey), and prairies (light grey); where the majority of Alberta grizzly bears were captured and radiocollared between 1999 and 2005. Specific study regions are labeled to show regions for individual chapter analyses.



Supporting data can be classified into line, polygon, point or grid data layers. Vector layers included human-use linear features such as major highways, secondary and gravel roads, seismic lines, railway lines, pipelines and powerlines (Figure 2-11). Natural landscape features included river features and polygon water features (Figure 2-12). The only point data layer used in this research was well site locations (Figure 2-12). Available grid data layers included: landcover classification, resource selection function, crown closure, species composition, elevation, slope, aspect, and vector ruggedness maps (Figure 2-13 to Figure 2-15).

All raster surfaces had a 30 m cell resolution. The study area land cover classification layers were generated using an object-oriented classification of Landsat TM satellite images (1999-2002) combined with topographic variables, GIS vegetation inventories, and field ground-truth sites. A total of 10 land cover classes were identified: upland trees, wetland trees, upland herbs, wetland herbs, shrubs, water, barren land, snow/ice, cloud, and shadow (Franklin et al. 2001, McDermid 2005). The overall accuracy of the base-level land cover map when compared to field sites was recorded at 91.8 % (Kappa = 0.904) (McDermid 2005). The original 10 land cover classes were reclassified to 7 land cover classes using the crown closure to identify open and closed forest types (Table 2-4).

Table 2-4. Original 10 land cover classes modified into 7 land cover classes used in large-scale and fine-scale movement analyses.

Land cover classes	**Modified land cover classes**
Upland trees	Open forest (0-50) Closed forest (50-100)
Wetland trees	Wetland forest
Upland herb Wetland herb	Herbaceous
Shrub	Shrub
Water	Water
Barren Snow/Ice Cloud/Shadow	Non-vegetated

Resource selection function surface (RSF) maps were created for the project by Scott Nielsen (Nielsen et al. 2002, Nielsen 2005). Input data layers included habitat classes, species composition, crown closure, distance to forest edge, distance to open edge, compound topographic index, and grizzly bear GPS locations. Roads were not used in RSF model creation as they tended to be correlated with a number of habitat elements. Final RSF surfaces use population-level coefficients to estimate the presence or relative probability of occurrence for grizzly bears on the landscape (Nielsen 2005).

Both species composition and crown closure were created as continuous grid surfaces ranging from 0% to 100% using generalized linear models (McDermid 2005). Crown closure was measured as the canopy gap fraction for each 30 m pixel where a high crown closure value indicated a closed or dense forest canopy. Alternatively, species composition was measured as the proportion of conifer trees within each 30 m pixel. A low species composition indicated a homogeneous broadleaf forest stand and a high species composition value indicated a homogeneous coniferous forest stand. Values ranging from 20% to 80% indicated varying levels of mixed forest.

Slope and aspect grid surfaces were derived from a digital elevation model (DEM) grid surface for the province and supplied by the FRI. Subsequently, using this baseline topographic information a vector terrain ruggedness measure (VRM) surface grid was also created (Sappington et al. 2007). Topographic variability or terrain ruggedness is a multivariate representation of terrain incorporating the heterogeneity of slope and aspect variables. The script was available online from the Environmental Systems Research Institute Arcscripts website: (www.esri.com/arcscripts). Further descriptions can also be found in Sapptinton et al. (2007).

Figure 2-11. Examples of provincial linear features showing a) highways and secondary highways, and b) seismic lines and herbaceous linear features, such as pipelines and powerlines.

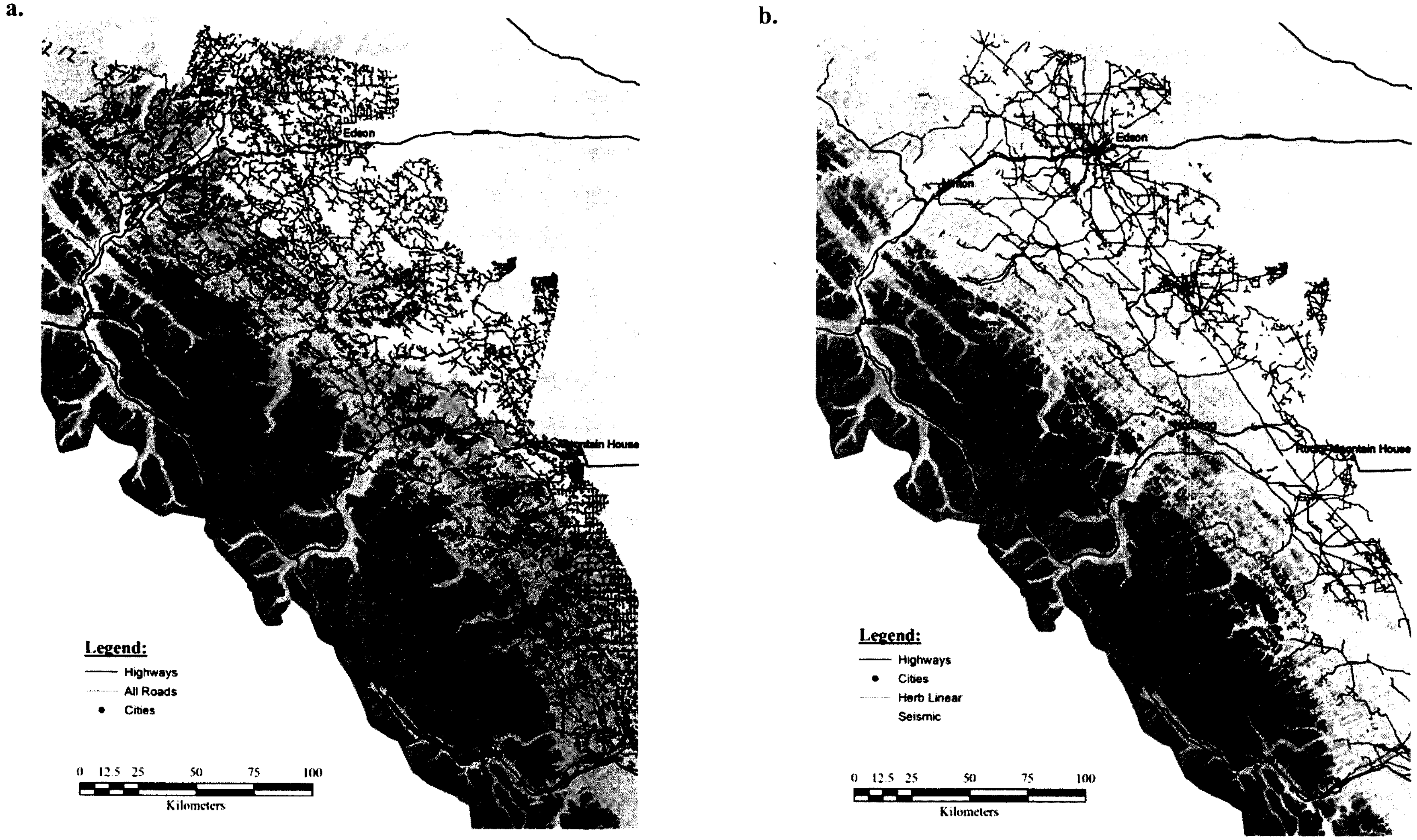


Figure 2-12. Provincial a) line and polygon water features (rivers and lakes), and b) point location oil and gas wellsites.

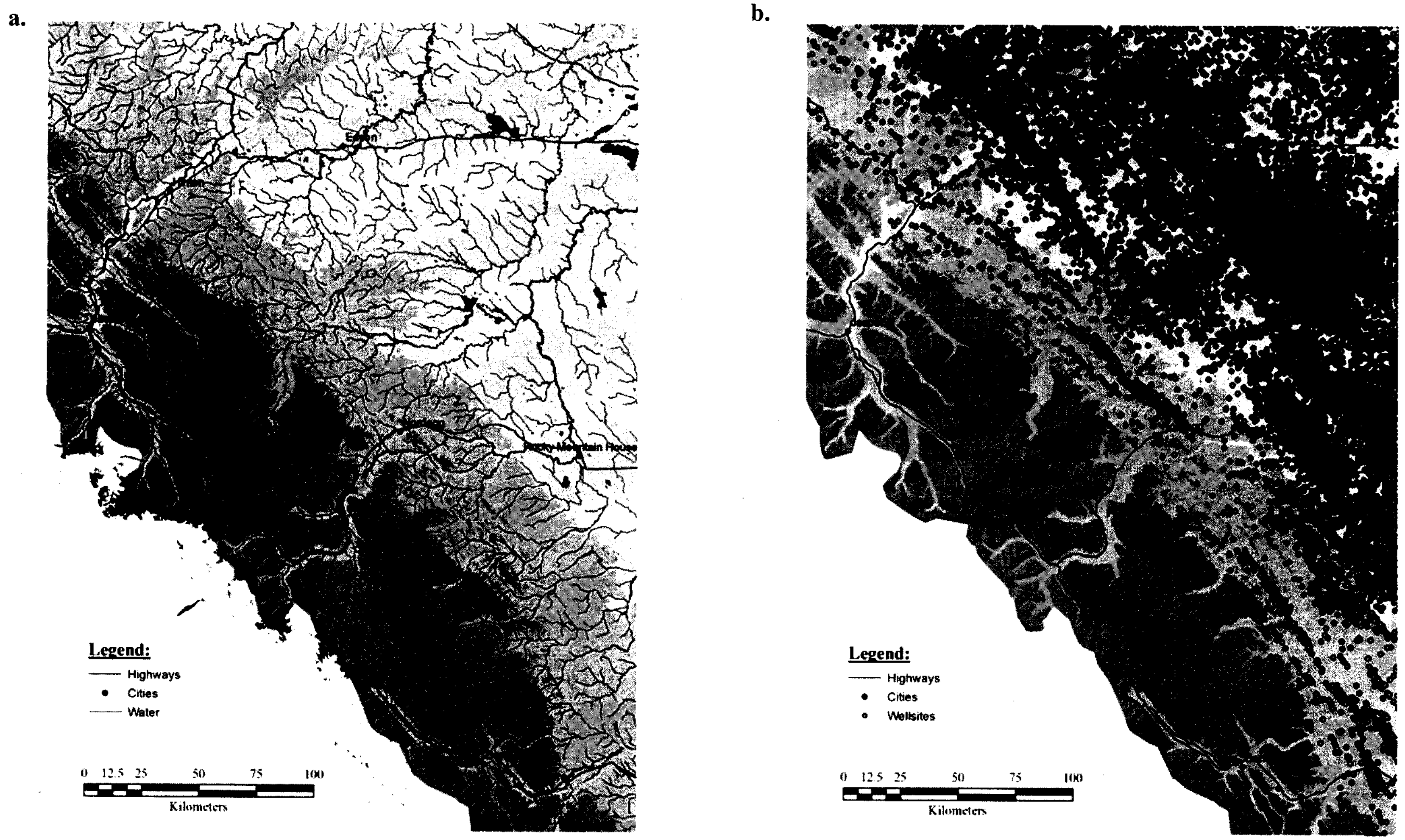


Figure 2-13. Remote sensing grid generated surfaces showing a) land cover classifications, and b) a resource selection function grizzly bear habitat preference map.

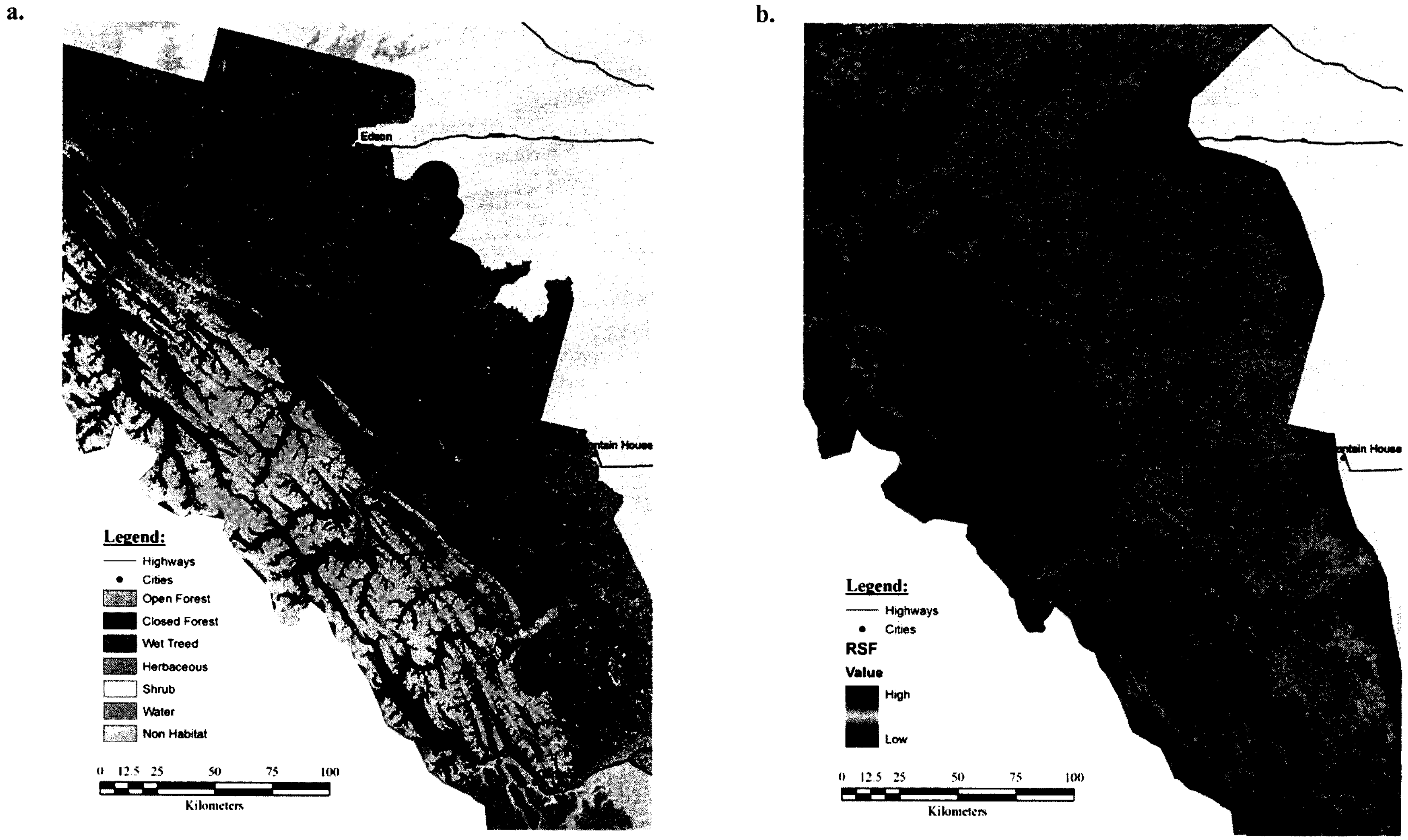
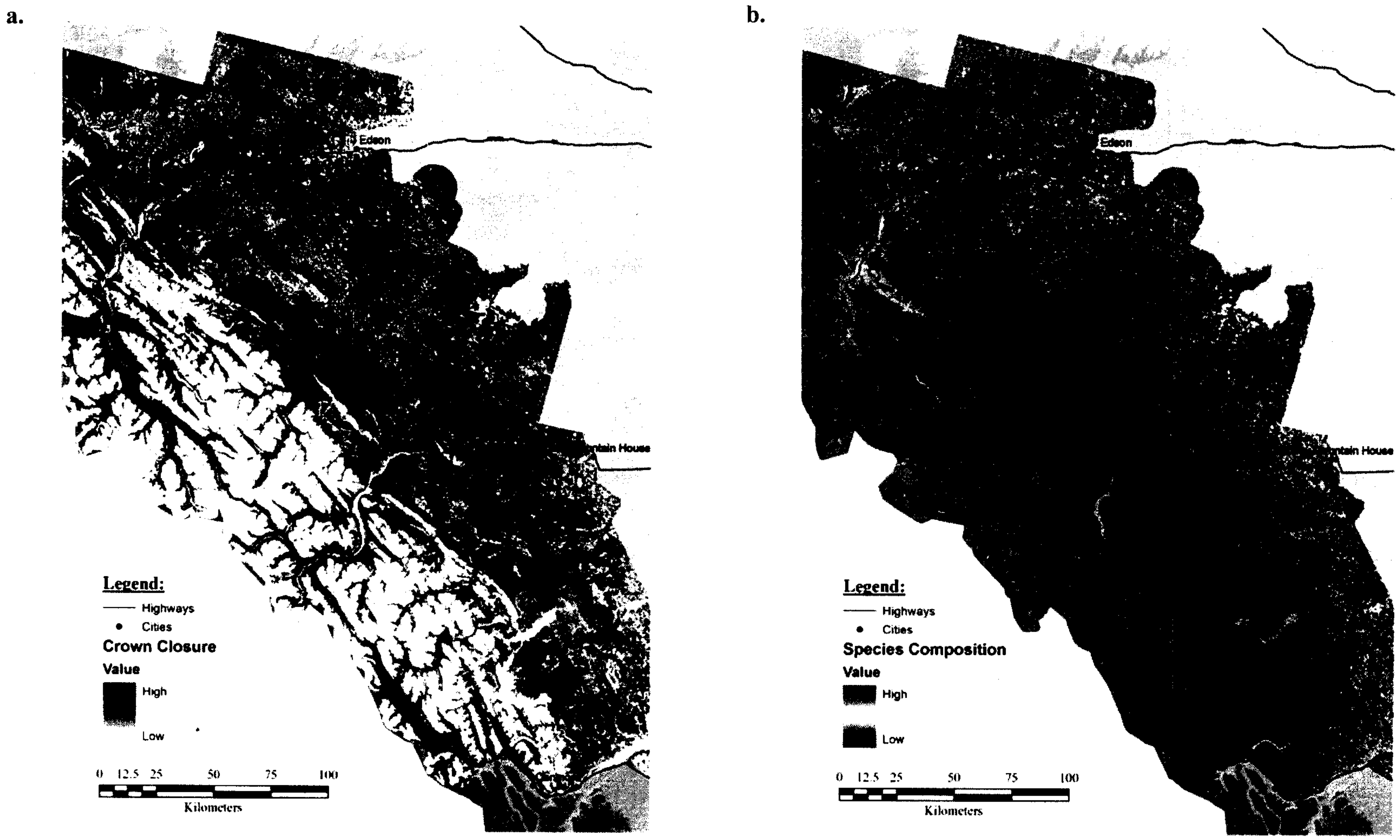
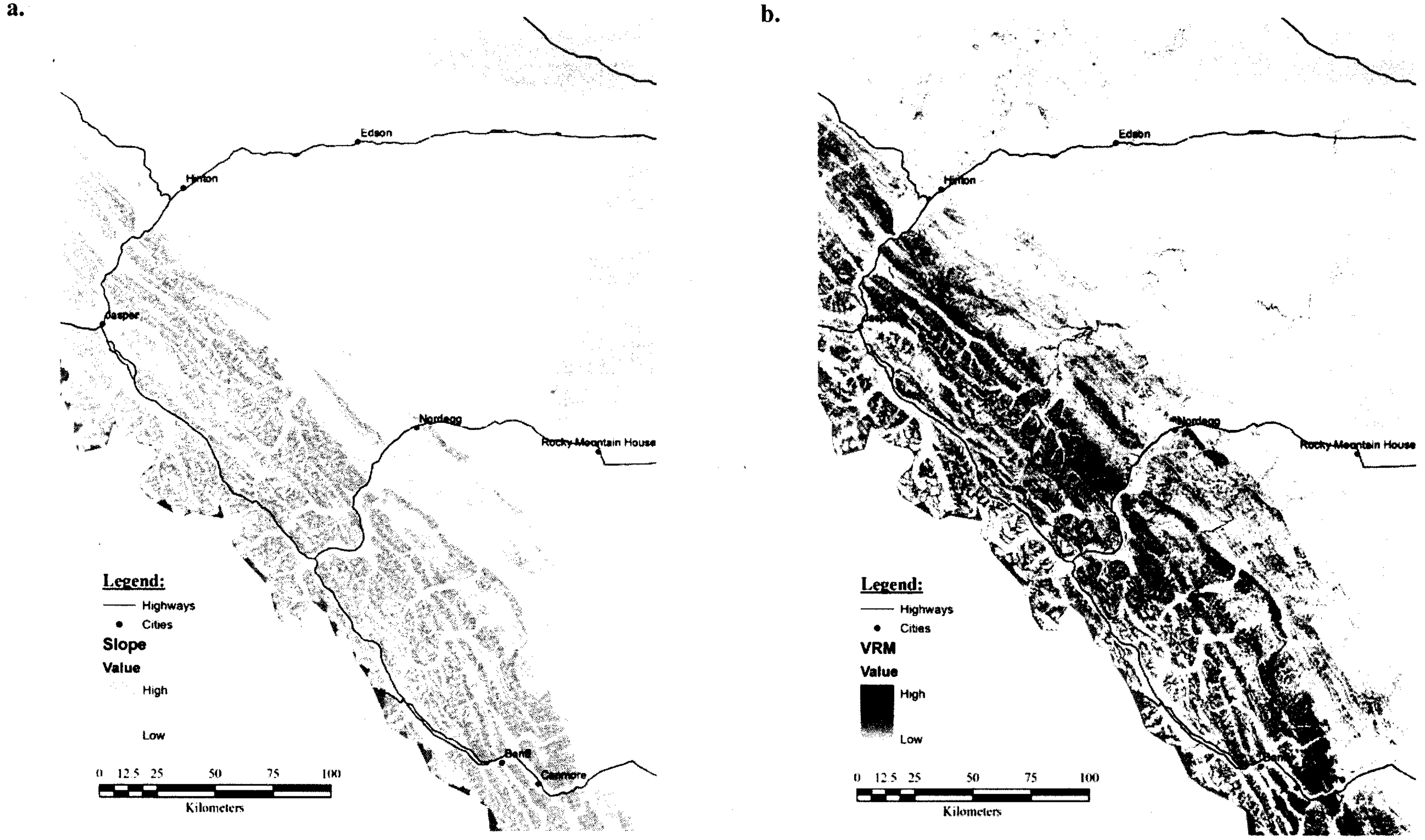


Figure 2-14. Remote sensing grid generated surfaces showing a) forest crown closure, and b) vegetation species composition maps.


a.

b.

Figure 2-15. Remote sensing grid generated surfaces showing a) an elevation derived slope map, and b) and elevation, slope and aspect derived vector ruggedness map.



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CHAPTER 3 – EXPLORING GPS-BASED VECTOR MOVEMENT CHARACTERISTICS IN RESPONSE TO CHANGING TEMPORAL DATA COLLECTION SCALE

3.1 Introduction

The ability to analyze and model grizzly bear movements and habitat use is strongly tied to the spatial and temporal scales of data collection (Morales and Ellner 2002). For grizzly bears, large temporal data collection intervals usually limit analyses to home range delineation, broad-levels of habitat use, dispersal or annual movements, and average daily movement rate (White and Garrott 1990). With the advancement of Global Positioning Systems (GPS) over recent years, the temporal frequency at which telemetry location data are collected has greatly improved resulting in data sets which are physically larger, more detailed, more accurate, and more evenly sampled. With improved finer-scale data sets, researchers can now explore changes in movement behavior, detailed habitat use, and spatial response to underlying landscape characteristics (Berland et al. 2008). However, the choice of an appropriate sampling interval remains poorly understood (Johnson et al. 2006). Wildlife may not respond to the landscape at the spatial scale of data collection (Nams et al. 2006). This chapter endeavors to explore the relationship between data sampling rates and the ability to address and answer wildlife research questions appropriately. For example, is it appropriate to examine bear activity and movements based on hourly, 4-hour, daily, or weekly time sampling intervals?

While GPS technologies have improved our ability to collect large amounts of individual movement data (Jonsen et al. 2003), researchers are still left with the difficult problem of how to study and quantify a continuous process based on static points in space and time (Turchin 1998). Commonly, GPS receivers are programmed to retrieve locations at discrete intervals providing snapshots of locations over time which the researcher can then translate into vector movements. At the most basic level, each path is a sequence of points characterized by their temporal and spatial coordinates (Turchin 1998). The standard approach is to generate a straight-line or Euclidean connection between sequential data points as discussed in Chapter 2. As such, knowledge of where an actual movement path occurred between these locations is unclear and depends on many unknowns, including individual behavior (Sundell et al. 2006, Hunter 2007). There is considerable room for discrepancy and error when the process of movement between locations is assumed (Flemming et al. 2006, Ganskopp and Johnson 2007, Hunter 2007). This uncertainty will increase or decrease depending on the temporal and subsequently spatial detail of data collection (Graves et al. 2007).

The detection of spatial patterns is directly tied to spatial and temporal scale (Fortin and Dale 2005). The appropriate or optimal temporal scale for data collection depends on the question being asked by the researcher and the subsequent analysis being conducted. For example, grizzly bears will select for and move through habitats at various temporal and spatial scales depending on time of day or characteristics of the landscape (Nams et al. 2006). Wildlife research and analyses are often conducted without any prior knowledge regarding the appropriate time interval best suited to the research being conducted. Concern arises when working with calculated vector-based movement parameters. Previous studies have highlighted that movement rate is biased by sampling interval (Johnson et al. 2006, Nams 2006b). For example, if we sample a movement path more intensively, we record more detail and the corresponding movement rate increases (Johnson et al. 2006, Graves et al. 2007). Furthermore, if recorded radiotelemetry locations are significantly under sampled, then the information required to make correct inferences regarding behavioral response may be absent (Turchin 1998). To my knowledge no studies currently exist which have examined the effect of data collection interval on grizzly bear movement characteristics, temporally or spatially.

The primary focus of this chapter will be to measure the impact of changing temporal scale on resulting spatial movement patterns. For example, how will varying the temporal scale of data collection affect information regarding grizzly bear spatial response using vector data representation and movement rate as indicators? Beginning with the finest-scale of data available (in this case, 20-min data) provides an opportunity to determine the appropriate time interval for data collection. The process of data resampling can be conducted by incrementing either the spatial or temporal resolution of the data set (Turchin 1998). As GPS data is commonly programmed to record locations at equal temporal intervals, it is easier to vary the temporal scale rather than the spatial scale of the data (Turchin 1998). For example, if a radiocollar is programmed to collect a point every hour, the data can then be resampled by selecting every fourth data point or one point every 4 hours. In this chapter analysis will be broken down into the following four sections according to two scales (global and local) of analysis: 1) global vector summary properties, 2) global vector distribution comparisons, 3) local one to one vector segment comparisons, and 4) local sequential vector data comparisons. Results reported in Section 3.4 will provide information regarding the amount of data necessary to answer specific wildlife-based research questions pertaining to the study of grizzly bears. The results will further directly influence what GPS radiotelemetry data sets are used in the upcoming chapters.

3.2 Study Area and Supplementary Data Layers

The research study area for Chapter 3 was situated along the eastern slopes of the Canadian Rocky Mountains (Figure 3-1). The specific region falls within west-central Alberta just north of the Yellowhead Highway or Highway 16 which runs east west in orientation. As demonstrated in Figure 3-1, 1 individual grizzly bear resided in the high elevation mountains (dark grey) to the west, 3 grizzly bears resided in the upper foothills (medium grey) northwest of Hinton and southeast of Grande Cache, and 1 grizzly bear resided in the Swan Hills to the east of the foothills (light grey). The mountains in this region are rugged high elevation peaks characterized by uplifted shale and sandstone with montane alpine valleys (Figure 3-2a). The Upper Foothills and Swan hills are characterized by rolling ridges with some rocky outcrops and predominantly closed-canopied coniferous forests (Beckingham et al. 1996). The primary industries in this region are forestry and oil and gas exploration with the landscape largely fragmented by cutblocks and secondary roads (Figure 3-2b). Human recreation activities include back country hiking, camping, and off road vehicling.

Figure 3-1. Chapter 3 study region and 95% kernel home range outlines for 2 female grizzly bears (reds) and 3 male grizzly bears (blues) where GPS radiotelemetry points were collected at 20-min intervals north of Highway 16.

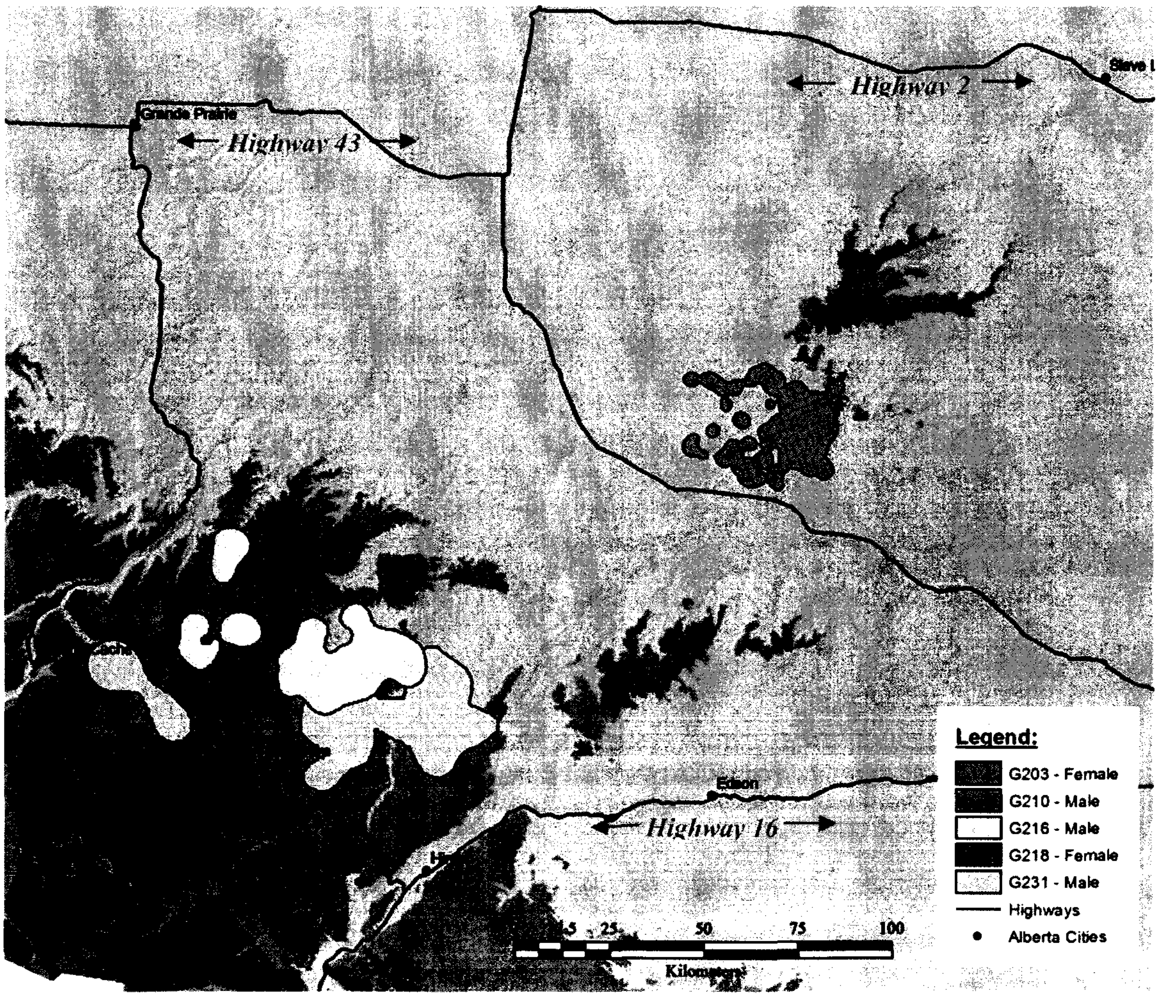
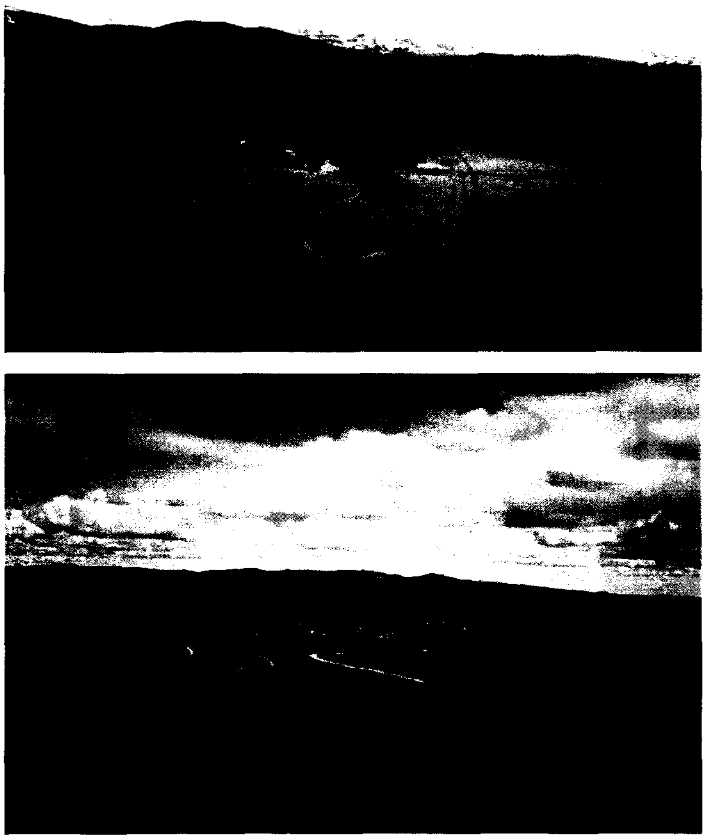


Figure 3-2. Photos taken of Chapter 3 study region highlighting a) an east west progression from foothill coniferous forests with riparian valley bottoms in the east to high elevation mountains in the west, and b) a foothills landscape with secondary industry roads, forestry clearcuts, and oil and gas wellsites.

a.



The only additional supplementary data used in the analysis was a FRI project generated remotely sensed 2005 landscape classification map (Section 2-5, Figure 2-13, p. 64). The landscape map originally had 10 active classifications which were subsequently reduced to 7 classes: closed forest, open forest, wet treed, herbaceous (upland and wetland herbaceous combined), shrub, water, and non-habitat (barren, snow/ice, cloud, and shadow combined) (Table 2-4, p. 60). The landscape surface was used to provide additional information regarding the effect of changing temporal lag on the spatial placement of GPS-based vector segments as related to underlying land cover classes.

3.3 Methods

GPS Data Preparation

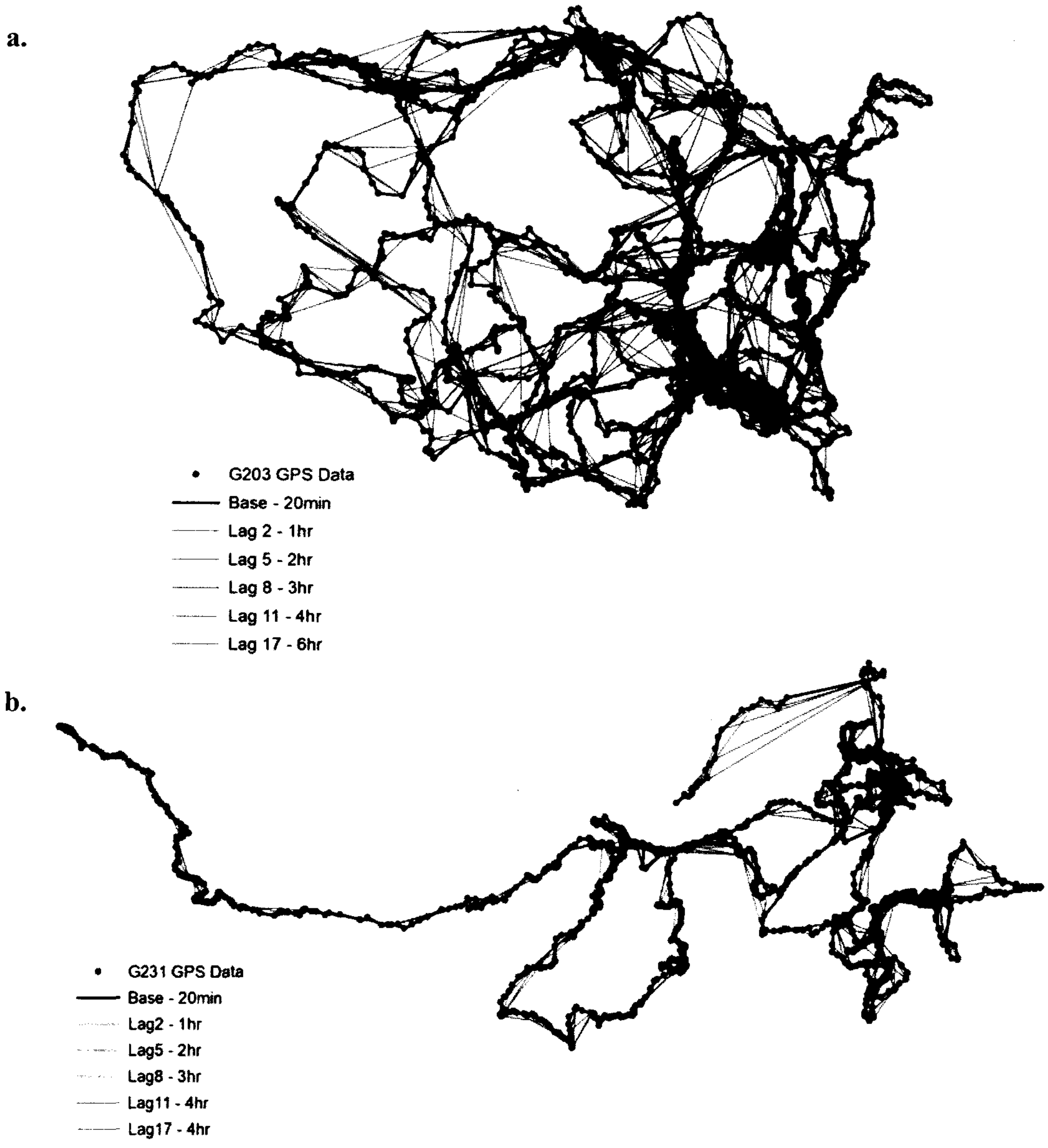
In 2005, 5 individual grizzly bears (male, $n = 3$; female, $n = 2$) were captured and fitted with Televilt Tellus 1 (Lindesberg, Sweden) GPS radiocollars. For each bear ($n = 5$), sex, reproductive status, age class, physical location of data set, data collection range, and number of resulting GPS data points were noted. Each collar was programmed to retrieve GPS radiotelemetry locations from approximately early May until late October at 20-min intervals. For detailed information on GPS location data classification and processing see Chapter 4, Section 3. For consistency, GPS data points with a DOP > 6 were removed from the data set (this standard was used across all chapters in this thesis). The individual data sets were inspected for exceptionally large time gaps corresponding to temporary failure or data corruption. Only individual grizzly bear G218 contained time gaps of concern at which point the data set was separated into two data sets and processed separately. While the resulting data sets contained the occasional missed fix or time gap, the data was assumed to be the best available data or 'gold standard' of GPS location data for each individual bear. Each 20-min data set was considered the base level of data analysis for each bear to which all resampled data sets were compared.

For all 5 individual bears, a total of 7 resampled temporal data collection levels were created and used in the following analyses. Temporal resample intervals were chosen to represent data collection schedules commonly employed in extensive large carnivore GPS telemetry research projects. As with the FRI, the majority of GPS radiocollars are programmed to record one telemetry location every 4 hours or 6 times a day. Data resampling was conducted by starting with the base level 20-min data set for each individual bear and selecting or resampling data points at predetermined increments. For example, by skipping 1 point and selecting every 2nd GPS telemetry point the resulting selection was then transformed into a new GPS data set representing a location point captured every 40-min. Further, by skipping 2 data points and selecting every 3rd GPS location, the resulting resampled data set represented a point captured every hour. Additional temporal resampling was conducted to create GPS telemetry data sets representing a recorded grizzly bear location for every 2-hr, 4-hr, 6-hr, and 12-hr interval. Here after, base level or lag 0 refers to the original or 'gold standard' data set, lag 1 refers to a point every 40-min, lag 2 refers to a point every 1-hr, lag 5 refers to a point every 2-hr, lag 8 refers to a point every 3-hr, lag 11 refers to a point every 4-hr, lag 17 refers to a point every 6-hr, and finally, lag 35 refers to a point every 12-hr.

Global Vector Summary Statistics

The primary unit of analysis for this chapter is the vector segment linking consecutive GPS telemetry locations. Post data resampling, straight-line or Euclidean vectors were created for each of the 7 resampled point data sets for each bear (see Figure 3-3). Generated vectors were used to measure distance (km), resulting mean movement rate (km/h), and path deviation angle or turning angle (deg) as temporal lag between captured GPS telemetry locations increased (see Figure 2-5, p. 33, for a detailed depiction of vector components). Distance (km) for each vector segment is simply the length in kilometers between consecutive data points. Mean movement rate (km/h) was calculated by dividing each vector length by time duration between data points t_1 and t_2. Deviation angle (deg) was calculated by measuring the bearing in degrees of each vector segment as it deviates from the vector segment preceding it (Jenness 2007). The angle of deviation will have a bearing of 0° if the next segment continues in the same direction and 180° if the vector segment doubles back in the opposite direction (Jenness 2007). Turning direction (left or right) was not considered in this analysis. Reported results will primarily focus on rates of movement and turning angle rather than vector distance. The use of movement rate as a summary measure helps to standardize some of the variation present in vector distance values. This is often due to the inability of collars to acquire GPS locations for all 20-min scheduled attempts resulting in slight measurement bias from the occasional missed fix or slight differences in the time of data acquisition (Johnson et al. 2002).

Figure 3-3. Example of 20-min data resampled to larger temporal data collection levels demonstrating variation of resulting vector paths for a) individual female G203, and b) individual male G231.



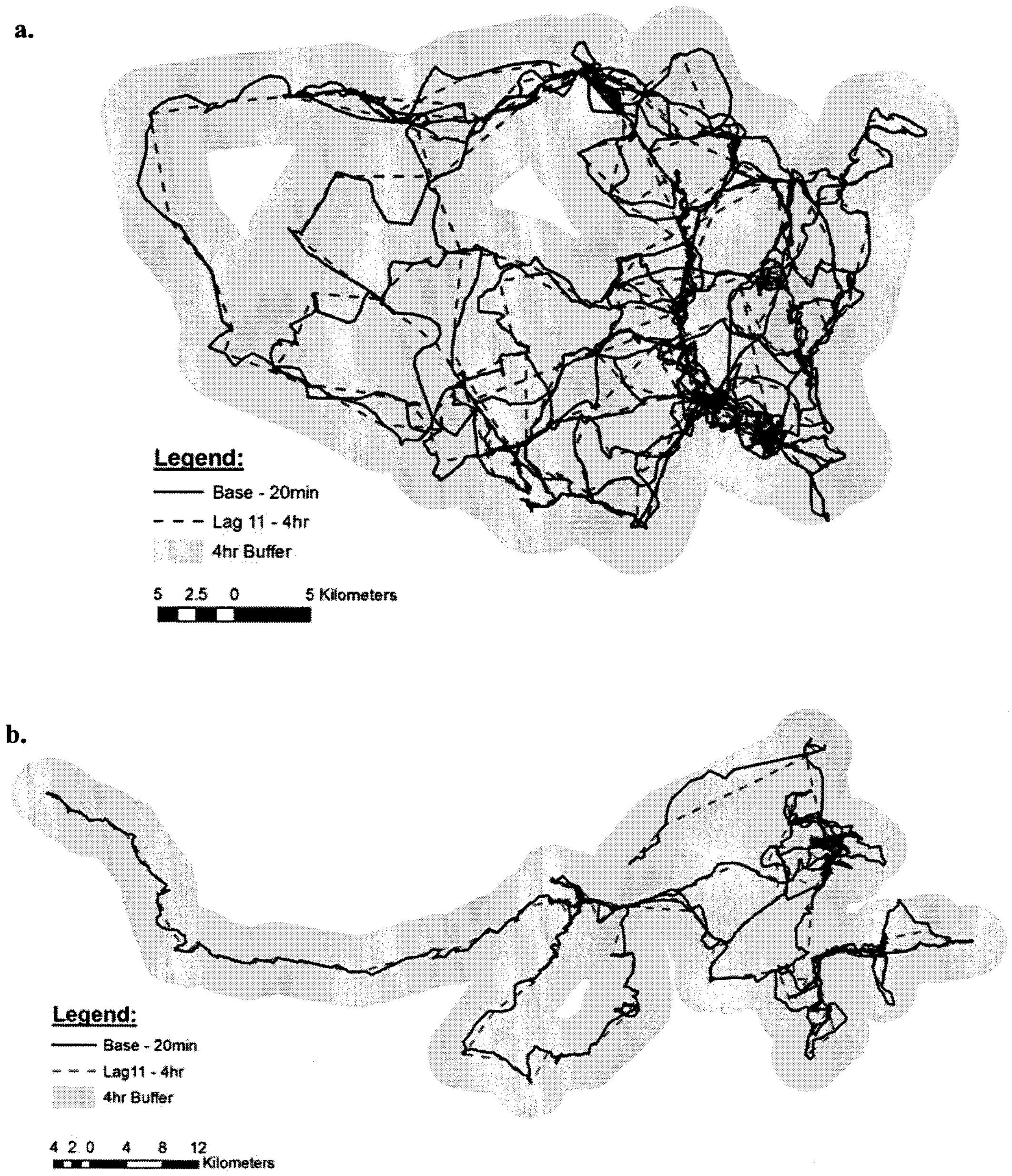
Beginning at the base level or lag 0, vector summary statistics were calculated and compared between temporal lags for each of the 5 individual bears. Mean movement rate (km/h), median movement rate (km/h), mean deviation angle (deg), and mean vector distance (km) for all bears across changing temporal lags or data collection levels were compared using line charts with ± standard error bars highlighting variance. Vector summary statistics were then compared for each individual bear between lags. Each resampled temporal lag (lag 1, 2, 5, 8, 11, and 17) was compared against the base level or 'gold standard' data set. Second order (e.g. lags 2 and 5) and third order (e.g. lags 5 and 11) lag differences were also compared for each individual grizzly bear. As the data (and variables) did not fulfill the assumptions of equal variance and normality, significant differences between temporal data collection levels by individual bear were evaluated using two independent samples Mann-Whitney U tests in SPSS. Significance was identified at both the $P < 0.05$ (**) and $P < 0.10$ (*) levels.

Global Vector Distribution Comparisons

The second level of analysis moves beyond general vector summary properties to assess overall vector distributions for each bear by temporal data collection level or temporal lag. This section of analysis can be broken down into three separate approaches: 1) general distribution comparisons, 2) comparison of vector spatial distributions, and 3) percent landscape change related to the spatial pattern of vector distributions. First, in order to properly assess measured distributions relative frequency histograms were generated for each bear across each temporal lag. Resulting mean movement rate (km/h), mean deviation angle (deg), and mean vector distance (km) distributions were then compared between the base level 20-min data set (lag 0) and all resampled temporal lags (lags 1, 2, 5, 8, 11, and 17) using nonparametric Kolmogorov-Smirnov Z tests. Second order and third order lag differences were again compared for each individual grizzly bear. Significance was identified for both the $P < 0.05$ (**) and $P < 0.10$ (*) levels.

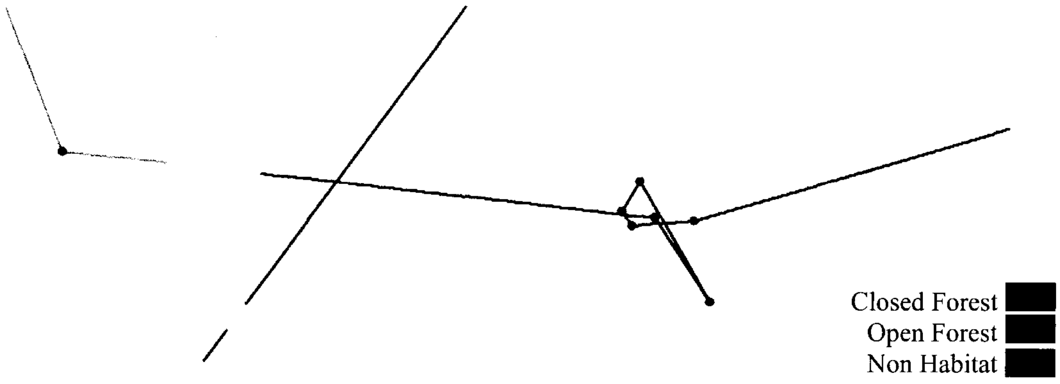
When working with spatial movement patterns, points and line segments are the primary geometric elements. The fundamental basis of error models for vector segments is typically a buffer or error-band as previously discussed in Chapter 2 (Shi and Liu 2000). Often studies employ a buffer or zone of influence around features without determining an appropriate distance *a priori*. In order to determine the amount of variation or error associated with an entire movement trajectory as the temporal resolution of the data decreases, this analysis compared vector distributions using standard GIS spatial buffers. To measure spatial differences between temporal lags for each individual bear, movement trajectories for each resampled temporal lag (lags 1, 2, 5, 8, 11, and 17) were spatially compared against the 'gold standard' or lag 0. That is, each temporal lag vector path was mapped against the original base level vector path for each bear. To measure the amount of departure between the two paths, the resampled vector path was buffered until the buffer included the original base level data (Figure 3-4). The distance in meters of the resulting buffer was recorded for each bear for each temporal lag. Finally, the resulting buffer distances were averaged across all bears. Results are intended to provide information regarding the amount of spatial uncertainty present when working with 4-hr or 6-hr data compared to finer-scale data.

Figure 3-4. Spatial distribution comparisons using buffering techniques to calculate the amount of vector variability as temporal data scale decreases for a) female G203 (3.2 km) and, b) male G231 (4.0 km).



Lastly, vector spatial distributions were compared for each temporal lag against the base level data using habitat proportion as an indicator of spatial change. Beginning with the 20-min or 'gold standard' data for each grizzly bear, mean habitat proportion as a percentage was extracted for all vectors along the movement trajectory (Figure 3-5). For example, while one vector may be 100% closed forest, another vector might contain closed forest (60%), open forest (20%), and non habitat (20%) classes. I acknowledge that there is inherent error in that the actual vector line between points is assumed. However, at the 20-min data level, this is the most accurate assumption available of where the bear might have been on the landscape without the added complexity of building movement models. For each individual grizzly bear across each resampled temporal lag (lags 1, 2, 5, 8, 11, and 17) mean habitat proportion was extracted along total vector path. Resulting mean habitat class proportion change was compared as data sampling resolution decreased from the base level assessment. Change between levels > 0.05 was deemed to be significant.

Figure 3-5. Example of vector habitat proportion extraction for G216 using 20-min baseline data where habitat proportion is calculated for each vector segment.

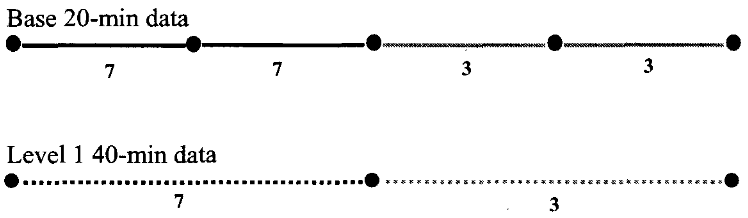


Local Vector One to One Comparisons

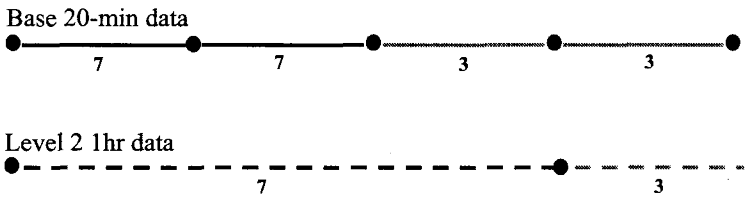
For the third level of analysis, this chapter moves from global vector comparisons to local vector comparisons. The intent of this analysis is to learn how data resampling affects the internal habitat variation within a grizzly bears movement trajectory. To further assess the error associated with vector comparisons across temporal data collection scales, one to one vector comparisons were conducted in a fashion similar to a remote sensing error matrix or contingency table analysis (NRC 2009). Here, rather than comparing two thematic maps, two vector maps were compared to assess the degree of misclassification among habitat classes as data resolution decreases.

First, habitat class type with the maximum proportion for each vector was extracted at the base level for each bear. This information was considered the 'reference map' for the analysis and thus was assumed to be 100% accurate. Second, for each individual grizzly bear across each resampled temporal lag (lags 1, 2, 5, 8, 11, and 17) maximum habitat proportion or the modal habitat type was extracted for each vector segment (Figure 3-6). To complete a vector-based contingency table analysis, one to one direct comparisons were conducted. To create the same number of vector segments within the resampled temporal lag movement trajectories, repeating vector segments were added similar to a moving window analysis. For example, if the 20-min base level data was resampled to 40-min data or a GPS location at every 2nd point, 4 vectors would be reduced to 2 vectors (see Figure 3-6). Therefore, to create a one to one comparison matrix, 1 repeating vector would be added back to the 40-min or lag 1 data table repeating the resampled vector maximum habitat type at every 2nd interval. For lag 2 or 1-hour interval data, 2 repeating vectors would be added in at every 3rd interval and so on. The resulting matrices were used as uncertainty information matrices for each resampled movement trajectory. The resulting matrices further describe the change in vector spatial placement via change in habitat classification when compared to the 'gold standard' or base level vector segments.

Figure 3-6. Example of vector contingency table analysis for habitat classification error assessment showing vector resampling taking the maximum habitat type for each vector segment across all temporal data collection levels and comparing them again the base level data or 'gold standard' data. Note: the asterisk (*) indicates repeating vectors added into data resampled tables for direct one to one vector comparisons.



Base	Level1
7	7
7	7*
3	3
3	3*



Base	Level2
7	7
7	7*
3	7*
3	3

Contingency tables were created to assess the resulting user accuracy and producer accuracy as well as the error of commission and omission for each resampled temporal lag (lags 1, 2, 5, 8, 11, and 17) compared to the original base-level data set (Table 3-1). User accuracy provided a measure of output map reliability while the producers accuracy indicated the percentage of resampled vectors which were correctly classified (NRC 2009). Resulting errors of omission indicated the number of vectors incorrectly excluded from each habitat class and errors of commission indicated the number of vectors incorrectly assigned to each habitat class but which actually belonged in a different habitat class (NRC 2009). Overall contingency table accuracies were reported as data collection resolution decreased for each individual bear. Results further identified the temporal data collection scale when overall user and producer accuracy reached 0% for each habitat class for all 5 individual grizzly bears.

Table 3-1. An example of a contingency table comparing base-level (20min) vector classification with level 1 (40-min) vector classification where numbers represent vector counts rather than raster cell counts. The overall contingency table accuracy is shown in the bottom right corner indicating that in this example, vector habitat type classification at the 40-min data collection scale is 80% correct when compared to the 20-min or 'gold standard' data.

	Classification Data (Level 1 or 40-min Data)									
Reference Data (Base-Level Data)	Open Forest	Closed Forest	Wet Treed	Herb	Shrub	Water	Non Habitat	**Row Total**	**Producer Accuracy**	**Error of Omission**
Open Forest	562	89	6	26	67	0	36	786	0.72	0.28
Closed Forest	64	2592	37	32	75	0	69	2869	0.90	0.10
Wet Treed	3	56	277	36	13	0	12	397	0.70	0.30
Herb	16	84	40	740	58	0	51	989	0.75	0.25
Shrub	59	95	12	58	1068	0	78	1370	0.78	0.22
Water	0	0	0	0	0	0	0	0	0.00	1.00
Non Habitat	34	111	18	88	85	0	810	1146	0.71	0.29
Column Total	738	3027	390	980	1366	0	1056	7557		
User Accuracy	0.76	0.86	0.71	0.76	0.78	0.00	0.77		**80.04**	
Error of Commission	0.24	0.14	0.29	0.24	0.22	1.00	0.23			

Local Vector Sequential Data Comparisons

Finally, after assessing overall vector summary properties, distribution comparisons, and individual vector segment comparisons, sequential vector movement characteristics were compared. As a movement trajectory is a collection of observations (GPS locations) made sequentially in time, it is necessary to maintain the consistency of the data structure in space and time. This section of the analysis examines the internal variation within the total movement trajectory for each individual bear across each data temporal collection scale. First, vector serial autocorrelation is examined using both movement rate (km/h) and angular deviation or turning angle (deg) variables. Second, spatial-temporal and spatial vector movement clusters were identified using time series analysis.

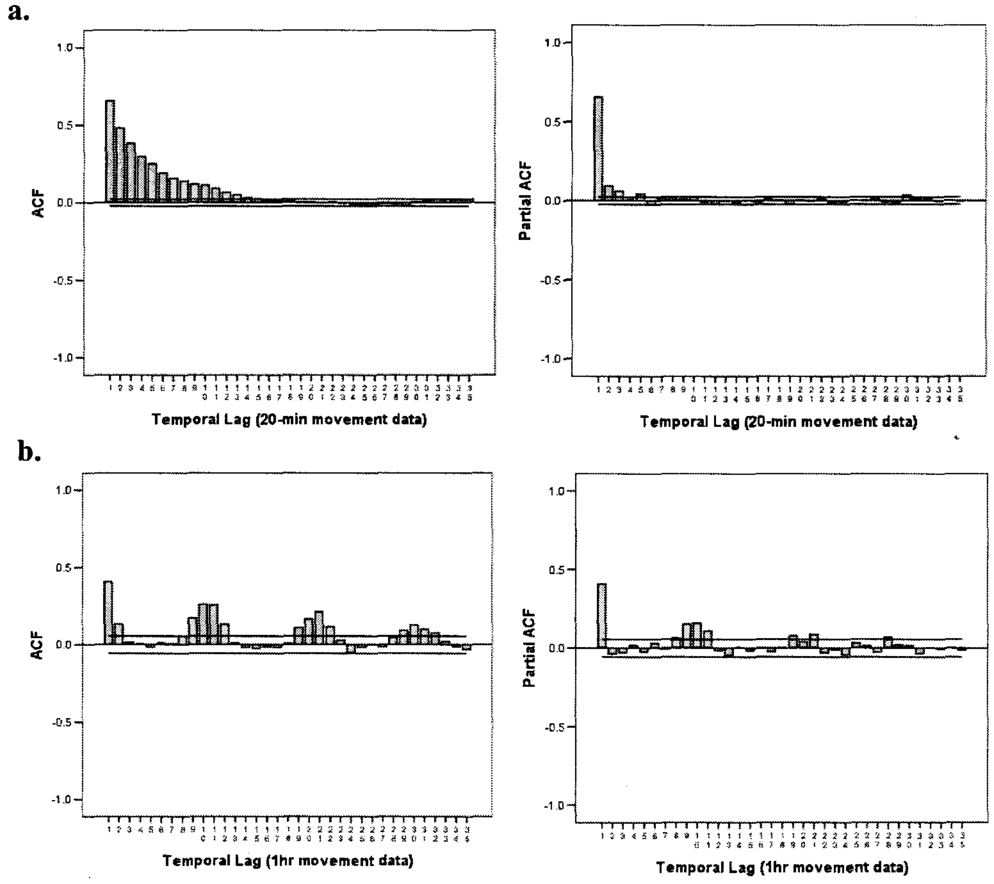
By employing a time series-based temporal autocorrelation function (ACF) and partial autocorrelation function (PACF), time to independence can be identified in a sequential data series (Chatfield 1980). A time series or sequential data chart was constructed for each grizzly bear using the 20-min GPS radiotelemetry data set (Figure 3-8). Both ACF and PACF functions were calculated and used to identify the temporal lag at which GPS observations were no longer correlated for each individual grizzly bear. Autocorrelations and partial autocorrelations were calculated to a lag of 35 (for 20-min data this = 12 hours). The equation of the autocorrelation function (ACF) is:

$$r_k = \frac{\sum_{i=1}^{n-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad \text{(Equation 3.1)}$$

Where r_k indicates the *k*th lag sample autocorrelation, x_i is the *i*th observation of input series, and $\bar{x}$ is the average of the *n* observations. Results for each were plotted as standard ACF and PACF charts highlighting the presence of autocorrelation across increasing time lags (Figure 3-7). The ACF is used to estimate the degree to which a vector segment is correlated with the previous segment across the entire movement trajectory. The PACF correlates the value of a vector after the effects of correlations at the intervening lags have been removed (Chatfield 1980). Significant autocorrelation was calculated using the independence model in SPSS.

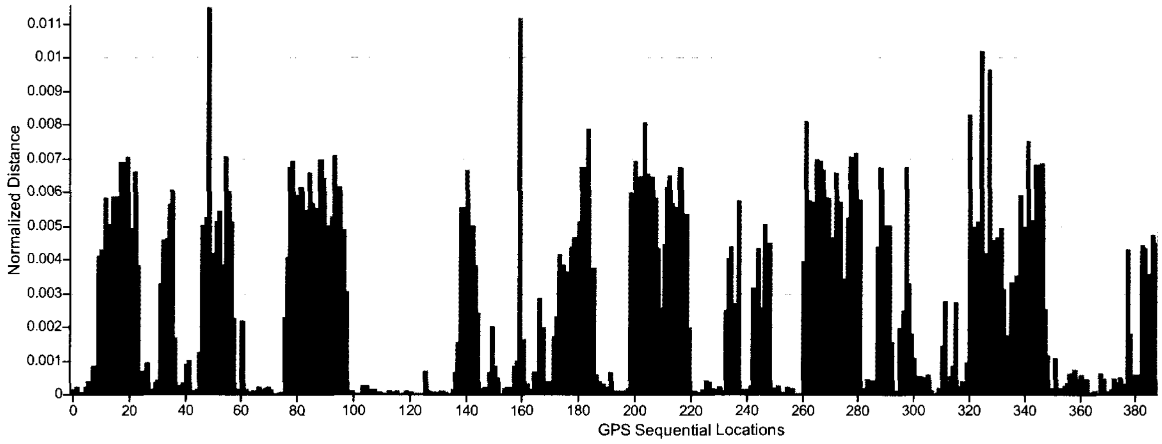
For each bear, ACF and PACF functions were also generated for each resampled data collection level or temporal lag (e.g. Figure 3-7b). Although autocorrelation is addressed in the data at the base level, by generating the ACF and PACF functions at coarser resolutions additional information may be generated. For example, will resulting ACF chart and PACF charts demonstrate the presence of autocorrelation when working strictly with 1-hr data or 4-hr data typical to large carnivore research studies? Results were examined to highlight at what ACF and PACF level movement rate and turning angle vectors were no longer correlated for each bear. For example, at what resampled temporal lag would time to independence be achieved when working with vector structures? The temporal data collection level where no serial autocorrelation was present in the data was further identified for each bear. For example, at what data collection scale would radiocollars have to be programmed at to record data independent and free of potential serial autocorrelation (e.g. 3 hour or 4 hour intervals)?

Figure 3-7. Example of resulting temporal autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis for female G203 for a) 20-min base level data, and b) 1-hour data for movement rate (km/h).



When dealing with consecutive vector data structures two possible cluster types exist: 1) vector clusters that are linked in time and therefore space, or 2) vectors clusters that are solely linked in space. The former often identify a change in movement behavior (e.g. bedding or foraging) where both vector distance and time (movement rate) between recorded locations is small. The latter type of cluster indicates site revisits where an individual has returned to a location previously visited. In order to identify space-time clusters, a time series sequence was generated for each bear using the 20-min sequential vector data. A time sequence graph can be used to identify variation in the data sequence (Figure 3-8). To do this assessment, it was assumed that slow small-scale movements were foraging activities while faster large-scale movement occurred when individuals moved between foraging areas. It was further assumed that movement could be classified into discrete events.

Figure 3-8. Example of a time series sequence graph highlighting the internal variation of a movement trajectory using consecutive vector data. Changes to normalized distance (speed) as time progresses are demonstrated as slow (red) versus fast (grey) or short versus long vectors.



To begin, a time sequence graph was generated for each individual at each temporal data capture level (lag 0, 1, 2, 5, 8, 11, and 17). Normalized distance was used to standardize the data and reduce the occasional errant data value due to missed fixes or location error. After some exploration, < 1.0 standard deviation below the mean for normalized distance was employed to separate small slow movement vectors from larger faster movement vectors. Within each time sequence graph, spatiotemporal clusters were identified by selecting 3 or more consecutive movement vectors which occur below the normalized distance threshold. The resulting sequentially linked vectors were then recorded as one individual temporal cluster. It was assumed that because clusters were temporally linked, they were also spatially joined thus forming a spatial-temporal cluster within the movement trajectory.

Clusters were recoded by the number of points in each cluster for mapping and graphing purposes. For example, cluster size and location were mapped for each bear at each temporal data collection level and reevaluated for site revisits. A spatial cluster or site revisit was defined as occurring when at least two spatiotemporal clusters overlapped. Previous studies have suggested that sampling interval could confound movement results (Nams 2006b). As such, the process was repeated for each bear across each resampled temporal lag (lags 1, 2, 5, 8, 11, and 17). Finally, the mean percent of clusters retained were recorded and compared across bears to identify at what temporal level, cluster information both decreased by 50% and further disappeared completely. For each bear, clusters or dominant site revisits that were retained across temporal data collection levels were examined for unique characteristics (e.g. a high number of night time points possibly indicating a resting location).

3.4 Results

Global Vector Summary Results

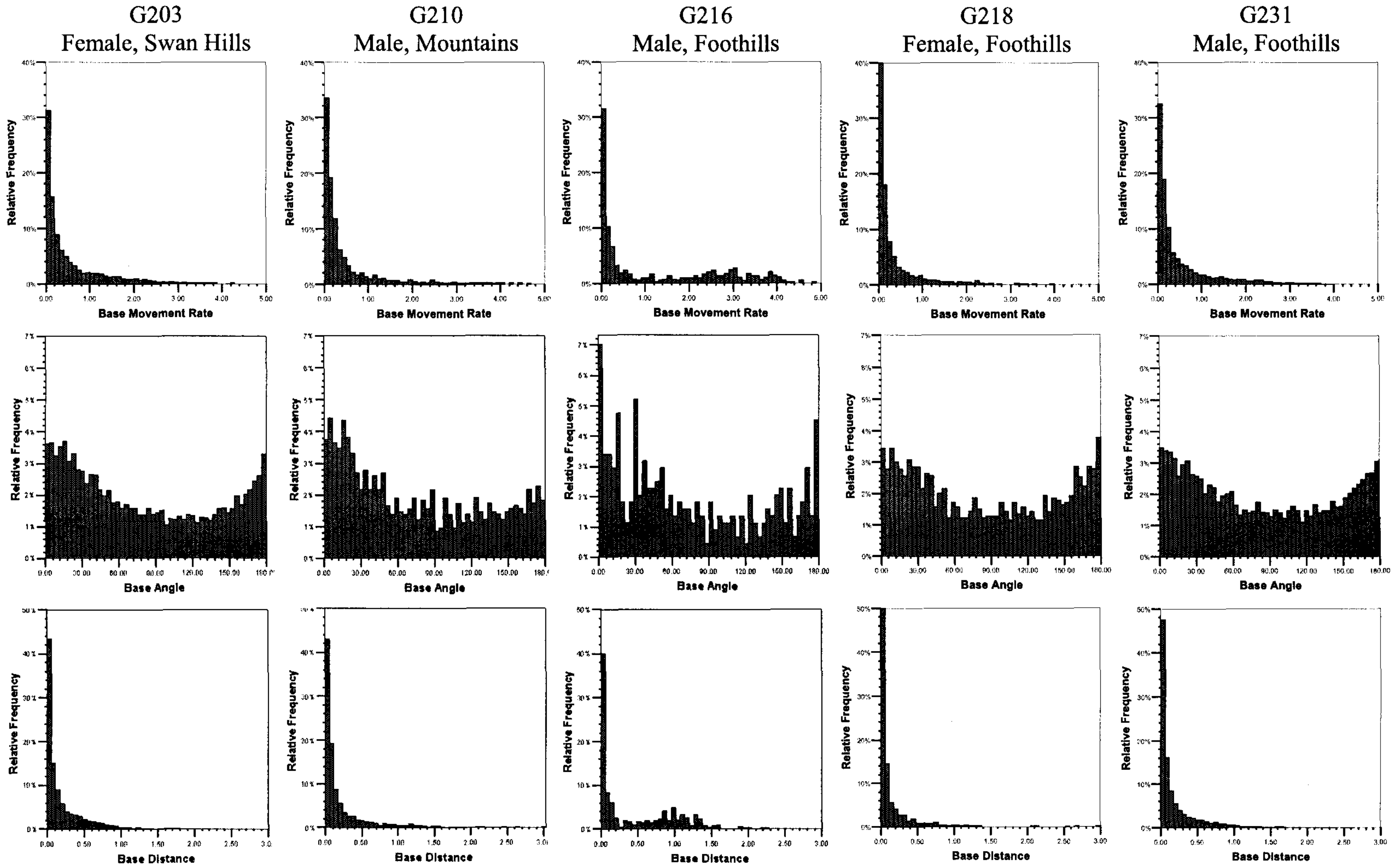
In 2005, GPS locations were collected for 3 male bears and 2 female bears. The temporal extent of the data collection ranged from May to September for female G203 (n = 7557), from June to September for males G210 (n = 1150) and G231 (n = 5208), from early June to mid June for male G216 (n = 442), and from July to September for female G218 (n = 1399) (Table 3-2). Overall fix rates (number of points successfully recorded at the 20-min capture rate) varied by bear: G203 = 94%, G210 = 78%, G216 = 95%, G218 = 88%, G231 = 94%. Individual male G210 located in the mountains recorded the largest number of missed fixes (22%) when compared to individuals located in the foothill environments. This result could possibly be due to large changes in elevation, topography and steep slopes resulting in fewer satellites within view of the collar.

Vector summary statistics, mean movement rate (km/h), mean deviation rate (deg), and mean vector distance (km), were examined for all 5 individual bears at the base level (20-min data) or lag 0 (Table 3-2). Base level histograms were created showing relative frequency for each vector summary statistic for each individual bear (Figure 3-9). Typically, slow movements occurred more frequently with faster movements being progressively less frequent. Distance and therefore movement rate values were highly skewed to the left indicating a large number of vectors with small distances and slow movement rates. Histograms for deviation angle demonstrated a U shape with larger numbers of values clustered near 0° indicating straight-line movements or 180° indicating large amounts of turning. Mean movement rates ranged from 0.31 km/h up to 1.24 km/h for female G218 and male G216, respectively. Both the slowest and fastest recorded movement rates belonged to grizzly bears residing in foothill environments. Individual male G210 recorded the lowest mean deviation vector angle at 75° while female G218 recorded the highest mean deviation vector angle at 85° (Table 3-2). Of interest, female G218 recorded both the slowest mean movement rate and the highest mean deviation angle indicating more turns. Mean vector distance results mirrored mean movement rate results for all bears as expected.

Table 3-2. Base level summary statistics for mean hourly movement rate (km/h), mean distance traveled (km), and mean angle of path deviation (deg), including classification information for 5 grizzly bears radiocollared in 2005.

				Summary Statistics		
Bear ID / Sex	Location	Data Collection Range	*n*	Mean Movement Rate (km/h)	Mean Distance Traveled (km)	Mean Turn Angle (deg)
G203F	Swan Hills	May 31 - Sept. 30	7557	0.55	0.202	79.15
G210M	Mountain	June 9 - July 19/Sept 7 - Sept 15	1150	0.49	0.23	74.85
G216M	Foothills	June 7 - June 14	442	1.24	0.45	76.09
G218F	Foothills	July 12 - July 17/Sept 6 - Sept 30	1399	0.31	0.13	85.31
G231M	Foothills	June 28 - Sept 21	5208	0.47	0.18	83.21

Figure 3-9. Base level histograms showing relative frequencies for movement rate (km/h), deviation angle (deg), and distance (km) for each grizzly bear showing sex and landscape type.



G203
Female, Swan Hills

G210
Male, Mountains

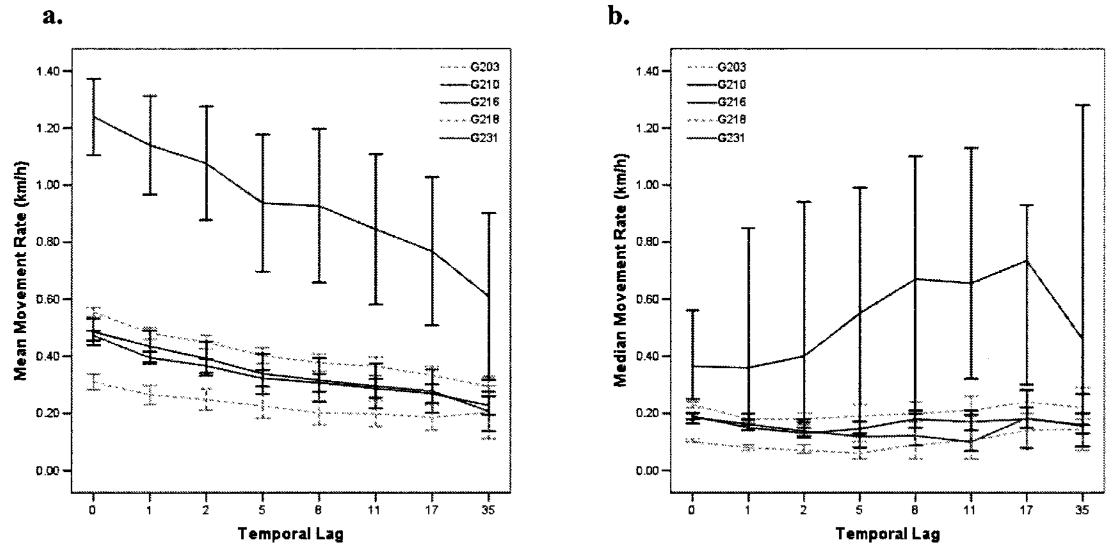
G216
Male, Foothills

G218
Female, Foothills

G231
Male, Foothills

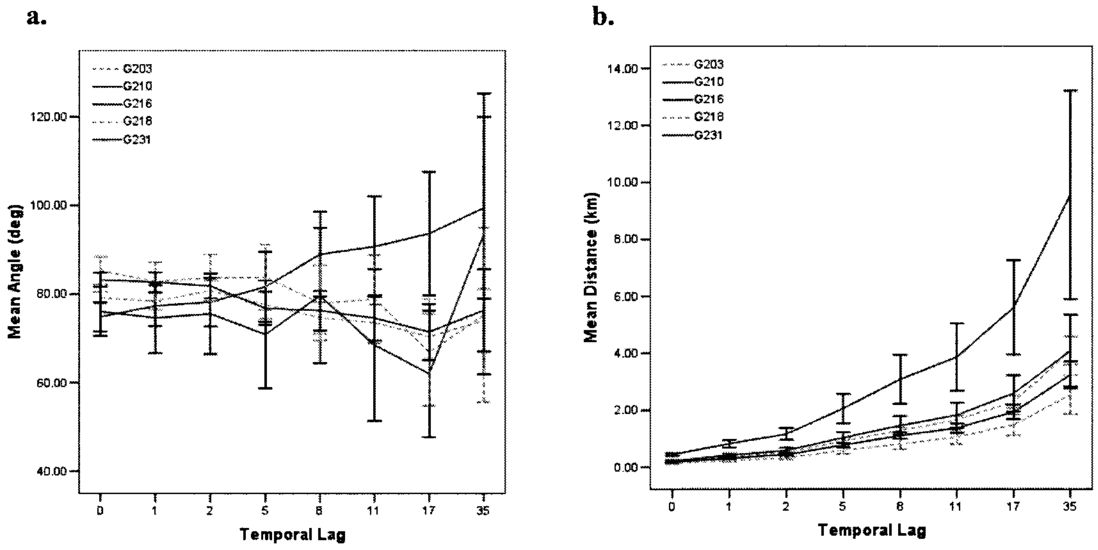
When mean movement rate (km/h) and median movement rate (km/h) were compared for all bears across all resampled data levels, mean movement rate was reported to decrease as temporal lag increased (Figure 3-10a). Median movement rate however demonstrated higher levels of variability and no discernible decrease in median movement rate value (Figure 3-10b).

Figure 3-10. Mean and median movement rate (km/h) line charts for 2005 individual grizzly bears for each temporal lag corresponding to data collection scale (20-min to 12-hr), bears are further coded according to sex where females are represented by dashed lines and males are represented by solid lines (note: male G216 is showing extreme differences in values).



As temporal lag increased, mean deviation angle or turning angle showed extreme variability indicating either an increase in straight-line vectors or vectors with high turning angles (Figure 3-11a). Depending on the original spatial patterns of the data set, as the data is resampled and spatial resolution decreases the resulting spatial pattern will either become more linear in nature or zigzag back and forth. As expected, mean distance increased as temporal lag increased (Figure 3-11b) with males showing slightly larger distances overall.

Figure 3-11. Line graphs for a) mean angle of path deviation (deg) and b) mean distance (km) for 2005 individual grizzly bears for each temporal lag corresponding to data collection scale (20-min to 12-hr), bears are further coded according to sex where females are represented by dashed lines and males are represented by solid lines (note: male G216 demonstrates extreme differences in values).



Mann-Whitney *U* results between temporal data collection levels varied by bear. Generally, mean distances were found to be significantly different between all temporal lag comparisons at the $P < 0.05$ level (Table 3-3). For individuals G203 and G231, mean movement rates significantly decreased ($P < 0.001$) across all temporal data collection levels when compared to the base level data. Both reported significant differences between base level deviation angles and resampled deviation angles at higher levels only (G203 = 4-hr and 6-hr; G231 = 2-hr up to 6-hr). For individuals G210 and G218, movement rates were significantly lower ($P < 0.001$) for temporal data collection levels up to level 11 (4-hr) when compared to 20-min data, with level 17 (6-hr) and level 35 (12-hr) showing no significant differences for both bears. Individual male G216 reported a slightly significant reduction ($P = 0.063$) to mean movement rate for level 2 (1-hr) data when compared to the base level (20-min) data.

Overall results concluded that as data sampling interval decreased from the 20-min or base level data, the resulting movement rate also significantly decreased. However, almost no differences were found as movement rate comparisons moved to second order or third order comparisons (e.g. level 2 to level 5 or level 5 to level 11). This indicated that when working with movement rate at lower sampling resolution moving from 2-hr data to 4-hr data should not impact resulting vector-based movement rates. Results further demonstrated that vector deviation angle significantly differed as temporal data sampling decreased indicating a loss of turning information or detail at higher levels (Table 3-3). Again, no significant differences were apparent between higher order data levels such as between 2-hr and 4-hr data levels. Distances however demonstrated significant differences across all resampling intervals.

Table 3-3. Mann-Whitney *U* results showing significant mean differences between temporal data collection levels for resulting movement rate (km/h), deviation angle (deg), and distance (km) by individual bear.

		G203			G210			G216			G218			G231		
Temporal Lag Comparisons		Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)
Base (20min)	Level 1 (40min)	**		**	*		**			**	**		**	**		**
Base (20min)	Level 2 (1hr)	**		**	**		**	*		**	**		**	**		**
Base (20min)	Level 5 (2hr)	**		**	**	*	**			**	**		**	**	**	**
Base (20min)	Level 8 (3hr)	**		**	**	**	**			**	**		**	**	**	**
Base (20min)	Level 11 (4hr)	**	*	**	**	**	**			**	**		**	**	**	**
Base (20min)	Level 17 (6hr)	**	**	**		**	**			**		**	**	**	**	**
Base (20min)	Level 35 (12hr)	**		**		**	**			**			**	**		**
Level 2 (1hr)	Level 5 (2hr)			**			**			**			**	*	**	**
Level 5 (2hr)	Level 8 (3hr)			**			**			*			**			**
Level 8 (3hr)	Level 11 (4hr)			**												**
Level 11 (4hr)	Level 17 (6hr)			**			**			*			**			**
Level 17 (6hr)	Level 35 (12hr)			**			**		*	*			**			**
Level 5 (2hr)	Level 11 (4hr)			**			**			**			**			**
Level 11 (4hr)	Level 35 (12hr)			**			**			**			**			**

Note: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level

Table 3-4. Kolmogorov-Smirnov test results showing significant distribution differences between temporal data collection levels for resulting movement rate (km/h), deviation angle (deg), and distance (km) by individual bear.

		G203			G210			G216			G218			G231		
Temporal Lag Comparisons		Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)	Move Rate (km/h)	Deviation Angle (deg)	Distance (km)
Base (20min)	Level 1 (40min)	**		**	*		**	*		**	**		**	**		**
Base (20min)	Level 2 (1hr)	**		**	**		**	**		**	**		**	**		**
Base (20min)	Level 5 (2hr)	**	*	**	**		**	*		**	**		**	**	**	**
Base (20min)	Level 8 (3hr)	**	**	**	**	**	**	*		**	**	**	**	**	**	**
Base (20min)	Level 11 (4hr)	**	**	**	**	**	**	**		**	**	*	**	**	**	**
Base (20min)	Level 17 (6hr)	**	**	**		**	**	**		**	*	**	**	**	**	**
Base (20min)	Level 35 (12hr)	**	*	**		*	**	*		**			**	**		**
Level 2 (1hr)	Level 5 (2hr)	**	*	**			**			**			**	**	*	**
Level 5 (2hr)	Level 8 (3hr)			**			**									**
Level 8 (3hr)	Level 11 (4hr)			**												**
Level 11 (4hr)	Level 17 (6hr)			**			**						*			**
Level 17 (6hr)	Level 35 (12hr)			**			**						**			**
Level 5 (2hr)	Level 11 (4hr)			**			**			*			**	*		**
Level 11 (4hr)	Level 35 (12hr)	**		**			**			**			**	**		**

Note: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level

Global Vector Distribution Results

Beyond overall movement trajectory summary measures, vector distributions were also compared across data sampling intervals for each bear using Kolmogorov-Smirnov tests. Again, the majority of distributions for vector distances were found to be significantly different between all temporal lag comparisons at the $P < 0.05$ level (Table 3-4). Movement rate distributions for individuals G203 and G231 showed significant differences ($P < 0.001$) for all resampled lags when compared to the base level data. Individuals G210, G216, and G218 demonstrated significant differences between movement rate distributions at varying levels when compared to the base level movement rate distribution (Table 3-4). All grizzly bears, except G216, reported significant differences between base level deviation angle distributions and resampled deviation angle distributions at higher levels. Finally, only G203 and G231 demonstrated significant differences to movement rate distributions at second order and third order data comparisons.

To assess the amount of vector spatial error or variance as data collection scale decreased, spatial buffer size was compared across bears and vector distributions. Using the base level data or 'gold standard' as the true vector movement trajectory, all subsequent data resampled vector distributions were compared using a simple distance-based buffer (Table 3-5). Results indicated when working with 1-hr data, buffers would have to range from 350 m (G218b) up to 1000 m (G231) to capture potential vector error between known locations. When working with 4-hr data, buffers ranged from 800 m for G218b up to 4000 m or 4.0 km for G231. The mean 4-hr buffer across all bears was 2.6 km. It is important to note that this measurement is one side of the buffer. That is, the mean true buffer distance when working with 4-hr data would total 5.2 km from edge to edge in order to potentially capture the original fine-scale vector path. Examples of individual 4-hr spatial buffer results are mapped in Figure 3-4. The resulting 4-hr buffers look similar to an individual bear's home range.

Table 3-5. Spatial buffer (m) results comparing generated paths at each temporal data collection level to the original 20-min path for all 5 individual grizzly bears.

	G203	G210	G216	G218a	G218b	G231	
Temporal Lag	Buffer Width (m)						Mean Buffer (m)
Base level (20min)	0	0	0	0	0	0	**0**
Level 1 (40min)	1000	875	625	400	500	800	**700**
Level 2 (1hr)	890	965	845	650	350	1000	**783**
Level 5 (2hr)	2200	1020	1700	600	530	1750	**1300**
Level 8 (3hr)	1600	1950	2300	1000	700	2800	**1725**
Level 11 (4hr)	3150	2400	3350	2100	800	4000	**2633**
Level 17 (6hr)	3550	2400	3100	2000	1200	4250	**2750**
Level 35 (12hr)	5900	4960	6000	2000	1600	4500	**4160**

The final analysis of this section focused on the relationship between changing vector distributions and general habitat class proportions. Assuming that the 20-min movement trajectory or vectors again represented the best data available, habitat proportion was extracted for each individual grizzly bear. The base level habitat proportions were then compared against all resampled vector habitat proportions (see Tables 3-6 and Tables 3-7). Significant changes were noted if habitat proportion increased or decreased by 5%.

All five grizzly bears showed significant habitat proportion change for at least one habitat class at upper temporal data collection levels. Individuals G203 (6-hr), G216 (12-hr), G218a (3-hr), G218b (12-hr), and G231 (12-hr) all reported a significant increase in the proportion of closed forest for vector distributions. Only individual G210 reported a significant decrease in the proportion of closed forest for 4-hr and 12-hr vector distributions. Interestingly, G210 is the only sample bear residing in a mountainous environment. Individual G210 was also the only bear who saw a significant increase in non habitat for 6-hr and 12-hr vector distributions. Other reported changes included a decreasing proportion of shrub (G210 and G218a) and decreasing proportion of non habitat (G203, G216, G218a, and G218b).

Across lower data resample levels, no significant changes to habitat class proportions were reported for any of the individuals. This indicated that until the data is largely reduced, vector collected habitat information is not overly sensitive to resampled vector distributions.

Table 3-6. Habitat proportion results highlighting significant changes to proportion of habitat type across each temporal data collection level when compared to the 20-min base level data for individual grizzly bears G203, G210 and G216.

G203 Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.11						-0.01	-0.02
Closed Forest	0.36	0.01	0.02	0.03	0.03	0.04	**0.05**	**0.07**
Wet Treed	0.05	0.01				0.01	0.01	0.01
Herbaceous	0.13		0.01	0.01	0.01		0.01	0.03
Shrub	0.18							-0.04
Water	0.00							
Non Habitat	0.16	-0.01	-0.02	-0.02	-0.03	-0.03	**-0.05**	-0.04

G210 Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.09		-0.01	-0.01		-0.01		-0.03
Closed Forest	0.19			-0.01	-0.02	**-0.06**	-0.04	**-0.06**
Wet Treed	0.00							
Herbaceous	0.08	0.01	0.02	0.03	0.03	0.03	0.04	0.02
Shrub	0.61			-0.02	-0.04	-0.01	**-0.08**	**-0.09**
Water	0.00				0.01	0.01		0.03
Non Habitat	0.02	0.01		0.02	0.04	0.04	**0.09**	**0.13**

G216 Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.05		0.01	0.02	0.02	0.02	0.03	0.02
Closed Forest	0.62	0.01	0.02	0.01		-0.04		**0.05**
Wet Treed	0.08	0.01	-0.01		0.01	0.01		-0.01
Herbaceous	0.05		-0.01	0.01	-0.02	-0.01		
Shrub	0.03	-0.01	-0.01		-0.01			-0.01
Water	0.00							
Non Habitat	0.17	-0.01	-0.01	-0.03		0.03	-0.03	**-0.05**

Table 3-7. Habitat proportion results highlighting significant changes to proportion of habitat type across each temporal data collection level when compared to the 20-min base level data for individual grizzly bears G218a, G218b, and G231.

G218a Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.10	0.01	-0.01	0.02	-0.01	0.01	-0.01	-0.03
Closed Forest	0.31	-0.01	0.01	-0.01	**0.05**	**0.05**	**0.07**	**0.15**
Wet Treed	0.02			0.01		0.02		0.02
Herbaceous	0.15	0.01		0.02	-0.02		**-0.06**	-0.02
Shrub	0.10	0.01	0.02			-0.03	-0.01	**-0.05**
Water	0.00							
Non Habitat	0.32	-0.02	-0.02	-0.03	-0.02	**-0.06**		**-0.08**

G218b Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.13		0.01	-0.02		-0.01	-0.02	-0.04
Closed Forest	0.26			0.02	0.02	0.03	0.03	**0.10**
Wet Treed	0.13						0.02	0.01
Herbaceous	0.26	0.01	-0.01	0.01	0.01		0.01	-0.01
Shrub	0.09	-0.01		0.01		0.02	0.01	0.02
Water	0.02					-0.01	-0.01	-0.02
Non Habitat	0.11		-0.01	-0.02	-0.02	-0.04	-0.03	**-0.07**

G231 Habitat Proportion Change (%)

Habitat Classes	Base Level	Level 1	Level 2	Level 5	Level 8	Level 11	Level 17	Level 35
Open Forest	0.21			-0.02	-0.02	-0.03	-0.02	-0.04
Closed Forest	0.59			0.01	0.01	0.02	0.02	**0.06**
Wet Treed	0.07							-0.02
Herbaceous	0.04							-0.01
Shrub	0.07	-0.01			-0.01	-0.01	-0.01	-0.02
Water	0.00							
Non Habitat	0.02			0.01	0.01	0.01	0.02	0.03

Local Vector One to One Results

A vector contingency table analysis was conducted to quantify vector classification accuracy by showing the degree of misclassification among habitat classes as vector resolution decreased. Resulting contingency table analysis produced a mean accuracy value for each bear across each temporal lag (Table 3-8). For example, across all bears 4-hr vector data will have a habitat classification accuracy of 62% when compared to the base level or 20-min data.

Table 3-8. Contingency table results highlighting overall accuracy of vector habitat proportion as temporal data collection level changes when compared to the 20-min base level data for all 5 individual grizzly bears.

	G203	**G210**	**G216**	**G218**	**G231**	
Temporal Lag	Overall Accuracy					Mean Accuracy
Base level (20min)	100.00	100.00	100.00	100.00	100.00	**100.00**
Level 1 (40min)	80.04	87.65	83.48	80.84	81.49	**82.70**
Level 2 (1hr)	73.75	84.70	80.32	76.20	75.92	**78.18**
Level 5 (2hr)	64.51	78.09	74.43	68.18	68.47	**70.74**
Level 8 (3hr)	60.26	71.39	74.66	58.54	65.46	**66.06**
Level 11 (4hr)	57.47	61.48	72.40	53.04	63.54	**61.59**
Level 17 (6hr)	52.52	64.35	70.81	49.61	61.64	**59.79**
Level 35 (12hr)	27.83	56.78	66.97	48.11	58.37	**51.61**

The above overall mean accuracy demonstrates the number of vectors at subsequent levels assigned to the correct class. This approach can also be used to examine at what temporal data collection level the producer's accuracy and users accuracy reach zero (Table 3-9). To reiterate, the producer's accuracy shows what percentage of the resampled vector classification was correctly identified. The user's accuracy tells the user for the resampled vector map what percentage of a vector class corresponds to the original class. While the actual user's and producer's accuracy are slightly different across each temporal lag, the lag at which each class reaches 0% is the same (Table 3-9).

Table 3-9. Contingency table results highlighting at what temporal data collection level overall user and producer accuracy reaches 0% for each habitat class for all 5 individual grizzly bears.

	Users Accuracy (level where accuracy = 0%)						
Bear ID	Open Forest	Closed Forest	Wet Treed	Herbaceous	Shrub	Water	Non Habitat
G203						no vectors	
G210	12 hr		no vectors	12 hr		2 hr	
G216	3 hr		6 hr	3 hr	1 hr	no vectors	12 hr
G218	12 hr					6 hr	
G231						no vectors	

	Producers Accuracy (level where accuracy = 0%)						
Bear ID	Open Forest	Closed Forest	Wet Treed	Herbaceous	Shrub	Water	Non Habitat
G203						no vectors	
G210	12 hr		no vectors	12 hr		2 hr	
G216	3 hr		6 hr	3 hr	1 hr	no vectors	12 hr
G218	12 hr					6 hr	
G231						20 min	

Results demonstrated that for G203 and G216 no water vectors were present at any lag. For all bears, the closed forest class never reached 0% accuracy. For individuals G203 and G231, no vector-based habitat proportions reached 0%. For G210, open forest (12-hr), herbaceous (12-hr), and water (2-hr) classes were no longer detectable at varying temporal levels. For individual G216, all habitat classes except closed forest reached an accuracy level of 0%. Lastly, individual G218 reported open forest and water classes to reach 0% accuracy levels for 12-hr and 6-hr vector data sets respectively. Individual user accuracy figures were generated to highlight the decreasing accuracy value for habitat classifications as vector data resolution decreased for each individual bear (Figures 3-12 and Figures 3-13). As a general trend, as vector temporal lag decreased, user's accuracy for each habitat class also decreased. In most cases, the user's accuracy value fell below 50% for each habitat class type by the 4-hr data lag. The exception to this trend is closed forest (Figure 3-12). Other exceptions include herbaceous (G218) and shrub (G210) classes which remained above 75% for all temporal lags.

Figure 3-12. User accuracy charts by habitat type (open forest, closed forest, wet treed, and herbaceous) for each bear.

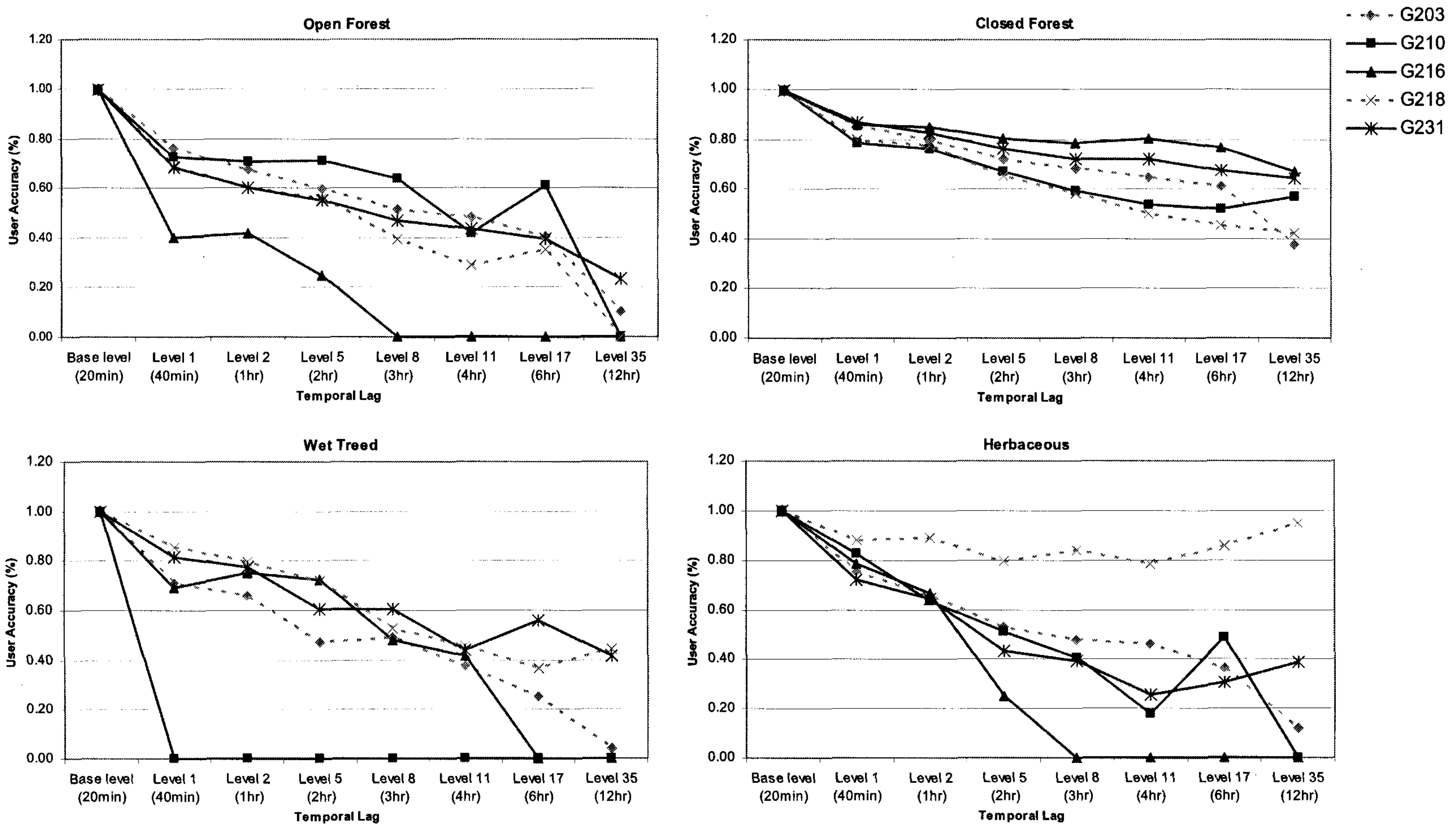
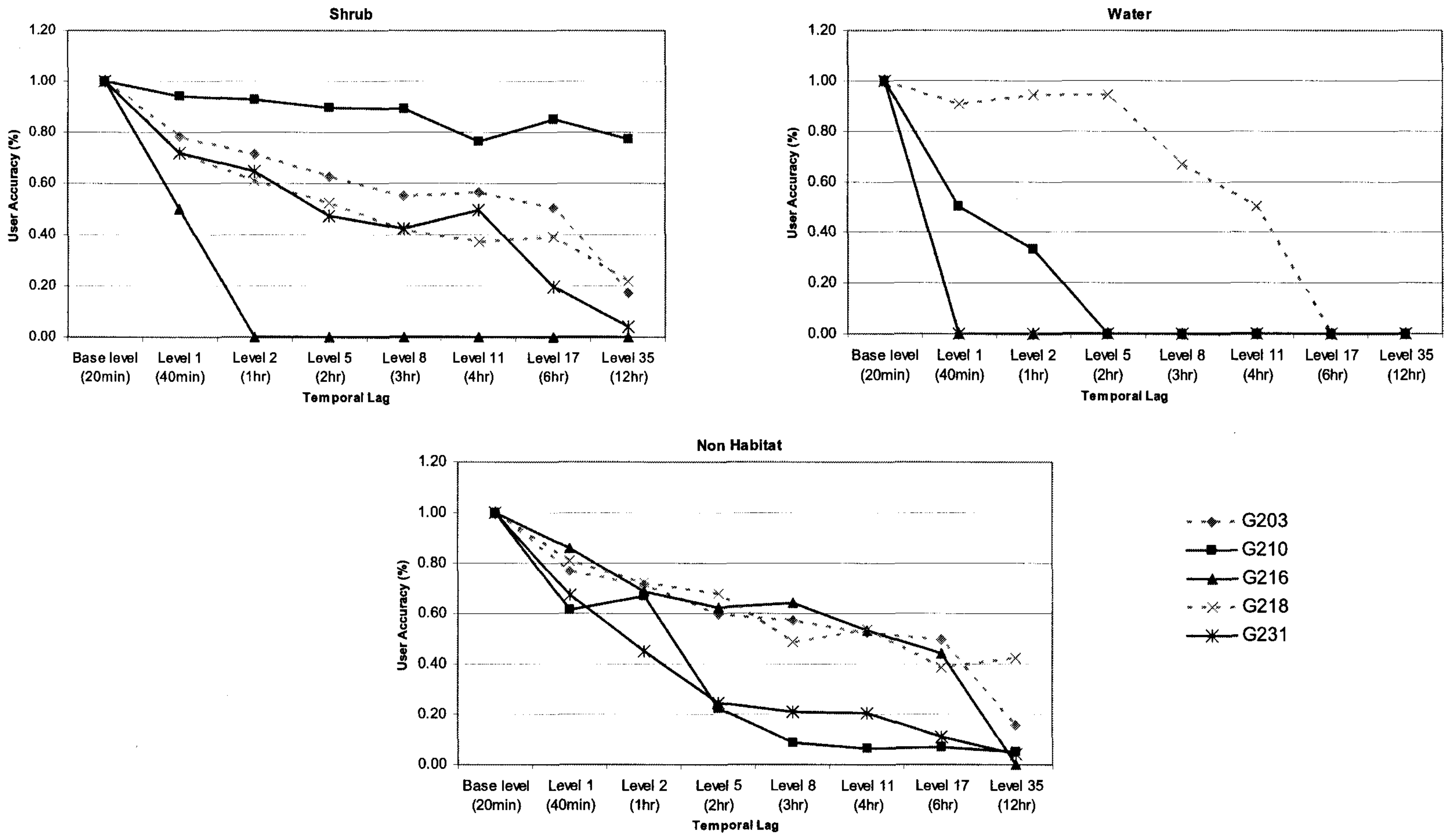


Figure 3-13. User accuracy charts by habitat type (shrub, water, and non habitat) for each bear.



Local Vector Sequential Data Results

Results of the ACF and PACF analysis are shown in Table 3-10. Across all individual grizzly bears, significant positive autocorrelation was found at minimum up to 2h40min for movement rate (km/h) and 1h40min for deviation angle (deg). Males G210 and G216 both reported the smallest times to independence, while female G203 reported the longest times to independence (4h40min for movement rate and 3h20min for turning angle). Of note, female G203 was the only individual bear residing in the Swan Hills, east of other foothills bears. Female G203 was classified as a female with cubs which may have had an impact on the resulting sequential vector serial autocorrelation structure.

PACF results were also examined and are shown in Table 3-10. Time to independence was reached at higher temporal lags for deviation angle when compared to movement rate. For individuals G210, G216, and G218 PACF results reported no partial autocorrelation beyond 20-min vectors for movement rate. Again, individual G203 reported the longest times to independence for PACF.

Table 3-10. Autocorrelation function and partial autocorrelation function results for movement rate (km/h) and deviation angle (deg) highlighting both the number of temporal lags and the temporal data collection level where data is no longer correlated for each individual grizzly bear. Data capture level where ACF and PACF are no longer present is based on results for resampled temporal lags.

				Movement Rate (km/h)					**Deviation Angle (deg)**				
				Base Data - 20min				Data Capture Level	Base Data - 20min				Data Capture Level
Bear ID	**Sex**	**Repro Status**	**Location**	ACF	Time	PACF	Time	No ACF/PACF Present	ACF	Time	PACF	Time	No ACF/PACF Present
G203	F	FC	Swan Hills	14	4h40m	5	1h40m	>12hrs	10	3h20m	5	1h40m	>12hrs
G210	M	AM	Mountain	8	2h40m	1	20min	4hr	7	2h20m	4	1h20m	2hr
G216	M	AM	Foothills	8	2h40m	1	20min	3hr	5	1h40m	2	40min	3hr
G218	F	AF	Foothills	10	3h20m	1	20min	4hr	9	3h	5	1h40m	2hr
G231	M	AM	Foothills	10	3h20m	4	1h20m	>12hrs	9	3h	5	1h40m	3hr

To examine the presence of serial autocorrelation at varying temporal data collection scales, ACF and PACF results were also generated for each resampled vector data collection level. Results demonstrated at what temporal data collection scale no serial autocorrelation would be present in the vector data set. For example, individuals G210 and G218 reported that a GPS data point collected every 4-hr would produce no presence of autocorrelation in resulting movement rate calculations (Table 3-10). For female G203, serial autocorrelation was present across all data collection scales for movement rate and turning angle. Data would subsequently have to be resampled beyond 12-hr to remove any dependence present in resulting calculated movement parameters. Beyond this, by examining the resulting ACF and PACF charts for other data collection levels (e.g. 1-hr data) cyclical trends in movement rate became apparent (Figure 3-7b). Movement rates were found to exhibit positive autocorrelation occurring at approximately 12-hr intervals across all bears.

The final section of this chapter identified and compared sequential slow moving vector clusters both temporally and spatially. Using a time series sequence graphing approach, movement characteristics for each individual bear were mapped at each temporal data collection scale (Figure 3-14a). Using normalized distance, two movement types were identified. Slow movements were characterized by vectors occurring below a normalized threshold of 1.0 mean standard deviation. All remaining movements were classified as fast vectors indicating travel behavior. Resulting time sequence graphs were analyzed for slow vector clusters that were linked sequentially and therefore temporally, as well as spatially due to low vector distances. Overlapping vector clusters were also identified to highlight site revisits for each individual grizzly bear (Figure 3-14a).

Spatiotemporal cluster results are identified in Table 3-11 for each individual bear across each data collection level. Again, the base level was assumed to provide the best available information and thus clusters identified at this level represented 100% of the identifiable clusters. The ability to identify slow moving vector clusters fell off significantly as data resolution decreased. That is, if a researcher was working with 1-hr data structures, only 43% of slow moving vector clusters would be present for identification. When working with 4-hr data, only 7.5% of slow moving clusters were identifiable. Results indicated that when working with typical GPS data sets, identifying fine-scale behaviors and internal vector variations will be limited. In fact, the identification of process-based movement behaviors may only be possible when working with 20-min or finer scale data sets.

Finally, spatial clusters or site revisits are identified in Table 3-12. Following the same format, the ability to identify site revisits for each individual bear decreased largely as data resolution subsequently decreased due to vector resampling. For example, only 50% of site revisits were identifiable when working with 2-hr data for all bears combined. Only individuals G203 and G210 retained spatial clusters at 4-hr and above data collection levels. For the other 3 individual grizzly bears, site revisits were not apparent in the data when working 4-hr vector intervals.

Figure 3-14. Resulting base level sequence graphs for male G216 demonstrating a) 24 spatiotemporal clusters with a normalized distance <1.0 standard deviation threshold (represented in light red), and b) 2 spatial clusters (site revisits) as indicated by star symbols (light red and white).

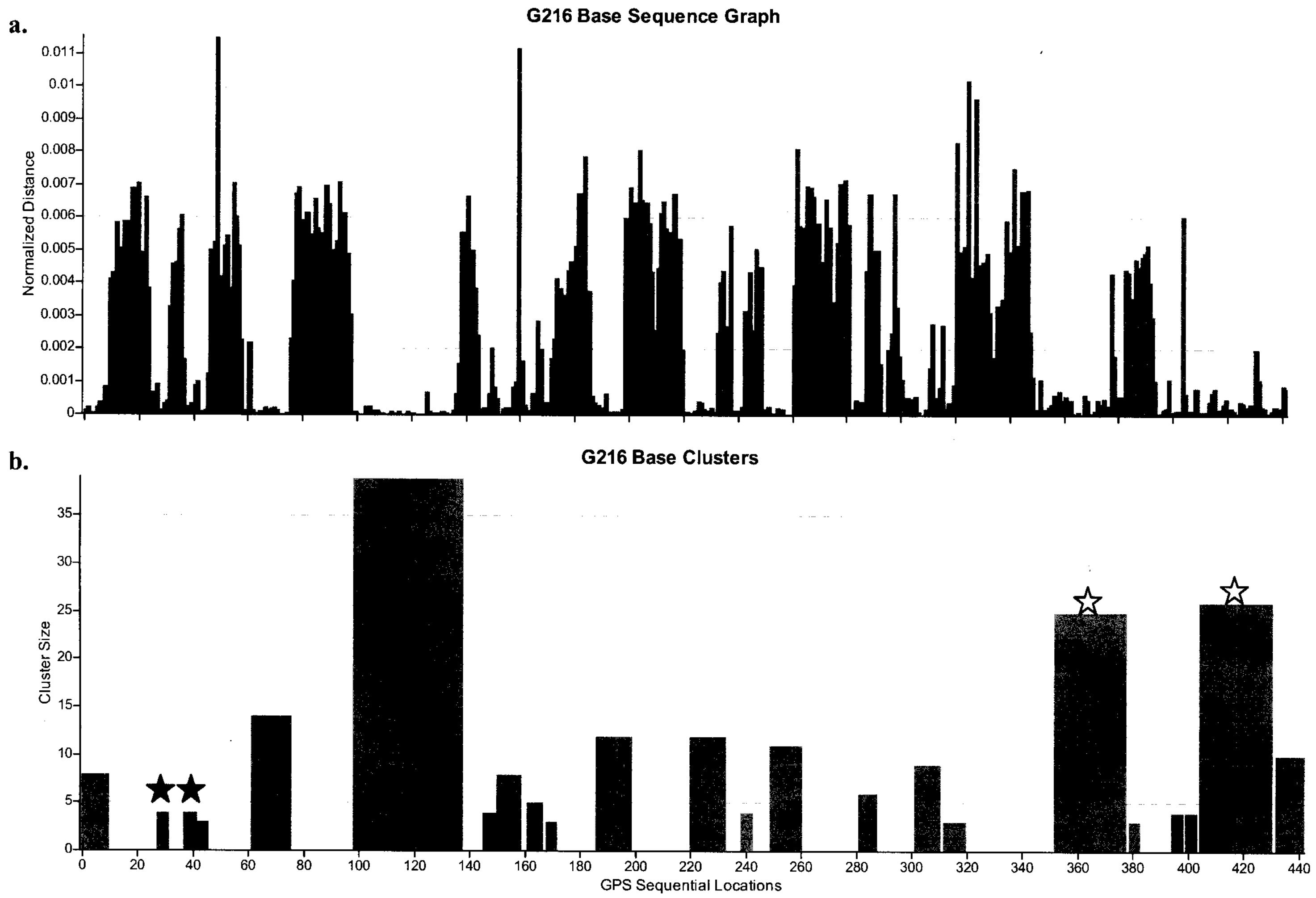


Table 3-11. Spatiotemporal cluster results showing number of clusters and percent of clusters retained for each bear across all temporal data collection levels.

	Spatiotemporal Clusters												
	G203		**G210**		**G216**		**G218a**		**G218b**		**G231**		
Temporal Lag	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent	**Mean Percent Retained**
Base level (20min)	402	100.00	73	100.00	24	100.00	21	100.00	66	100.00	311	100.00	**100.00**
Level 1 (40min)	220	54.73	40	54.79	14	58.33	12	57.14	26	39.39	171	54.98	**53.23**
Level 2 (1hr)	167	41.54	33	45.21	12	50.00	8	38.10	24	36.36	140	45.02	**42.70**
Level 5 (2hr)	87	21.64	15	20.55	3	12.50	6	28.57	14	21.21	57	18.33	**20.47**
Level 8 (3hr)	49	12.19	11	15.07	3	12.50	3	14.29	3	4.55	21	6.75	**10.89**
Level 11 (4hr)	35	8.71	5	6.85	2	8.33	3	14.29	2	3.03	12	3.86	**7.51**
Level 17 (6hr)	6	1.49	2	2.74	1	4.17	0	0.00	2	3.03	6	1.93	**2.23**
Level 35 (12hr)	5	1.24	0	0.00	0	0.00	0	0.00	1	1.52	2	0.64	**0.57**

Table 3-12. Spatial or site revisit cluster results showing number of clusters and percent of clusters retained for each bear across all temporal data collection levels.

	Spatial Clusters												
	G203		G210		G216		G218a		G218b		G231		
Temporal Lag	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent	**Mean Percent Retained**
Base level (20min)	25	100.00	4	100.00	2	100.00	0	0.00	3	100.00	10	100.00	**100.00**
Level 1 (40min)	19	76.00	3	75.00	2	100.00	0	0.00	2	66.67	10	100.00	**83.53**
Level 2 (1hr)	15	60.00	3	75.00	2	100.00	0	0.00	2	66.67	9	90.00	**78.33**
Level 5 (2hr)	10	40.00	3	75.00	1	50.00	0	0.00	1	33.33	4	40.00	**47.67**
Level 8 (3hr)	8	32.00	1	25.00	1	50.00	0	0.00	0	0.00	1	10.00	**23.40**
Level 11 (4hr)	7	28.00	1	25.00	0	0.00	0	0.00	0	0.00	0	0.00	**10.60**
Level 17 (6hr)	0	0.00	1	25.00	0	0.00	0	0.00	0	0.00	0	0.00	**5.00**
Level 35 (12hr)	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	**0.00**

3.5 Summary

In order to analyze and understand the movement patterns created from consecutive GPS radiotelemetry data, researchers must first decide on an appropriate data approach. However, before modeling it is imperative a solid understanding be achieved regarding GPS vector-based movement characteristics. Information regarding both movement patterns and processes change according to the spatial and temporal scale of data collection. Furthermore, individual grizzly bears will respond to or interact with the environment at various spatial and temporal scales. For example, males and females have different home range sizes, move at different rates, and select for different habitats (Nielsen et al. 2002, Schwab 2003, Nielsen 2005, Stenhouse et al. 2005). This makes it difficult to understand and generalize bear movements at the population level.

Ideally, all GPS radiotelemetry location data should be collected at the finest scale possible. Unfortunately, this is not always logistically and financially possible. This chapter worked with 20-min data, a quality and quantity previously not available for grizzly bear data analyses. Beginning with the gold standard (20-min data) and resampling to lower vector resolutions provided an opportunity to highlight differences regarding available vector information and characteristics across different temporal levels of data collection.

Previous studies have demonstrated that movement rate is biased by sampling rate (Johnson et al. 2002, Nams 2006a). The choice of appropriate sampling interval is therefore an important consideration. Typically, as a movement path is sampled more intensively, more detail is recorded, net displacement is greater, and movement rate increases while vector distance decreases (Johnson et al. 2006). Generally, the opposite occurs when data is undersampled. However, while significant differences to movement rate existed between the base level (20-min) data when compared directly to larger data temporal scales, no significant differences were found between higher order lags. That is mean movement rate differences were not significant when comparing 1-hr versus 2-hr or 2-hr versus 4-hr vector data sets. This result was similar for mean turning angle. As such, when working with larger-scale vector sets, researchers should be able to group vector data across various temporal collection levels without concern. This applies the use of both mean movement rate and mean turning angle as global descriptive measures.

Often wildlife studies calculate movement rate as a mean value, rather than a median or mode movement rate. This chapter examined the differences between mean and median movement rate as temporal data collection scale changed. The resulting mean movement rate behaved as expected, slightly decreasing as temporal lag increased. The resulting median movement rate however demonstrated variable results, neither obviously decreasing nor increasing as temporal lag changed. The calculation of mean movement rate itself is an average of the distance traveled between two points given a specific duration of time. The resulting mean is therefore expressing the average at each lag given a number of mean movement rates for each vector segment. The resulting median chart is expressing the median movement rate summarizing the middle movement rate value as temporal lag changes. While the median value may be more appropriate when working with highly skewed data, the mean was used here for direct comparison to other wildlife study results.

It is further important to consider the influence of fix rate on the estimation of movement parameters distributions (movement rate and turning angle) (Jerde and Visscher 2005). A study conducted by Johnson et al. (2002) recorded no differences to movement rate distributions when data was sampled ≥ 3 hr and ≤ 16 hr for caribou. Similarly, we found no significant differences for grizzly bears movement distributions between larger lag sampling intervals. Distributions were significantly different however when 20-min movement rate distributions were compared against all other resampled vector lags. Results indicated again that higher order lags could be combined with no significant influence to vector-based movement parameters.

Vector distributions were also assessed spatially. That is, total movement path placement was compared at decreased temporal resolutions to the original vector movement path for each bear. Resulting buffer widths provided both a quantitative measure of potential vector error, as well as a visual interpretation of this variability. The amount of departure increased considerably as vector resolution decreased across all bears. Results provided a measure of spatial uncertainty when working with vector data layers for all bears individually and grouped. For example, on average when working with 4-hr data, movement paths would require a 2.6 km buffer to capture any potential vector error between known GPS locations. These results are useful when determining where a bear may have travelled between locations and the extent of habitat that may have possibly influenced resulting movement patterns.

Changes to spatial vector placement were also examined using changing habitat class proportions. Significant changes were reported if change equaled or exceeded 5% for each habitat class between resampled temporal lags and the original baseline data. Significant differences to the proportion of habitat class were only reported at higher temporal lags indicating that vector collected habitat information is not overly sensitive to resampled vector information at lower temporal resolutions. For all bears, closed forest showed significant changes at higher levels. For 4 out of 5 bears the change to closed forest proportion was positive. However, for mountain bear G210 the change of closed forest class proportion was negative with a corresponding increase in the presence of non habitat class proportion. This result indicates that as vector resolution changes, vector spatial placement in environments with mountain landscape features is an especially important consideration.

Local vector one to one comparisons were also used to quantify the degree of change as data collection resolution decreased. This was completed using a vector-based contingency table analysis for each individual bear. When grouped, contingency table results indicated that local vector habitat classification accuracies dropped to approximately 80% for 40-min data, 70% for 2-hr data, 60% for 4-hr data, and to 50% for 12-hr data. To reiterate, this assumes that 20-min data represents the most accurate representation of movement segments between known locations.

The use of a vector-based contingency table analysis further provided habitat class specific accuracy results. Spatial vector placement and corresponding habitat proportions responded differently for each bear across changing vector resolutions. The contingency table approach provided an opportunity to highlight when specific vector-based habitat classes reached a 0% accuracy level or reached the equivalent 100% error level. For all individual bears across all resampled temporal levels, closed forest never reached 0% when compared to the other habitat class types. Every other habitat class type fell below 50% accuracy levels when working with 4-hr vector data. Results further provided additional information regarding the spatial pattern of underlying habitat patches. Habitat patch types which are small and fragmented, such as shrub or open forest are more sensitive to changing vector resolutions. For habitat classes with limited size and shape, resampled vectors which may have indicated selection at fine temporal resolutions could potentially miss or avoid patches at coarser temporal resolutions. Overall persistence of closed forest vector accuracy may directly reflect the fact that closed forest patches are large and contiguous across the landscape. As such, vector-based contingency results must take habitat placement and structure into consideration.

Most movement models (e.g. CRW and SSF) assume that vector lengths (movement rate) and turning angles are not serially autocorrelated (Austin et al. 2004). In fact, this is often the case when working with data points that are separated by large temporal intervals. However, when working with fine-scale movement data for grizzly bears it is expected that data would be serially autocorrelated. All base level data for all 5 individual bears were highly significantly autocorrelated. It was found that by resampling vector data structures to a capture rate of 3-hr or 4-hr serial autocorrelation could be eliminated. However, in the case of one individual grizzly bear (G203) serial autocorrelation was present across all vector sampling lags. Resampling fine-scale data to achieve independence was further found to significantly reduce the information available within the data structure. For example, if this study reduced each individual data set to the point where autocorrelation was no longer present, the ability to detect fine-scale spatial and temporal data clusters within the consecutive data structure would disappear. Non-stationary movement patterns, such as those indicated when examining the autocorrelation structure of 1-hr data points, would not be apparent if the data was resampled at the resolution of time to independence (Cushman et al. 2005).

The presence of serial autocorrelation in both movement rate and turning angle indicate the propensity of individual bears to maintain the same speed and make sequential movements in similar directions. This is known as directional persistence (Zollner and Lima 1999). For turning angle, this means that individual bears will either continue in straight directions or continue turning when compared to the previous vector segment. For movement rate, this implies that if one vector is a slow moving vector the preceding vector will likely also be a slow moving vector. Therefore, positively autocorrelated slow movement or high turning angle vectors could indicate the presence of a sustained foraging behavior. Resulting ACF and PACF charts for 1-hr vector data segments demonstrated cyclical patterns when examining movement rate for individual bears. For example, ACF results for individual G231 highlighted positively autocorrelated vectors up to 4-hr, negatively autocorrelated values from 4-hr to 10-hr, positively autocorrelated values from 11-hr to 14hr, and then again at 20-hr to 24-hr (see Figure 3-7b for an example). This pattern indicates movements to be similar at smaller lags (up to 4-hr), different at middle lags (up to 10-hr), and similar again across the range of 24-hr or a single day. Grizzly bear movements are therefore non-stationary across both small and long time lags indicating a possibility of non-random movements or changes to movement behaviors along trajectories.

While use the of time sequence graphs is a relatively straight-forward and simplistic analysis, it offers a novel method for retaining the consecutive nature of large GPS vector data structures which most complicated movement models do not. The approach further provided a method for distinguishing between types of movement behaviors and examining internal vector structure. The use of a normalized distance threshold may not be the strongest statistically in terms of developing a separation threshold, yet it worked well in the examples provided here. I believe this is largely because movement data is so heavily skewed to zero with the majority of vector steps and subsequently movement rates having small values. As such, separating vector distributions into a dichotomous classification (the smallest vectors versus everything else) is possible. The resulting threshold provides a conservative estimate closer to zero than might be needed when working with a two-process behavior model.

As the sampling interval increases or temporal resolution decreases, the ability to detect finer-scale responses equally decreases. This was evident as data collection resolution decreased the ability to identify slow moving clusters diminished. When working with 4-hr data the ability to identify changes in movement behavior decreases, not only in the quantity of behavior shifts but also in the duration or length of the existing clusters. In addition to losing sequential vector clusters, site revisits also disappeared. As demonstrated by this chapter, low to moderate amounts of data may be adequate for estimating home range size but inadequate to identify movement clusters. When working with 4-hr GPS data sets, researchers should focus on working within the context of a home range. The opposite, large amounts of data, while the typically more attractive option, may be excessive and difficult when the analysis stage is reached further producing high levels of autocorrelation and variability (Turchin 1998). Yet, unless a grizzly bear researcher is working with 20-min or 40-min data at most, differences in movement processes will not be discernible.

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CHAPTER 4 – QUANTIFYING LARGE-SCALE GPS-BASED GRIZZLY BEAR MOVEMENT RATES AND HOME RANGE SIZES

4.1 Introduction

Current Global Positioning Systems (GPS) – based studies have generated extensive telemetry data sets providing information regarding the movement rates of large ranging species (Amstrup et al. 2001, Mauritzen et al. 2001, Rettie and Messier 2001, Taylor et al. 2001). The major goal of these studies is often a management driven long-term conservation plan for the species in question (Chetkiewicz et al. 2006). In Alberta, habitat loss resulting from oil and gas exploration, industrial extraction and increased human activities (such as tourism, recreation and suburban/rural development) has threatened the survival of grizzly bear populations (Gibeau et al. 2002, Nielsen et al. 2006). In the case of the Foothills Research Institute Grizzly Bear Research Program, understanding movement rates and the related activity patterns of grizzly bears is required to provide management with the scientific information needed to balance industry requirements with conservation imperatives (NESERC 2000).

Movements of grizzly bears are highly variable and difficult to investigate. At a basic level, they are governed by the individuals need to acquire resources, reproduce, avoid conspecifics, and limit human interactions (Mace and Waller 1997, Dahle and Swenson 2003a, 2003b, Mueller et al. 2004, Stenhouse et al. 2005). At a more complex level, resulting movement rates are influenced by seasonal climate, related food production, time of day, interaction with external factors, and physical location on the landscape (Weaver et al. 1996, Stenhouse et al. 2005, Kaczensky et al. 2006). Differences in movement rates are further defined by sex, reproductive status and age of individual bears (Dahle and Swenson 2003a, 2003b). For example, the movements of males are found to be more extensive than those of females especially during mating season (Amstrup et al. 2001, McLellan and Hovey 2001b, Dahle and Swenson 2003b, Stenhouse et al. 2005). Movement rates and related home range size are additionally impacted by the amount of human-induced habitat fragmentation and loss (Chruszcz et al. 2003, Dickson et al. 2005, Berland et al. 2008) which inherently alters the configuration and composition of the natural landscape (Linke et al. 2005). Reduced connectivity and impeded movements may result in higher mortality and lower rates of reproduction, leading to smaller populations and reduced population viability (Chruszcz et al. 2003, Proctor 2003, Proctor et al. 2005). To my knowledge, only one other study has reported on grizzly bear movement rates specific to human development in Alberta (Gibeau 2000, Gibeau et al. 2001). Generally, there appears to be an overall lack of research focusing on the spatial and temporal quantification of grizzly bear movements in regions with varying levels of human presence and development.

As demonstrated in Chapter 3, the ability to measure and analyze movement rates and related vector characteristics is largely related to the scale of data collection. Limitations exist when measuring and quantifying spatial temporal movement patterns based upon GPS location data collected at large temporal intervals (Morales and Ellner 2002). This is especially true when studying large carnivores where the majority of radiocollars are programmed to record locations with larger time gaps (e.g. 1 GPS location every 4 or 5 hours) to maximize collar life or study duration on a specific animal. The majority of GPS location data for the FRI is collected at 4-hour intervals. Unfortunately, when dealing with more than one individual over large spatial scales, modeling or simulating movement between thousands of known GPS locations is computationally intensive and unrealistic. Home range estimation and simple vector-based movement statistics offer a basic first step in understanding the general biological requirements and spatial response of grizzly bears (Dahle and Swenson 2003a, 2003b, Collins et al. 2005).

The goal of this chapter is not to model movement but to empirically quantify GPS-based movement rates and related activity patterns for grizzly bears across multiple temporal and spatial scales using previously obtained GPS radiotelemetry locations. The description and quantification of movement patterns, both spatially and temporally, are important first steps to understanding the complexity of underlying movement processes (Fortin and Dale 2005). Prior to data analysis, a large portion of the required methods section focuses on data preparation and processing in effort to minimize biased movement results. Specific chapter objectives are three-fold: 1) to examine population-level differences in hourly movement rates and home range size across multiple temporal and spatial scales; 2) to identify and describe relationships between movement rates and the presence of human activity (development) in different landscape regions; and 3) examine female-specific differences in hourly movement rates and home range size according to reproductive status and landscape type. Results reported in Section 4.4 will provide a theoretical basis for future chapters and analyses. Furthermore, the findings have significance for future modeling efforts which attempt to replicate or predict grizzly bear movement patterns across landscapes. Finally, identifying differences to movement rates among individual bears and bear subgroups will aid management in making localized site-specific conservation decisions (Chetkiewicz et al. 2006).

4.2 Study Area and Supplementary Data Layers

The research study area for Chapter 4 was situated along the eastern slopes of the Canadian Rocky Mountains ranging from west-central Alberta south to the Canada-US border (Figure 4-1). The region is comprised of two major landscape types: 1) the high elevation mountains in the west (dark grey), and 2) the industry dominated foothills in the east (medium grey). The mountain landscapes (> 1700 m in elevation) run northwest to southeast in orientation and are characterized by rugged terrain, douglas fir (*Pseudotsuga menziesii*), lodgepole pine (*Pinus contorta*), or aspen (*Populus tremuloides*) forests, and alpine meadow valley bottoms (Beckingham et al. 1996). Moving to the east, foothills landscapes (< 1700 m elevation) are dominated by conifer forests such as lodgepole pine or white spruce (*Picea glauca*), deciduous forests such as aspen or balsam poplar (*Populus balsamifera*) and mixed forests. Additional landscape types include wet meadow and wet treed complexes consisting of black spruce (*Picea mariana*) and tamarack (*Larix laricina*) stands, riparian valleys, regenerating (post-fire and clearcut harvesting) forest stands, and agricultural lands (Beckingham et al. 1996). Human activities in the foothills include tourism, recreational uses (hunting, hiking, and off-road vehicles), mining, agriculture, forest harvesting, oil and gas exploration and extraction, and transportation routes, all of which contribute to landscape fragmentation. Mountain landscapes, although mostly protected from industrial development, contain major highways and extensive recreational use. In Alberta, where grizzly bear populations occupy both mountain and foothills environments, valuable information can be gained by studying movement rates across regions with varying levels of human activity (Gibeau et al. 2002).

Supplementary linear features such as highways, secondary and gravel roads, railways, pipelines, and powerlines were used to calculate total linear distance (km) and human access density (km/km^2) for both landscape type and bear management areas (BMA). Well sites, represented as point features, were additionally compiled and used to quantify presence of human activity across the study region (see Table 4-1).

Figure 4-1. Map of central and south-western Alberta showing Chapter 4 study regions with major cities, highways, provincial bear management areas (BMAs), and provincial mountain parks represented in relief.

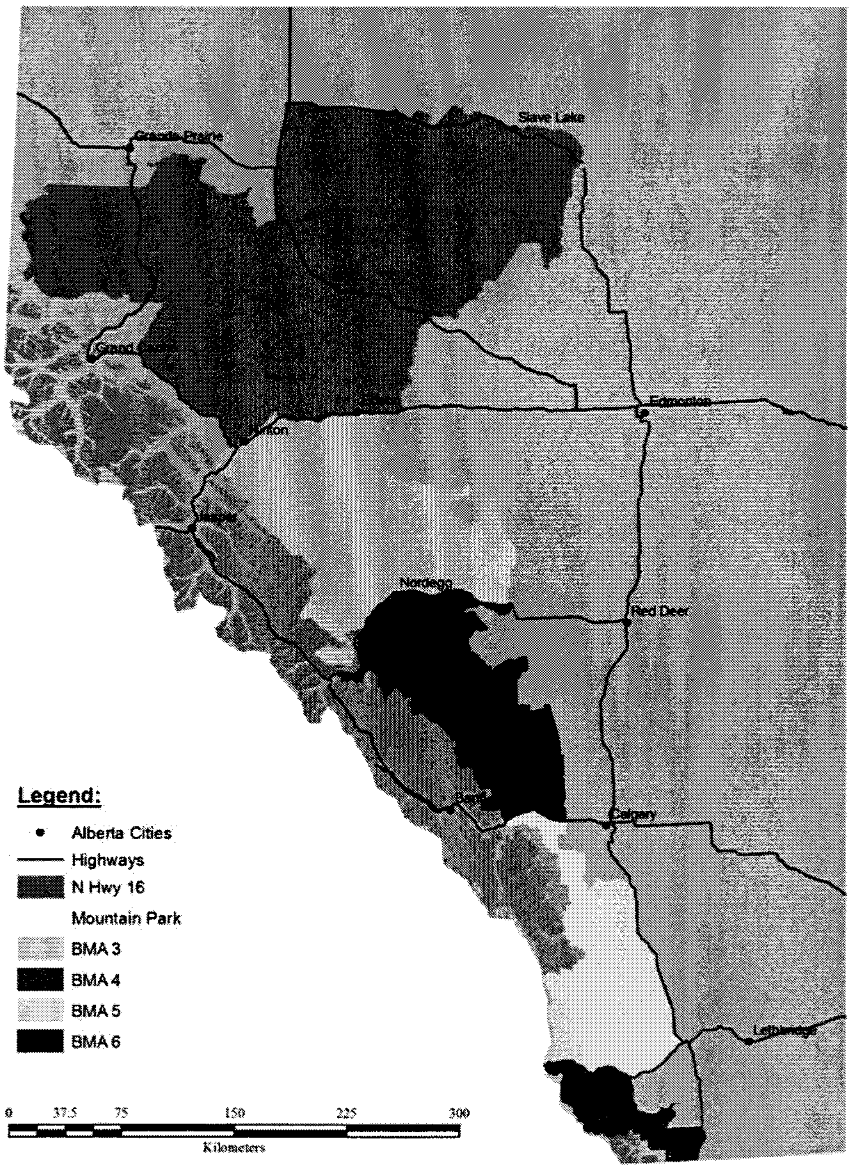


Table 4-1. Total distance (km) and densities (km/km^2) for human access linear features and well sites grouped according to landscape type and bear management area.

	Summary Statistics			
	Total Area (km^2)	# of Segments	Total Distance (km)	Density (km/km^2)
Landscape Type				
All Linear Access				
Mountains	34453.0	7178	6923.39	0.201^-
Foothills	89484.4	149301	89770.10	1.003^{+}*
Well Site Locations				
Mountains	34453.0	334	-	0.0097^-
Foothills	89484.4	23766	-	0.2656^+
Bear Management Areas				
All Roads				
BMA 3	16786.2	17399	9960.42	0.593
BMA 4	11280.6	29699	12391.00	1.098^{+}*
BMA 5	9005.5	11348	6247.09	0.694*
BMA 6	3083.9	4375	2308.85	0.749*
N Hwy 16	49328.3	56342	33537.72	0.680*
Mountain	34453.0	6758	5727.37	0.166^-
Railways				
BMA 3	16786.2	300	332.20	0.020
BMA 4	11280.6	63	150.46	0.013
BMA 5	9005.5	56	265.75	0.030
BMA 6	3083.9	100	116.46	0.038^+
N Hwy 16	49328.3	535	570.26	0.012^-
Mountain	34453.0	114	442.65	0.013
Pipelines				
BMA 3	16786.2	2654	4167.88	0.248
BMA 4	11280.6	712	1655.82	0.147
BMA 5	9005.5	544	1061.59	0.118
BMA 6	3083.9	137	495.12	0.161
N Hwy 16	49328.3	22962	13148.35	0.267^+
Mountain	34453.0	187	313.62	0.009^-
Well Site Locations				
BMA 3	16786.2	4506	-	0.268
BMA 4	11280.6	1109	-	0.098
BMA 5	9005.5	1178	-	0.131
BMA 6	3083.9	174	-	0.056
N Hwy 16	49328.3	16799	-	0.341^+
Mountain	34453.0	334	-	0.010^-

$^+$Values represent the highest density for each group.

$^-$Values represent the lowest density for each group.

*Values represent linear densities which exceed the 0.6 km/km^2 threshold (Forman et al. 1997)

4.3 Methods

GPS Data Preparation

Between 1999 and 2005, the FRI grizzly bear research project captured and collared 167 grizzly bears, some of which were collared multiple times (*n* = 34). Each bear was fitted with either a Televilt Simplex (Lindesberg, Sweden) GPS radiocollar, an Advanced Telemetry Systems (ATS) (Isanti, Minnesota, USA) GPS radiocollar, or a Televilt Tellus 1 (Lindesberg, Sweden) GPS radiocollar. Capture protocols followed the Canadian Council on Animal Care accepted procedures and were reviewed by the Animal Care Committee at the Western College of Veterinary Medicine in Saskatoon, Saskatchewan (CCAC 2003). Over 7 years, 18 known bear mortalities and 20 confirmed collar failures were recorded but not analyzed as part of this research. Mortalities were generally classed as unknown (*n* = 5), illegal (*n* = 6), legal hunt (*n* = 2), research (*n* = 2), self-defense (*n* = 1), management action (*n* = 1), or other bear (*n* = 1). Confirmed collar failures represented GPS radiocollars that upon retrieval were found to have no data, erroneous data files, or valid data but had stopped recording locations at an earlier date. Collars retrieved with valid data prior to a mortality or collar failure event were included in the analyses. Collars were discarded from analyses if annual GPS radiotelemetry recorded locations were < 50. This excluded 17 radiocollars at the onset of this study reducing the initial sample size to 150 grizzly bears.

Collars were programmed to retrieve GPS radiotelemetry locations from den emergence in early spring to denning in late fall at either 5-hr time intervals (*n* = 45), 4-hr intervals (*n* = 86), 2-hr intervals (*n* = 6), 1-hr intervals (*n* = 4), or 20-min intervals (*n* = 9). Only 50.4 % of total attempted recorded fixes were successfully downloaded for processing. Locations for each year were divided into 4 seasons: hypophagia or den emergence (May 1 - June 15), early hyperphagia or pre-berry (June 15 - August 15), late hyperphagia or berry (August 15 - October 15) and denning (October 15 - May 1). Seasonal classifications correspond to documented grizzly bear feeding behavior (Hamer and Herrero 1987, Hamer et al. 1991, Nielsen 2005, Nielsen et al. 2006). In addition to seasonal categories, locations were further classed according to month (April – November) and time of day to assess finer scales of movement (Nielsen et al. 2003, Munro et al. 2006). Following Munro et al. (2006), annual sunrise, sunset, and civil twilight tables (http://www.cmpsolv.com/los/sunset.html) were used to define crepuscular (predawn and dusk), diurnal (sunrise to sunset) and nocturnal (dusk to predawn twilight periods) time of day classes. All tables were generated to approximate daylight conditions for the center of our study area at Robb, Alberta (53°N and 117°W). While North American brown bears are largely diurnal and bed most frequently at night (Munro et al. 2006), it is speculated that nocturnal movement behavior may increase in regions with high levels of human activity (Gibeau et al. 2002, Kaczensky et al. 2006). As such, times of day classifications were used to assess whether movement patterns differed over a 24-hour period according to landscape type.

Radiocollared grizzly bears across each year were categorized first by sex (male, n = 55; female, n = 95), then by age (subadult, 2-4 yrs old or adult, ≥ 5 yrs old) (Mace and Waller 1997, Gibeau et al. 2002), and further combined to represent reproductive status (adult male, n = 36; subadult male, n = 19; adult female, n = 36; subadult female, n = 19; and females with cubs, n = 40) (Table 4-2). Reproductive status was assessed based on individual observation during den emergence, capture events and/or radio telemetry uploads to aircraft. Grizzly bears were then grouped according to landscape type. Individual bears with ≥ 75% of GPS locations above 1700 m were categorized as mountain bears with all remaining bears categorized as foothills bears (Munro et al. 2006). Individual bears were further stratified according to provincial BMA. Bear management areas were classified as mountain, BMAs 3, 4, 5 or 6, or all lands occurring north of Highway 16 (Figure 4-1). Mountain BMAs, which included provincial parks, typified landscapes with lower levels of human activity; while foothill BMAs and lands occurring north of Highway 16 were characterized as regions with extensive resource extraction and increased human access.

Table 4-2. Final 148 grizzly bears used in Chapter 4 analysis classified by year and reproductive status.

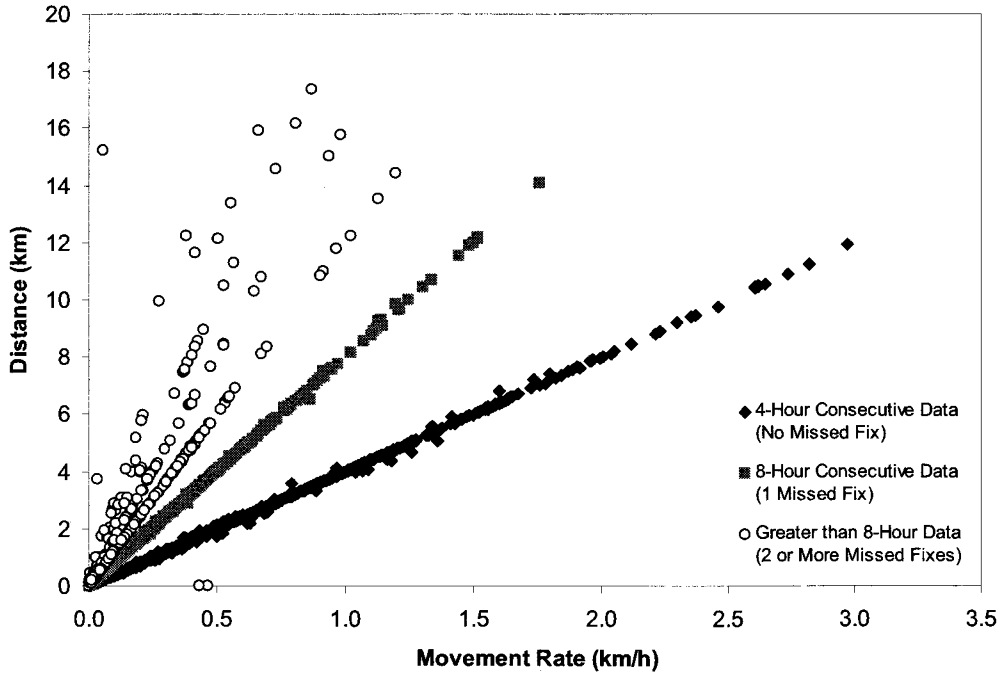
	Reproductive Status (Sex + Age)					
Year	Adult Female	Adult Male	Female with Cubs	Subadult Female	Subadult Male	Total
1999	4	3	1	2	1	11
2000	7	5	4	2	1	19
2001	5	4	6	3	1	19
2002	1	3	10	3	2	19
2003	7	6	8	4	4	29
2004	8	6	8	3	2	27
2005	4	8	3	1	8	24
Total	36	35	40	18	19	148

Movement Rate and Home Range Size Analysis

Prior to the analyses, several data filtering tasks were preformed to retain the most accurate and least biased movement data. In total, the 150 GPS radiocollars provided 88,656 raw GPS radiotelemetry locations. Movement rates were calculated by measuring Euclidean distance (meters) between consecutive GPS locations and dividing by time (hours) separating those locations. As collars were programmed to retrieve GPS data at various intervals, movement rates were standardized to km/hr for all grizzly bears across all years. It has been suggested that a lower Dilution of Precision (DOP) score indicates higher quality locations resulting from improved satellite geometry and position (Hofmann-Wellenhof et al. 2001). As such, all GPS radiotelemetry locations with a DOP score > 6 were deleted (Lewis et al. 2007). This reduced the total GPS radiotelemetry data set from 88,656 to 81,012 (8.6 % loss of GPS events) locations.

Further studies, as well as Chapter 3 in this study, have found movement rates to be significantly underestimated as time between subsequent locations increases (Rettie and McLoughlin 1999, Amstrup et al. 2000, Rettie and Messier 2001, Johnson et al. 2002). As such, the effect of time gaps due to missed GPS fixes on both distance (km) between recorded locations and calculated movement rate (km/hr) was assessed for each GPS data point. GPS radiotelemetry locations from 1999 (11 collars, *n* = 5429) were classified into 3 groups for testing: consecutive locations with 4-hr separations or no missed fix (group 1), consecutive locations with 8-hr separations or 1 missed fix (group 2), and consecutive locations with greater than 8-hr separations or 2 or more missed fixes (group 3) (Figure 4-2). After confirming the relationship between missed GPS fixes and underestimated movement rates, this filtering technique was also applied to 5-hr data, 2-hr data, 1-hr data and 20-min data sets across all years. Subsequently, the total number of GPS radiotelemetry locations was reduced to 60,695.

Figure 4-2. Hourly movement rate trajectories (km/h) for 1999 resulting from increased time gaps (missed fixes) between consecutive GPS data locations.



Cattet et al. (2008) conducted an independent study using a subset of the GPS radiotelemetry data which analyzed the post-capture movement rates of 91 radiocollared bears to determine if capture and handling had any long-term effects on mobility. Post-capture response curves suggested that lower movement rates (approximately 43% below population normal) existed for at least 3 weeks (and up to 6 weeks) following a capture and handling event (Cattet et al. 2008). In an effort to eliminate biased movement results, I excluded all GPS telemetry locations for days 1 through 21 post-capture and handling. In total, this reduced the overall radiocollar sample to 148 individual bears (Table 4-1) and the total GPS radiotelemetry data set from 60,695 to 49,987 locations for all subsequent movement rate analyses.

For the majority of movement analyses the sampling unit was each individual bear or radiocollar. First, grouping all years of data, mean hourly movement rates (km/hr) were compared for all 148 bears by (*i*) year, (*ii*) sex, (*iii*) age class, (*iv*) reproductive status, (*v*) landscape type, and (*vi*) BMA. Second, to assess finer scale movements, GPS radiotelemetry data locations across all years were pooled and mean hourly movement rates were compared across (*i*) seasons, (*ii*) months and (*iii*) time of day classes. Finally, to assess if grizzly bear activities varied according to time of day and physical location, crepuscular, diurnal, and nocturnal hourly movement rates were compared across landscape types and BMAs.

To assess annual activity or home range areas used by individual bears, 95% kernel home ranges (km^2) were calculated using the Animal Movement V. 2 Extension in ArcView 3.2a (Hooge et al. 1999). See Chapter 5 for a detailed description on home range generation. First, home range size (km^2) was assessed to see if changes in size varied by year. Annual home range size (km^2) was then compared for 145 bears by (*i*) sex, (*ii*) age class, (*iii*) reproductive status, (*iv*) landscape type, and (*v*) BMA. Three additional individuals were excluded from home range analysis due to number of available GPS telemetry data points. Home ranges were not calculated by season, month or time of day due to a lack of GPS radiotelemetry data ($n \geq 50$) required for proper home range generation (Seaman et al. 1999). It was expected that movement rates for individual bears would be directly related to annual home range size.

Due to the reproductive importance of female grizzly bears (Gibeau et al. 2002, Nielsen et al. 2004b), additional comparisons were conducted using 12 individual radiocollared females. Each female was radiocollared for a minimum of three consecutive years ranging from 1999 to 2004. For each year, individual females were classified by reproductive status (female (F), n = 20; female with cubs of the year (FCOY), n = 13; or female with yearlings (FY), n = 12). For example, an individual female (G016) would be classed as a solitary female in 1999, then classed as a female with COYs in 2000, and finally classed as a female with yearlings in 2001 (Table 4-3).

Table 4-3. Summary of reproductive status over consecutive years for 12 individual female grizzly bears radiocollared from 1999 to 2004.

	Reproductive Status by Year						
Bear ID	1999	2000	2001	2002	2003	2004	*n*
G002	FY	FY	F				1229
G003	F		F	FCOY	FY		1400
G004	F	F	FCOY			FCOY	2074
G007		F		FCOY	FY		69
G010	F	F	F	FCOY	FY		1098
G012		F	FCOY	FY	FY		1233
G016	F	FCOY	FY				797
G020	F	F	FCOY	FY			1322
G023		FY	FCOY	FY	FCOY		958
G028		F	F	FCOY	FY		2145
G040			F	F	FCOY		731
G100			F	FCOY	F	F	730

In some cases, only two of the classifications were present. To begin, mean hourly movement rates (km/h) and annual home range size (km^2) were compared for all females by reproductive class. In effort to understand the effect of human development and activity on movement behavior, individual females were then grouped by landscape type (mountain or foothills) and mean hourly movement rates (km/h) were again compared by reproductive class.

Differences between means were evaluated using analysis of variance (ANOVA) within SPSS. For data that did not fulfill the assumptions of equal variance and normality, the nonparametric Kruskal-Wallis and Mann-Whitney tests were used to identify differences between groups. Pairwise comparisons for multiple groups were assessed with Tukey's honestly significant difference (HSD) and Games-Howell procedures, respectively. Significance was held at $P < 0.05$ for all tests.

4.4 Results

GPS Data Processing Results

During data preparation, movement rates (km/h) for 1999 GPS data were found to be significantly underestimated ($\chi^2 = 42.87$, df = 2, $P < 0.001$) as time between consecutive locations increased (Figure 4-2). More specifically, movement rates for consecutive locations with 4-hr separations or no missed fixes (group 1, $n = 4181$) were significantly higher (mean = 0.25, SE = 5.29, $P < 0.001$) than consecutive locations with 8-hr separations or 1 missed fix (group 2, $n = 833$) or consecutive locations with greater than 8-hr separations or 2 or more missed fixes (group 3, $n = 415$). Comparatively, mean distances (km) were found to significantly increase ($\chi^2 = 156.48$, df = 2, $P < 0.001$) as time between consecutive locations increased (Figure 4-2). In result, only data from group 1, consecutive locations with 4-hr separations or no missed fixes (also applied to 5-hr data, 2-hr data, 1-hr data and 30-min data), were selected for all subsequent analyses in this chapter.

Population Movement Rate Results

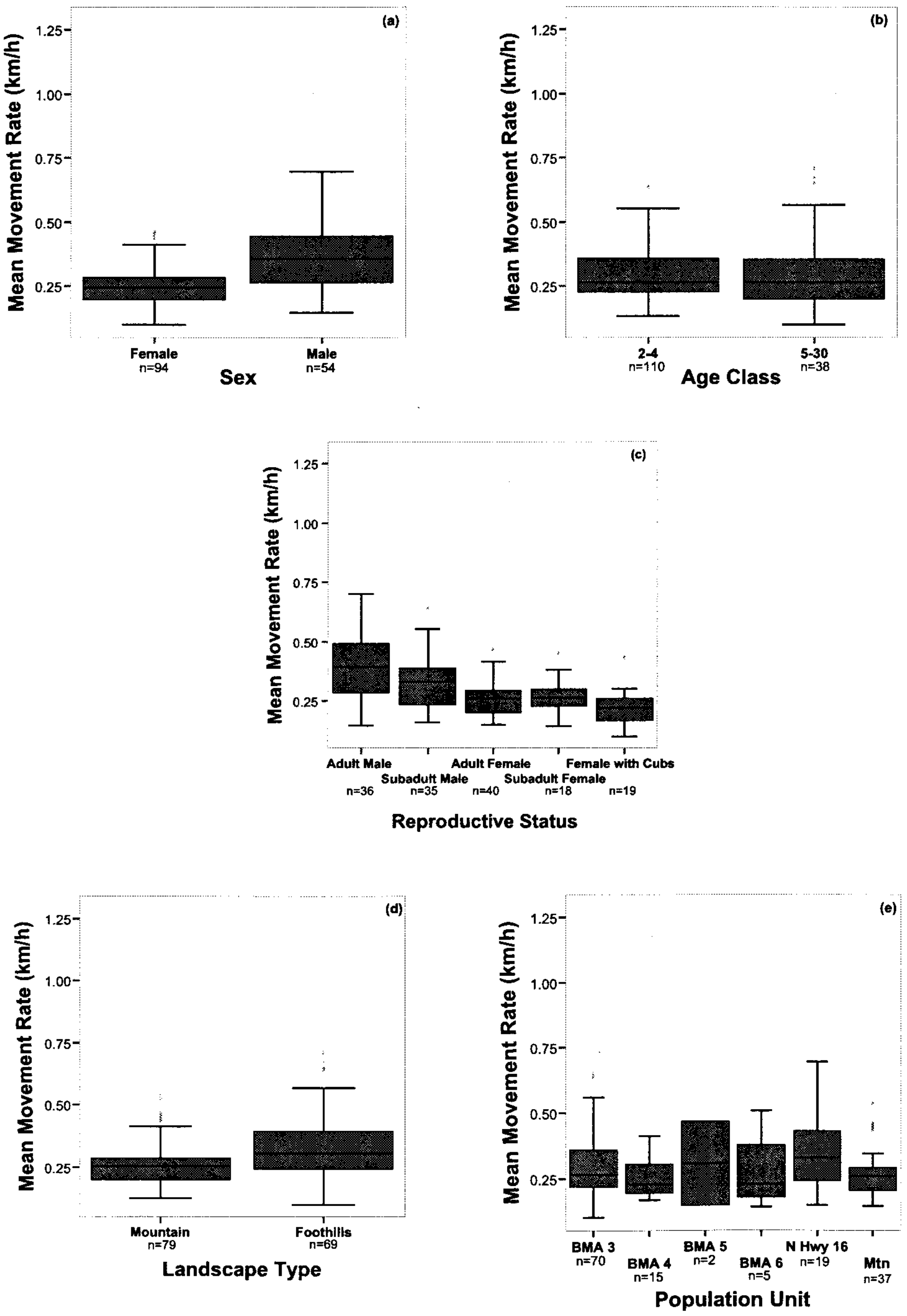
Over 7 years, GPS locations were collected for 54 male and 94 female bears. While the study attempted to collar both sexes of the population, more females than males were captured (Table 4-4). Results indicated average movement rates between years were not significantly different ($\chi^2 = 11.150$, df = 6, $P = 0.084$). However, average rates of movement were found to significantly vary when grouped by sex ($U = 1120.0$, $Z = -5.648$, $P < 0.001$), and reproductive status ($\chi^2 = 42.137$, df = 4, $P < 0.001$) but not by age class (Figure 4-3). The overall average movement rate for bears across Alberta was 0.3 km/h or 7.2 km/day. Generally, movement rates were found to be significantly higher for males (mean = 0.39 km/h, SE = 0.03) than females (mean = 0.25 km/h, SE = 0.01). When classified by reproductive status (Table 4-4), adult males demonstrated significantly higher movement rates than adult females ($P = 0.001$), subadult females ($P = 0.004$) and females with cubs ($P < 0.001$). In comparison, mean movement rates for females with cubs were significantly lower than adult males ($P < 0.001$) and subadult males ($P = 0.022$), but not adult females or subadult females.

Table 4-4. Average mean hourly movement rates (km/h) of grizzly bears (n = 148) by i) reproductive status (sex combined with age) and by ii) bear management area from 1999 to 2005.

	Summary Statistics (km/h)					
	n	Mean	Std. Error	Median	Minimum	Maximum
Reproductive Status						
Adult Males	35	0.42	0.03	0.39	0.15	1.3
Subadult Males	19	0.33	0.03	0.33	0.16	0.63
Adult Females	36	0.26	0.01	0.26	0.15	0.45
Subadult Females	18	0.28	0.02	0.26	0.14	0.44
Females with Cubs	40	0.22	0.01	0.22	0.1	0.57
Total	148	0.3	0.01	0.26	0.1	1.3
Bear Management Area						
Mountain	37	0.27	0.02	0.26	0.14	0.53
BMA 3	70	0.29	0.01	0.27	0.1	0.64
BMA 4	15	0.27	0.03	0.23	0.17	0.67
BMA 5	2	0.31	0.16	0.31	0.15	0.47
BMA 6	5	0.29	0.07	0.23	0.14	0.51
N Hwy 16	19	0.39	0.06	0.33	0.15	1.3
Total	148	0.3	0.01	0.26	0.1	1.3

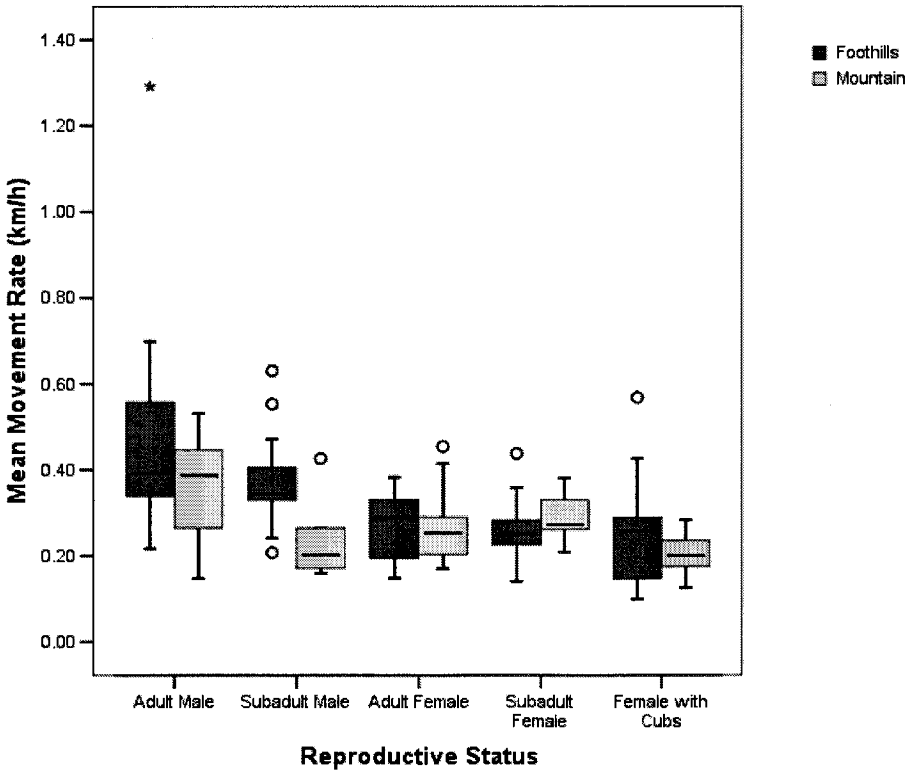
Bears were further grouped according to landscape type and BMA to determine if physical location impacted population movement rates. Average rates of movement were found to vary significantly by landscape type (U= 1727.0, Z = -3.838, $P < 0.001$) but not by BMA (Figure 4-3). In total, 79 bears resided predominantly in mountain landscapes while the remaining 69 bears resided in foothills landscapes (Figure 4-3d). Grizzly bears located in mountain environments were found to have significantly slower movement rates (mean = 0.26 km/h, SE = 0.01) than grizzly bears located in foothill environments (mean = 0.35 km/h, SE = 0.02) where linear human access densities are approximately five times higher (Table 4-1).

Figure 4-3. Box plots demonstrating differences to mean movement rates (km/h) for 148 bears from 1999 to 2005 grouped by a) sex, b) age, c) reproductive status, d) landscape type, and e) provincial bear management areas.



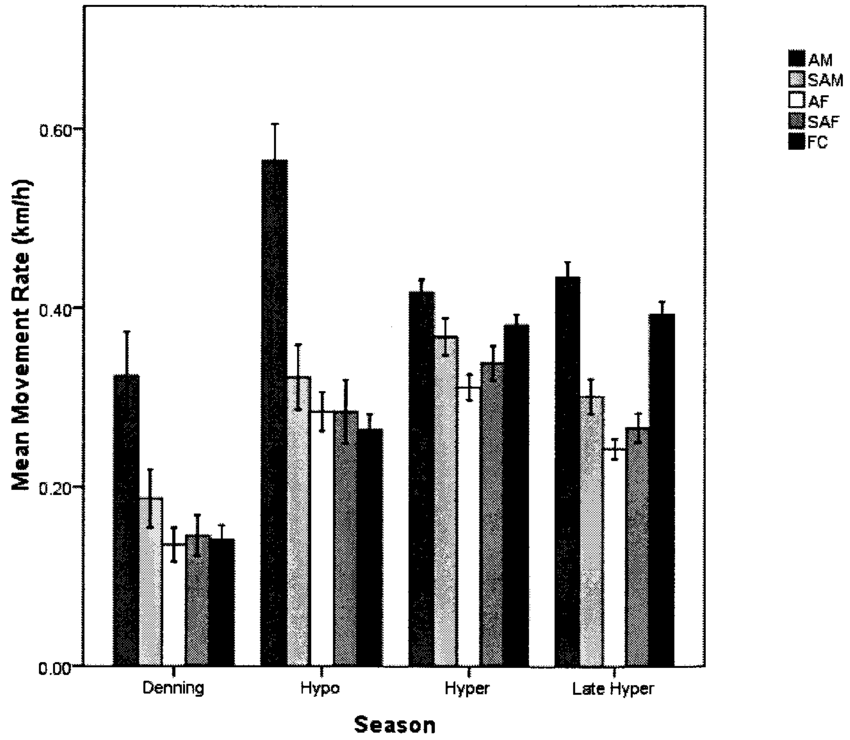
When grouped by both landscape type and reproductive status, only subadult male grizzly bears demonstrated significantly faster movement rates (*U*= 14.0, Z = -2.193, *P* = 0.028) in foothill environments over mountain environments (Table 4-5, Figure 4-4). Mean differences between bear management areas, while not significant, revealed movement rates to be higher for bears residing north of Highway 16 (mean = 0.39 km/h, SE = 0.06) than those found in mountain BMAs (Table 4-4, Figure 4-3). North of Highway 16 also recorded the highest density of well sites (0.34 pt/km^2) and corresponding pipelines (0.27 km/km^2) (Table 4-1).

Figure 4-4. Differences in movement rates (km/h) for 148 bears from 1999 to 2005 grouped by reproductive status and physical location – significant differences were found for subadult males only.



To assess movements across varying temporal scales, I further grouped GPS radiotelemetry data (49, 987 locations) for all 148 bears and compared mean hourly movement rates (km/h) across seasons, months, and times of day. Movement rates were significantly greater ($\chi^2 = 1538.91$, df = 3, $P < 0.001$) for hypophagia (den emergence), hyperphagia (pre-berry), and late hyperphagia (berry) seasons relative to denning or the winter season (mean = 0.17 km/h, SE = 0.01). Of the 4 seasonal comparisons, no significant differences ($P = 0.956$) were found between hypophagia (mean = 0.36 km/h, SE = 0.01) and late hyperphagia (mean = 0.36 km/h, SE = 0.003) hourly movement rates. Movements were found to be the greatest during the hyperphagia or pre-berry (mean = 0.38 km/h, SE = 0.004) season. When grouped by reproductive status, adult males recorded a peak in movement rate (mean = 0.56 km/h) during hypophagia or the late spring / early summer season (Figure 4-5).

Figure 4-5. Differences in movement rates (km/h) for 148 bears from 1999 to 2005 grouped by reproductive status over seasons.



Results further demonstrated that movement rates significantly varied according to month ($\chi^2 = 2594.69$, df = 7, $P < 0.001$). Mean movement rates for all bears were found to increase from April (mean = 0.23 km/h, SE = 0.02) to August (mean = 0.42 km/h, SE = 0.01), however a slight decreased occurred during the month of July (0.37km/h, SE = 0.004, Figure 4-6). From September (mean = 0.36 km/h, SE = 0.005) through October (mean = 0.19km/h, SE = 0.004) movements began to decrease as bears prepared to hibernate. When grouped by reproductive status, adult males demonstrated above average movement rates for the month of June (mean = 0.59 km/h) while females with cubs peaked during the month of August (mean = 0.5 km/h, Figure 4-6).

Figure 4-6. Differences in movement rates (km/h) for 148 bears from 1999 to 2005 grouped by reproductive status over month.

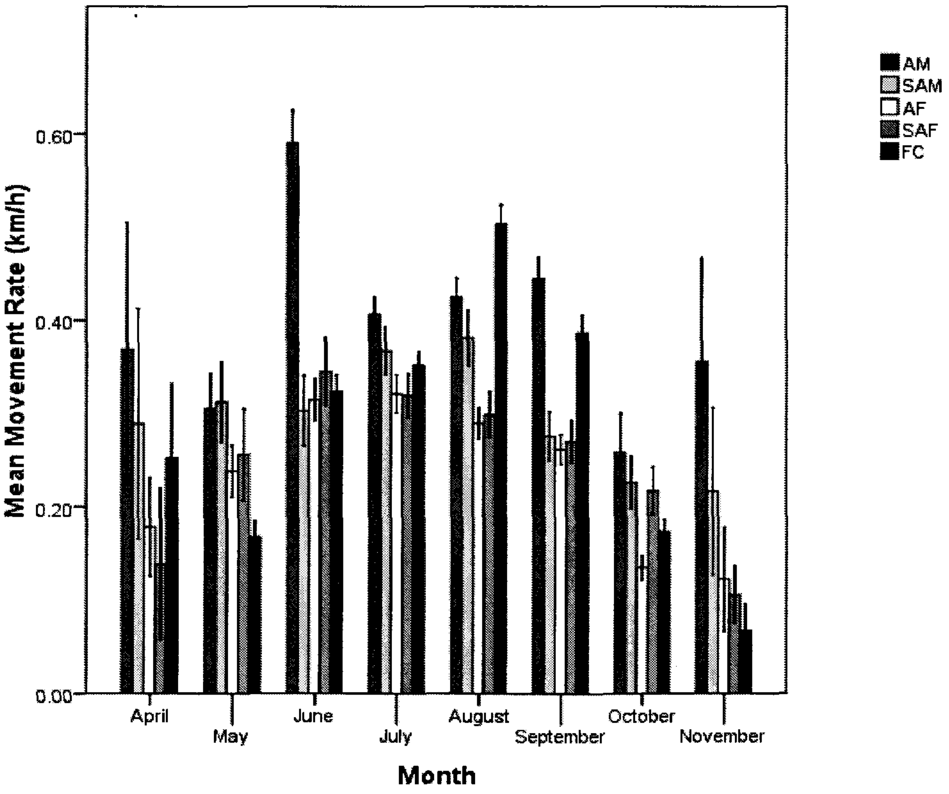
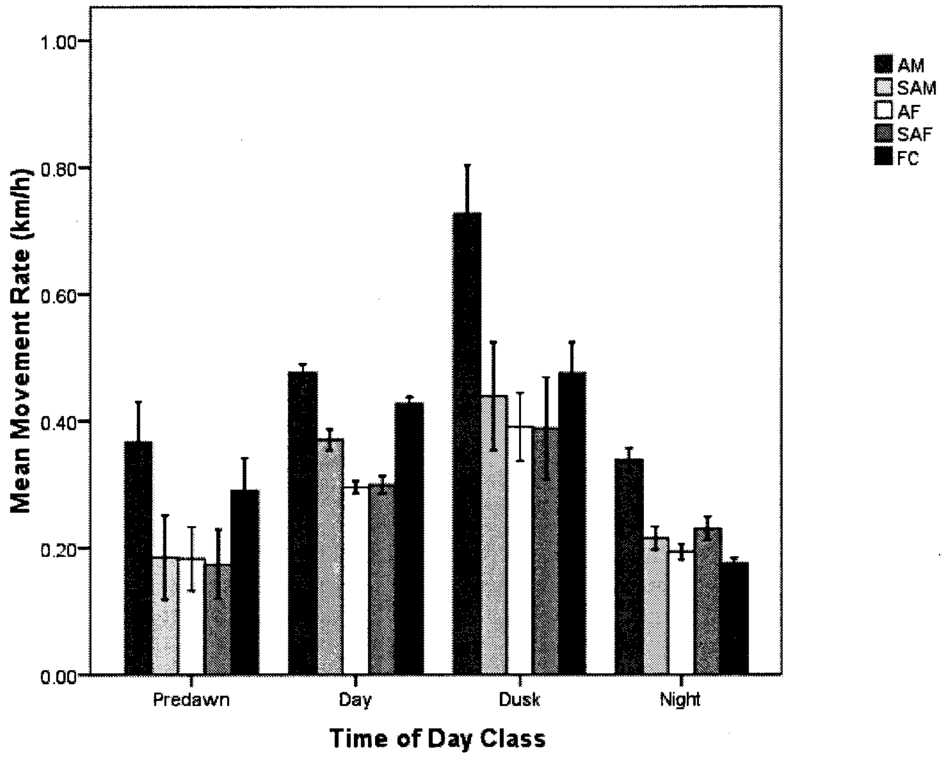


Table 4-5. Mean movement rate (km/h) comparisons by landscape type (mountain versus foothills) for reproductive status and time of day classes.

Mean Comparisons	**Differences in mean movement rate (km) ± SE**	**Mann-Whitney U**	**Z Score**	***P* Value**
All bears grouped	M: 0.26 ± 0.01, F: 0.35 ± 0.21	1727.0	-3.838	***0.000***
Adult males	M: 0.36 ± 0.03, F: 0.46 ± 0.05	112.0	-1.179	0.239
Subadult males	M: 0.24 ± 0.04, F: 0.37 ± 0.03	14.0	-2.193	***0.028***
Adult females	M: 0.26 ± 0.01, F: 0.28 ± 0.03	108.0	-0.777	0.437
Subadult females	M: 0.29 ± 0.02, F: 0.27 ± 0.02	26.0	-1.132	0.258
Females w cubs	M: 0.20 ± 0.01, F: 0.26 ± 0.03	124.0	-1.645	0.100
Adult males predawn	M: 0.38 ± 0.06, F: 0.36 ± 0.04	16566.0	-0.057	0.954
Adult males day	M: 0.42 ± 0.01, F: 0.51 ± 0.01	9464573.0	-6.513	***0.000***
Adult males dusk	M: 0.53 ± 0.06, F: 0.82 ± 0.05	16429.5	-5.26	***0.000***
Adult males night	M: 0.25 ± 0.01, F: 0.39 ± 0.01	1720152.0	-7.946	***0.000***
Subadult males predawn	M: 0.29 ± 0.07, F: 0.10 ± 0.02	1348.0	-3.304	***0.001***
Subadult males day	M: 0.36 ± 0.01, F: 0.38 ± 0.01	1346670.0	-0.544	0.586
Subadult males dusk	M: 0.42 ± 0.07, F: 0.45 ± 0.06	2319.0	-0.25	0.803
Subadult males night	M: 0.17 ± 0.01, F: 0.25 ± 0.01	682624.0	-3.356	***0.001***
Adult females predawn	M: 0.11 ± 0.01, F: 0.33 ± 0.07	5473.5	-3.343	***0.001***
Adult females day	M: 0.29 ± 0.01, F: 0.32 ± 0.01	2569302.0	-6.081	***0.000***
Adult females dusk	M: 0.36 ± 0.03, F: 0.48 ± 0.06	7037.5	-1.746	0.081
Adult females night	M: 0.17 ± 0.01, F: 0.24 ± 0.01	700906.5	-4.393	***0.000***
Subadult females predawn	M: 0.33 ± 0.06, F: 0.10 ± 0.02	538.0	-2.334	***0.020***
Subadult females day	M: 0.31 ± 0.01, F: 0.29 ± 0.01	532741.5	-1.151	0.250
Subadult females dusk	M: 0.27 ± 0.06, F: 0.43 ± 0.05	708.5	-1.229	0.219
Subadult females night	M: 0.29 ± 0.02, F: 0.20 ± 0.01	135756.0	-4.633	***0.000***
Females w cubs predawn	M: 0.10 ± 0.01, F: 0.44 ± 0.04	13128.5	-8.493	***0.000***
Females w cubs day	M: 0.24 ± 0.004, F: 0.59 ± 0.01	13045829.0	-27.90	***0.000***
Females w cubs dusk	M: 0.27 ± 0.02, F: 0.63 ± 0.04	31984.5	-6.36	***0.000***
Females w cubs night	M: 0.15 ± 0.01, F: 0.20 ± 0.01	2769635.0	-7.411	***0.000***

Results indicated that mean movement rates also differed significantly by time of day class ($\chi^2 = 2821.09$, df = 3, $P < 0.001$). Grizzly bears in Alberta show highest movement rates during dusk (mean = 0.53 km/h, SE = 0.02) and then day (mean = 0.4 km/h, SE = 0.003) time classes when compared to predawn (mean = 0.27 km/h, SE = 0.01) and night (mean = 0.23 km/h, SE = 0.003) time classes (Figure 4-7). The highest maximum movement rates were recorded during the evening crepuscular (7.34 km/h) and daytime (6.96 km/h) times of day. When grouped by landscape type, foothills grizzly bears showed increased movement rates over mountain bears across all times of day (*P* < 0.001, Figure 4-8) with the greatest mean differences occurring during the day (foothills = 0.49 km/h; mountain = 0.29 km/h) and at dusk (foothills = 0.64 km/h; mountain = 0.36 km/h).

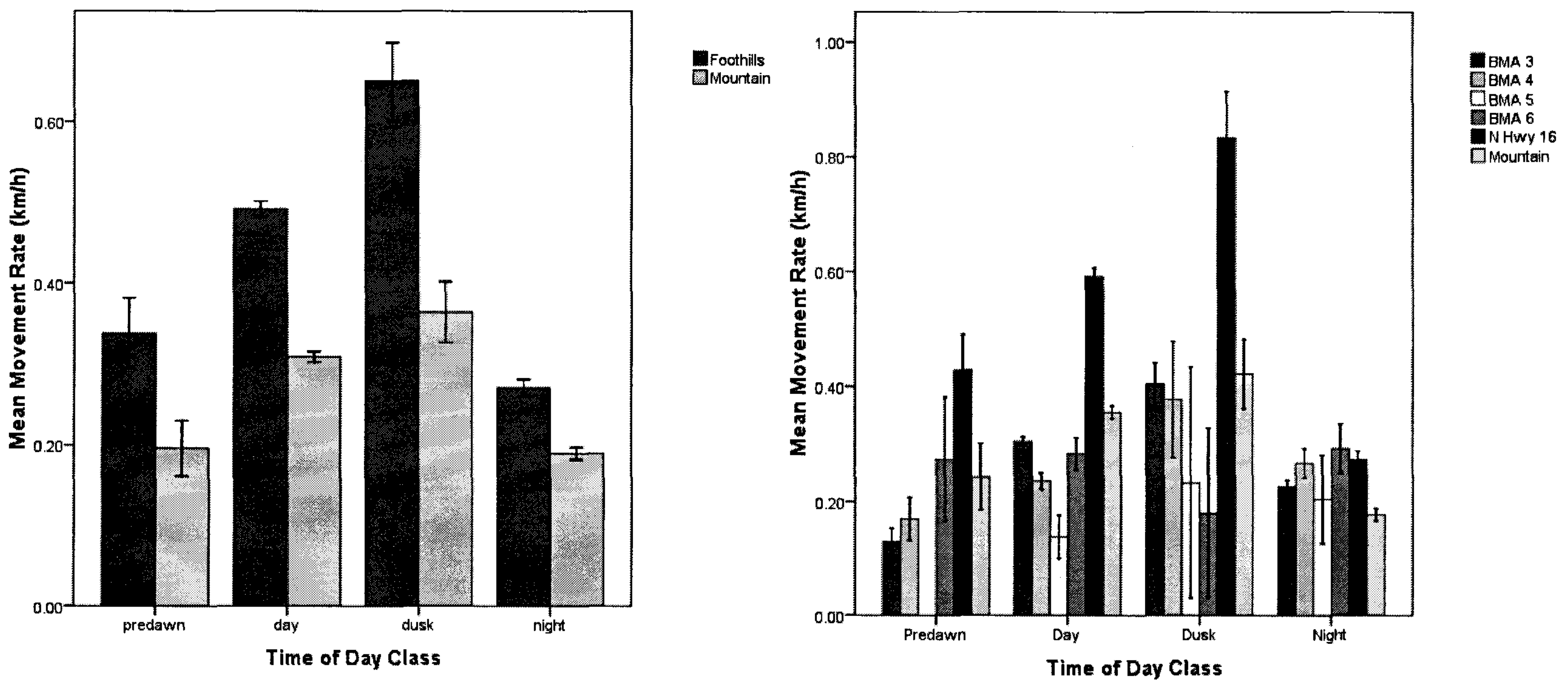
Figure 4-7. Differences in movement rates (km/h) for 148 bears from 1999 to 2005 grouped by reproductive status over time of day.



More specifically, when grouped by landscape type and reproductive status (Table 4-5), foothills adult males moved significantly faster than mountain adult males during day (*P* < 0.001), dusk (*P* < 0.001) and night (*P* < 0.001) times of day while foothills adult females were found to move significantly faster than mountain adult females during predawn (*P* = 0.001), day (*P* < 0.001), and night (*P* < 0.001) times of day. Females with cubs were found to have significantly faster movement rates when residing in the foothills for all times of day (*P* < 0.001).

As a corollary, subadult females demonstrated significantly slower movement rates during predawn ($P = 0.02$) and night ($P < 0.001$) times of day when residing in foothills environments. Lastly, foothills subadult males were found to move significantly slower during predawn ($P = 0.001$) times of day but significantly faster during night ($P = 0.001$) times of day when compared to mountain subadult males. Finally, when grouped by BMA (Figure 4-8), results indicated that grizzly bears residing north of Highway 16 ($P < 0.001$) moved significantly faster than bears in other BMA's for predawn, day and dusk classes.

Figure 4-8. Differences between time of day class movement rates (km/h) for 148 bears from 1999 to 2005 grouped by landscape type and bear management area (BMA).



Population Home Range Size Results

Mean annual 95% kernel home range size (km^2) was calculated and compared for 145 individual bears. No significant differences were found to indicate home range size varied across years ($\chi^2 = 9.124$, df = 6, $P = 0.167$). Activity areas ranged from a minimum of 42 km^2 for a female with cubs to 7,263 km^2 for a subadult male with a population mean of 878 km^2 (Table 4-6).

Table 4-6. Average mean annual kernel home range size (km^2) of grizzly bears (n = 145) by i) reproductive status combined with age and by ii) bear management area from 1999 to 2005.

	Summary Statistics (km^2)					
	n	Mean	Std. Error	Median	Minimum	Maximum
Reproductive Status						
Adult Males	33	1450.35	229.23	996.37	94.55	6129.01
Subadult Males	18	2201.24	492.25	1709.21	67.91	7263.34
Adult Females	36	336.32	31.26	302.21	57.72	917.83
Subadult Females	18	534.96	87.39	410.21	93.94	1494.04
Females with Cubs	40	452.4	81.23	257.64	41.69	2363.9
Total	**145**	**878.05**	**99.28**	**459.13**	**41.69**	**7263.34**
Bear Management Area						
Mountain	37	462.51	68.03	380.86	81.94	2065.42
BMA 3	69	824.83	105.61	512.07	41.69	4402.76
BMA 4	15	380.53	94.39	211.52	47.39	1328.06
BMA 5	1	1968.37	--	1968.37	1968.37	1968.37
BMA 6	4	555.94	130.01	545.48	288.84	843.94
N Hwy 16	19	2283.73	529.10	1364.16	67.91	7263.34
Total	**145**	**878.05**	**99.28**	**459.13**	**41.69**	**7263.34**

Overall, mean home range size significantly varied by sex ($U = 698.0$, $Z = -7.035$, $P < 0.001$), age ($U = 1445.0$, $Z = -2.508$, $P < 0.001$), and reproductive status ($\chi^2 = 52.481$, df = 4, $P < 0.001$). On average, females (mean = 424 km^2, SE = 40.58) occupied approximately 75% less landscape than males (mean = 1,715 km^2, SE = 231.13). Additionally, subadult bears (mean =

1,337 km^2, SE = 277.83) were found to occupy larger home ranges than most adult bears (mean = 721 km^2, SE = 89.47). When grouped by reproductive status (Table 4-7, Figure 4-9), post-hoc test results indicated that home ranges occupied by subadult males were significantly larger than adult females (P = 0.011), subadult females (P = 0.027) and females with cubs (P = 0.019), but not significantly larger than adult male bears (P = 0.643). No significant differences were found between females with cubs, adult females and subadult female groupings (Figure 4-9).

Table 4-7. Mean home range size (km^2) comparisons by landscape type (mountain versus foothills) and reproductive status.

Mean Comparisons	Differences in home range size (km^2) ± SE	Mann-Whitney U	Z Score	*P* Value
All bears grouped	M: 399.1 ± 40.1, F: 1420.6 ± 186.7	1123.0	-5.923	***0.000***
Adult males	M: 738.8 ± 138.0, F: 1912.8 ± 331.1	49.0	-2.984	***0.003***
Subadult males	M: 855.1 ± 272.5, F: 2720.4 ± 620.7	14.0	-1.824	0.068
Adult females	M: 308.7 ± 31.6, F: 408.3 ± 75.2	100.0	-1.06	0.289
Subadult females	M: 317.9 ± 64.9, F: 673.1 ± 121.4	20.0	-1.675	0.094
Females w cubs	M: 254.0 ± 34.4, F: 820.9 ± 190.4	85.0	-2.751	***0.006***

Mean annual home range sizes (km^2) also significantly varied according to landscape type (U= 1123.0, Z = -5.923, $P < 0.001$), and population unit ($\chi^2 = 17.663$, df = 4, $P = 0.001$). Grizzly bear activity areas were found to be extensively larger in foothill (mean = 1,420 km^2, SE = 186.65) environments than mountain (mean = 399 km^2, SE = 40.08) environments. Annual home ranges of mountain grizzly bears ranged from 42 km^2 to 633 km^2 (mean = 286, SE = 21.9) for females and from 95 km^2 to 2065 km^2 (mean = 771, SE = 121.3) for males. Annual home ranges of foothills grizzly bears ranged from 90 km^2 to 2364 km^2 (mean = 656.6, SE = 90.4) for females and 68 km^2 to 7263 km^2 (mean = 2231, SE = 318.2) for males. Results further emphasized that individual bears residing north of Highway 16 occupied the largest home ranges (mean = 2,283 km^2, SE = 529.1) in the FRI study region (Figure 4-9). Mountain home ranges were found to be significantly smaller than only two bear management areas: BMA 3 ($P = 0.038$) and north of Highway 16 ($P = 0.022$).

Figure 4-9. Box plots demonstrating differences to mean kernel home ranges (km^2) for 145 bears from 1999 to 2005 grouped by a) sex, b) age, c) reproductive status, d) landscape type, and e) provincial bear management areas.

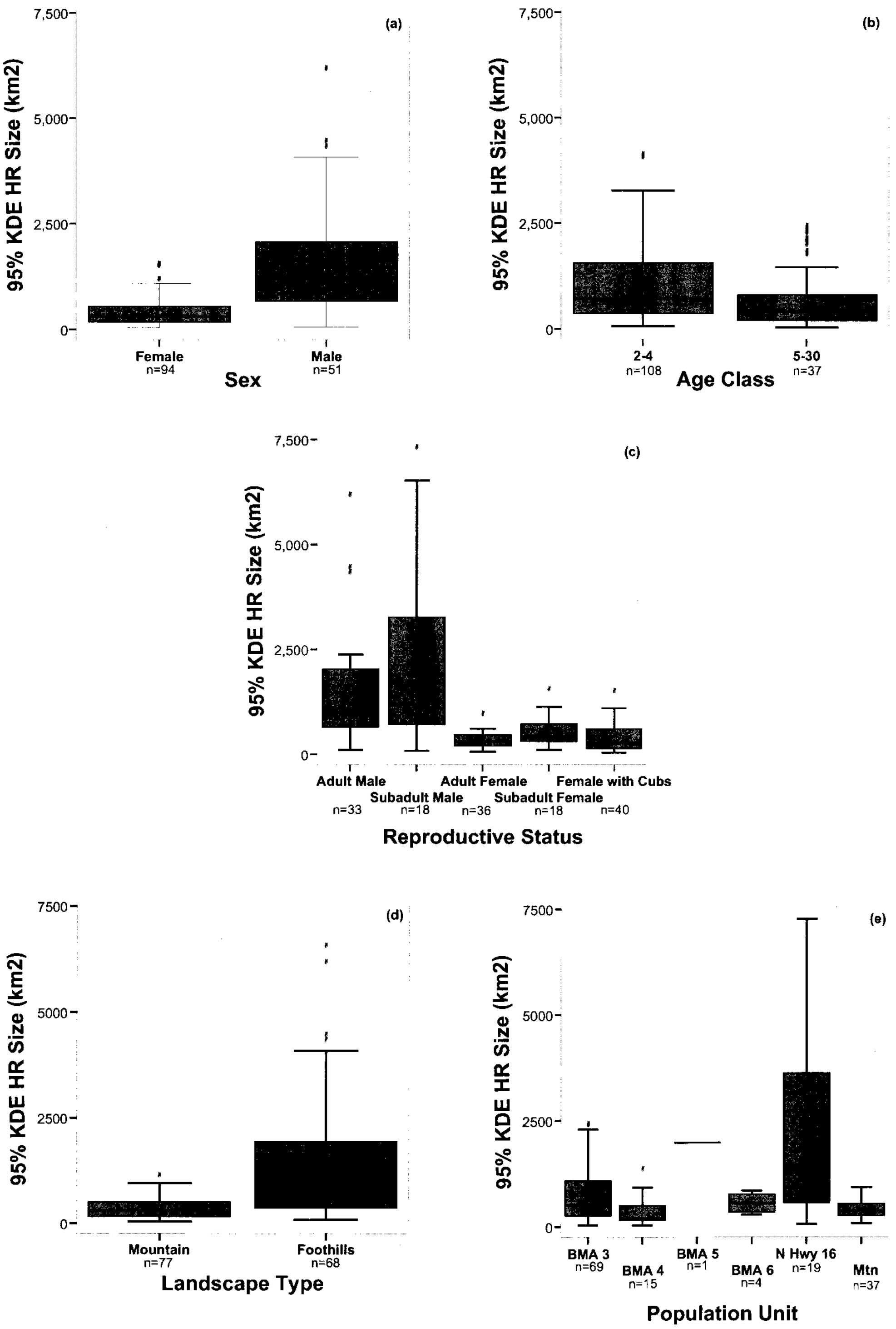
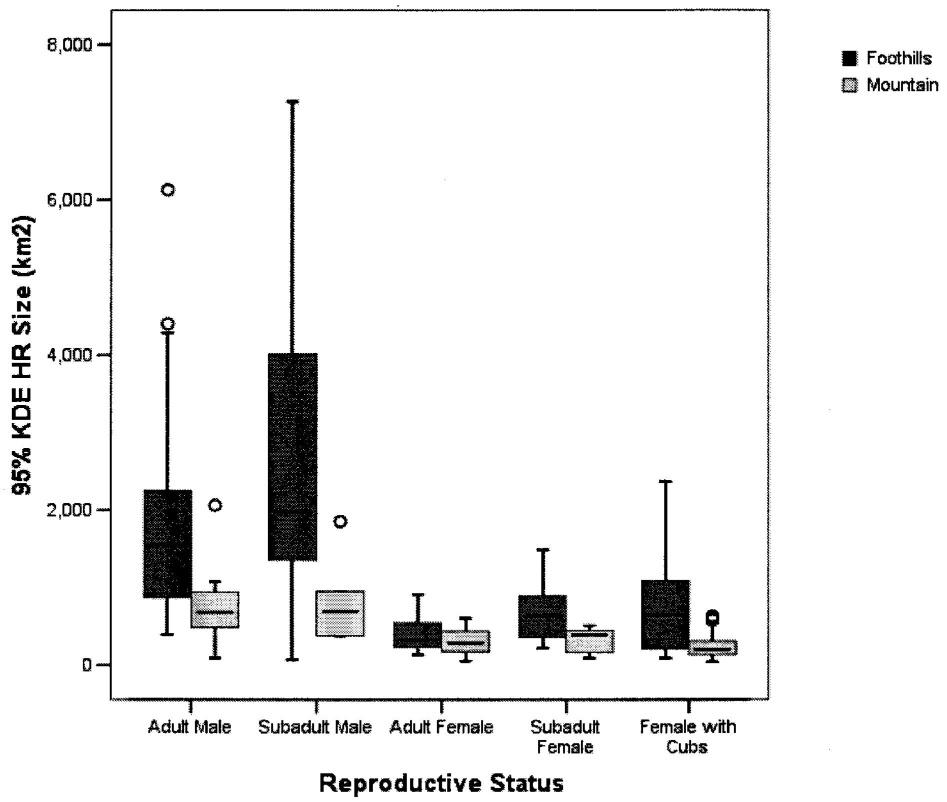


Figure 4-10. Differences to mean kernel home ranges (km^2) for 145 bears from 1999 to 2005 grouped by reproductive status and physical location – significant differences were found for adult males and females with cubs.

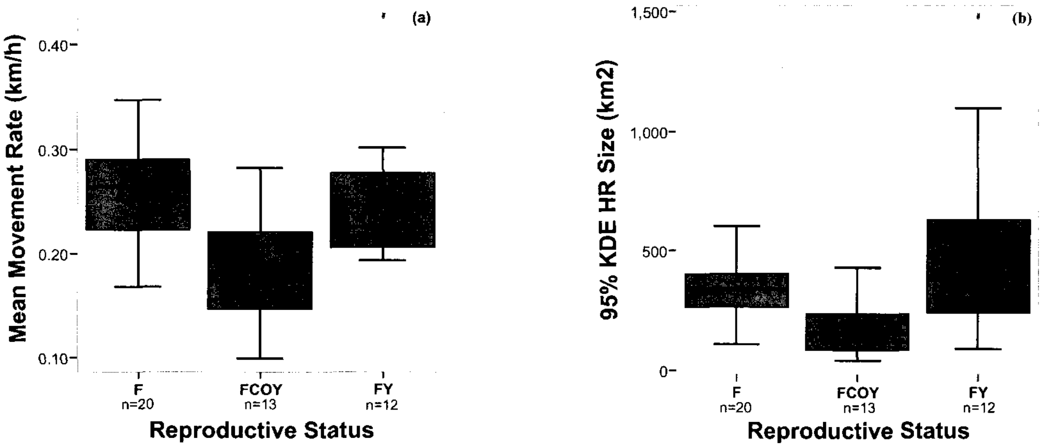


When grouped by landscape type and reproductive status, only adult males (U= 49.0, Z = -2.984, P = 0.003) and females with cubs (U= 85.0, Z = -2.751, P = 0.006) reported significantly larger home ranges in foothill environments over mountain environments (Table 4-7, Figure 4-10).

Female Movement Rate and Home Range Size Results

Between 1999 and 2004, 12 individual females were collared over at least 2 consecutive years demonstrating change to reproductive status (Table 4-3). Female-specific results demonstrated a significant difference in hourly movement rate ($F_{2,42}$ = 8.01, P = 0.001) when grouped by reproductive status (Figure 4-11). Solitary females recorded the highest mean movement rate (mean = 0.26 km/h, SE = 0.01) over both females with yearlings (mean = 0.25 km/h, SE = 0.019) and females with COYs (mean = 0.19 km/h, SE = 0.016). Post-hoc comparisons revealed significant differences existed between solitary females and females with COYs (*P* = 0.001) and between females with yearlings and females with COYs (*P* = 0.009), but not between solitary females and females with yearlings (*P* = 0.951).

Figure 4-11. Box plots demonstrating differences to hourly movement rate (km/h) and mean kernel home ranges (km^2) for female bears from 1999 to 2004 grouped by reproductive status.

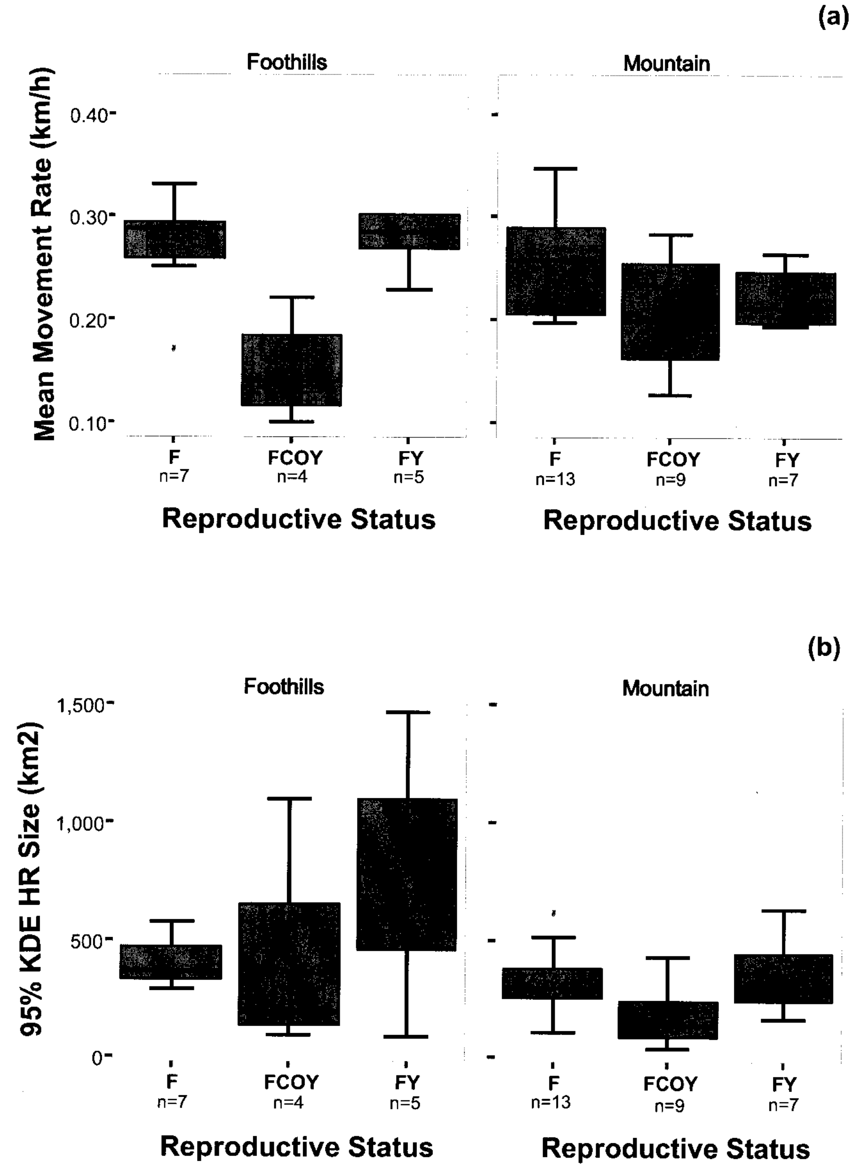


Similar to movement rate, differences for mean annual home ranges were also recorded as significant when grouped ($\chi^2 = 9.35$, df = 2, *P* = 0.009). However, while differences to home range size were quite large (females with COYs: mean = 239.42 km^2, SE = 77.37; solitary females: mean = 366.48 km^2, SE = 40.44; females with yearlings: mean = 515.61 km^2, SE = 117.62), only females with COYs and females with yearlings were found to differ significantly (*P* = 0.05) (Figure 4-11).

When grouped by landscape type (Figure 4-12a), mountain females (*n* = 29) showed slight significant differences ($F_{2,28} = 3.77$, *P* = 0.04) between hourly movement rates for solitary females and females with COYs (*P* = 0.033), but not females with yearlings. No significant differences were noted between females with yearlings (mean = 0.22 km/h, SE = 0.01) and solitary females (mean = 0.26 km/h, SE = 0.01) or females with COYs (mean = 0.2 km/h, SE = 0.02). Foothills females ($n = 16$) however reported strong significant differences ($F_{2,15} = 8.0$, $P = 0.005$) to hourly movement rates by reproductive status. Solitary females (mean = 0.27 km/h, SE = 0.02, $P = 0.017$) and females with yearlings (mean = 0.3 km/h, SE = 0.03, $P = 0.006$) both demonstrated significantly higher movement rates than females with COYs (mean = 0.15 km/h, SE = 0.03, Figure 4-12a). On average, mountain females (0.23 km/h) reported slower movement rates than foothills females (0.25 km/h). This is consistent with population movement results. One notable exception is that females with COYs residing in foothill environments had 25% slower movement rates than females with COYs residing in mountain environments (Figure 4-12a).

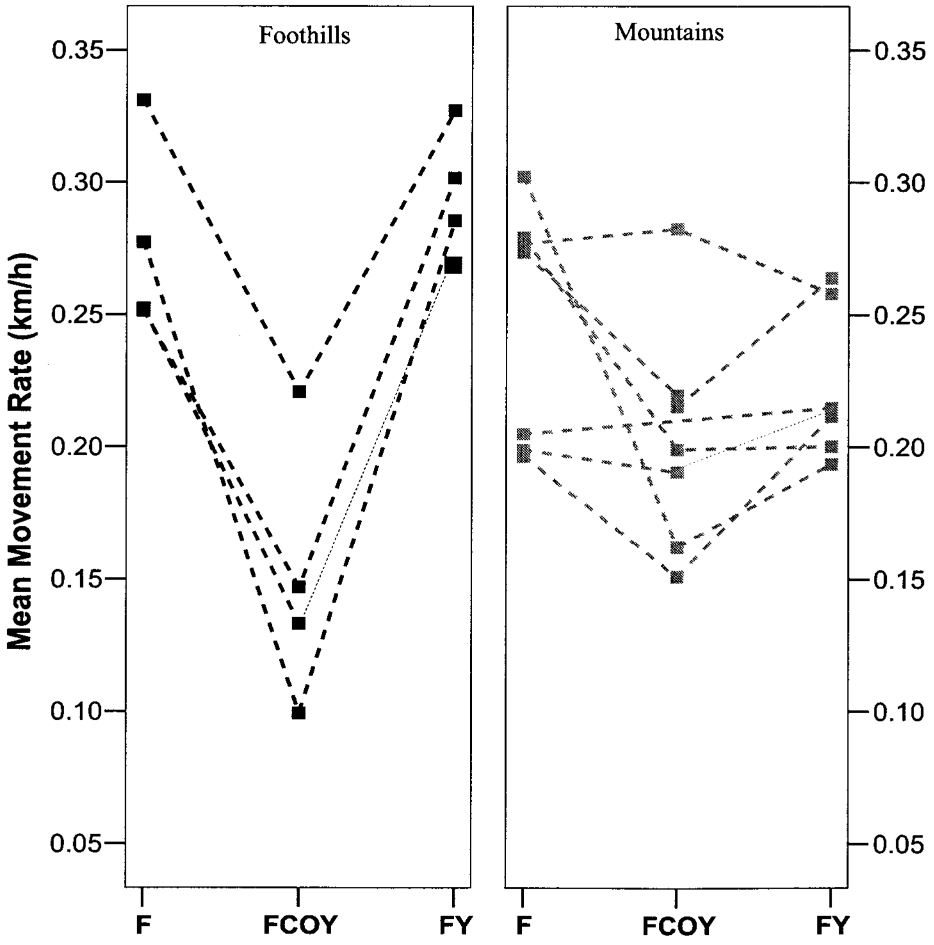
When grouped by landscape type, mean home ranges were 47% larger in foothill (mean = 531.05 km^2, SE = 101.56) environments than mountain (mean = 280.43 km^2, SE = 30.08) environments. Further, results emphasized significant differences ($F_{2,28} = 3.67$, $P = 0.04$) in home range size for mountain females but not foothills females (Figure 4-12b). Only solitary mountain females recorded significantly larger home ranges (mean = 318.82 km^2, SE = 38.94, $P = 0.033$) than females with COYs (mean = 170.72 km^2, SE = 43.39). Finally, box plots demonstrated little variability in home range size for mountain females, but increased variability to movement rates. Comparatively, box plots highlighted large variability in home range size for foothills females with less variability present in movement rates (Figure 4-12b).

Figure 4-12. Box plots demonstrating differences to a) hourly movement rate (km/h), and b) mean kernel home ranges (km^2) for female bears by reproductive status and grouped by landscape type from 1999 to 2004.



When individuals were compared over consecutive years grouped according to landscape type, results highlighted trend differences between mountain and foothills females by reproductive status (Figure 4-13). Movement rates for foothills females clearly decreased as reproductive status change from solitary female to female with COYs, while movement rates for mountain females appeared to be more random. This result was echoed as reproductive status changed from females with COY's to females with yearlings.

Figure 4-13. Line graphs individual female grizzly bears grouped by landscape type a) foothills versus b) mountain; showing changes to mean movement rate (km/h) related to reproductive status over 3 consecutive years.



4.5 Summary

This chapter focused on an empirical, pattern-based approach to quantifying movement rates and home range size differences typical of that found in many wildlife studies (Amstrup et al. 2000, Amstrup et al. 2001, Rettie and Messier 2001, Ager et al. 2003, Theuerkauf et al. 2003, Ferguson and Elkie 2004). Grizzly bear movements, although highly individual in nature, can provide information regarding group-level movement patterns spatially and temporally across large landscapes. However, no studies to date have linked spatial and temporal movement patterns to underlying landscape type in such detail as reported here. It was expected that home range size and movement rate would be influenced by landscape type. For this large-scale analysis, landscape characteristics were simplified into either mountain and foothills classifications, or bear management area (BMA) classifications. In Alberta, mountain landscapes have less human activity and industry-based development than foothills landscapes. Final results emphasized significantly different home range sizes and movement rates occurring across different landscapes, spatially and temporally.

Previous research had identified daily movement rates ranging from 3.4 km (Gibeau et al. 2001) to 4.9 km (Schwab 2003). When grouped, the sample population used in this analysis reported a mean movement rate of 0.30 km/h or a 7.2 km daily movement rate over the entire study region. Mountain results were reported as 0.26 km/h or 6.24 km/day, while foothills results reported 0.35 km/h or 8.4 km/day. Finally, grizzly bears residing north of Highway 16 recorded 0.39 km/h or 9.36 km/day. Movement rates for grizzly bears in Alberta were found to be double than what was previously reported. Further, grizzly bears north of Highway 16 on average were found to move three times faster when compared to bears residing in the Banff – Bow Valley region (Gibeau et al. 2001). These varying results will have significant impact on modeling attempts which incorporate movement parameters as baseline information, especially those in industry dominated landscapes.

Given that grizzly bears in general occupy large annual home ranges, human development landscape features may generate local disturbances which are not obvious based on the scale of this analysis. To understand local variations in movement patterns finer-scale GPS data are required as demonstrated in Chapter 3. Unfortunately, the majority of data collected over the years for the FRI has been collected across larger spatial and temporal scales (e.g 1 point every 4 hours). As such, it is still necessary to understand large-scale home range patterns and daily movement rates relative to the scale of data collection. Further, analysis conducted using more than one individual provides an opportunity to obtain information regarding population trends. This is especially important given the opportunity to also compare spatial patterns over different landscape types.

Intraspecific variation in movement behavior is an important characteristic of grizzly bear movement ecology. Overall, average movement rates were highly influenced by sex and reproductive status, but not by age class. As anticipated, males and subadult males moved faster and traveled further than adult females, subadult females and females with cubs. The movement rates of adult females and subadult females were found to be quite similar.

Movement rates were further influenced by spatial location. Grizzly bears residing in mountain environments were found to move slower that grizzly bears residing in foothill environments. In Alberta, the industrial development of natural resources has become a prominent landscape feature along the eastern slopes of the Rockies (Table 4-1). However, when analyzed by reproductive status, only subadult males demonstrated significantly faster movement rates in foothill environments over mountain environments. Previous research suggests that subadult bears are especially vulnerable (Mueller et al. 2004) and may be displaced by adult bears to lower quality habitats (Gibeau et al. 2002) resulting in increased movements and activity ranges. Further, subadult bears have been found closer to high-use roads than adult bears regardless of time of day (Mueller et al. 2004). Increased levels of human interaction translates directly to increased risk of mortality (Mueller et al. 2004).

Increased human access can lead to greater disturbance and human-bear encounters. The reported linear threshold density for functioning landscapes with large carnivores is approximately 0.6 km/km2 (Forman et al. 1997, Gibeau 2000). That is, landscapes with linear densities above this threshold are largely fragmented and less likely to sustain large carnivore populations long-term. The majority of foothills bear management areas occurring outside mountain parks reported combined linear densities above this threshold. Although, indirectly related, grizzly bear movement rates were also found at higher rates in these regions. Further, grizzly bear mortality densities are also highest in the foothills due to increased access and human-bear encounters (Nielsen et al. 2004b).

Movement rates were further influenced temporally according to season, month and time of day. Population movement rates were found to be the greatest during hyperphagia or the pre-berry season which runs from June 15 to August 15. During this season, bears are found to feed on green vegetation such as grasses, forbs and horsetails (Munro et al. 2006). Habitat selections further include streamsides, alpine regions, herbaceous areas, open forests, some cutblocks, and shrub-wetland complexes (Nielsen et al. 2002). It is possible that prior to berry season or late hyperphagia, more extensive travels are required to obtain multiple types of food resources. When examined by month, adult male bears moved fastest during June while females with cubs movement rates were found to peak in August. Stenhouse et al. (2005) examined movement rates immediately proceeding and following male-female associations to identify movement behavior in response to possible mating events. The majority of male-female associations occurred from mid May until the end of July, peaking in mid June (Stenhouse et al. 2005). During this time, males exhibited a significantly faster movement rate prior to and after an association event. It is thought that a male must likely cover long distances and travel faster to mate with as many females as possible (Stenhouse et al. 2005). Results of this study highlighted a significant increase of movement rates for males and females during the month of June. The rate of movement then decreased into the remainder of summer.

The daily movement patterns of grizzly bears have been found to vary substantially. Grizzly bears in Alberta were additionally found to engage in different activities according to time of day. For example, bears were found to be more active (root digging and frugivory) during diurnal and crepuscular times of day, with bedding most likely to occur at night and in forested habitats (Munro et al. 2006). Results reported here corroborated findings by Munro et al. (2006). Bears showed higher movement rates during day and evening dusk times of day. It has been suggested that grizzly bears may modify their temporal and spatial activity patterns in response to human activity level (Gibeau 2000). Some studies have reported movements to be diurnal (Munro et al. 2006) while others have reported movements to be crepuscular (Gibeau 2000, Nielsen et al. 2004a) or even nocturnal (Kaczensky et al. 2006). When landscape type was factored into this analysis no change in behavior was found related to time of day movements for Alberta grizzly bears.

Grizzly bears residing in foothill environments moved faster than grizzly bears residing in mountain environments over all times of day. Daily movement patterns were further complicated by reproductive status. Of interest, subadult females demonstrated significantly slower movement rates in foothill environments during predawn and night times of day, while subadult males moved slower during predawn but faster during night times of day in foothill environments. Results of previous studies analyzing female grizzly bear behavior found that adult females were the most risk-adverse, choosing ultimately to avoid humans rather than seek out high quality habitat. Further, females were found to be farther away from roads than males

(Gibeau 2000). When dealing with subadult bears residing in a highly fragmented landscape, this behavior may be amplified. This might explain why subadult females have significantly slower movement rates when compared to subadult males in the same environment at the same time of day.

Annual areas used by grizzly bears in Alberta did not significantly vary. However, when grouped, home range sizes were found to vary according to sex, age and reproductive status for various bear subgroups. As with bear populations in general, female grizzly bears occupied significantly smaller home ranges than did males. Subadult male grizzly bears reported the largest annual home ranges over other reproductive classes. One subadult male in particular ranged widely and its annual home range (7,263 km^2) was larger than any adult male bears. This subadult bear resided north of Highway 16 where the majority of available landscape is classified as foothills with corresponding high densities of oil and gas exploration features (well sites and pipelines) (Table 4-1). While this individual may be an outlier, it may also be important in understanding the relationship between bears and landscapes. Overall, no significant differences were found between solitary females, subadult females, or females with cubs when grouped.

Annual home range size was found to further vary by landscape type and population unit. Home range sizes demonstrated significant differences when separated by landscape type. Bears residing in the foothills travel more extensively than bears residing in the mountains. However, when examined by reproductive status, only adult males and females with cubs reported differences by landscape type. Interestingly, while females with cubs reported the smallest mean home ranges in mountain environments, home ranges in foothill environments were larger than adult females and subadult females (Figure 4-10). What does this tell us about females with cubs in industry dominated landscapes? This result could have important implications for cub survival outside mountain parks. Results indicated that subadult males ($P = 0.07$) and subadult females (P

= 0.09) home range size responded, but not significantly (Table 4-7). Adult females showed no differences to home range size by landscape type.

When examined according to BMA, individual bears residing north of Highway 16 reported the largest home range sizes. While BMA 3 reported significantly larger home ranges when compared to mountain ranges, BMA 4 did not. In fact, grizzly bear home ranges in BMA 4 reported similar home range characteristics to grizzly bears residing in mountain landscapes. BMA 4 is situated along the eastern slopes north of Banff and Highway 1 and south of Nordegg and Highway 11 (Figure 4-1). BMA 4 further reported the highest density of roads when compared to all other bear management areas. While high road density may not influence home range size and therefore grizzly bear spatial distributions and related movements on the landscape, it does allow increased access and possible human-bear encounters.

The survival of adult female grizzly bears is necessary in maintaining viable populations (Mueller et al. 2004) and is the key to long term persistence (Gibeau 2000, Gibeau et al. 2001). While studies often assess movement rates and annual home range size (Mace and Waller 1997, Collins et al. 2005), few have incorporated the affect of reproductive status (Mace and Waller 1997, Dahle and Swenson 2003a, 2003b) and none have coupled reproductive status with physical location. Further, adult females have been found to be most influenced by human activities and development when compared to other bear subgroups (Gibeau et al. 2002). As such, this chapter specifically addresses movement rates for adult females during different reproductive phases. As anticipated, as female reproductive status changed from solitary females to females with COYs to females with yearlings, movement rates decreased and subsequently increased. These results were further reflected in home range size changes.

However, when grouped by landscape type (mountains vesus foothills) results were slightly more complicated. In mountain environments, both movement rate characteristics and home range size characteristics were consistent as reproductive status changed showing slight reductions for females with COYs. In foothills environments, results varied largely as reproductive status changed. For foothills females, FCOYs movements were reduced by approximately 50% when compared to solitary females or females with yearlings. While this reduction in movement rates is expected, the differences between foothills and mountain females may be due to additional external factors. For example, one study found that adult females with cubs of the year did not cross highways (Waller and Servheen 2005). While another study suggested that home range size for females with cubs of the year may be restricted in effort to reduce contact with infanticidal males (Dahle and Swenson 2003b). For mountain females with COYs, resulting home ranges were small with little variability. Comparatively, foothills females with COYs and yearlings, showed home ranges with large amounts of variability.

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CHAPTER 5 – INFLUENCE OF UNDERLYING LANDSCAPE CHARACTERISTICS ON GRIZZLY BEAR HOME RANGE SIZE AND CORRESPONDING MOVEMENT RATE

5.1 Introduction

Grizzly bears utilize the entire landscape (habitat and non-habitat) and respond to gradients of habitat quality. At a larger-scale, these interactions are reflected within seasonal movements across home ranges (Graves et al. 2007). At a finer-scale, these interactions are reflected in daily movement patterns within or around varying habitat types. Understanding large-scale movements or bear response to landscape structure is difficult and relies on the combined use of GPS radiotelemetry data, supplementary data layers and multivariate statistics. For example, individual bear home range size and movement rate may vary depending on the amount of human development, habitat or resource availability, landscape terrain and ruggedness, and habitat preference or knowledge of the individual animal (Koehler and Pierce 2003). Understanding the relationship between home range size and underlying landscape properties and habitat characteristics may help provide insights into grizzly bear ecology.

The focus of this chapter is to explore landscape-level movement patterns using home range size as an indicator for large-scale movements. As grizzly bear interaction with the landscape is largely related to the distribution, availability, and quality of resources (Nielsen et al. 2002, 2003, Nielsen et al. 2004a, Nielsen et al. 2004c, Munro et al. 2006) home range studies often assume that an inverse relationship between home range size and habitat quality exists (Koehler and Pierce 2003). Extending this assumption, it is often assumed that larger home ranges are positively correlated with faster movement rates. For grizzly bears it is expected that small home range sizes indicate concentrated high quality habitat requiring individuals to travel less in search of resources. The alternative is that larger home ranges indicate lesser quality habitat (possibly dispersed over larger areas) requiring individuals to travel further and likely faster in search of resources. Other factors which also influence home range size of grizzly bears include social interactions, reproductive requirements, population density, and human-bear interactions (Dahle and Swenson 2003b, 2003a). Finally, home range estimates may be influenced by generation technique (e.g. type of kernel estimator) including number of GPS data points and duration of collection (White and Garrott 1990).

Classical home range analysis is tailored to work with data points separated by relatively large time intervals between observations (Dettki and Ericsson 2006). Most commonly, wildlife habitat use is determined by the distribution of radiotelemetry 'use' points. Typically, each location is classified by the type of habitat in which they occur often by computing habitat proportion at the individual GPS location site or inside fixed circle buffers applied to each location (Potvin et al. 2003). Statistical tests often compare the 'use' locations to what is available or the expected pattern of occurrence based on habitat availability. Critical assumptions of this approach are that all locations are independent, the sample size is sufficiently large, and that quantitative variables achieve normality. Bias may further result from sampling strategy and locational error, especially if the habitat patches are small.

As explored in Chapters 3 and 4, GPS-based movement data are not normally distributed and are temporally autocorrelated, specifically at fine data collection scales due to the sequential nature of the data. One advantage of computing habitat influence using a home range estimator is that independence of locations can be dismissed as long as the full range of habitat is captured within the home range (Kernohan et al. 1998, Otis and White 1999). Further, the proportional area calculated within a home range provides a viable method of quantifying habitat 'use' and addresses the potential biases associated with GPS data by estimating the complete utilization distribution of the individual grizzly bear (Kernohan et al. 1998). Finally, where inherent telemetry error is unavoidable, coupled with a fragmented landscape, using proportional area of home range (e.g. 95% contours) to define habitat use helps to limit standard error problems present when using locational point data. For example, as demonstrated in Chapter 3, when working with GPS locations collected at 4-hr intervals, the assumed movement path would have to be buffered at minimum 5.2 km to account for potential error. Additionally, as demonstrated in Chapter 3, each resulting 4-hr buffer basically mimicked that of a home range for each individual grizzly bear.

While the previous chapter (Chapter 4) examined the relationship between annual home range size and landscape type, bear management area, sex, age, and reproductive status, Chapter 5 will focus specifically on large-scale movement patterns using individual home range size and spatial distribution. As demonstrated in Chapter 3, when working with radiotelemetry data collected at larger intervals (e.g. 4-hr), analysis is restricted to large-scale spatial comparisons such as daily movement rate or home range size. The intent of this chapter is to evaluate the relationship between landscape characteristics and spatial movement pattern as defined by an individual bear's home range size. For example, do relationships exist between specific landscape class types and foothills grizzly bears where home ranges are significantly larger and movement rates are significantly higher? To learn more about the relationship between several independent variables and home range size, a multiple linear regression (MLR) analysis was employed. Although a secondary consideration in this chapter, a MLR analysis was also employed to explore the relationship between movement rate and underlying landscape properties. Finally, model residuals were examined for spatial autocorrelation.

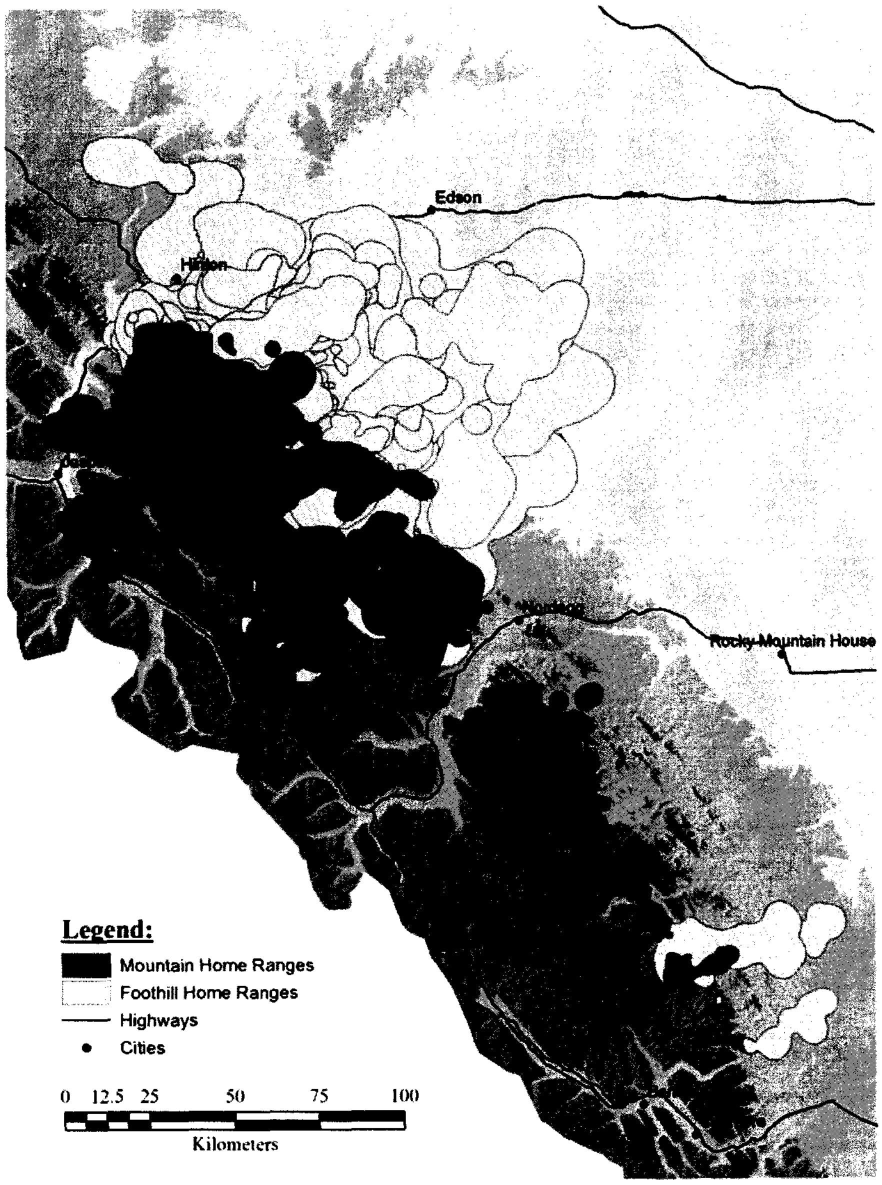
5.2 Study Area and Supplementary Data Layers

In Chapter 5, the research area focused on a subset of the greater FRI study region (Figure 5-1). The study region was situated between Highway 1 - the Trans Canada Highway to the south, Highway 16 to the north, the Alberta – British Columbia border to the west, and the prairies to the east. The size of the total study region is approximately 135,500 km^2. Within the region there are two primary landscape types: 1) the high elevations mountains in the west (dark grey), and 2) the lower elevation foothills to the east and northeast (medium grey) (Figure 5-1). Numerous mesoclimates exist due to the variable landscape characteristics such as rugged mountains, steep ridged foothills, flat and rolling uplands, subdued lowlands, and deeply incised valleys (Beckingham et al. 1996). Mountain features maintain a northwest to southeast orientation ranging from less than 500 meters in elevation to a maximum elevation of 3680 meters. The lower foothills range from elevations of less than 500 meters up to 1150 meters (Beckingham et al. 1996). Vegetation types and human-use features are as previously described in Section 4.2.

Supplementary data layers included lines, polygon and grid data layers for the entire study region (Section 2-5). For all home range and movement comparisons, vector data layers included all roads, railways, pipelines, power lines and seismic lines (Figures 2-11 and 2-12, p. 62-63). Individual oil and gas well sites were also included as a polygon data layer where each well site represented a square area of 1 ha. For the following analyses, I grouped major roads and railways into a single paved human-use linear layer, and further grouped pipelines and power lines into a single herbaceous human-use linear layer. Linear features were then used to calculate densities (km/km^2) for each home range. All the above vector and polygon data layers were updated yearly (1999, 2000, 2001, 2002, 2003, and 2004) with the exception of seismic lines. Seismic lines were retained as a static individual vector layer representing approximate seismic line densities from 1999 to 2004.

Grid data layers utilized included a digital elevation model (DEM), DEM derived slope and aspect layers, a topographic vector ruggedness (VMR) layer (Sappington et al. 2007), a resource selection function (RSF) model layer (Nielsen et al. 2002, Nielsen 2005), species composition and crown closure layers (McDermid 2005), a distance to water surface layer, and finally a land cover classification layer (McDermid 2005) (Figure 2-12 to Figure 2-15, p. 63-66). Of the grid data layers included in the analysis; elevation, slope, aspect, VMR, RSF, and distance to water were static and non-changing from 1999 to 2005. The remaining grid surfaces: land cover classification, species composition layer, and crown closure layer, were all updated annually from 1999 to 2004. As such, annual home range extractions reflected landscape change from year to year.

Figure 5-1. Map of central Alberta study region showing Chapter 5 study region with mountain and foothill grizzly bear 95% kernel home ranges. Additional features include major cities, highways, mountainous regions represented in dark grey relief, foothill regions represented in medium grey relief, and prairies represented in light grey.



5.3 Methods

Home Range Data Preparation

Between 1999 and 2004, GPS radiotelemetry data was collected for 109 grizzly bears residing between Highway 1 and Highway 16. See Section 4.3 for a detailed description on GPS data processing and individual grizzly bear classification procedures. For each year of GPS radiotelemetry data, 95% kernel home ranges (km^2) were generated using the Animal Movement Extension in ArcView 3.2a (Hooge et al. 1999). The fixed kernel home range utilization distributions (Worton 1989) were calculated using the ad hoc calculated smoothing parameter (Silverman 1986). Attempts to employ the least squares cross validation (LSCV) smoothing parameter failed due to computational processing difficulties. In addition, it has been suggested that the original ad hoc smoothing parameters provide a less biased estimator than a user selected correction (Hooge et al. 1999). Most users will find the ad hoc calculations are very similar to LSCV for large-scale exploratory analysis (Hooge et al. 1999). Further, because the LSCV process increases the amount of smoothing, resulting home ranges may have estimates that are too large (Seaman et al. 1999). Here, I am only interested in the 95% kernel outline as an expression of home range size and delineation and not internal variation in intensity. Home ranges were not calculated for individuals if GPS radiotelemetry data sets had ≤ 50 locations as suggested for proper home range generation (Seaman et al. 1999).

To assess the relationship between home range size and landscape type, each grizzly bear was classified as residing in the mountains ($n = 62$) or foothills ($n = 47$). As previously described, individual grizzly bears with $\geq 75\%$ of GPS locations above 1700 m were categorized as mountain bears with all remaining bears categorized as foothills bears. As demonstrated in Figure 5-1, some mountain and foothills home ranges overlapped where individual bears resided near the 1700 m elevation threshold or home ranges were exceptionally large. Both mean hourly movement rate (km/h) and annual home range size (km^2) were then compared according to landscape type using the nonparametric Kruskal-Wallis and Mann-Whitney U tests to examine if significant differences were present between groups. It was expected that results would mirror those reported in the previous chapter with some slight changes due to spatial boundary differences resulting in a smaller data set. Significance was held at $P < 0.05$ for all tests.

Multiple Linear Regression Analysis

To evaluate the influence of underlying landscape features on home range size (km^2) and related movement rate (km/h), landscape classes (open and closed forest, wet treed, herbaceous, shrub, water and non habitat), human linear densities (roads, railways, seismic lines, power lines and pipelines), well sites, general topographic characteristics (elevation, slope, aspect and ruggedness), resource selection function (RSF) values, species composition, forest crown closure, and distance to water were extracted for each of the 109 kernel home ranges. See Table 5-1 for a complete list of independent variables. Prior to model development and outlier removal, basic scatter plots were generated to assess whether linear relationships between home range size or average movement rate and underlying landscape characteristic variables existed.

Before carrying out the multiple regression analyses, variable data were screened for normality, multicollinearity, and outliers using bivariate scatterplots. Both dependent variables (home range size and average movement rate) were log transformed to improve normalization. Likewise, transformations were conducted on the independent variables but when examined, the transformations were minimally helpful. The residual plots were not significantly changed by the transformation and as such the independent variables remained untransformed. As multivariable regression analysis is sensitive to collinearity among predictor variables, variables were assessed for multicollinearity prior to modeling using Pearson's correlation tests and variance inflator function (VIF) diagnostics. All variables with strong correlations ($r > 0.6$) and individual VIF scores > 10 were assumed to be collinear and excluded from the model in a hierarchical approach.

For example, elevation ($r = 0.91$) and slope ($r = 0.98$) were strongly correlated with vector landscape ruggedness and were excluded from the final model. Individual case outliers were also identified and removed from the analysis using centered leverage value (> 0.5) and Cook's distance (> 0.2). Before finalizing the multiple regression analyses, model residuals were also examined to check for violations of the assumptions.

Table 5-1. Names and definitions of 19 variables used in a multiple linear regression of factors influencing home range size for 109 individual bears from 1999 to 2004.

Model Variable	Code	Definition
Habitat Classes		
Open Forest	OpenFor%	Proportion of open forest (0 to 100)
Closed Forest	ClosedFor%	Proportion of closed forest (0 to 100)
Wet Treed	Wettreed%	Proportion of wet treed (0 to 100)
Herbaceous	Herb%	Proportion of herbaceous (0 to 100)
Shrub	Shrub%	Proportion of shrub (0 to 100)
Water	Water%	Proportion of water (0 to 100)
Non Habitat	Nonhab%	Proportion of non habitat (0 to 100)
Linear Features		
Road and railway	RdRwyDen	Road and railway densities (km/km^2)
Linear herbaceous	LinHerbDen	Linear herbaceous densities (km/km^2)
Seismic lines	SeismicDen	Seismic line densities (km/km^2)
Wellsites	WellsitesHa	Wellsites areas in hectares (ha)
Landscape Features		
Elevation	AvgElevation	Average elevation in meters (m)
Slope	AvgSlope	Average slope in degrees (°)
Aspect	AvgAspect	Average aspect in degrees (°)
Topographic variability	AvgVMR	Average topographic vector ruggedness (0 to 1)
Habitat Features		
Resource selection function	AvgRSF	Average RSF value based on categories (1 to 6)
Species composition	AvgSC	Average species composition (0 to 100)
Crown closure	AvgCC	Average crown closure (0 to 100)
Distance to water	DistWater	Average distance to water in meters (m)

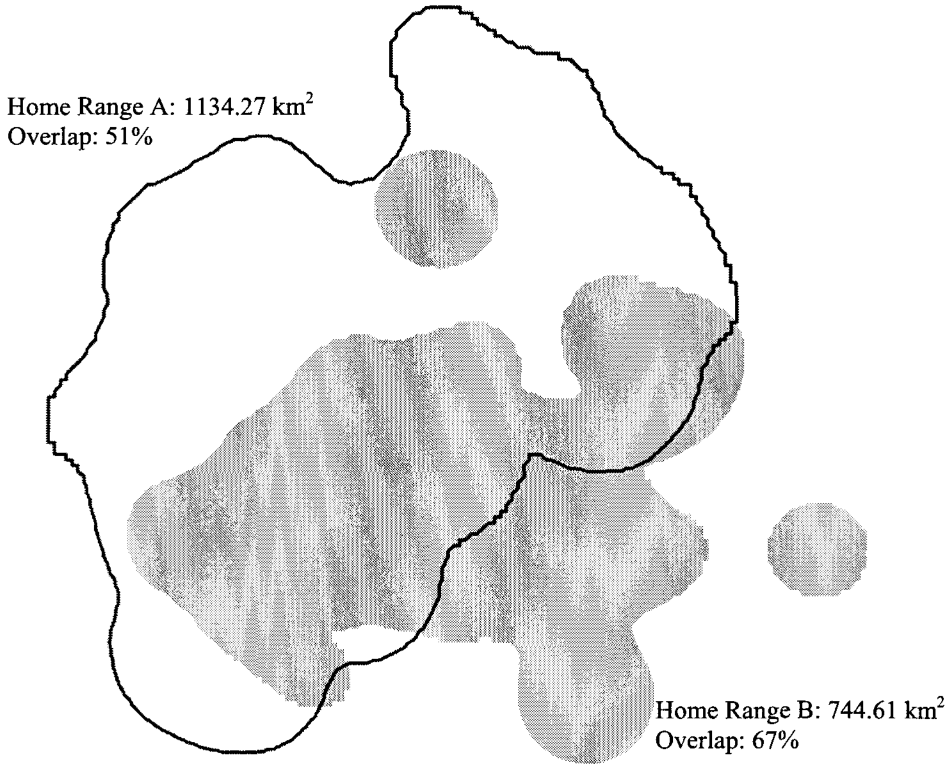
To identify which combinations of landscape variables best predicted movement rate and home range size, multiple linear regression (MLR) models were performed for 109 individual home ranges initially, further reduced to 106 home ranges and 104 movement rates grouped. For each model, contributing variables were ranked according to the standardized coefficient value. Independent variables were deemed significant at $P < 0.05$. All home ranges were initially grouped to assess whether a population-level model was viable. However, as demonstrated in Chapter 4, home range size and movement rate significantly differed according to landscape type. Further, certain habitat types available to foothills grizzly bears may be absent for mountain grizzly bears. As such, both home range size and movement rate MLR models were also computed for separate groups: mountain bears versus foothills bears. Other breakdowns were not considered due to sample size of subgroups.

Resulting model standardized residuals (ordinary residuals recomputed to a standard deviation of 1.0) were subsequently examined for spatial dependence. If the presence of spatial autocorrelation is demonstrated, one approach is to select a random sample of home ranges that are not spatially autocorrelated and reapply the statistical model (Fortin and Payette 2002). However, this is a loss of information. As previously mentioned, home ranges were separated according to landscape type and the multiple linear regression models were rerun. Model residuals were then reassessed for the presence of spatial autocorrelation according to landscape type. It is the hope that individual models will reduce the presence of spatial autocorrelation in model residuals and provide additional information regarding the relationship between home range size and independent variables.

Spatial Autocorrelation Analysis

Global and local spatial statistics are typically used to examine if data are spatially autocorrelated (Ord and Getis 2001). The spatial distribution of model residuals was examined for spatial dependence by calculating the global and local Moran coefficients (Anselin 2003, Osborne et al. 2007). First, a total spatial weights matrix was created for all 106 individual home ranges. Rather than adopting the standard inverse distance approach, binary weights were calculated using the proportion or percentage of overlap between each pair of home ranges (Figure 5-2). Any pair of home ranges that had at least 10% mutual overlap was considered connected and given a value of 1. This resulted in all home ranges having at least one connection. Using this criterion, four situation specific weights matrices were created in the following analysis.

Figure 5-2. Example of home range overlap calculation, where home ranges were required at least 10% mutual overlap to be considered connected and included within the spatial weights matrix.



Both the global and local Moran calculations were conducted with the program GeoDA version 0.9.5 (Anselin 2003). The value of Moran's *I* generally varies between 1 (extreme positive spatial autocorrelation) and – 1 (extreme negative spatial autocorrelation), although values beyond – 1 or + 1 are occasionally obtained. Positive global Moran's *I* occurs when the residuals at neighboring locations are similar and negative when they are dissimilar (Osborne et al. 2007). Moran's *I* is approximately zero when no spatial autocorrelation is present. The resulting Moran's *I* spatial autocorrelation statistic was visualized using the scatterplot slope with the spatially lagged standardized residuals on the vertical axis and the original standardized residuals on the horizontal axis. The four quadrants in the scatter plot correspond to different types of spatial autocorrelation (Nelson and Boots 2008). For example, spatial clusters of like values are plotted in the upper right (high-high) and lower left (low-low) quadrants. Spatial outliers are plotted in the upper left (low-high) and lower right (high-low) quadrants. Randomizations (99 permutations) were conducted to test significance and obtain a reliable result. Results will focus largely on the presence of high-high and low-low locations which indicate clusters of large residual values.

While global measures are useful for summarizing spatial autocorrelation for the entire data set, local measures are necessary to identify areas which differ from the typical situation (Boots 2002). Even when significant global autocorrelation is absent, global Moran's coefficients can be decomposed further to examine spatial autocorrelation around each data point. This calculation is termed local indicators of spatial association (LISA) and is also available in the GeoDa program (Anselin 2003). The resulting local Moran coefficients can be used to identify clusters of residuals that deviate from the mean in a like fashion (Boots 2002). Using this approach, local measures (LISA) were also calculated for each standardized residual to create individual significance (*p*-value) and cluster maps for each individual home range (Anselin 2003). Positive local Moran's *I* indicate values that are extreme relative to the mean. Local

Moran's *I* values near zero indicate no spatial autocorrelation is present or that it is present in values near the mean (Nelson and Boots 2008). The resulting LISA value was applied to the mapped centroid for each home range for visualization.

5.4 Results

Preliminary Home Range Size and Movement Rate Comparisons

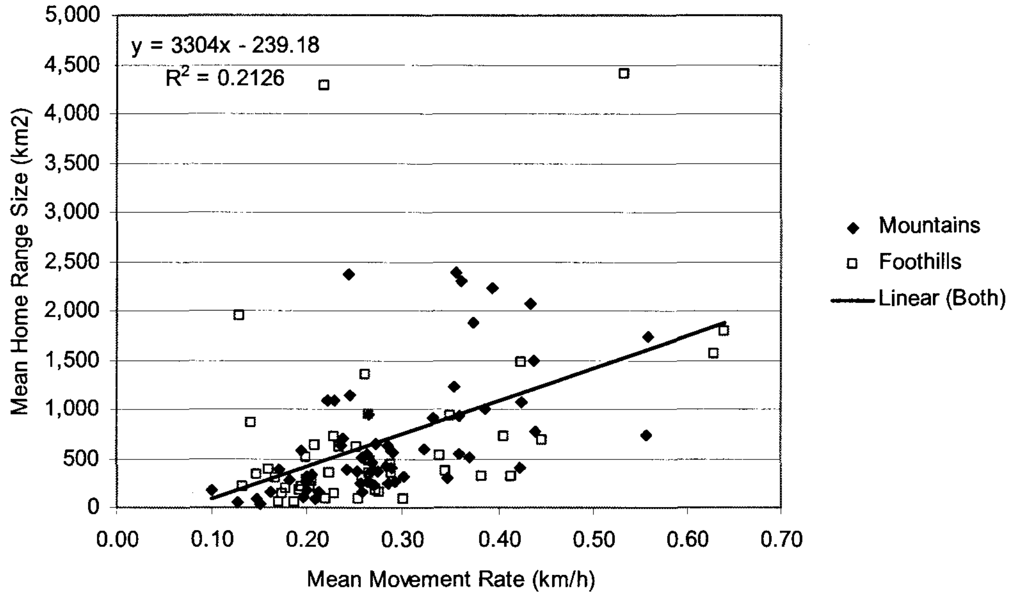
Within the west-central study region, GPS locations for 109 individual grizzly bears were collected from 1999 to 2004. When grouped by landscape type, 47 bears were found to reside in foothill environments while 62 bears were found to reside in mountain environments. Results for this particular subset of grizzly bears indicated average movement rate ($U = 926.0$, $Z = -3.249$, $P = 0.001$) and home range size ($U = 664.0$, $Z = -4.852$, $P < 0.001$) to be significantly different when grouped by landscape type. The overall average movement rate for bears used in this assessment was recorded at 0.28 km/h or 6.72 km/day which is slightly lower than the overall average movement rate results reported in Chapter 4 (0.3 km/h or 7.2 km/day). Grizzly bears located in mountain environments (mean = 0.25 km/h, SE = 0.01) were again found to move significantly slower than grizzly bears located in foothill environments (mean = 0.32 km/h, SE = 0.02).

Mean annual kernel home range size for all bears was reported at 682 km^2 which is approximately 200 km^2 smaller than the overall population home range size reported in Chapter 4 (878 km^2). When grouped by landscape type, mountain home ranges (mean = 394 km^2, SE = 41.2) were again found to be significantly smaller than foothill home ranges (mean = 1062 km^2, SE = 140.1). While mountain home range sizes are consistent with the results presented in Chapter 4.0, foothill home range sizes were found to be approximately 400 km^2 smaller. The reduction to both movement rate and home range size is likely a response of removing individual bears (largely subadult males) from the analysis which reside north of Highway 16.

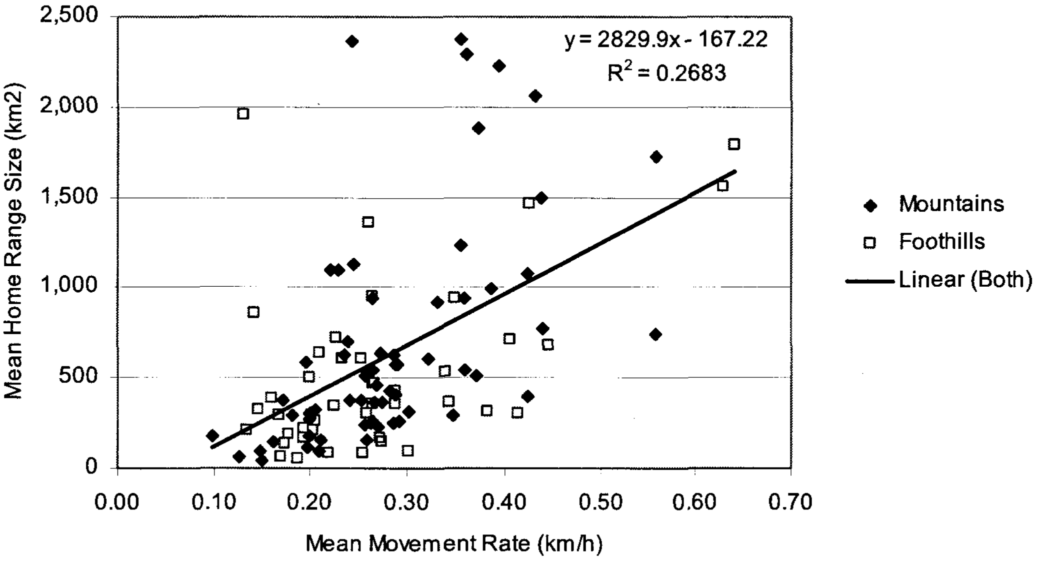
As expected (Figure 5-3), results demonstrated that movement rate (km/h) and home range size (km^2) are positively associated ($R^2 = 0.21$) although this relationship wasn't exceptionally strong. Three individual bears were identified as potential outliers. Two of the outliers were individual males residing in the foothills (G045 and G062) and reported exceptionally large home ranges (4402.8 km^2 and 4286.9 km^2 respectively – Figure 5-3a). The third outlier was a female grizzly bear (G092) residing in the mountains. The cases were also confirmed as outliers using the centered leverage value and Cook's distance. The removal of these data points improved resulting linear relationships and as such, they were also removed from the following MLR analyses. As demonstrated by Figure 5-3b, the linear relationship between movement rate and home range size increased slightly to $R^2 = 0.27$.

Figure 5-3. Scatterplots demonstrating the relationship between home range size (km^2) and movement rate (km/h) for a) all grizzly bears prior to outlier removal, and b) for all bears after outlier removal.

a.



b.



Home Range Size Multiple Linear Regression Results

Initial linear explorations were conducted using non transformed home range size for interpretation. Resulting scatter plots highlighted weak relationships between home range size and underlying landscape characteristics for all 106 remaining individual bears after outlier removal (Figure 5-4 to Figure 5-6). When compared to home range size (km^2), road and railway densities ($R^2 = 0.04$), linear herbaceous densities ($R^2 = 0.03$), seismic densities ($R^2 = 0.27$), and proportion crown closure ($R^2 = 0.24$) values all expressed weak positive relationships. Only wellsite area expressed a strong positive relationship ($R^2 = 0.52$). Results indicated that as home range size increased, the above variables also increased in value. As a corollary, elevation ($R^2 = 0.25$), slope ($R^2 = 0.24$), aspect ($R^2 = 0.18$), RSF ($R^2 = 0.25$), vector ruggedness ($R^2 = 0.21$), and species composition ($R^2 = 0.22$) values expressed negative relationships. This indicated that as home range size increased, these values decreased. For species composition, a lower species composition value indicates a mixed to deciduous forest type rather than a mixed to coniferous forest type. No relationship was found between home range size and mean distance to water ($R^2 = 0.00$).

Linear relationships were also examined between home range size and proportion of habitat class for all 106 individual bears (Figure 5-7 and Figure 5-8). When compared to home range size (km^2), open forest ($R^2 = 0.03$), closed forest ($R^2 = 0.21$), wet treed ($R^2 = 0.31$), and water ($R^2 = 0.09$) habitat class proportions all expressed positive relationships. The remaining habitat classes, proportion of shrub ($R^2 = 0.18$), proportion of herbaceous ($R^2 = 0.22$), and proportion of non habitat ($R^2 = 0.12$) all expressed negative relationships. In the following MLR models, elevation, slope and RSF have subsequently been eliminated due to collinear relationships with other variables. Of the remaining independent variables, wellsite area, proportion wet treed, and seismic line densities reported the three best linear relationships with R^2 values above 25%.

Figure 5-4. Scatterplots demonstrating the relationship between home range size (km^2) and landscape variables used in MLR analyses.

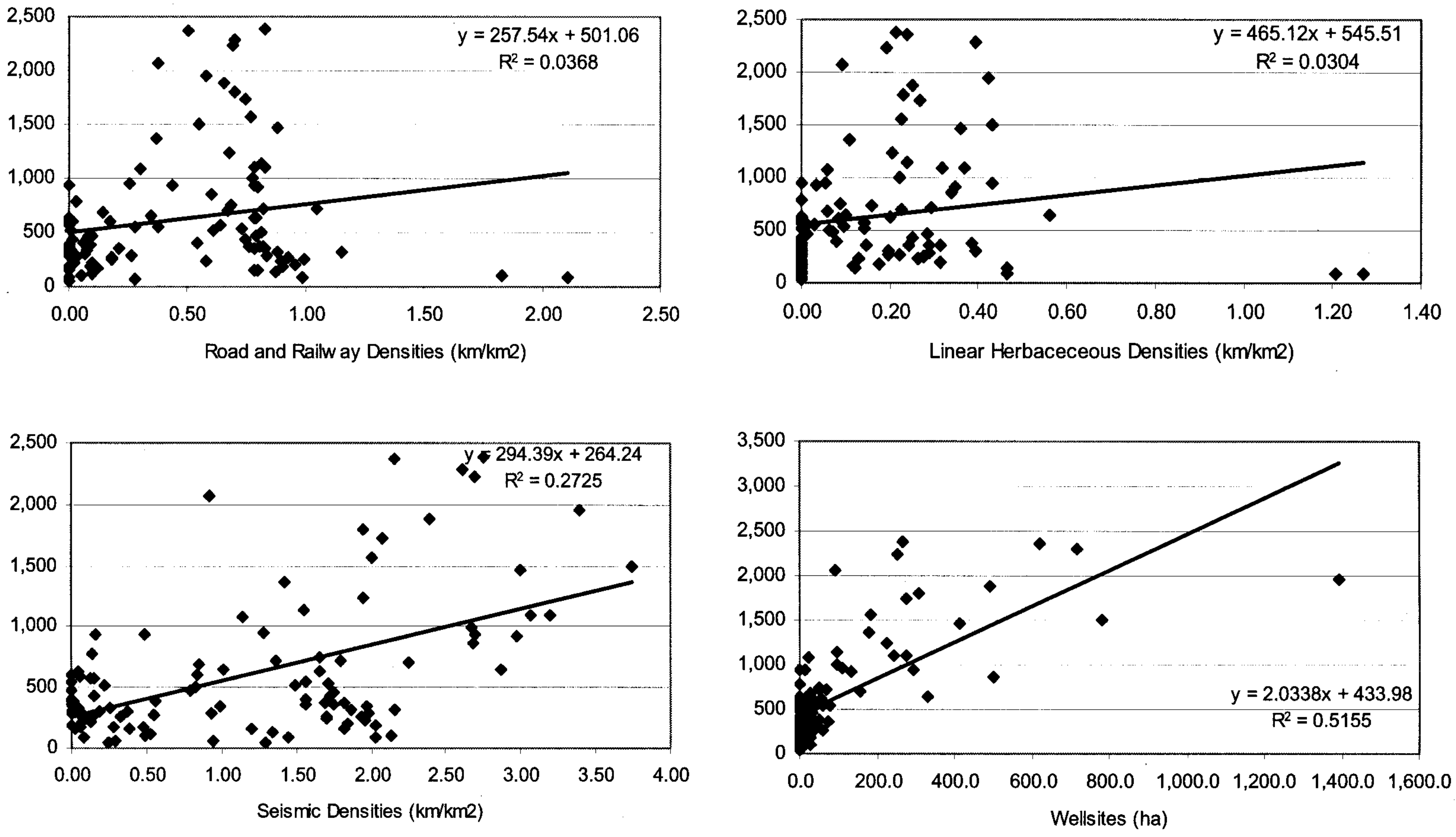


Figure 5-5. Scatterplots demonstrating the relationship between home range size (km^2) and landscape variables used in MLR analyses.

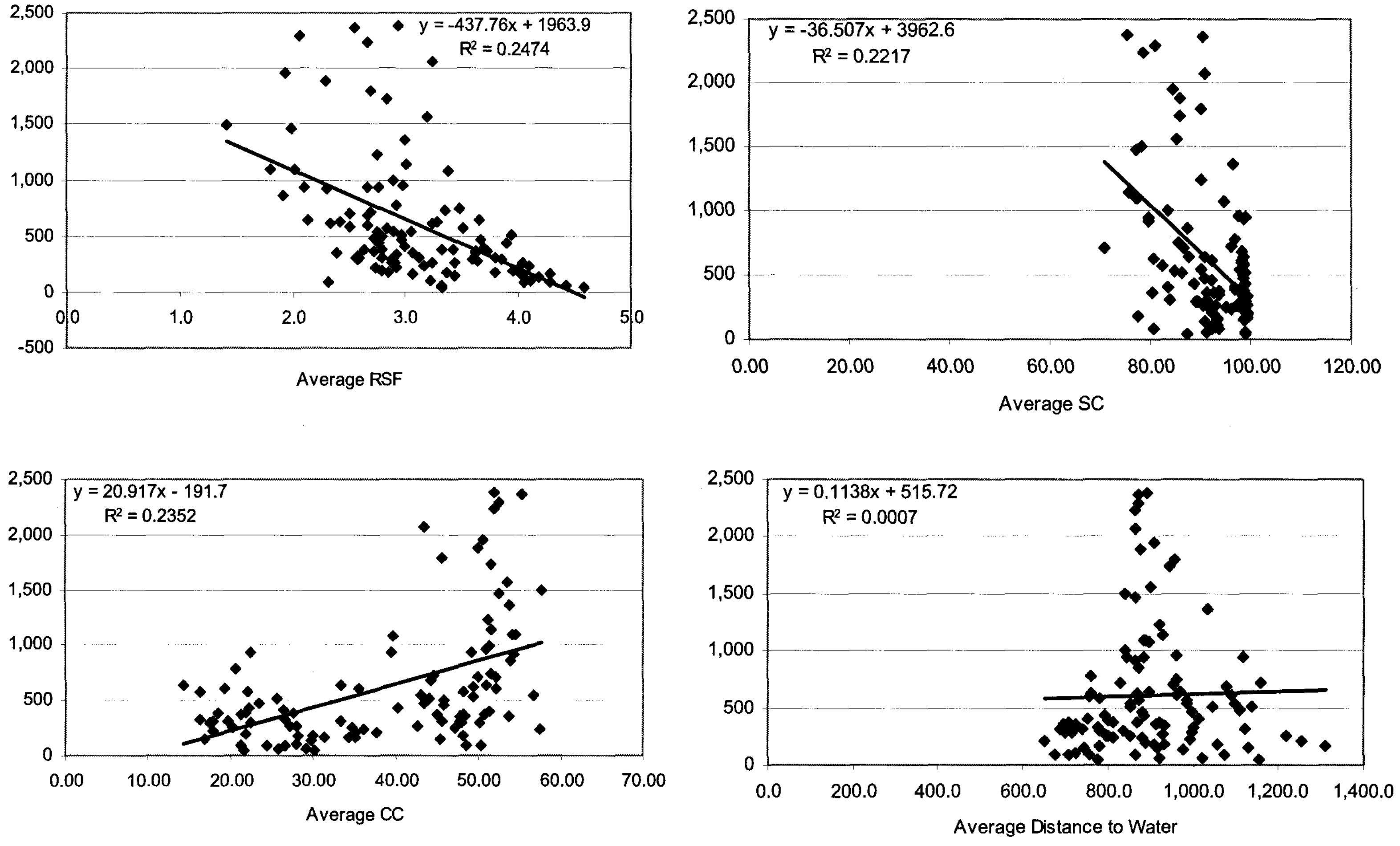


Figure 5-6. Scatterplots demonstrating the relationship between home range size (km^2) and landscape variables used in MLR analyses.

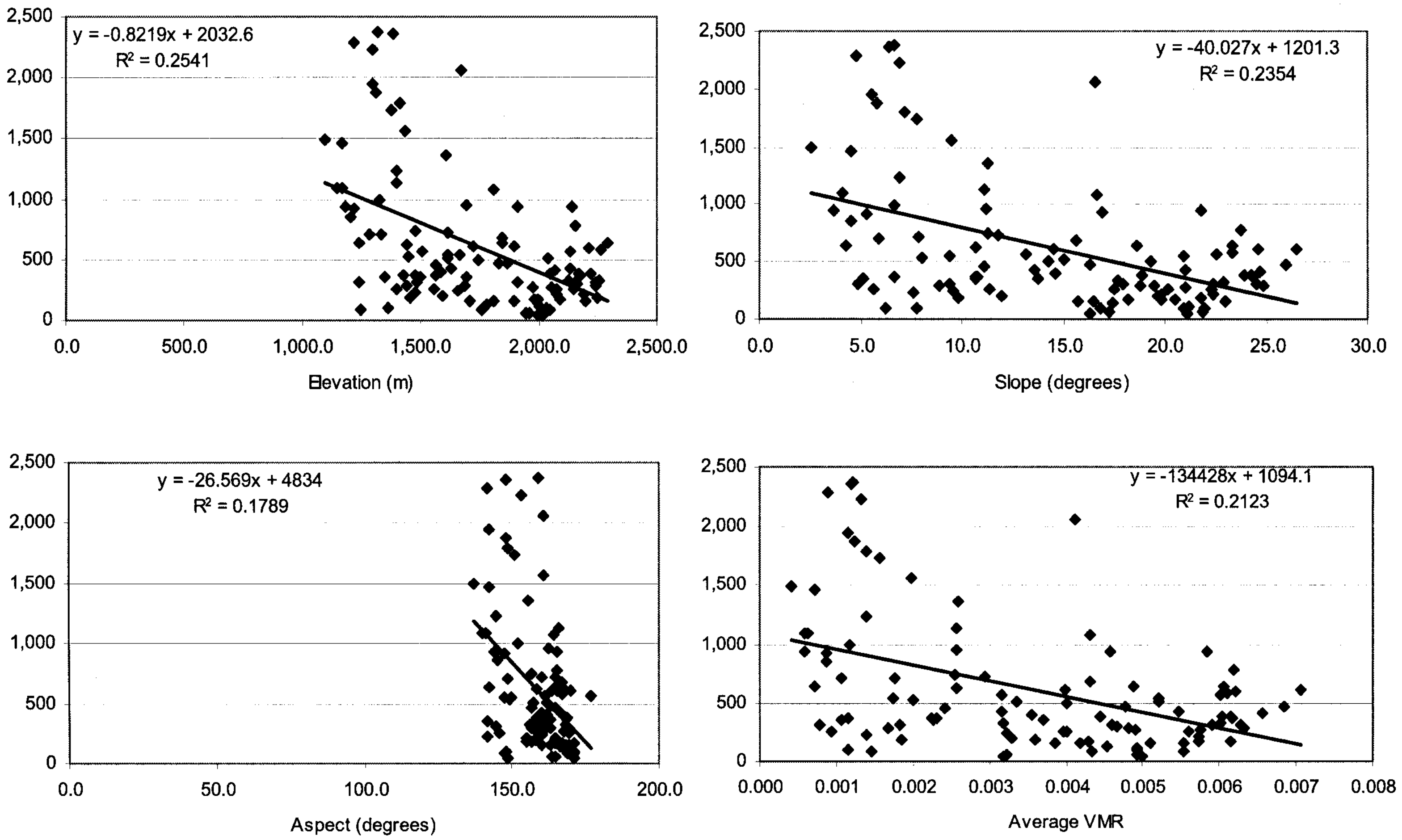


Figure 5-7. Scatterplots demonstrating the relationship between home range size (km^2) and landscape variables used in MLR analyses.

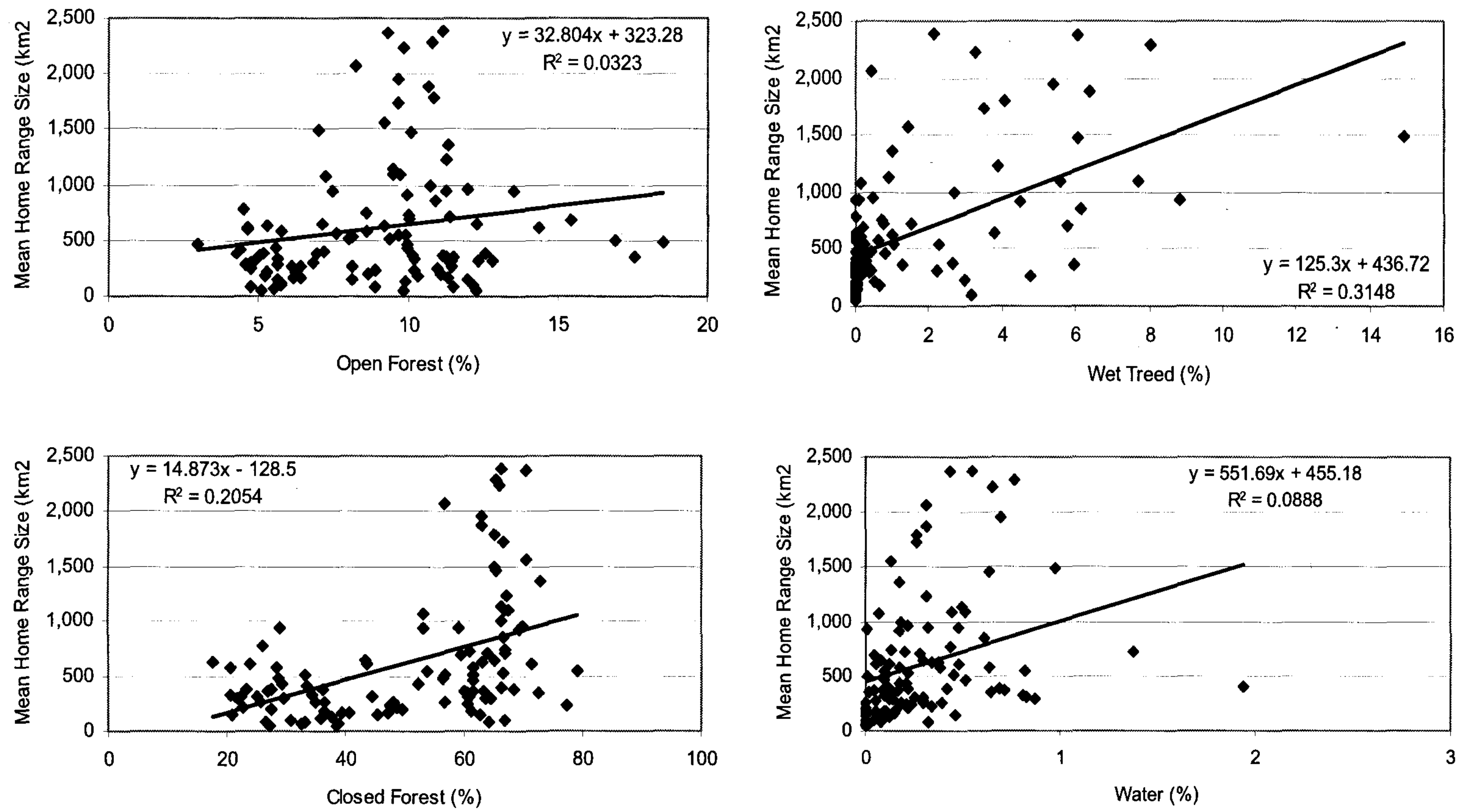
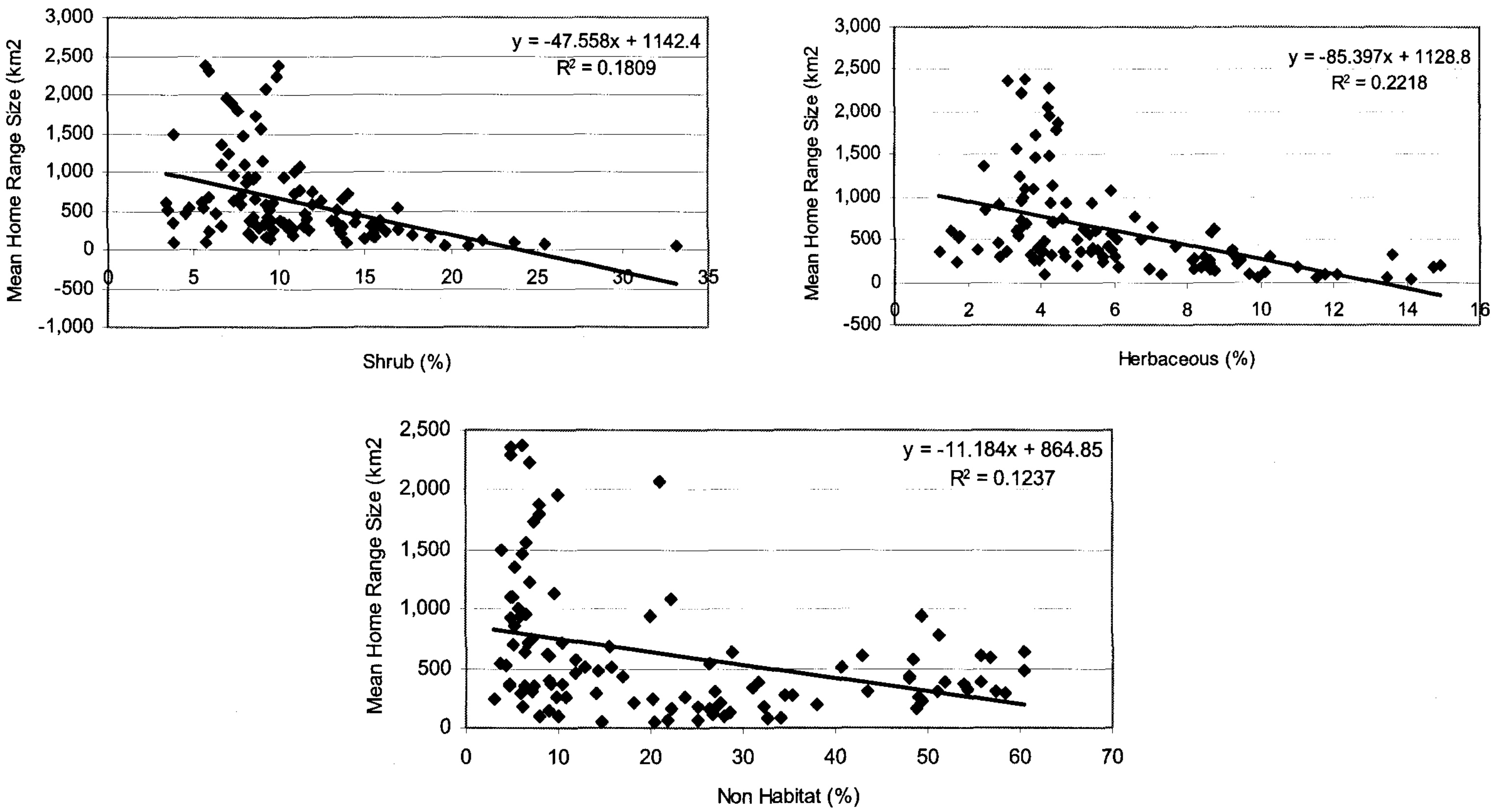


Figure 5-8. Scatterplots demonstrating the relationship between home range size (km^2) and landscape variables used in MLR analyses.



Stepwise multiple regression models were developed to assess the contribution of independent variables (landscape properties) to the dependent variable (log transformed home range size). When grouped for all bears, the resulting multiple regression model described a significant proportion of the variation in home range size ($P < 0.001$). The coefficient of determination (R^2) for all home ranges combined was reported at 0.781. The resulting model responded to five independent variables (Table 5-2). Proportion of shrub was reported as the highest contributing variable and was negatively correlated with home range size (-0.516). Linear herbaceous density (-0.486), proportion of herbaceous habitat (-0.389), and average species composition (-0.387) all contributed negatively to home range size. Finally, well site area (0.360) was reported as positively correlated to home range size. Upon examination, the partial regression coefficients were equivalent to the beta values reported below.

Table 5-2. Results of multivariate linear regression models for 106 individual home ranges showing contributing variables with standardized beta coefficients, standard error, significance, and variable ranking.

Variable	**Beta**	**SE**	***P*-value**	**Rank**
LinHerbDen	-0.486	0.517	0.000	2
WellsitesHa	0.360	0.000	0.000	5
AvgSC	-0.387	0.012	0.000	4
Herb	-0.389	0.027	0.000	3
Shrub	-0.516	0.014	0.000	1

To examine for possible differences due to landscape type, a separate MLR model was run for mountain home ranges ($n = 61$) and foothills home ranges ($n = 45$). The resulting MLR produced significant models for both mountain bears and foothills bears ($P < 0.001$). Coefficients of determination were high for both mountain home ranges ($R^2 = 0.79$) and foothills home ranges ($R^2 = 0.81$). Mountain home range size responded to three landscape variables (Table 5-3).

Proportion of shrub was the most important variable (-0.751), followed by proportion of closed forest (-0.507) and proportion of herb (-0.431) landscape classes.

Table 5-3. Results of multivariate linear regression models for mountain home ranges ($n = 61$) and foothills home ranges ($n = 45$) showing contributing variables with standardized beta coefficients, standard error, significance, and variable ranking.

Variable	Beta	SE	*P*-value	Rank
Mountain HRs				
ClosedFor	-0.507	0.011	0.013	2
Herb	-0.431	0.035	0.004	3
Shrub	-0.751	0.018	0.000	1
Foothill HRs				
LinHerbDen	-0.607	0.416	0.000	1
WellsitesHa	0.454	0.000	0.001	3
AvgSC	-0.494	0.019	0.002	2
OpenFor	0.257	0.070	0.024	7
Wettreed	0.371	0.051	0.046	5
Herb	-0.377	0.103	0.009	4
Shrub	-0.364	0.030	0.005	6

Foothills home ranges responded to seven landscape variables. Linear herbaceous density was the highest contributing variable (-0.607). This was followed by average species composition (-0.494), well site area (0.454), proportion of herb (-0.377), proportion of wet treed forest (0.371), proportion of shrub (-0.364), and proportion of open forest (0.257). For mountain home ranges, shrub, closed forests and herbaceous landscape classes were all negative factors influencing home range size. For foothills home ranges, wellsite area, open forests, and wet treed forests were all positively correlated with home range size. Linear herbaceous densities, species composition, herbaceous and shrub landscape classes were all negatively correlated with home range size.

Movement Rate Multiple Linear Regression Results

In addition to the three previously identified outliers, two additional cases were identified and removed prior to finalizing the movement rate multiple linear regression analyses. Both cases were identified as extreme values and having a large effect on the regression coefficients using the centered leverage value and Cook's distance. This reduced the sample size from 106 individuals to 104 individuals. An individual female with cubs (G007) residing in the foothills in 2002 represented one of the cases. The second outlier was a subadult female (G048) residing in the mountains during 2003. Initial linear explorations between mean daily movement rate (km/h) and landscape variables were again examined for the remaining 104 grizzly bears. Resulting scatter plots demonstrated slight improvements to relationships after outlier removal. Relationships were significantly weaker than those reported for home range size above and thus weren't included visually. When compared to average movement rate (km/h), road and railway densities ($R^2 = 0.07$), linear herbaceous densities ($R^2 = 0.03$), seismic densities ($R^2 = 0.09$), wellsite area ($R^2 = 0.02$), and crown closure ($R^2 = 0.14$) all demonstrated very poor positive linear relationships. Scatterplots further highlighted poor negative relationships between average movement rate (km/h) and elevation ($R^2 = 0.13$), slope ($R^2 = 0.11$), aspect ($R^2 = 0.05$), RSF ($R^2 = 0.03$), vector ruggedness ($R^2 = 0.09$), and species composition ($R^2 = 0.09$).

Linear relationships were also examined between movement rate and proportion of habitat class for all 104 individual bears. When compared to movement rate (km/h), open forest ($R^2 = 0.03$), closed forest ($R^2 = 0.14$), wet treed ($R^2 = 0.07$), and water ($R^2 = 0.01$) habitat class proportions all expressed weak positive relationships. The remaining habitat classes, proportion of shrub ($R^2 = 0.09$), proportion of herbaceous ($R^2 = 0.13$), and proportion of non habitat ($R^2 = 0.08$) all expressed weak negative relationships. Of the remaining independent variables not eliminated due to multicollinearity, only crown closure, closed forest, and proportion of herbaceous reported R^2 values above 10%.

Stepwise multiple regression models were developed to explore the contribution of independent variables (landscape properties) to the dependent variable (log movement rate). Model results were poor and only two of the three models produced significant results. When grouped, the analysis produced a significant model ($R^2 = 0.29$, $P = 0.002$) involving only one landscape variable. Proportion of shrub (negatively correlated) was the only contributing variable ($\beta = -0.346$, $P = 0.018$). Separately, mountain movement rates also produced significant model results ($R^2 = 0.38$, $P = 0.031$) while foothills movement rates did not ($R^2 = 0.27$, $P = 0.590$). Again, proportion of shrub (negatively correlated) was the only contributing variable ($\beta = -0.461$, $P = 0.049$) to movement rate. No other variables were found to be contributing factors.

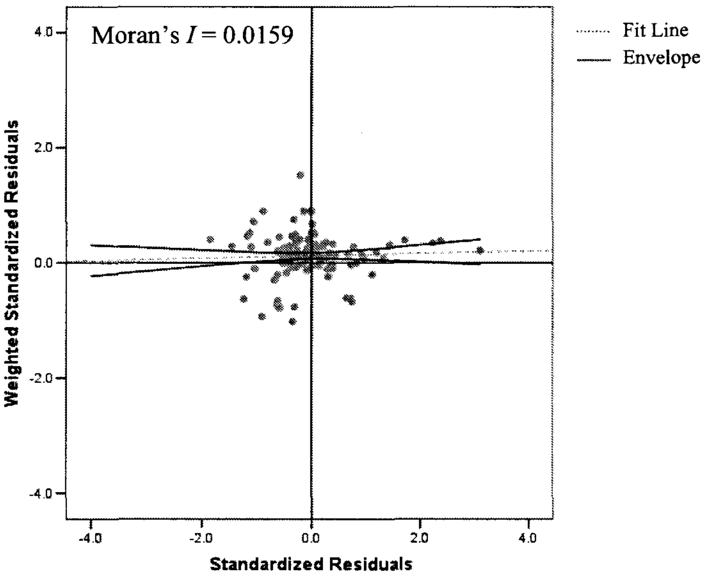
Spatial Autocorrelation Results

A total of 4 symmetric weights matrices (derived from the original) were used to calculate Moran's *I* based on mutual overlapping home ranges (Table 5-4). The first symmetric weights matrix was created to test the standardized residuals of the home range size grouped MLR model. While all 106 home ranges were connected (having at least one neighbor), only 13% of the possible home range pairings met the mutual >10% overlap criterion. When broken down by landscape type, symmetric matrices were created using all 61 mountain grizzly bear home ranges and 45 foothills grizzly bear home ranges. For mountain home ranges, 14% of the possible home range pairings met the mutual >10% overlap criterion while 29% of the possible foothills home range pairings met the mutual >10% overlap criterion. Finally, the last symmetric weights matrix was created to examine the resulting movement rate model residuals using 13% of the possible home range pairings.

Table 5-4. Symmetric spatial weights characteristics showing total number of home range comparisons, home range pairs with 0% overlap, home range pairs with < 10% mutual overlap, and home range pairs with > 10% mutual overlap for all MLR models.

Weights Matrix	Possible # of HR Connections	# of HRs = 0%	# of HRs < 10%	# of HR > 10%
HR MLR Model (*n* = 106)	11,130	9,062	638	1,430
HR Mtn MLR Model (*n* = 61)	3,660	2,972	160	528
HR Fthill MLR Model (*n* = 45)	1,980	1,142	258	580
Moverate MLR Model (*n* = 104)	10,712	8,682	608	1,422

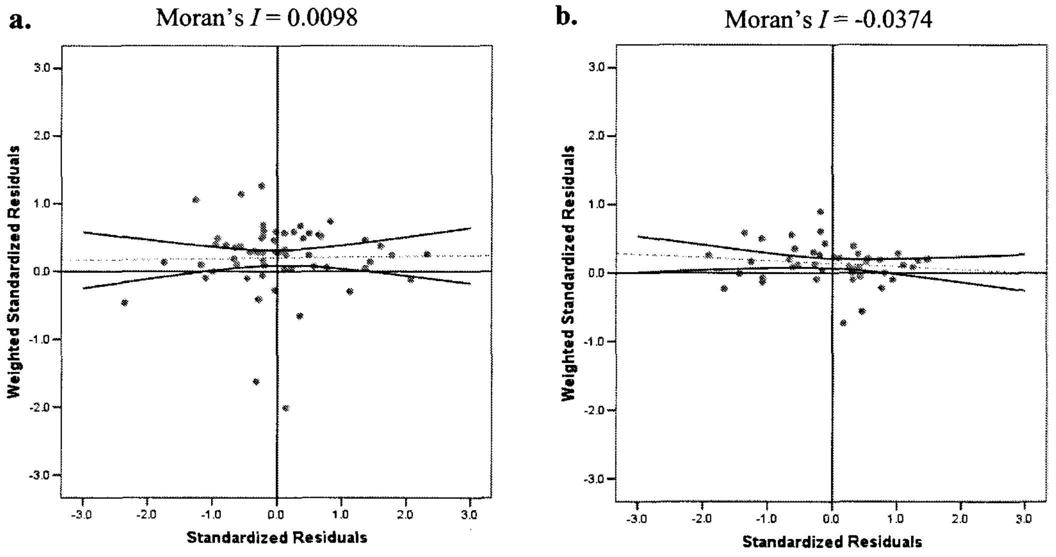
Figure 5-9. Classic global Moran's *I* scatterplot highlighting residual values against weighted residual values using percentage home range overlap for grouped home range size MLR model. Fit line and envelope are generated within Geoda.



Global Moran's results differed according to MLR model. For all home range sizes grouped (*n* = 106) across the entire study region, the resulting MLR model residuals demonstrated positive spatial autocorrelation (Moran's *I* = 0.0159) (Figure 5-9).

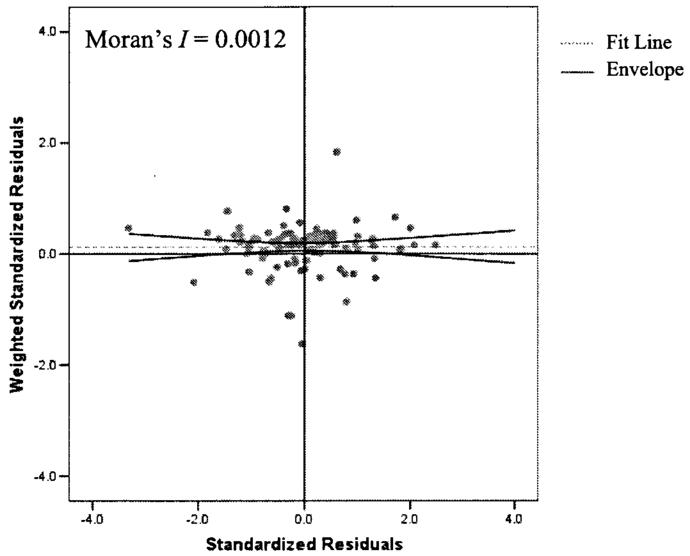
Post analysis randomizations indicated that this was not significant ($P = 0.300$). When broken down according to landscape type, the mountain home range size MLR model ($n = 61$) also showed no significant spatial autocorrelation (Moran's $I = 0.0098$, $P = 0.332$) was present in model residuals (Figure 5-10). Interestingly, the foothills home range size MLR model ($n = 45$) demonstrated a small negative (Moran's $I = -0.0374$, $P = 0.4340$) Moran's I coefficient. Again, no significant spatial autocorrelation was reported for model residuals.

Figure 5-10. Classic global Moran's *I* scatterplot highlighting residual values against weighted residual values for a) mountain home range size, and b) foothills home range size MLR models.



Finally, global Moran's I was also calculated for the movement rate MLR model (Figure 5-11). For all movement rates grouped ($n = 104$), the resulting model residuals showed that no significant positive spatial autocorrelation was present (Moran's $I = 0.0012$, $P = 0.4230$). As previous MLR models reported poor results for movement rate, no attempt was made to assess the presence of spatial autocorrelation for model residuals according to landscape type.

Figure 5-11. Classic global Moran's I scatterplot highlighting residual values against weighted residual values using percentage home range overlap for grouped movement rate MLR model.



Although the proportion of home range overlap produced non-significant global spatial autocorrelation results for all four MLR models, pockets of outlier residuals remained and were detected by LISA (Figure 5-12 to Figure 5-13). For all models, non significant residual values were primarily situated between the -1.0 and 1.0 interval lines. Individual cases that were classified as significantly autocorrelated were clustered in the lower left and upper right quadrants, indicating values were either low-low spatial clusters or high-high spatial clusters (Table 5-5). In terms of regression residuals, high-high residual cases are locations where the observed value of the dependent variable is underpredicted while low-low residual cases are locations where the observed value of the dependent variable is overpredicted.

Table 5-5. Local indicators of spatial association (LISA) for model residuals for all four MLR models. The three columns show the resulting cases and percentages according to LISA cluster class type.

	Cluster Classes (n, %)		
SWM	H-H	L-L	No Sig
HR MLR Model (*n* = 106)	12 (0.11)	3 (0.03)	91 (0.86)
HR Mtn MLR Model (*n* = 61)	8 (0.13)	1 (0.02)	52 (0.85)
HR Fthill MLR Model (*n* = 45)	2 (0.04)	0 (0.00)	43 (0.96)
Moverate MLR Model (*n* = 104)	10 (0.10)	1 (0.01)	93 (0.89)

Resulting local spatial autocorrelation values were mapped according to resulting positive and negative LISA values for significant cases only ($P < 0.05$). For the home range size MLR model residuals, the north-central part of the study area demonstrated the major concentration of highly significant ($P < 0.05$) positive or negative local Moran's I values (Figure 5-12a). Residual clusters indicated that in this particular location of the study region the MLR model performed poorly. Non significant small residuals near zero were also mapped demonstrating where the model fit well. While the grouped home range size MLR model residuals reported no significant positive spatial autocorrelation, the number of individual cases reporting significant local spatial autocorrelation was the largest ($n = 15$) (Figure 5-12a). Three of the cases were low-low residual clusters and twelve or 11% of the cases were high-high residual clusters.

For comparison, results were also mapped for the grouped movement rate MLR model residuals (Figure 5-12b). While global Moran's I was not reported as significant, a large number of individual cases ($n = 11$) also reported significant local spatial autocorrelation. Ten of the eleven cases (10% of the overall cases) were classified as high-high residual cluster locations.

The remaining case was classified as a low-low residual cluster. When compared visually, results demonstrated that the concentration of highly significant cases were also located in the north-central part of the study area. For both models, the region where model performance was poor was situated along the boundary between mountain and foothills landscape types where home ranges overlapped considerably.

Resulting local spatial autocorrelation values were further mapped according to landscape type. For mountain home range size model residuals, nine individual home ranges were reported as being highly positively significant (Figure 5-13a). Eight cases were high-high residual clusters and one individual home range was classified as a low-low residual cluster. When mapped, the concentrations of highly significant cases were constricted to a small north central portion of the study region. While the global Moran's *I* coefficient was the smaller than the grouped and foothills MLR, the mountain home range size model residuals further reported the largest percentage (13%) of high-high residual clusters over the other two MLR models (Table 5-5). For foothills home range size model residuals, only two individual home ranges were reported as being highly positively significant (Figure 5-13b). In both cases, significant residuals were classified as high-high cluster types. The remaining cases were classified as non significant and having a small local Moran's value near zero indicating that the model fit well overall.

Figure 5-12. Resulting LISA significance at $P < 0.05$ showing positive, negative, and near zero local Moran's I for each home range centroid based on a) home range size MLR model ($n = 106$), b) movement rate MLR model ($n = 104$). Non significant values are also represented. Foothills home range outlines are represented by dark grey while mountain home range outlines are light grey.

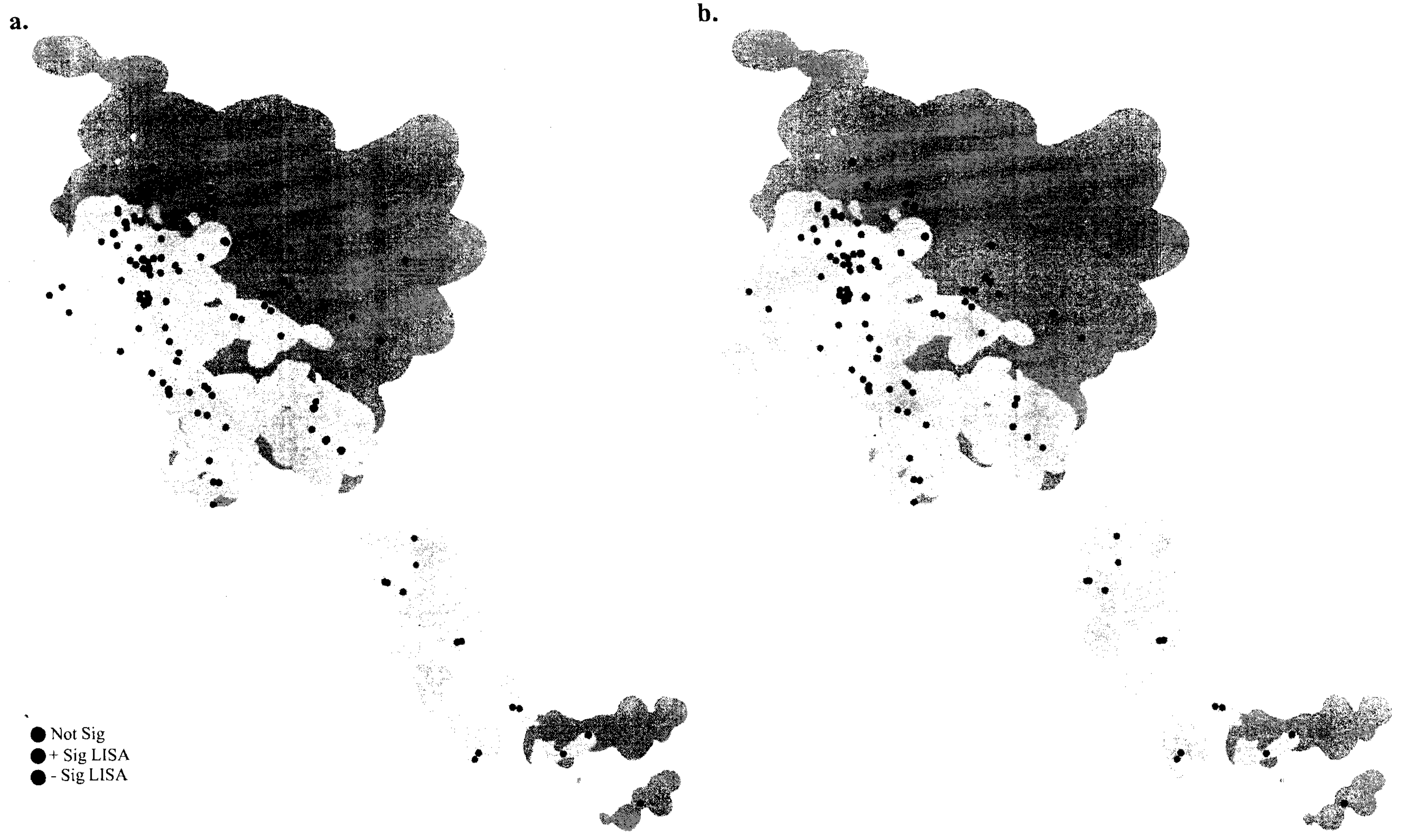


Figure 5-13. Resulting LISA significance at $P < 0.05$ showing positive, negative, and near zero local Moran's I for each home range centroid based on a) mountain MLR model ($n = 61$), b) foothills MLR model ($n = 45$). Non significant values are also represented. Foothills home range outlines are represented by dark grey while mountain home range outlines are light grey.

5.5 Summary

As expected, home range sizes and movement rates reported differences between mountain and foothills landscape types. Although, depending on the individual grizzly bears included in the analysis, results varied slightly to those reported in the previous chapter (Chapter 4). The relationship between home range size and movement rate was found to be positively correlated as expected. Yet, this relationship was not as strong ($R^2 = 0.27$) as predicted. This observation suggests that even as home range size increases and the individual distances traveled may subsequently increase, daily movement rates based on large-scale GPS radiotelemetry may not. Understanding the direct relationship between home range size and movement rate may be difficult due to the different scales at which these indicators are measured and occur.

In modeling efforts, such as this one, issues include variable selection, the absence of additional contributing variables, multicollinearity among explanatory variables, and the failure to meet model assumptions (Christman 2007). With standard statistical methods such as linear regression, the data are assumed to be statistically independent (Overmars et al. 2003). However, typical spatial data have a tendency to be dependent providing additional information regarding spatial pattern and process. For multiple linear regression models, this presence of spatial dependence can provide a biased estimation of error variance and an overestimation of the R^2 value (Overmars et al. 2003). As such, in addition to examining the relationship between home range size and landscape properties, model residuals were subsequently examined for spatial autocorrelation.

For grizzly bears, previous studies have suggested that there is a relationship between landscape characteristics and home range size. Typically, smaller home range sizes indicate more profitable environments. In mountain environments, usable habitats and related movements are often restricted to lower-elevation valley bottoms (primarily consisting of shrub and herbaceous habitat classes) and higher-elevation alpine meadows (Noss et al. 1996). Previous studies have noted that grizzly bears commonly use ridgetops, mountain saddles, and riparian networks for travel across mountain landscapes (Noss et al. 1996, Nielsen et al. 2002). Additionally, in mountain environments where landscapes are more restricted, home ranges are often smaller in size due to topographic constraints. In comparison, in foothills environments where landscapes are varied, resulting home ranges tend to be larger and less restricted topographically. As such, foothills-based movement through landscapes is more complicated and varies depending on habitat availability, amount of human disturbance and resulting spatial pattern and distribution (Berland et al. 2008).

When all home ranges were grouped, MLR results indicated that percentage of shrub habitat was the largest contributing variable to overall home range size. For grizzly bears, home ranges were smallest when proportion of shrub was largest. The next highest ranked contributing variables were linear herbaceous (pipeline and powerline right of ways) densities, percentage of herbaceous habitat, and mean species composition (all negatively related). Overall, smaller home ranges were related to high linear densities, high proportions of herbaceous, and high mean species composition (coniferous forests). The only positively related variable was area of wellsites indicating larger home ranges were related to increased numbers of well sites. However, because the availability of certain landscape types changes depending on physical location, it was important to fit the model separately for mountain home ranges and foothills home ranges.

Model results suggest that the influences on foothills home range size are more complex than the influences on mountain home range size. When conducted separately, the total number of contributing variables for mountain home range size was three, while seven were reported for foothills home range size. Results indicated that proportion of shrub remained the highest contributing variable for mountain home ranges but not for foothills home ranges (it fell to rank

6). The other two contributing variables for mountain home ranges were proportion of closed forest and proportion of herbaceous habitats. For grizzly bears residing in mountain environments, smaller home ranges have higher percentages of shrub, closed forests, and herbaceous landscape classes. Previous regional habitat assessments promote open herbaceous and shrub habitats as well as coniferous forest stands as secure landscapes for grizzly bears (McLellan and Hovey 2001a, Nielsen et al. 2002, 2003, Nielsen et al. 2006) which compliment the mountain MLR results presented above.

Model results for foothills home range size indicated that density of linear herbaceous features was the overall largest contributing variable. This was followed by average species composition and wellsite area. Proportion of herbaceous, wet treed forest, shrub, and open forest habitat classes were ranked four through seven respectively. Overall, larger foothills home ranges were related to lower densities of linear herbaceous, lower values of species composition (indicating mixed to deciduous forest types), larger numbers of well sites, lower percentages of herbaceous and shrub habitats, and higher percentages of open forest and wet treed forest types.

Of interest was the absence of contribution from human-use features such as road density and seismic line density when explaining home range size. Further, distance to water which has been found important in grizzly bear habitat use and travel also did not show up as a contributing variable (Hunter 2007). While this type of analysis provides a general interpretation and understanding of the relationship between home range size and landscape properties, to fully understand the spatial interactions of grizzly bears and landscape, analyses should be conducted at finer spatial and temporal scales. The MLR analysis conducted here further emphasized the need to explore models specific to different landscape types. It additionally indicated which variables may be important to grizzly bear landscape interactions at finer-scales.

Specifying a model using average movement rate for each individual bear was a secondary consideration of this chapter. Results were poor and only one contributing variable produced significant results. When grouped, the model results were the weakest.
By separating the model according to landscape type, only mountain grizzly bear movement rates reported significant results that were slightly improved. The only contributing variable to mountain movement rates was the percentage of shrub habitat. Again, this relationship was negatively correlated suggesting that faster movement rates occurred when lower percentages of shrub habitats were present.

Unfortunately, using a variable such as mean movement rate (km/h) for each individual bear assumes stationarity in the statistical sense (Blackwell 1997). While providing information regarding annual or seasonal trends, it fails to provide behavioral details of finer-scale movements. One approach to improve model results may be to either include new or different variables or to transform variables until linear relationships are improved. However, in this study linear transformations did little to improve the distribution of independent variables. Likely, a global measure such as daily movement rate cannot not be meaningfully related to extracted home range properties due to the differing scale at which movement processes operate. It is likely better results would be achieved through the use of a finer-scale approach. Further, detailed examination of linear relationships between home range size and landscape variables (Figure 5-8) indicated that two possible relationships exist. Subsequent removal of exceptionally large home ranges (> 1,500 km^2) may further improve MLR model results.

Spatial autocorrelation occurs when a variable is correlated with itself displaced in space (Christman 2007). Consequently, the characteristics of homes ranges that are closer in space are anticipated to be more correlated than those farther apart. Analysis of model residuals that indicates the presence of significant spatial autocorrelation implies that the data are not independent and type I errors may occur (Fortin and Payette 2002, Diniz-Filho et al. 2003). While individual global Moran's *I* results differed depending on the multiple regression model examined, none were significant which suggests that MLR results are valid.

However, the global Moran's *I* coefficient should be interpreted with caution as local variability may exist regardless of global results. As demonstrated in this chapter, local explorations can complement the general global results (Osborne et al. 2007). Consequently, spatial autocorrelation testing was extended to examine the local indicators of spatial association (LISA). The analysis of residuals through LISA provided an approach to explore where significant local spatial autocorrelation exists within the study region itself. In this context, the mapping of Moran's coefficients can be utilized to distinguish positive and negative spatial autocorrelation based on the residual value of a location in relation to the residual value of its neighbors (Nelson and Boots 2008). For example, high-high and low-low Moron scatterplot values indicate residual values surrounded by similar values and highlight clusters rather than outliers. By identifying the spatial patterns where residuals are positively spatially autocorrelated, we can further identify where model errors may occur and where approaches to the modeling technique may have to be modified. Improvements to overall model results could be achieved by selectively removing cases which are significantly autocorrelated, by random case selection, or finally, by creating smaller subpopulation models as was conducted here to examine local spatial autocorrelation in mountain and foothills landscape types (Fortin and Payette 2002).

The presence of significant positive local spatial autocorrelation in model residuals indicated that the standard multiple linear regression model cannot capture all spatial dependency in the home range data. Such spatial autocorrelation could potentially indicate that non-linear relationships between the dependent and the independent variables are present or that important regressor variables, including spatial ones are missing (Cliff and Ord 1981, Griffith 1992, Overmars et al. 2003, Christman 2007). In this study, it is most likely that the relationship between home range size and underlying environmental processes are complex given differences to individual bear spatial response. Second, it is likely that some influential variables are missing from the analysis. For example, the presence of local autocorrelation in the residuals may be caused by intrinsic (individual behavior or conspecific interactions) or extrinsic (environment) factors not included here but relevant to grizzly bears (Aarts et al. 2008). Based on the clustered location of significant residuals, a variable not included but potentially influential, could be social interactions between individual bears. Another example may be the number of overlapping home ranges with a singular home range. For example, often the home range of subadult grizzly bears will contain some portion of overlap with its mother's home range after dispersing (McLellan and Hovey 2001b). An additional consideration is the absence of stationarity in the data, indicating that the relationship being modeled (e.g. home range size and proportion of habitat class) will vary spatially over the region (Christman 2007, Osborne et al. 2007). For example, a preferred resource may be present in one location of the study region but absent in another. Individual grizzly bears in this region may also demonstrate different habitat associations or responses despite similar habitat resources being available.

In this study, by examining the geographically mapped LISA clusters types and LISA significance values, high-high residual clusters were found to be concentrated in the north-central portion of the study area. The presence of localized spatial autocorrelation suggests that further examination of like-residual clusters may explain why the model fits poorly in this location. Detailed examination of individual cases for the grouped home range size MLR model residuals revealed that the majority of significantly spatially autocorrelated home ranges were located within BMA 3 (Figure 5-12a). More specifically, eleven out of twelve high-high residual clusters were located in BMA 3 with the remaining case being located in the mountains bordering BMA 3. Half of the home ranges exceeded (1,731 km^2 to 2,378 km^2) the mean annual foothills home range size (1,420 km^2) reported in Chapter 4. All three of the low-low residual clusters were also located in BMA 3 although these were situated approximately 100 km to the south. Detailed examination of the significant spatial autocorrelated mountain home range model residuals revealed the majority of high-high residual clusters to be situated near to and around the Cadomin coal site. It is possible that the presence of local spatial autocorrelation in this region may result from conflicting variables such as good grizzly bear habitat types mixed with high levels of human development and very high densities of roads. Individual home ranges in this region may include variables in quantities opposite of what would typically be expected (e.g. open mine sites and mining roads).

5.6 References

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CHAPTER 6 – ANALYZING MOVEMENT CHARACTERISTICS USING TIME SERIES SEGMENTATION AND DISCRIMINANT ANALYSIS

6.1 Introduction

The parameterization of least-cost path (Singleton et al. 2004, Drielsma et al. 2007, LaRue and Nielsen 2008), diffusion (Boone and Hunter 1996), individually-based (Blackwell 1997, Horne et al. 2007), step selection function (Fortin et al. 2005, Coulon et al. 2008), and corridor models (Graves et al. 2007) for large ranging species, such as grizzly bears, depends on reliable empirical movement data (Dickson et al. 2005). Process-based models are commonly tested post-generation with GPS radiotelemetry data to validate their accuracy or not tested at all. These models often reflect large-scale movements linking conservation areas across major divides or valley regions (Singleton et al. 2004, Graves et al. 2007, LaRue and Nielsen 2008). However, the role of landscape properties on grizzly bear movements is little understood and often neglected in such research. Few grizzly bear studies have described large-scale movement patterns and the underlying processes influencing those movements. Furthermore, only a couple of studies to my knowledge have assessed fine-scale movement patterns in relation to underlying landscape characteristics (Horne et al. 2007, Hunter 2007). For grizzly bears, the surrounding spatial environment facilitates or impedes movement between resource patches and is therefore a vital consideration when analyzing movement behavior or spatial response. Before beginning to understand the relationship between landscapes and movement, it is imperative that movements are appropriately classified according to movement behavior type (Fryxell et al. 2008).

Distinguishing between movement types is essential for studying the spatial movement patterns, habitat use, and behavior of individual grizzly bears. According to Turchin (1998), because the actual movement path of an individual, combined with underlying landscape properties, can be recorded, we can test mechanistic hypotheses about processes that affect movement (Fortin et al. 2005). Direct observation of a movement path may be the best approach for accomplishing this (Turchin 1998, Horne et al. 2007). The various components of a movement path (i.e. speed or step length) can provide insight regarding how individuals move through a landscape (Goodwin et al. 1999). For example, do the rates of vector-based movements differ in relation to landscape properties? What does this tell researchers about grizzly bear behavior? To understand how grizzly bears exist in landscapes, it is important to understand how individual grizzly bears interact (via movement) with landscape properties. This would require a direct analysis of movement trajectories both quantitatively and qualitatively (Goodwin et al. 1999). The most common first step is to separate movement behaviors into a dichotomous classification: slow versus fast or foraging versus traveling. To do this, both large amounts of fine-scale GPS radiotelemetry data are required, as well as quantitative approaches which deal with sequential data structures.

As reviewed in Chapter 2 and briefly explored in Chapter 3, times series graphing is one way of analyzing a sequence of data points which are typically recorded consecutively at equally spaced time intervals. This approach is most commonly used in economic forecasting, stock market analysis, and signal processing (Chatfield 1980). More recently, time series analysis has made indirect gains in ecology research via Fourier spectrums and wavelet analyses although primarily for the task of assessing internal autocorrelation structure (Hunter 2007, Wittemyer et al. 2008). One of the benefits of employing time series analysis is that data can be partitioned into internally homogeneous data segments (Dettki and Ericsson 2006). The goal of segmentation in the case of an individual grizzly bear data set would be to identify internal clusters of maintained similar movement characteristics. It has further been suggested that time series segmentation can be used to identify periods of second-order homogeneity or local stationarity (Clemencon and Slim 2004). For a grizzly bear movement time sequence, a period of local stationarity would be defined as a section of sequential vectors where the mean or variance remained constant over a portion of the entire path.

In this chapter, time series segmentation of movement vectors was utilized to differentiate between types of movement behavior. By segmenting consecutive movement vectors into a series of homogeneous slow and fast movement classes, it is possible to identify their distribution with respect to landscape features (Phillips et al. 2004, Barraquand and Benhamou 2008). Specifically, the overall intent of this chapter is three-fold. First, it is necessary to devise a separation method by which resulting movement parameters in each category would be significantly different. This analysis focuses on identifying both the slowest and fastest movement vectors, separated from possible transition vectors, using upper and lower normalized distance thresholds (as per the foraging cluster technique applied in Chapter 3). The second objective of the chapter is to explore the affect of landscape properties on segmented grizzly bear movement patterns. To do this, a discriminant analysis was conducted to determine what landscape variables best predicted movement behaviors. Finally, vector-based kernel surface maps were created to visualize potential representations of slow and fast movements for each individual bear using the predetermined movement classification. Results are intended to provide information regarding grizzly bear movement behavior at fine-scales, and further emphasize the need to distinguish between movement types or rates when examining landscape interactions.

6.2 Study Area and Supplementary Data Layers

In Chapter 6, the research area is again focused on the region north of Highway 16 as per Chapter 3. Within this region, 5 individual grizzly bears were captured and collared to retrieve GPS telemetry locations at 20-min intervals. The study region encompassed a total area of 71,084 km^2. The region is primarily characterized as an industry-based environment (Figure 6-1). Large numbers of roads, seismic lines, oil and gas well sites, and forestry cutblocks typify this landscape resulting in an extensive network of linear features. The region is surrounded to the north, east and south by highways and agricultural business. To the west and southwest, a mountainous high elevation area exists with rock, snow, and ice dominating the landscape.

Figure 6-1. Detailed map of Chapter 6 study region north of Highway 16 showing change in elevation, major cities, highways and secondary roads.

Supplementary data layers generated in 2005 were used to coincide directly with the 20-min GPS radiotelemetry data also collected in 2005 (Figures 2-12 to 2-15, p. 62-66). The first grid layer employed was the FRI project landscape classification map (McDermid 2005). As in Chapter 3 and Chapter 5, the original 10 land cover classes were modified into 7 land cover classes (Table 2-4, p.60).

Human use linear and point features included paved roads, secondary roads, herbaceous linear features (powerlines and pipelines), seismic lines, and wellsites. Natural linear features included rivers and streams. Distances to feature surfaces were created using the straight-line distance function in the Spatial Analyst extension in ArcGIS 9.3 for all supplementary linear and point features. According to Goodwin et al. (1999) it may be insightful to see if movement behavior changes as individuals wander closer to specific landscape features. Therefore, using linear data features, 30-m grid surfaces were created that represented the distance (m) to any nearest feature (water, major roads, all roads, seismic lines, herbaceous linear, and wellsites). It is further assumed that using distance to features rather than presence or absence of feature (e.g. within a pre-defined distance or not) will allow details that might be missed to be retained in the analysis.

To assess the influence of terrain or ruggedness on the movement rates for grizzly bears, a 30 meter digital elevation model (DEM) was used. From the DEM, slope and aspect surfaces were generated. A terrain ruggedness measure (VRM) was further derived from the same DEM and resulting slope and aspect layers (Sappington et al. 2007). The terrain ruggedness grid surface was created to provide a multivariate representation of topography. Final supplementary grid surfaces included in the analysis were a resource selection function (RSF) surface (Nielsen 2005), a crown closure surface, and a species composition surface (McDermid 2005).

6.3 Methods

GPS Data Preparation

In 2005, the Foothills Research Institute introduced Televilt Tellus 1 (Lindesberg, Sweden) GPS radiocollars to the study. Of the 167 grizzly bears previously noted in Chapter 4, a total of 5 individuals (males, *n* = 3; females, *n* = 2) were fitted with the Televilt Tellus 1 GPS radiocollars capable of retrieving locations at 20-min intervals. Specific details regarding data processing and individual bear classifications can again be found in Chapter 3. The following analysis utilizes the same base level 20-min data as it was previously processed for missed fixes, post-capture data reduction, and DOP accuracy levels.

Again, as in Chapter 3, the primary unit of analysis is the vector segment created as a function of linking consecutive GPS telemetry locations. Using the 20-min consecutive data points, movement vectors were estimated as straight lines between consecutive locations. Because the problem of identifying the actual track between known locations is difficult to solve when working with GPS radiotelemetry data, I continued with the working assumption that 20-min data represents the 'gold standard' of grizzly bear data. For each vector, mean hourly movement rate (km/h), mean vector distance (km), and mean turning angle or angular deviation (deg) were calculated to represent primary movement parameters. Using total vector distance or path length (km), normalized distance was also calculated for each vector segment or movement step.

Underlying landscape characteristics were extracted for each movement vector for each grizzly bear using the following grid surfaces: a 7-class landscape habitat class map (McDermid 2005), a species composition and crown closure surface, a resource selection function surface (Nielsen 2005), distance to landscape features (water, herbaceous linear features, seismic lines, wellsites, paved roads, and all roads surfaces), and lastly, elevation, slope, aspect, and vector ruggedness measurement grids. When working with landscape habitat classes, rather than selecting a central position along the assumed vector, all habitat classes along the entire portion of each vector were extracted (Fortin et al. 2005). This provided a proportion or average for each habitat type along each vector (Figure 3-5, Chapter 3, p. 86). For example, one vector could possibly be classified as 100% closed forest while another vector could be classified as 20% closed forest, 30% open forest, and 50% shrub. Further, when working with habitat classes, I also extracted the mode or maximum habitat class for each individual vector.

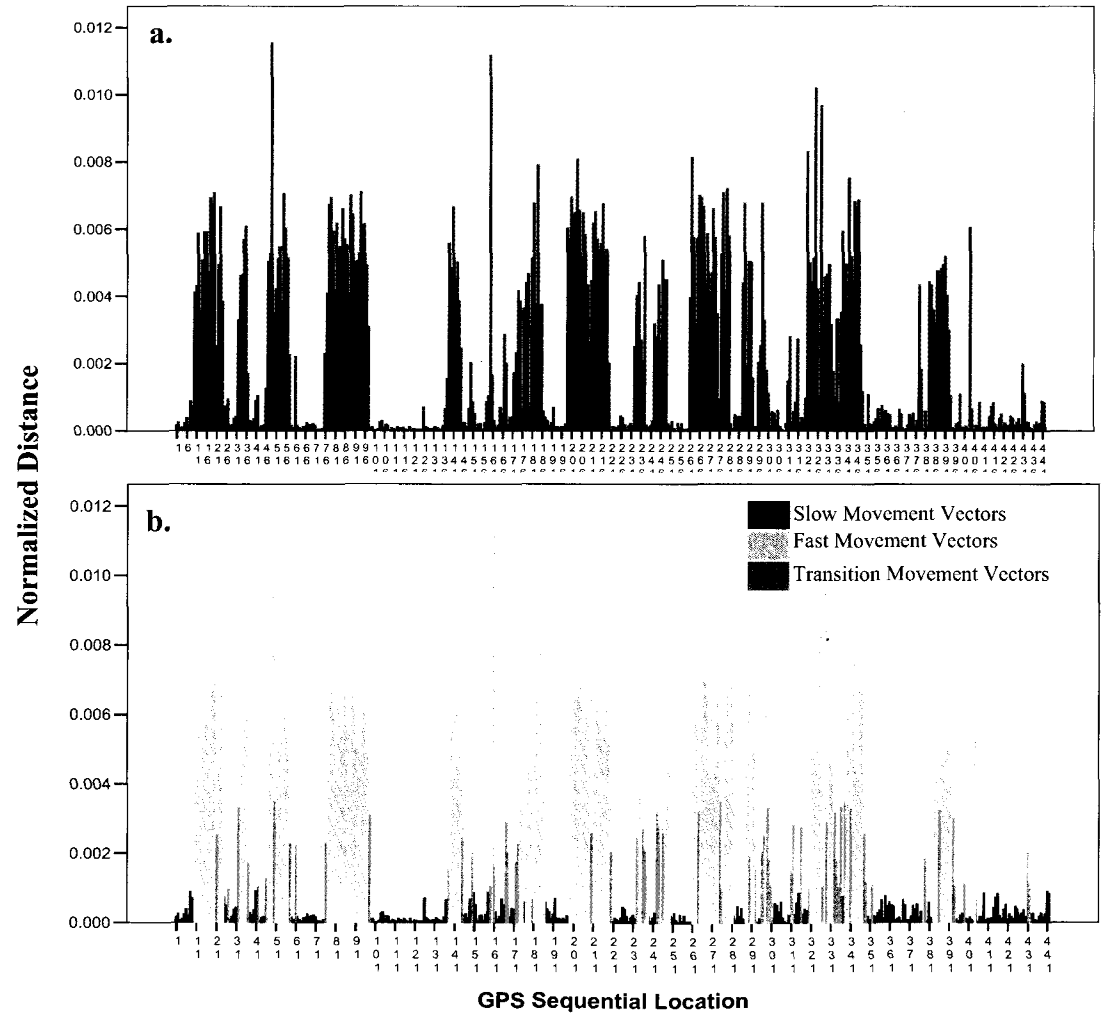
Figure 6-2. Example of grid vector extraction where vectors properties are averaged twice, first the value for each vector start or end location is averaged based on the value of the four closest grid cells, and second the value for the entire vector is based on the average between each start and end point for that particular vector.

For the remaining grid surfaces, resulting variables were calculated by acquiring the values for each vector start and end (GPS locations) and averaging between the two. At each GPS location, landscape variable values were calculated by averaging the values of the 4 nearest cells (Figure 6-2). This approach provided a method for averaging the potential location error as well as habitat classification variability for each vector start and end location. This approach followed the same assumption made when calculating movement rate, which is a mean or average representation of distance over time applied to the entire vector length.

Movement Behavior Segmentation and Classifications

Time series segmentation graphs were created for each individual bear where normalized distance was plotted over time by case number creating a data series for sequential vector steps (Figure 6-3a). Using standard deviation for normalized distance (<1.0 for slow moving vectors and >1.0 for fast moving vectors) three types of movement vectors were identified (Figure 6-3b). More information regarding the use of normalized distance can be found in Chapter 3 on p. 91-92 and p. 123.

Figure 6-3. Time series sequence graph for individual G216 showing a) normalized distance over time, and b) normalized distance over time classified using <1.0 mean SD and >1.0 mean SD to separate out slow from fast vectors creating the baseline three-class movement classification.

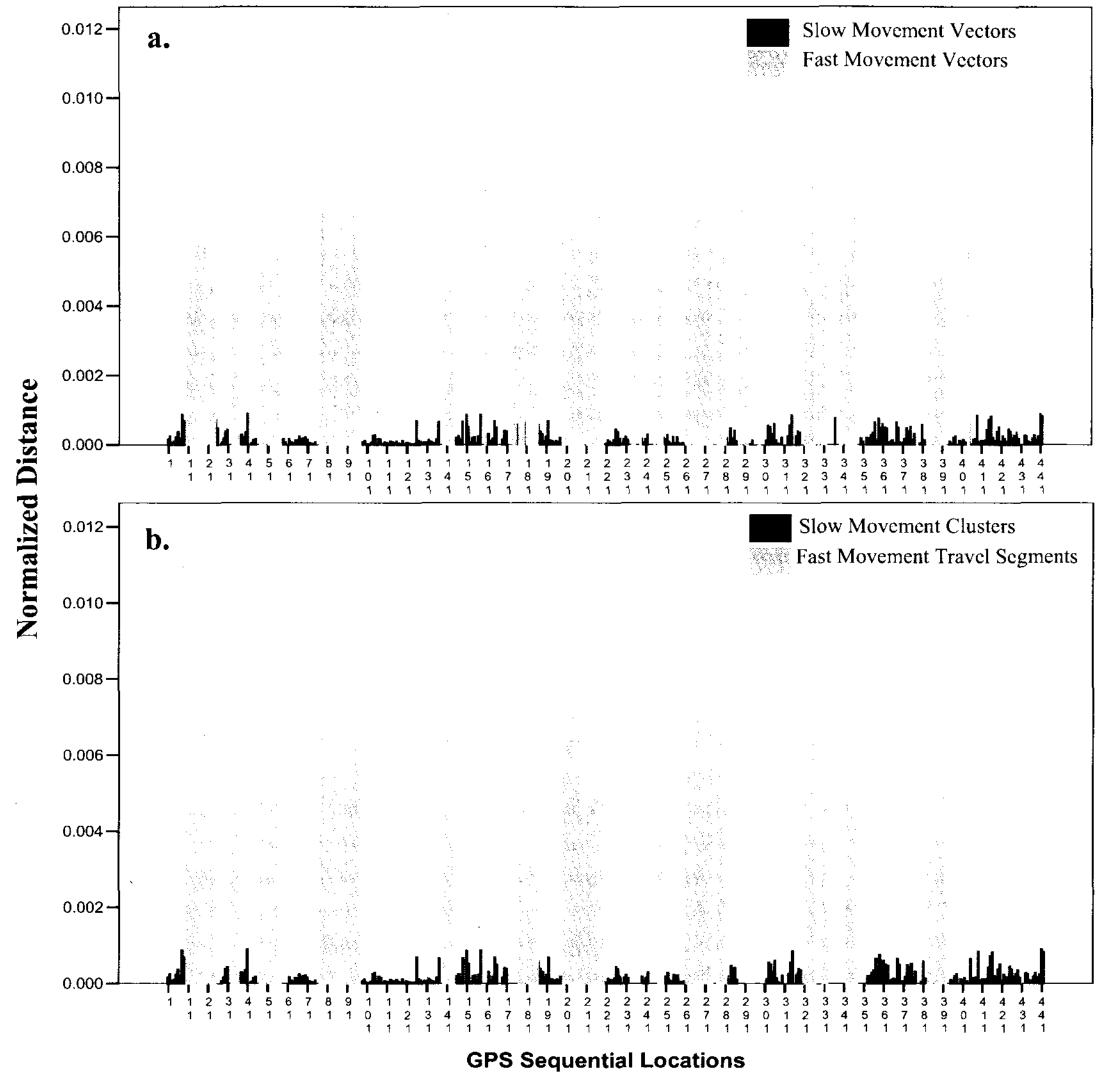


The two primary movement types are represented in green (slower movements) and beige (faster movements). Change or transition movements (grey) were identified as vectors that fell between the identified slow and fast movement normalized distance thresholds. By retaining transition or change vectors within the time series sequence graph a three-class movement classification was created (Figure 6-3b).

By ignoring and removing vectors which occurred between the thresholds, a two-class movement classification was created (Figure 6-4a). Below, vectors classified as slow moving vectors are green while fast moving vectors are beige. Lastly, by only including vectors that occurred in sequences of 3 or more, slow movement clusters and travel segments were identified and separated into a two-class cluster movement classification (Figure 6-4b). In the below time series sequence graph, vectors that do not maintain a 'slow' or 'fast' normalized distance for at least 3 or more sequential vectors are excluded from data set. As such, data sets were partially reduced with the occasional time gap occurring. However, by identifying spatial temporal vector clusters, it was possible to both reduce movement variability or noise from the data set while also examining segments of data characterized by similar movement behaviors.

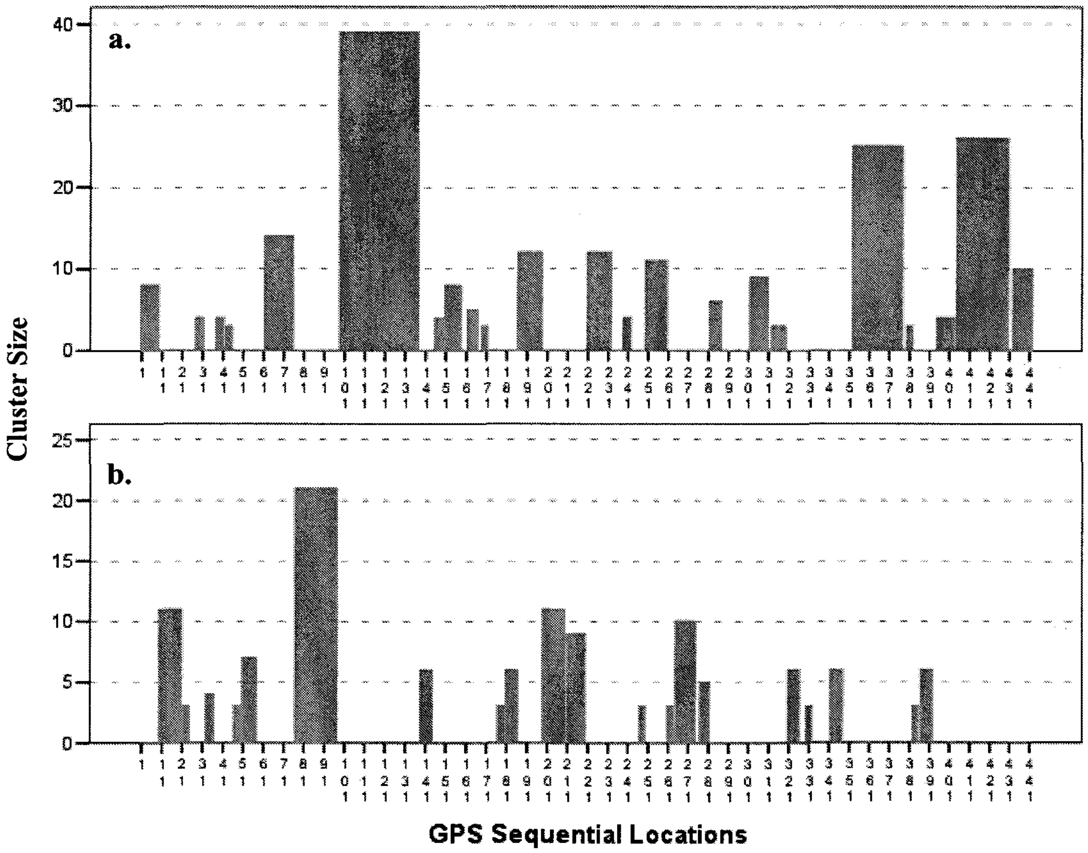
A threshold value of 3 sequential vectors was chosen to represent a continued movement behavior lasting at least 1-hr in duration. As there is no precedent for a threshold selection of this kind, the selection was based primarily on resulting time series graphs and data explorations within a GIS environment. However, the use of a 1-hr minimum (at least 3 sequential vectors) eliminated vectors potentially prone to error (e.g. an errant GPS point) or vector sequences that were highly variable in pattern (e.g. long to short to long etc.).

Figure 6-4. Time series sequence graph for individual G216 showing a) the two-class movement classification (with transition vectors removed), and b) the two-class cluster classification where three or more sequential vectors were selected as slow movement clusters and those above the threshold were fast moving travel segments.



As previously explored in Chapter 3, time sequence graphing can be utilized to identify spatial and spatial temporal vector clusters (i.e. periods of local stationarity). In Chapter 3, this technique was used to examine the effects of changing temporal data scale on the identification of slow movement or foraging clusters and spatial site revisits. Here, the same technique is employed to identify both slow movement clusters (Figure 6-5a) and fast movement travel segments (Figure 6-5b) along the length of a total movement path. As demonstrated in the provided examples, by identifying clusters of similar movement patterns, prolonged movement behaviors can be explored both visually and quantitatively. For example, in Figure 6-5b only one fast moving travel segment was identified with greater than 20 sequential data points indicating that this bear moved further distances at faster rates for approximately 6.5 to 7.0 hours (GPS locations 80 – 100). Alternatively, one slow movement cluster was identified which extended for approximately 13.0 hours (Figure 6-5a). In this case, the cluster may indicate prolonged foraging or a bedding event.

Figure 6-5. Time series graphs modified to demonstrate sequential clusters of like behaviors where a) slow moving clusters are highlighted and b) fast moving or travel segments are highlighted for one individual bear.



To establish a working baseline, individual grizzly bear movement parameters (movement rate, distance, and turning angle) were examined and compared both individually and grouped. For each of the three movement classification approaches, the number of identified slow and fast moving vectors were examined by individual bear. Mean hourly movement rate (km/h) and mean turning angle or angular deviation (deg) were further compared to identify significant differences for each bear for each movement classification grouping. Comparisons were again conducted for all bears grouped to see if differences were maintained regardless of individual variations. As the vector data movement parameters do not fulfill the assumptions of equal variance and normality, overall mean differences between the movement types classifications were identified using the nonparametric Kruskal-Wallis test with significance held at $P < 0.05$. Post-hoc comparisons were conducted using Games-Howell for data where equal variances are not assumed. All attempts to transform and improve movement parameters distributions were unsuccessful in meeting the assumptions of normality. As such, data was retained in its original form.

Finally, three discriminant analyses were conducted for each individual bear to predict whether vectors were classified correctly using the time series segmentation approach. One of the advantages of using discriminant analysis is its ability to measure the percent of correct classifications. As vectors were initially segmented using normalized distance, predictor variables for the following discriminant analysis models were speed (km/h) and turning angle (deg). For all analyses, the dependent variable was the movement classification type. The three-class movement classification was coded as 1 = slow, 2 = transition, and 3 = fast. The two-class movement classification was coded as 1 = slow and 2 = fast. Lastly, the two-class cluster movement classification was coded as 1 = slow moving clusters and 2 = fast moving travel segments.

Classification results were reported in terms of both percent of original grouped cases correctly classified and as percent of cross-validated grouped cases correctly identified. It is expected that the two-class cluster movement classification group will perform the best, followed by the two-class movement classification, and lastly the 3-class movement classification group. To compare classification results with results potentially occurring by chance, a proportional chance criterion (C_{pro}) was calculated for each analysis. The proportion of chance accuracy rate was computed by squaring and summing the proportion of cases in each group from the table of prior probabilities for groups (Table 6-1).

Table 6-1. SPSS output of prior probabilities for groups used in proportion of chance accuracy rate calculation.

Prior Probabilities for Groups

		Cases Used in Analysis	
ClusterCode	Prior	Unweighted	Weighted
Foraging Cluster	.636	225	225.000
Travel Segment	.364	129	129.000
Total	1.000	354	354.000

In the above example, 54% ($0.636^2 + 0.364^2 = 0.536$) would be calculated as occurring by chance. Operationally, the resulting classification from the discriminant function should be 25% or higher (at least 67% correctly classified) than the proportional by chance accuracy rate. Final classification results were averaged across all bears and the best movement classification approach was adopted for all following movement-landscape analyses.

Individual Two-class Cluster Movement Landscape Comparisons

Before examining multivariate relationships by grouping all variables and movements for all bears, individual dichotomous vector comparisons were conducted separately for each bear. Using the two-class cluster movement classification approach discussed above, slow moving clusters were compared against fast moving travel segments for each landscape variable. Mean landscape properties were compared using Mann-Whitney U tests. For example, mean proportion crown closure was compared for slow moving clusters and fast moving travel segments. Significance was held at $P < 0.05$. Resulting bar charts were plotted and examined for all landscape variables which demonstrated significance. Where possible, attempts were made to draw relationships beyond the individual to the subpopulation.

Individual Two-class Cluster Landscape Discriminant Analysis

Discriminant analysis is applicable to a range of wildlife and ecological problems in which multiple measurements (landscape properties) are made on samples of observations (vectors) possessing an identifiable group structure (movement type). It is employed here because the variable being predicted is categorical. A discriminant analysis behaves like a cluster analysis in reverse. For example, we can separate clusters of vectors as slow moving vectors (foraging clusters) and fast moving vectors (travel segments) in advance. By including multiple potential contributing variables, the model will then best predict which landscape properties can be used to discriminate between the slow and fast movement groups. Similar to other statistical procedures, the independent variables must meet assumptions for normality, homogeneity of variance/covariance, mulitcollinearity and data outliers. First, all independent landscape variables (Table 6-2) were examined for normality through the use of histograms and by examining skewness and kurtosis. Failing this, all variables were transformed and retested but still failed tests for normality. Proportional data such as % crown closure and % species composition are bounded between 0 and 100, making it difficult to transform as there are large amounts of zeros. It has been noted however that violations of the normality assumption are not fatal and the resulting significance tests are still reliable as long as non-normality is caused by skewness and not outliers (Tabachnick and Fidell 1996). As transformations were not statistically successful in improving distributions, independent variables were retained in their original forms for interpretation.

Finally, as discriminant analysis is highly sensitive to the inclusion of outlier data, multivariate outliers were identified using Mahalanobis distance to measure each case relative to the group centroid and covariance matrix for the distribution of all cases. The centroid and covariance matrix are the multivariate equivalents to the mean and standard deviation. Cases greater than the critical value, indicating a large Mahalanobis D^2 distance, were removed for each individual bear. Homogeneity of variance was tested using Box's M test which tests the null hypothesis that the group variance-covariance matrices are equal. Because this test is sensitive to large sample sizes, a significant result is not regarded as problematic. However, when rejecting the null hypothesis due to the variances being heterogeneous, the working response is to substitute separate covariance matrices into the classification. The classifications were then reassessed for improvements.

Table 6-2. Independent variables extracted for each vector and used in discriminant function analysis.

Model Variable	Code	Definition
Habitat Classes		
Closed forest	ClFor	Proportion of closed forest
Open forest	OpFor	Proportion of open forest
Wet treed	WetTr	Proportion of wet treed
Herbaceous	Herb	Proportion of herbaceous
Shrub	Shrub	Proportion of shrub
Non Habitat	NonHab	Proportion of non habitat
Human Use Features		
Primary roads	PavedRds	Distance to primary roads (m)
Secondary roads	AllRds	Distance to secondary roads (m)
Linear herbaceous	LinHerb	Distance to linear herbaceous (m)
Seismic lines	Seismic	Distance to seismic lines (m)
Wellsites	Wellsites	Distance to wellsites (m)
Landscape Features		
Elevation	AvgElevation	Average elevation in meters (m)
Slope	AvgSlope	Average slope in degrees (°)
Aspect	AvgAspect	Average aspect in degrees (°)
Topographic variability	AvgVMR	Average topographic vector ruggedness (0 to 1)
Habitat Features		
Resource selection function	AvgRSF	Average RSF value based on categories (1 to 30)
Species composition	AvgSC	Average species composition (0 to 100)
Crown closure	AvgCC	Average crown closure (0 to 100)
Distance to water	DistWater	Distance to water (m)

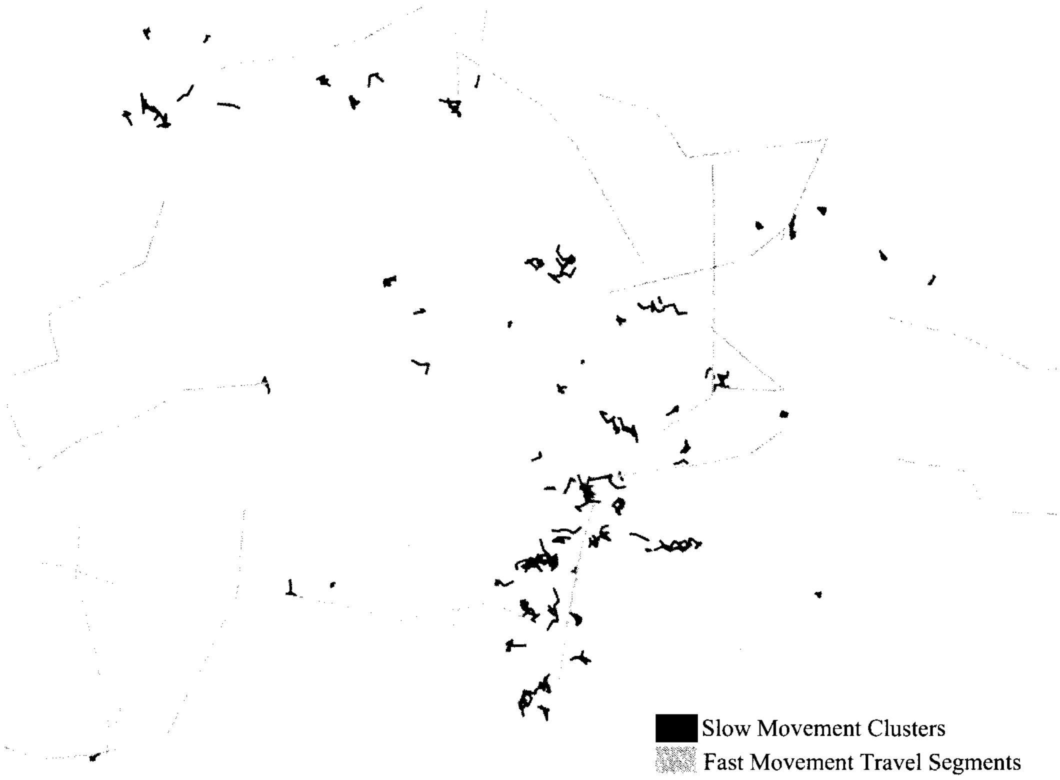
Final discriminant function analysis model runs were conducted for each bear for each two-class cluster movement classification. Each model examined only the vectors grouped into sequential slow moving clusters and fast travel segments as it was expected to perform the best. Mahalanobis distance criterion was used in a step-wise fashion for variable entry and removal. The stepwise approach has the advantage of preventing problems of co-linearity among independent variables (Dussault et al. 2005). To the extent that the independent variables are correlated, the standardized discriminant function coefficients will not reliably assess the relative importance of the predictor variables. Since non-linearity between independent variables only reduces the power to detect relationships, linearity between independent variables was not tested. Overall, the landscape variables used in this analysis were not linearly related.

The overall power of the model was estimated by scrutinizing the eigenvalues, Wilk's lambda, canonical correlation coefficients, and the percentage of correctly classified classes. As each individual bear resided in different locations on the landscape and subsequently had different variable ranges, all models were conducted individually. Variable importance was expressed in terms of standardized coefficients and resulting structure matrices. Comparisons were made between individual bears when possible. Again, classification results were reported for each model run and compared to the proportional by chance accuracy rate. Final discriminant scores were compared using two-independent samples *t* tests where equal variances are not assumed.

Sequential Movement Patterns and Mapping

To further examine and emphasize the importance of separating movement behaviors for grizzly bears, kernel surfaces were created for each individual bear. First, vectors were separated into individual layers, one representing slow moving clusters and one representing fast moving travel segments. Figure 6-6 demonstrates the obvious differences in vector characteristics and spatial patterns between the two movement behavior types. By nature, slow movement clusters are significantly shorter with greater variation in vector direction. Alternatively, fast moving travel segments are highly linear and cover greater distances.

Figure 6-6. Example of a spatial movement pattern generated by the two-class cluster segmentation approach where sequential slow movement vectors (green) and fast movement travel segments (beige) are highlighted for one grizzly bear.



To explore this dichotomous representation of movements beyond the use of vectors, kernel density line surfaces were created for each vector type. This was completed for spatial extent or home range of each individual grizzly bear resulting in a slow movement cluster surface and a fast movement travel segment surface. To emphasis the length or duration of movement behavior, each linear kernel density surface was weighted according the number of vectors associated with each cluster. Final vector-based kernel density surfaces were reclassified to outline the 50% and 95% boundaries for slow movement clusters and fast movement travel segments. For each, the ArcGIS defaults were used to define the smoothing band.

6.4 Results

Movement Behavior Segmentation and Classifications

First, movement parameters for all vectors were compared to establish a baseline. Of the 5 individual grizzly bears, 1 adult female (G203) was located in the Swan Hills region, 2 adult males and 1 adult female (G216, G218, and G231) were located in the foothills directly north of Hinton, and 1 adult male grizzly (G210) was located in the higher elevations mountains northwest of Jasper (Table 6-3). Baseline results indicated that mean movement rate ($\chi^2 = 306.8$, df = 4, $P < 0.001$), mean turning angle ($\chi^2 = 37.902$, df = 4, $P < 0.001$), and mean distance ($\chi^2 = 265.4$, df = 4, $P < 0.001$) were all significantly different between individual bears.

Table 6-3. Average mean hourly movement rate (km/h) 2005 (*n* = 5) grizzly bears showing sex, reproductive status, age, location of home range, number of GPS radiotelemetry locations, average movement rate, average distance traveled and average turning angle based on straight-line vectors.

					Summary Statistics 2005			
Bear ID	Sex	Repro Status	Age	Location	*n*	Mean Movement Rate (km/h)	Mean Distance Traveled (km)	Mean Turning Angle (deg)
G203	F	FC	10	SwanHills	7557	0.55	0.19	79.15
G210	M	AM	11	Mountain	1150	0.49	0.22	74.72
G216	M	AM	16	Foothills	442	1.27	0.44	76.09
G218	F	AF	.	Foothills	1399	0.32	0.13	85.37
G231	M	AM	.	Foothills	5197	0.47	0.17	83.21

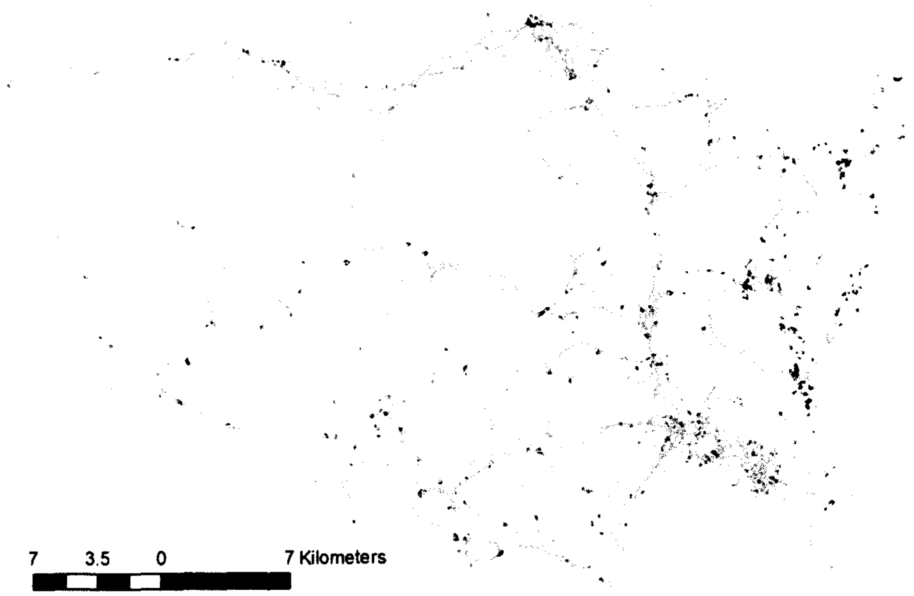
When compared individually, movement rates for individual males G210 (mountain) and G231 (foothills) were not significantly different ($P = 0.984$). All other individual comparisons were significantly different between bears. Results emphasized the need for individual processing when identifying different types of movement behaviors for each individual. Movement threshold levels are therefore unique to each individual grizzly bear.

Three-class and Two-Class Movement Comparisons

Resulting three-class time series sequential graphs were generated for each individual grizzly bear (Figure 6-7 to Figure 6-11). Each time series graph provided a baseline from which the two-class and two-class cluster movement classifications were subsequently generated and analyzed. While transition vectors were explored, results focused primarily on comparing results between slow moving vectors and fast moving vectors. As resulting segmentation graphs maintained the consecutive nature of GPS spatial moving data for each individual grizzly bear visual explorations were also conducted (Figure 6-7 to Figure 6-11). The resulting time series graphs provided information regarding the overall spatial movement pattern of each individual for temporal duration of data collection. As such, seasonal differences could also be visualized.

The separation of movement behaviors into slow, transition, and fast movements is most apparent when analyzing the resulting graph structure for individual G216 (Figure 6-9). By combining both the sequence graph structure with the mapped vector pattern, changes to movement behavior for G216 were easily distinguished. Travel movements were relatively straight-lined (mean = 32.2 deg, SE = 2.47) with longer and faster (mean = 3.1 km/h, SE = 0.053) vector segments while slow movements (mean = 0.14 km/h, SE = 0.009) were quite clustered with short vector segments and high turning rates (mean = 106.7 deg, SE = 3.52). This type of movement separation was also apparent when examining the resulting graph structures and vector maps for individuals G210 (Figure 6-8) and G218 (Figure 6-10). When working with large amounts of vector data (> 4000 sequential GPS locations) as demonstrated in Figure 6-7 and Figure 6-11, the time series segmentation technique continued to work for dichotomizing movement behavior, however results became more difficult to visualize. While time sequence graphs are highly detailed, resulting vector maps respond well and clearly demonstrated the difference movement types for large data files as demonstrated by individuals G203 and G231.

Figure 6-7. Time sequence graph for individual female G203 demonstrating consecutive vector movement data segmented into 3 behavioral classes (slow and fast) with a resulting transition (grey) category between slow (green) and fast (beige) movements.



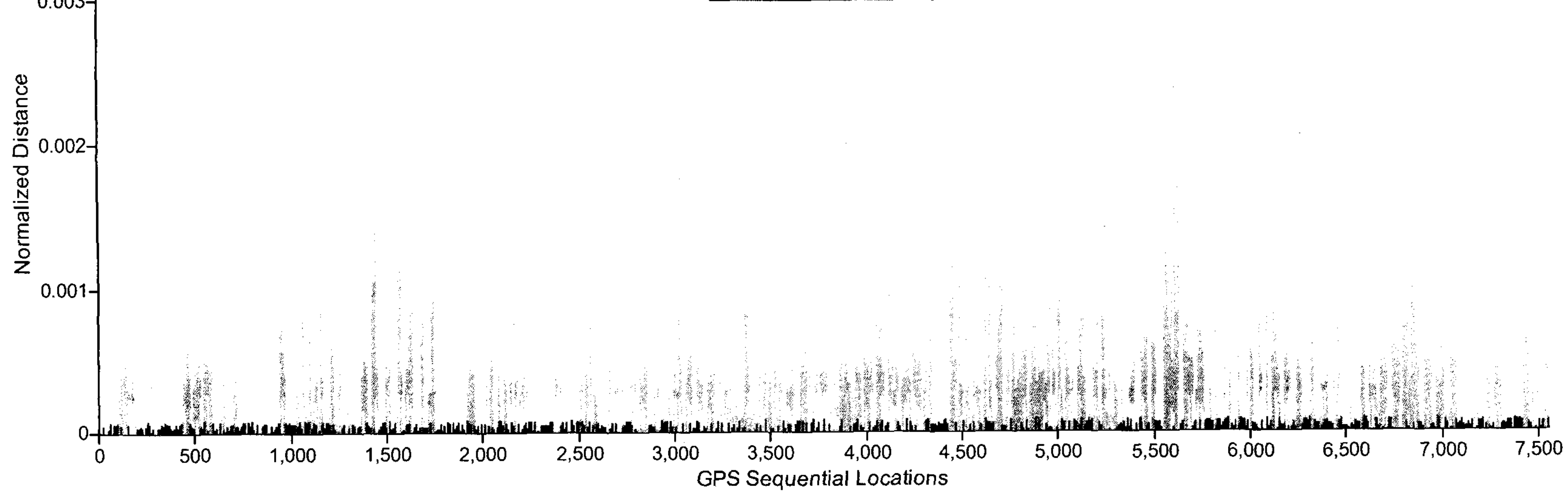


Figure 6-8. Time sequence graph for individual male G210 demonstrating consecutive vector movement data segmented into 3 behavioral classes (slow and fast) with a resulting transition (grey) category between slow (green) and fast (beige) movements.

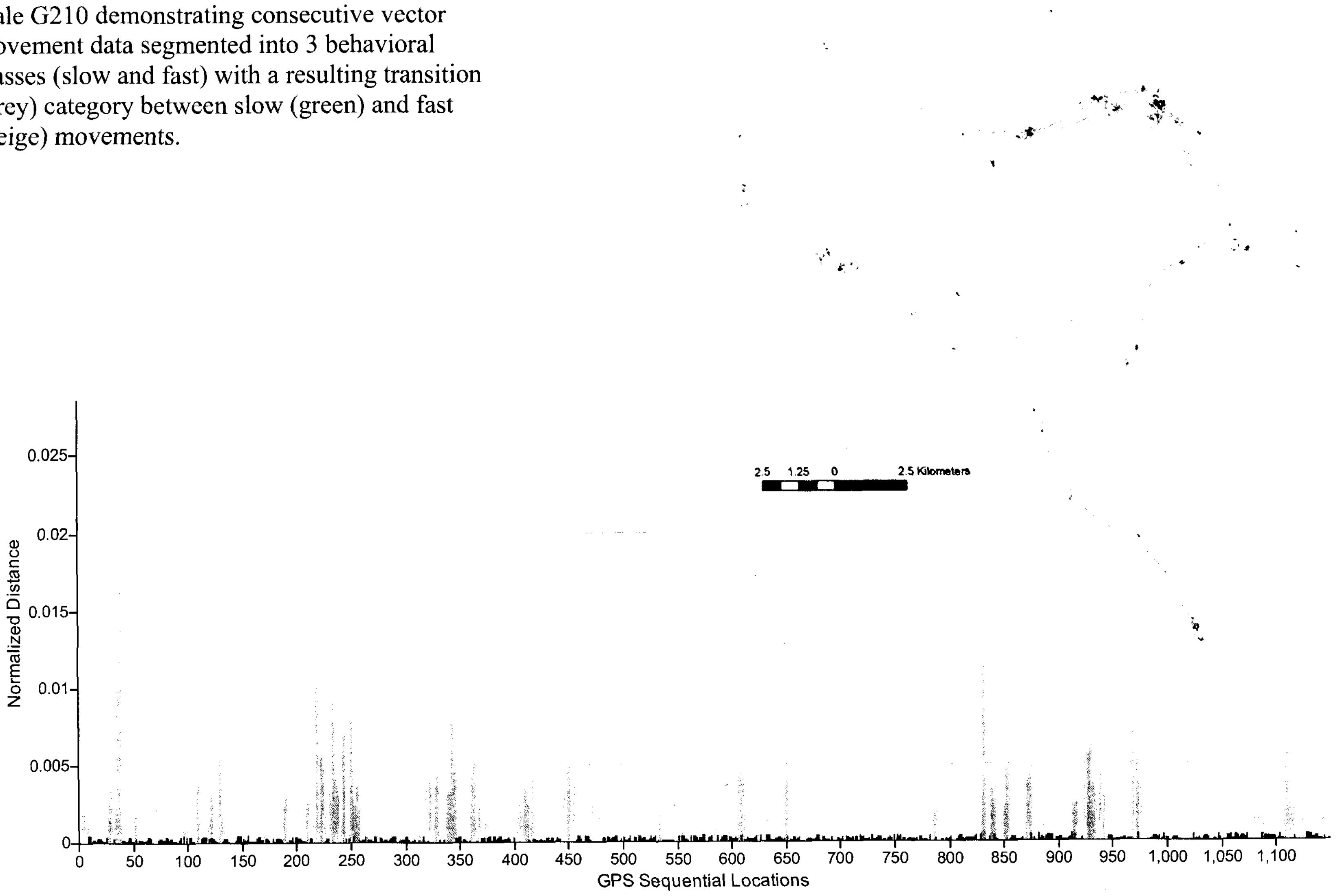


Figure 6-9. Time sequence graph for individual male G216 demonstrating consecutive vector movement data segmented into 3 behavioral classes (slow and fast) with a resulting transition (grey) category between slow (green) and fast (beige) movements.

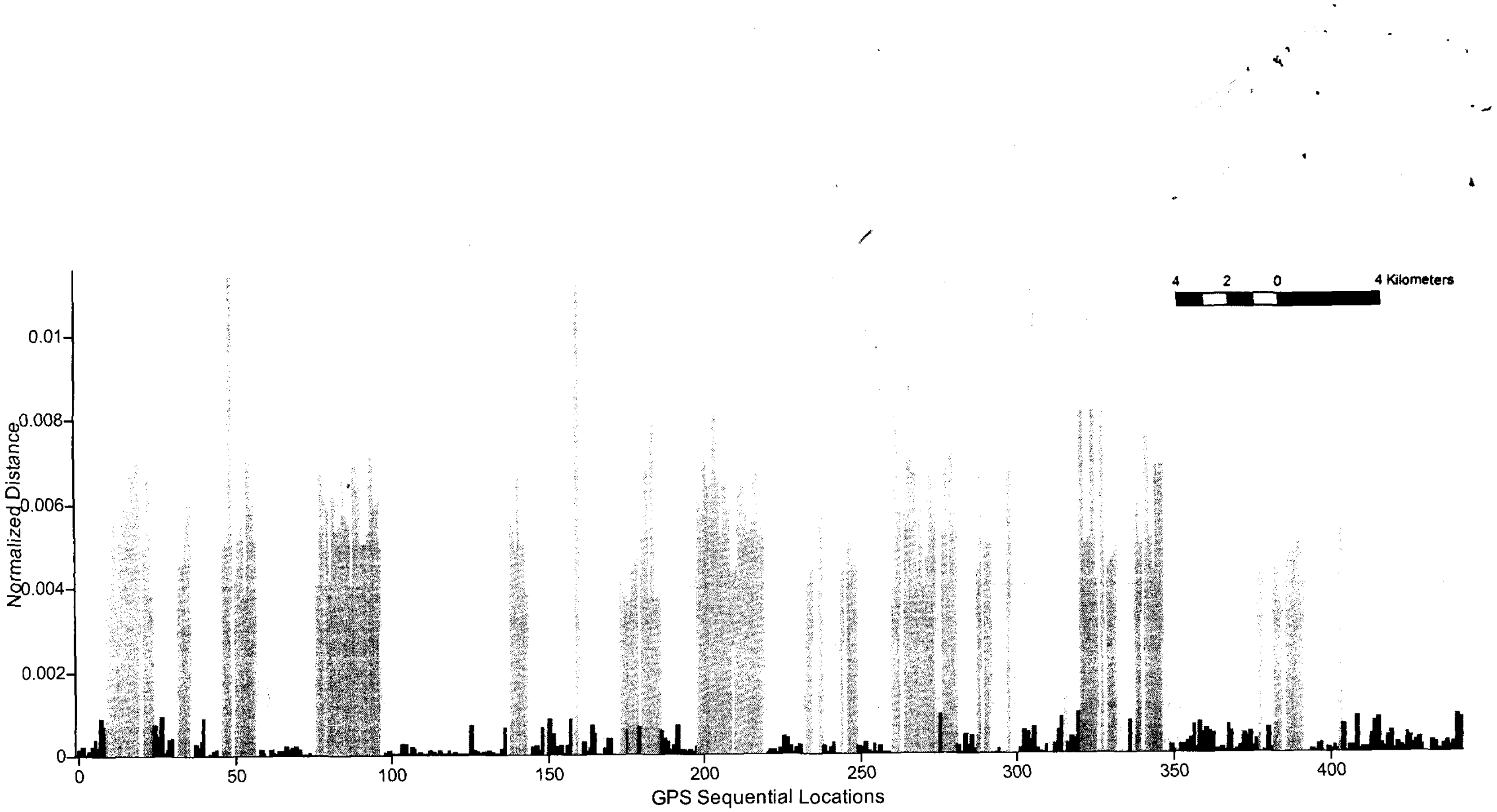


Figure 6-10. Time sequence graph for individual female G218 demonstrating consecutive vector movement data segmented into 3 behavioral classes (slow and fast) with a resulting transition (grey) category between slow (green) and fast (beige) movements.

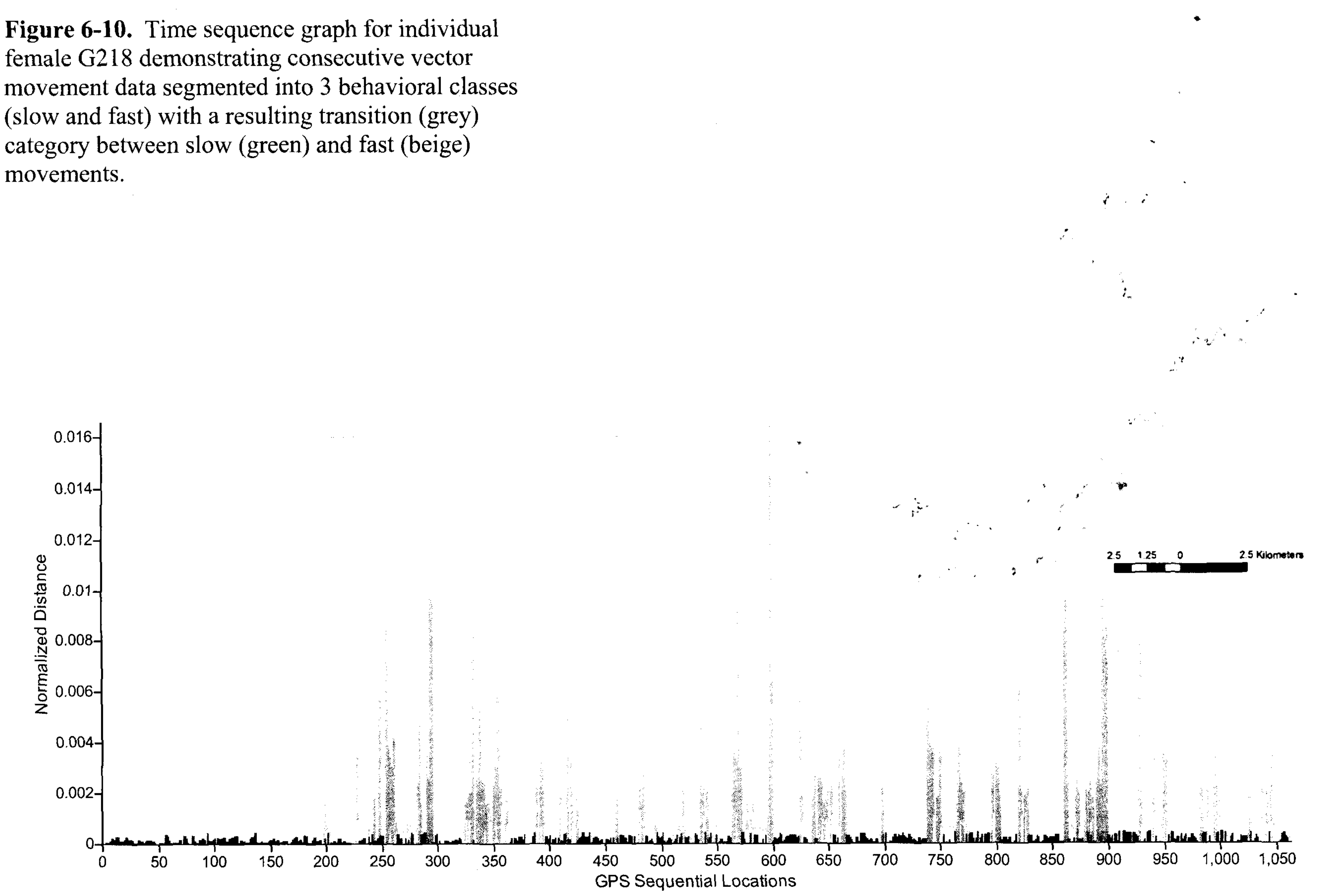
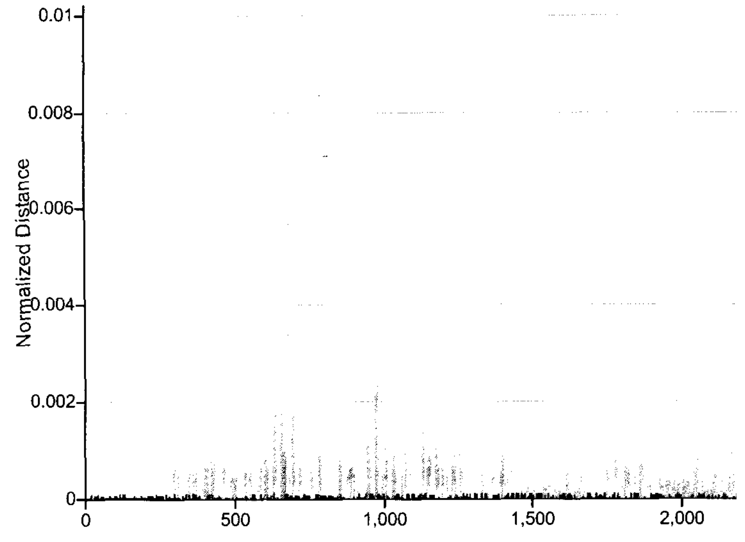
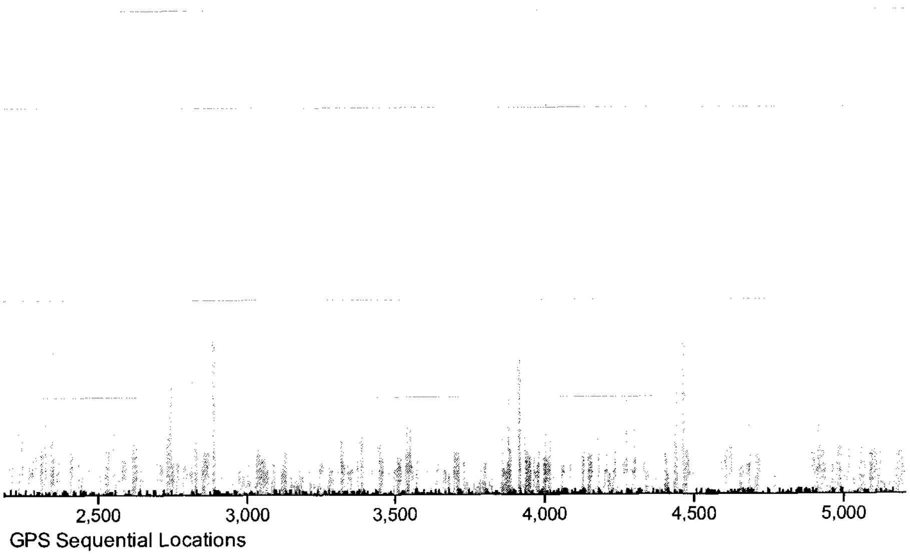


Figure 6-11. Time sequence graph for individual male G231 demonstrating consecutive vector movement data segmented into 3 behavioral classes (slow and fast) with a resulting transition (grey) category between slow (green) and fast (beige) movements.




10 Kilometers


2,500
3,000
3,500
4,000
4,500
5,000
GPS Sequential Locations

The resulting time series sequence graphs provided a means to quantify summary statistics for vectors by movement classification groupings. First, the number of slow moving vectors, transition vectors and fast moving vectors were calculated for each bear using the three-class movement classification grouping (Table 6-4). Overall results indicated that the identified number of slow movement vectors ranged from 53% for G216 to 64% for G218 of total available vectors. Transition vectors for 3 out of 5 bears represented the next largest proportion of total vectors ranging from 20% to 26%. Individuals G203 and G206 were the exception with fast moving vectors being the next largest proportion at 27% and 33% respectively. For individuals G216, G218, and G231 fast moving vectors ranged from 11% to 16% of the overall proportion of available vectors.

Table 6-4. Three-class vector movement classifications for each grizzly bear (*n* = 5) showing total vectors, number of slow movement vectors, number of transition vectors, and resulting number of fast movement vectors.

					Vector Movement Classifications		
Bear ID	Sex	Repro Status	Location	*n*	No. of Slow Moving Vectors	No. of Transition Vectors	No. of Fast Moving Vectors
G203	F	FC	SwanHills	7557	4553	1795	1209
G210	M	AM	Mountain	1150	714	304	132
G216	M	AM	Foothills	442	236	60	146
G218	F	AF	Foothills	1399	889	285	225
G231	M	AM	Foothills	5208	3201	1318	689

Three-class movement vectors were also compared for differences to mean movement rates (km/h) and mean turning angles (deg) for each bear. Overall vector movement classification results were similar for all five individual bears (Table 6-5). Results demonstrated significant differences between mean movement rates ($P < 0.001$) and mean turning angles ($P < 0.001$) between movement type classifications for all bears. Resulting movement rate vectors were ranged from 0.07 km/h to 0.14 km/h for slow moving vectors and from 1.27 km/h to 3.11 km/h for fast moving vectors. Transition movement rates ranged from 0.32 km/h and 1.23 km/h, depending on the individual bear. Overall, female G218 demonstrated the lowest movement rates (mean = 0.07 km/h, SE = 0.002) across classes, while male G216 demonstrated the highest movement rates (mean = 3.11 km/h, SE = 0.053) across classes. Resulting slow movement turning angles ranged from 85° to 107° for individuals G210 and G216, respectively. Fast movement turning angles results demonstrated significantly straighter or directed vector segments ranging from 32° to 55° in direction. Overall results indicated similar trends existed for all individual bears.

Table 6-5. Vector movement classifications for each grizzly bear ($n = 5$) showing mean movement rate (km/h) and mean turning angle (deg) after movement segmentation into slow, transition, and fast movement behavior classes based on normalized distance thresholds. Significance tests were conducted using the Kruskal-Wallis test.

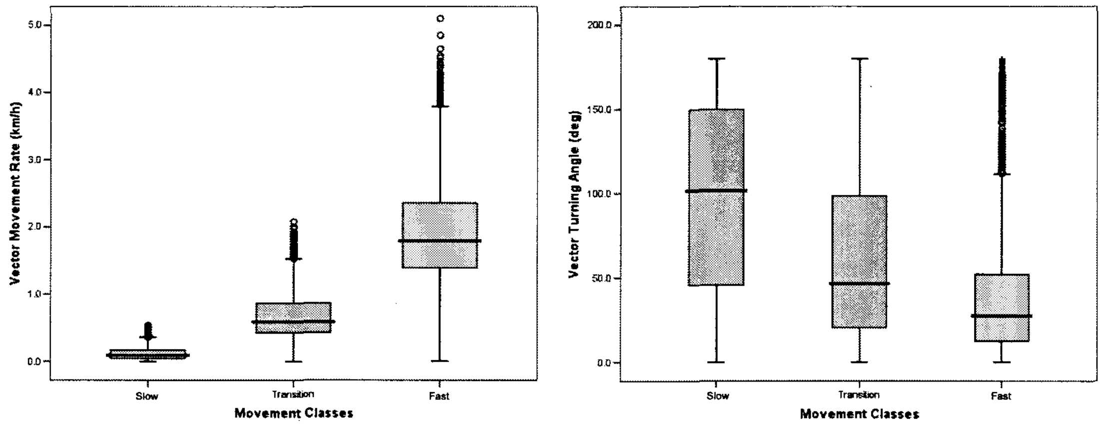
	Mean Movement Rate (km/h)				**Mean Turning Angle (deg)**			
Bear ID	Slow	Transition	Fast	*P*	Slow	Transition	Fast	*P*
G203	0.13	0.71	1.91	*0.001*	97.96	60.79	35.63	*0.001*
G210	0.13	0.65	2.10	*0.001*	85.66	62.5	43.58	*0.001*
G216	0.14	1.23	3.11	*0.001*	106.71	62.94	32.22	*0.001*
G218	0.07	0.32	1.27	*0.001*	94.7	80.32	54.83	*0.001*
G231	0.12	0.62	1.82	*0.001*	99.25	66.21	41.39	*0.001*

When grouped for all 5 individual bears, movement classes maintained a consistent trend regarding movement rate and turning angle parameters (Figure 6-12). Results for this subpopulation of grizzly bears reported mean vector movement rate ($\chi^2 = 11084.61$, df = 2, $P < 0.001$) and mean vector turning angle ($\chi^2 = 2334.52$, df = 2, $P < 0.001$) to be significantly different when comparing the three movement behavior classes. More specifically, slow (mean = 0.12 km/h, SE = 0.001) movement rates were significantly smaller than fast traveling (mean = 1.91 km/h, SE = 0.017) movement rates ($U = 80218.5$, $Z = -75.37$, $P < 0.001$) and slow (mean =

97.4 deg, SE = 0.58) turning angles were significantly larger than fast moving (mean = 39.3 deg, SE = 0.78) turning angles (U= 4832986.0, Z = -43.91, $P < 0.001$).

While grizzly bear movement behaviors can be segmented, variability within each unique vector classification remained as noted by outlying data points as demonstrated in Figure 6-12. This was specifically true for fast moving vector classifications. Grouped results indicated that while mean values may vary by individual bear; overall subpopulation trends regarding movement behaviors are still identifiable when working with vector-based movement parameters. Statistical comparisons were not conducted for the two-class movement classification as the results would remain the same minus the presence of transition vectors.

Figure 6-12. Boxplots for movement rate (km/h) and turning angle (deg) classified according to movement behavior for all five grizzly bears combined.



Two-Class Cluster Movement Comparisons

The resulting time series graphs were manually processed to identify slow movement clusters and fast travel segments where similar movement behaviors occurred for 3 or more sequential vectors. New cluster graphs were created for each individual bear highlighting the sequential pattern of slow and fast moving clusters. By examining the difference between the number of identified fast movement vectors and the number of sequential fast travel segments simple data trends can be identified (Table 6-6). For individual G216, of the total fast movement vectors identified, 88% of these were sequentially linked forming distinct travel segments. Also, of the total slow moving vectors identified, 95% of these were identified as slow movement clusters. Resulting comparisons (assuming the segmentation technique correctly classified the cases) indicated that for this individual, two types of movement behaviors are easily distinguished and tend to be quite distinct in pattern.

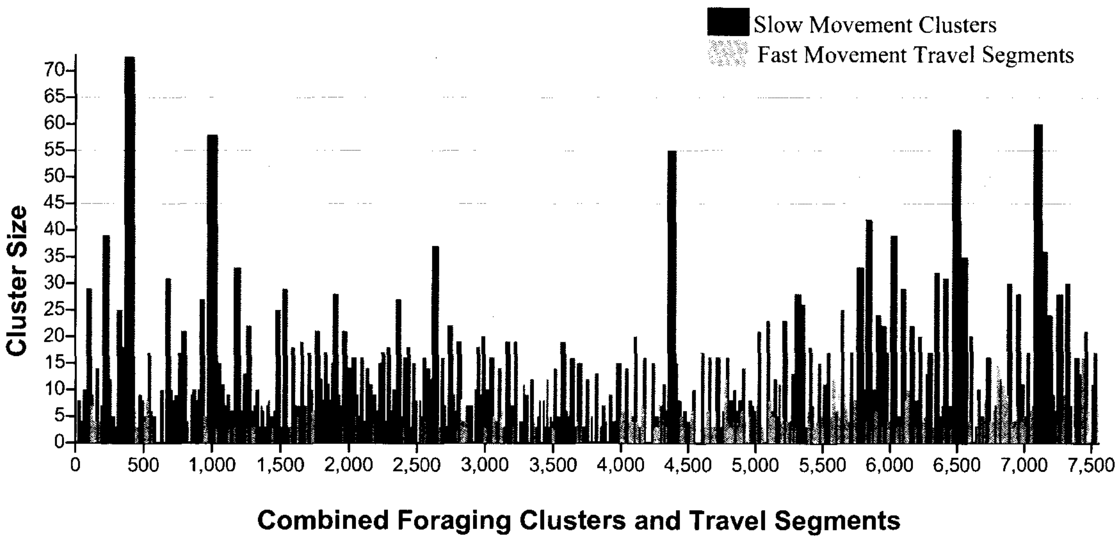
Table 6-6. Differences between vectors classified as slow moving or fast moving vectors compared to the number of vectors identified as sequential slow cluster vectors or sequential fast travel segment vectors where difference indicated the percentage of vectors classified as clusters for each bear.

			Vector Classifications					
Bear ID	Sex	Location	No. of Slow Vectors	No. of Slow Cluster Vectors	Slow Difference %	No. of Fast Vectors	No. of Fast Segment Vectors	Fast Difference %
G203	F	SwanHills	4553	4040	88.7	1209	766	63.4
G210	M	Mountain	714	610	85.4	132	60	45.5
G216	M	Foothills	236	225	95.3	146	129	88.4
G218	F	Foothills	889	782	88.0	225	125	55.6
G231	M	Foothills	3201	2897	90.1	689	389	56.5

However, it appeared that male G216 may be the exception to the group (Table 6-6). For every other bear examined, differences between total vectors and vectors which were sequentially clustered resulted in lower percentages for slow movements and more so with fast movement vectors. For all bears, over 85% of slow moving vectors were further classified as occurring within a slow movement cluster indicating that foraging or bedding type behaviors tend to extend for more than one individual vector segment and over longer time periods. As such, slow moving clusters were easier to identify regardless of both bear individuality and duration of the GPS radiotelemetry collar data. The identification and separation of fast moving segments appeared to be less obvious. With the exception of individual G216, sequential fast movement segments only make up 46% to 63% of the classified fast moving vectors. While fast moving vectors were identified and present for each bear, fast movement behaviors did not consistently last for the 3 or more consecutive vectors as needed to form a travel segment. As such, resulting percentages were lower indicating the fast movements were sporadic and short lasting.

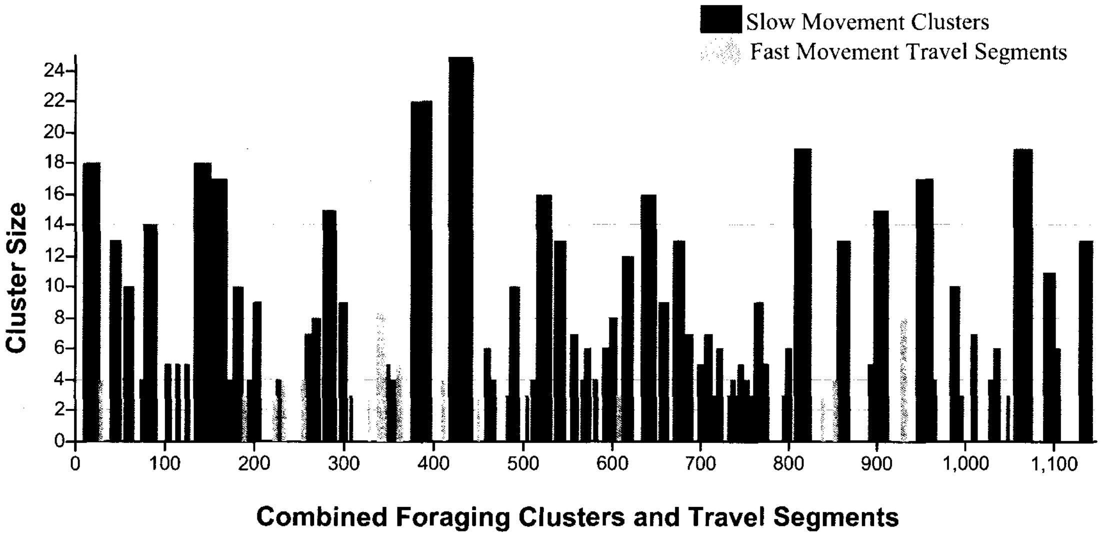
Clusters were further ranked by the number of vectors occurring within each cluster (Figure 6-13 to Figure 6-17). Resulting spatial movement patterns for each individual grizzly bear were examined via time sequence graphs and compared to known date time information to identify seasonal or daily trends. Resulting cluster graphs for Swan Hills female G203 identified 402 slow movement clusters and 162 unique fast moving travel segments (Figure 6-13). Visually, slow movement clusters appeared to extend over longer time periods at the beginning and end of the below graph.

Figure 6-13. Final resulting two-class cluster graphs showing 402 identified slow movement clusters and 162 fast moving travel segments for individual G203.



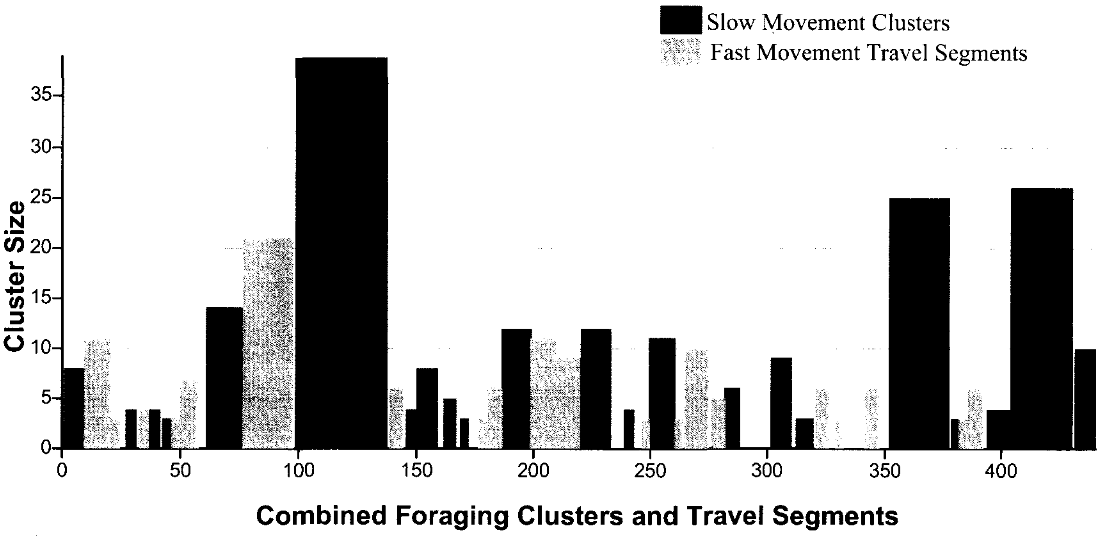
When compared to GIS data layer information, longer lasting slow movement clusters occurred during the months of June and September. One slow movement cluster (mid-graph) occurred in early August and lasted for 55 sequential vectors or 18 hours. Fast movement travel segments, while occurring throughout, appeared more often from case number 4,000 to 5,800 and again from 6,600 to 7,000. When examined, the former occurred during the month of August and tended to result in frequent travel vectors of short linear movements (e.g. 3 to 5 vector segments equaling 1.0 to 1.5 hours). The latter, occurred during the month of September and extended for longer periods of time ranging outward to the most western portion of the home range (Figure 6-7).

Figure 6-14. Final resulting two-class cluster graphs showing 73 identified slow movement clusters and 14 fast moving travel segments for individual G210.



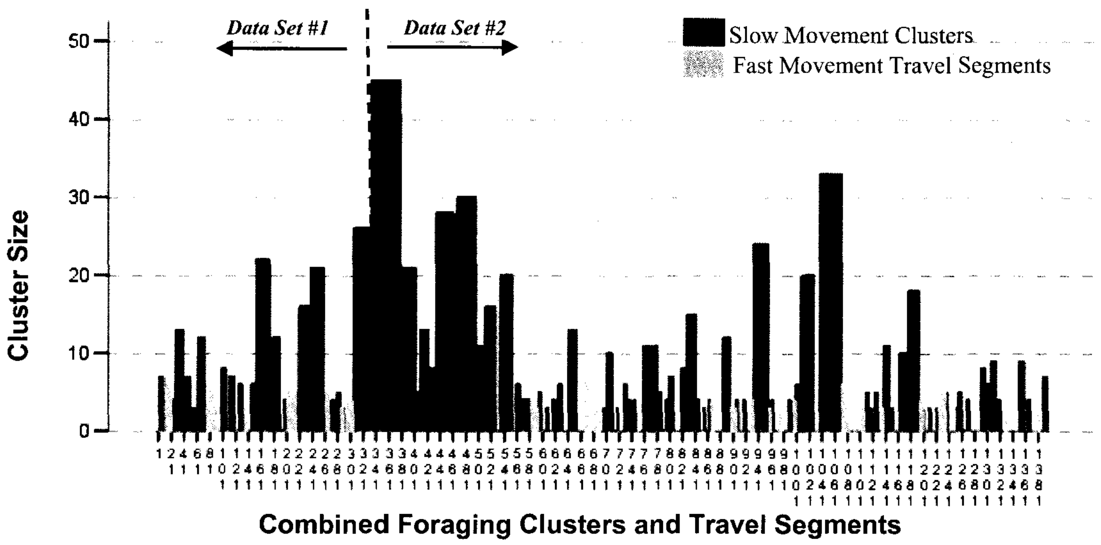
The resulting cluster graph for individual G210 above identified 73 slow movement clusters and only 14 fast movement travel segments (Figure 6-14). For this mountain male, slow movement clusters appeared to be fairly consistently spaced over the duration of the data collection period. The largest proportion slow movement clusters took place during the month of July in the most heavily used portion of the vector home range. While the majority of vectors were classified as slow movement clusters, when the resulting vector map was examined (Figure 6-8) it visually appeared that the majority of vectors were fast movement travel segments. Results suggest that the majority of movements are localized slow movements with long lasting travel segments occurring between. Of the few occurring fast movement travel segments, an early grouping occurred in June and a final grouping occurred in September.

Figure 6-15. Final resulting two-class cluster graphs showing 24 identified slow movement clusters and 20 fast moving travel segments for individual G216.



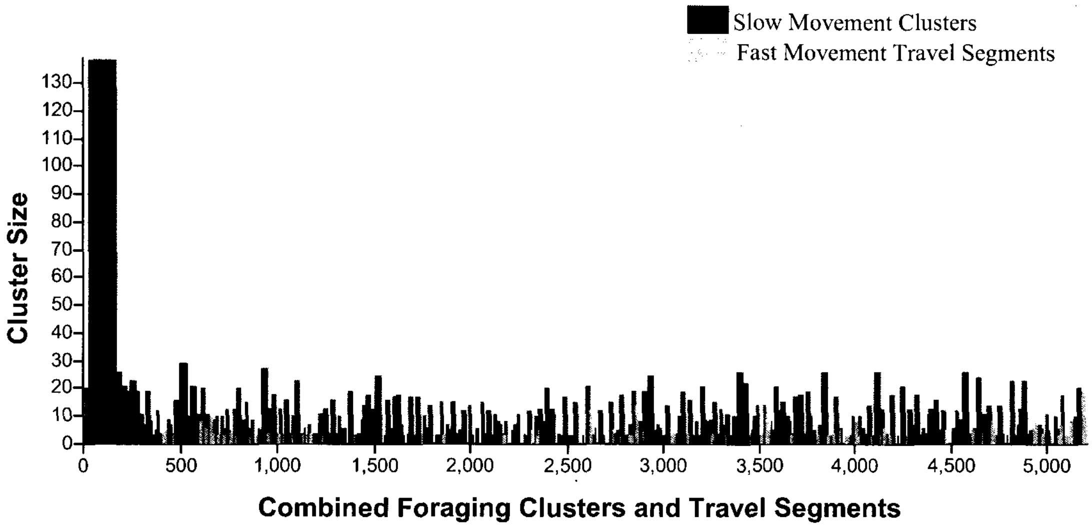
The resulting cluster graph for individual foothills male G216 (Figure 6-15 above) had the shortest duration of collected GPS radiotelemetry locations and therefore vector sequence. For this bear, the data collection sequence only lasted for the span of a week. Here, explorations will be examined by time of day. Three major slow movement cluster events were identified. The first occurred on June 8th beginning at 14:00 hours and ending at 05:30 hours indicating a possible resting or bedding event. The second cluster of slow movement vectors, while not lasting as long, was also largely characterized by night time GPS locations. The last slow movement cluster was predominantly made up of daytime locations. The largest occurring fast movement travel sequence occurred during daylight hours from 06:00 hours to 13:30 hours (7.5 hours) and covered a total distance of approximately 70 km. This equates to 10 km/hr indicating a much directed travel oriented movement. All other travel segments appeared to occur primarily during the day.

Figure 6-16. Final resulting two-class cluster graphs showing 87 identified slow movement clusters and 31 fast moving travel segments for individual G218. Note the data separation at case #341 where a significant time gap prompted the data to be processed as two unique data sets but are combined here for illustrative purposes.



The resulting cluster graph sequence for individual foothills female G218 demonstrated a large section of slow movement clusters occurring at the beginning portion of data set #2 (Figure 6-16). This large slow movement cluster occurred during early September. Four other slow movement cluster events occurred where sequential vector segments were > 20. All of these were characterized by a day to night to day transition. The remaining smaller slow movement clusters were interspersed with short lasting travel segments. Explorations highlighted a pattern where movement vectors switched from slow to fast movement behaviors at approximately 1.5 to 2.0 hour intervals.

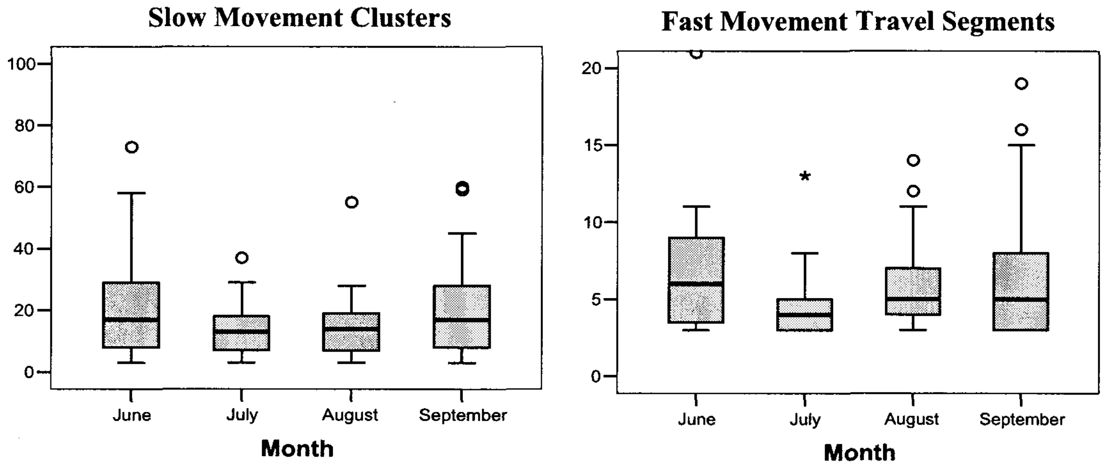
Figure 6-17. Final resulting two-class cluster graphs showing 311 identified slow movement clusters and 83 fast moving travel segments for individual G231.



Finally, the cluster graph for foothills male G231 was examined. The largest slow movement cluster occurred at the end of June and lasted for approximately 2 days or 48 hours in total. Compared to the other bears and the average size of slow movement clusters, this is exceptionally large. A large portion of the remaining cluster graph demonstrated the presence of slow movement clusters separated by small sequences of fast travel vectors some of which were large enough to generate a travel segment cluster (Figure 6-17). For this bear the mean cluster size of fast movement travel segments was 6.4 vector events or approximately 2.0 hours. Excluding the large slow movement cluster event, the remaining slow movement clusters had a mean size of 13.5 vector events which lasted 4.5 to 5.0 hours.

With all bears grouped both slow and fast vector cluster sizes were compared by month (Figure 6-18) as well as day or night classes. Comparisons indicated that slow movement cluster size by month differed significantly ($\chi^2 = 284.69$, df = 4, $P < 0.001$). Overall results indicated that mean slow movement cluster size was largest in June (mean = 28.4, SE = 0.838, time = 9.5 hr) and September (mean = 19.5, SE = 0.288, time = 6.5 hr) while the smallest mean slow movement cluster size was reported for the month of July (mean = 13.4, SE = 0.147, time = 4.5 hr). Resulting mean fast movement travel segment size while smaller when compared to slow movement clusters, also differed significantly by month ($\chi^2 = 38.39$, df = 3, $P < 0.001$). Comparisons indicated that fast moving travels segments were shortest in July (mean = 4.8, SE = 0.156, time = 1.5 hr) and longest in June (mean = 6.88, SE = 0.29, time = 2.3 hr). Of the post-hoc comparisons, travel segment comparison between June and September were not significantly different ($P = 0.586$).

Figure 6-18. Resulting box plots for all 5 grizzly bears grouped showing slow movement cluster and fast movement travel segment size (number of vectors) by month.



Slow Movement Clusters

Fast Movement Travel Segments

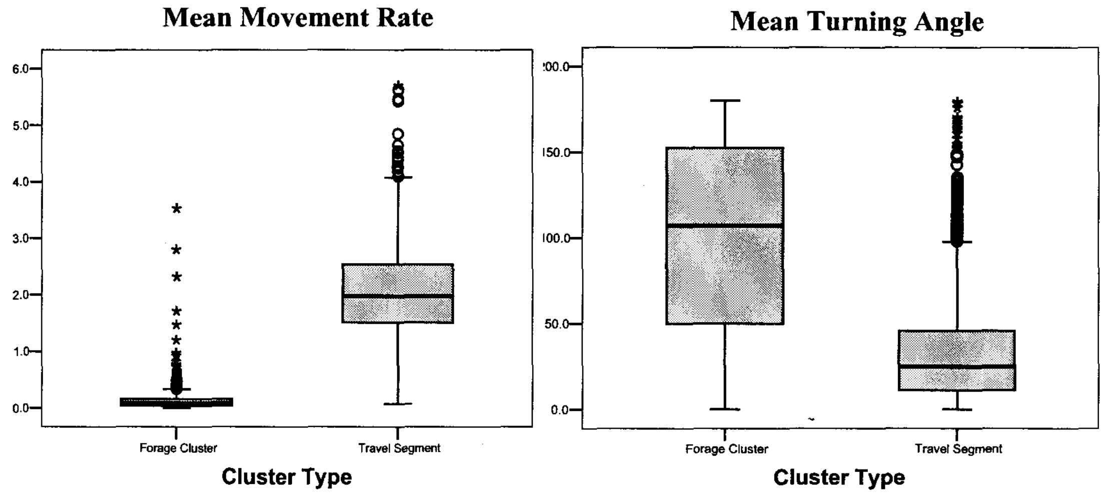
Grouped daytime / nighttime cluster comparisons for all bears revealed that while slow movement clusters were significantly different ($U = 6946946$, $Z = -19.202$, $P < 0.001$), fast moving traveling segments were not ($P = 0.29$). Results demonstrated that mean slow movement cluster size was larger for night (mean = 19.07, SE = 0.237, time = 6.4 hr) when compared to day (mean = 18.0, SE = 0.354, time = 6.0 hr) classifications. Although the mean values were similar, manual explorations revealed that large slow movement clusters where 24 or more (8 hr) segments were present contained 10% more nighttime classes than daytime classes. While not significantly different, mean consecutive fast moving travel segments were marginally longer during the day (mean = 6.13) than at night (mean = 6.04).

Finally, movement parameters such as mean movement rate (km/h) and mean turning angle (deg) were compared individually (Table 6-7) and grouped for the two cluster classification group (Figure 6-19). Mean results mirrored those reported for the three-class movement grouping. Yet, results for the two-class cluster grouping reported larger mean separations for both movement rate and turning angle movement parameters. When grouped, mean movement rates remained significantly slower for slow movement clusters (mean = 0.113, SE = 0.001) when compared to travel segments (mean = 2.10, SE = 0.21) for all bears. Further, slow movement clusters (mean = 100.5, SE = 0.605) maintained higher turning angles than fast movement travel segments (mean = 33.26, SE = 0.819) for all bears. Results were significant for all grouped comparisons (*P* < 0.001). Although variation was substantial among individuals, grouped data suggested movement parameters could be simplified to a single distribution.

Table 6-7. Vector movement classifications for each grizzly bear (*n* = 5) showing mean movement rate (km/h) and mean turning angle (deg) after movement segmentation into slow movement clusters and fast movement travel segments. Significance tests were conducted using the Kruskal-Wallis test.

	Mean Movement Rate (km/h)			**Mean Turning Angle (deg)**		
Bear ID	Slow Moving Clusters	Fast Travel Segments	*P*	Slow Moving Clusters	Fast Travel Segments	*P*
G203	0.12	2.05	*0.001*	101.32	30.97	*0.001*
G210	0.12	2.59	*0.001*	88.20	33.75	*0.001*
G216	0.13	3.17	*0.001*	107.60	32.04	*0.001*
G218	0.07	1.43	*0.001*	97.79	43.39	*0.001*
G231	0.11	1.98	*0.001*	102.12	34.85	*0.001*

Figure 6-19. Resulting box plots for all 5 grizzly bears grouped showing mean movement rate (km/h) and mean turning angle (deg) for slow movement clusters and fast movement travel segments.

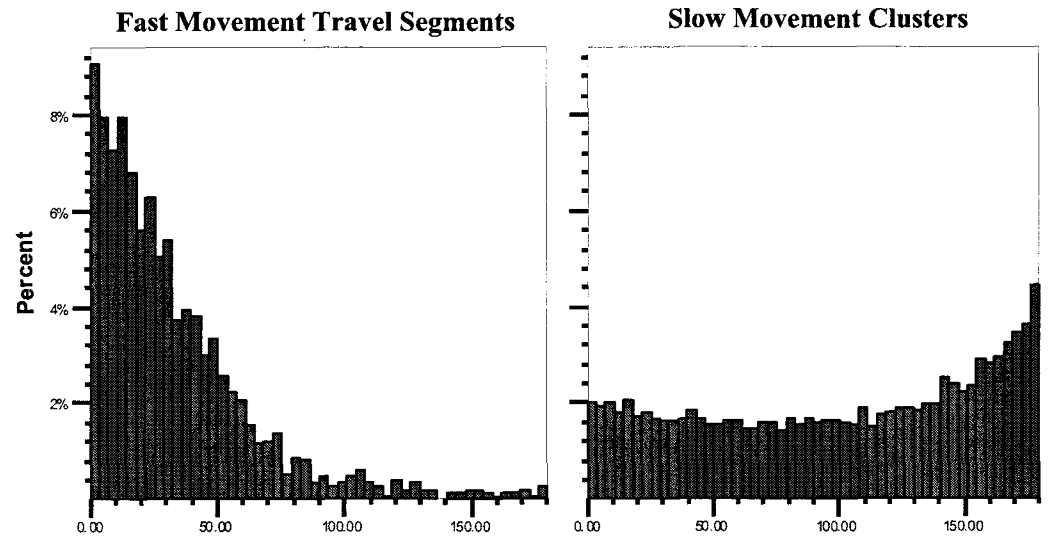


Mean Movement Rate

Mean Turning Angle

Separation of turning angle distributions provided additional information regarding travel segment outliers (Figure 6-19 and Figure 6-20). By examining the variation in frequency distributions of turning angles for all grizzly bears, the difference between fast movement travel segments and slow movement clusters can be better understood. For all bears, slow movement clusters contained a range of turning angles (from straight-line movements to highly tortuous movements). As a corollary, fast movement travel segment frequencies were largely skewed indicating that while some turning vectors were present the majority of consecutive vectors were straight-lined and highly directed. As such, resulting slow movement vector clusters had a wider spread when compared to travel segment vectors.

Figure 6-20. Turning angle distributions for all 5 grizzly bears by fast movement travel segments and slow movement foraging clusters.



Movement Segmentation Classification Accuracies

For all three model classification approaches for all five individual bears, significant mean differences were observed for both predictor variables (movement rate and turning angle). While the log determinants were quite similar; Box's M indicated that the assumption of equality of covariance matrices for all comparisons was violated. However, given the large sample sizes for each bear, this problem was not regarded as serious. For all bears and all 3 grouping types, Wilk's lambda indicated a highly significant function ($P < 0.000$) with speed (km/h) reported as the strongest predictor while low turning angle (deg) was secondary.

Table 6-8. Discriminant classification accuracy results for vector movement types (3 movement classification types) based on speed and turning angle variables for individual bears with the proportional by chance accuracy rate for each classification strategy.

	Discriminant Classification Accuracy Results (%)					
Bear ID	3-Class Move Accuracy	3-Class By Chance Rate	2-Class Move Accuracy	2-Class By Chance Rate	2-Class Clusters Accuracy	Cluster By Chance Rate
G203	88.3	56.3	98.6	82.5	99.3	92.5
G210	78.4	58.5	95.9	91.3	98.7	96.9
G216	96.8	51.3	100.0	66.3	100.0	67.0
G218	83.4	59.0	96.7	84.8	98.2	95.3
G231	92.9	57.5	98.4	88.5	99.3	99.0
Mean	**88.0**	**56.5**	**97.9**	**82.7**	**99.1**	**90.1**

Overall discriminant classification accuracy results showed that vectors were correctly classified but varied from the low 80's for 3 movement behavior types to 100% for sequentially clustered movements (Table 6-8). The best classification results were achieved for the two-class cluster classification as expected. When all bears were grouped, combined classification accuracy was 99.1% for the two-class cluster movement grouping. Results respond as expected given that speed is derived from and thus highly correlated with distance; however the results provide information as to the accuracy of different classification approaches. For example, going from a cluster classification approach to one that includes transition vectors decreases accuracy levels by 11%. All classification results accuracies listed above were greater than the indicated proportional by chance accuracy criteria, supporting the breakdown of vectors into distinct movement types (Table 6-8).

Results varied individually. When examining the 3-class movement classification for individual G203, slow movement vectors (99.7%) reported the best classification results over transition vectors (62.5%) and fast movement vectors (83.8%). The two-class movement dependent variable correctly classified 99.9% of slow moving and 93.4% of fast moving vectors.

The two-class cluster grouping again correctly classified slow movement vectors at 99.9% but improved upon the fast vector classification to 96.1%. For individual G210, the 3-class movement classification correctly classified 99.9% of slow, 31.7% of transition, and 69.7% of fast vectors. Removing transition vectors improved the classification of fast moving vectors to 74.2% while slow moving vectors remained constant at 99.9%. The final two-class cluster dependent variable improved the classification result to 100% for slow moving vectors and 85% for fast moving travel segments with 15% remaining as misclassified. For male G216, the 3-class movement classification correctly classified 99.6% of slow, 86.7% of transition, and 96.6% of fast movement vectors. Both the two-class classification and the sequential movement cluster classification correctly identified 100% of slow moving vectors and 100% of fast moving vectors. When examining the 3-class movement classification for individual G218, slow moving vectors (90.2%) reported the best classification results over transition vectors (71.7%) and fast moving vectors (71.0%). After removing transition vectors, 100% of slow movement vectors were correctly classified and 83.7% of fast movement vectors were correctly classified. The final grouping correctly classified slow vector clusters at 100% and fast vector segments at 87.1%. Finally, for individual G231, the 3-class movement classification correctly classified 98.2% of slow, 82.5% of transition, and 88.3% of fast movement vectors. Removing transition vectors improved the classification of fast moving vectors to 91.2% while slow moving vectors improved to 99.9%. The cluster classification dependent variable correctly classified slow clusters at 99.9% and fast segments at 94.4%.

Individual Two-class Cluster Movement Landscape Results

Using the two-class cluster vector segmentation approach, mean landscape values for slow moving vectors and fast moving vectors were assessed for each individual grizzly bear. Depending on the amount of data processed, each individual grizzly bear had a related unique number of slow and fast movement vectors. For Swan Hills female G203, 4040 sequential vectors were classified as slow and 766 were classified as fast moving vector clusters. For mountain male G210, 610 and 60 vectors were classified as slow and fast moving vector clusters, respectively. For foothills male G216, 225 vectors were classified as slow vectors and 129 vectors were classified as fast. For foothills female G218, 782 slow vectors and 125 fast vectors were identified. Finally, for foothills male G231, 2897 vectors were classified as slow and 389 vectors were classified as fast. Vector comparisons were reviewed according to three variable groups: habitat proportions, natural landscape variables, and distance to linear variables.

For four out of five grizzly bears, all mean proportions for vector habitat types were significantly different ($P < 0.001$) when comparing slow and fast moving vectors (Figure 6-21). Of all five bears, only foothills female G218 reported non-significant results when examining herbaceous habitat class proportions. For individuals G210, G216 and G218 fast vector segments reported higher means for open forest when compared to slow moving vectors. Mountain male bear G210 reported the largest differences between slow (mean = 0.06, SE = 0.009) and fast vectors (mean = 0.17, SE = 0.032) for open forest proportions. The opposite was reported for G203 and G231. For three out of five grizzly bears (G203, G210, and G216), fast vector segments reported higher mean proportions of closed forest than slow vectors. Interestingly, 3 of 5 bears (G210, G218 and G231) reported higher means for both open and closed forest proportions when fast vectors were compared to slow vectors. The other two individuals (G203 and G216) reported higher slow vector proportions for open forest and higher fast vector proportions for closed forests.

Results for wet treed habitat proportions were split, 2 of the 4 bears (G203 and G216) reported higher means for fast vectors over slow vectors while the other 2 bears (G218 and G231) reported higher means for slow vectors over fast vectors. Only mountain male (G210) reported no wet treed proportions for vectors due to a lack of wet treed habitat in mountain environments. For males G210, G216 and G231 herbaceous habitat class reported higher means for fast moving vectors when compared to slow moving vectors. The largest significant difference was reported for mountain bear G210 (fast mean = 0.16, SE = 0.03; slow mean = 0.07, SE = 0.01). For Swan Hills female G203 the result was opposite with higher proportions of herbaceous for slow moving vectors (mean = 0.15, SE = 0.005) over fast moving vectors (mean = 0.12, SE = 0.008). Female G218 reported no significant differences (*P* = 0.652) between the two movement types. Visually, mean differences for G218 herbaceous appeared exceptionally large, however further exploration through the use of histograms and box plots revealed that the majority of slow movement vector proportions were either 0.0 or 1.0. This resulted in an overestimated mean with a large standard deviation (mean = 0.32, SD = 0.46) for slow movement clusters when compared to travel segments (mean = 0.11, SD = 0.19) resulting in a non significant result.

For Swan Hills female G203, mountain male G210, and foothills female G218, slow moving vectors reported higher proportions of shrub than fast moving vectors. Mountain individual G210 again reported the largest differences between slow (mean = 0.68, SE = 0.018) and fast (mean = 0.35, SE = 0.041) vectors. Results for foothills bears G216 and G231 demonstrated higher shrub means for fast moving vectors when compared to slow moving vectors. Finally, non-habitat results reported higher mean proportions for fast moving vectors over slow moving vectors for 3 of 5 bears (G210, G218 and G231). Again, the largest differences were reported for mountain male G210 where non-habitat fast moving vectors (mean = 0.12, SE = 0.03) had significantly higher means than slow moving vectors (mean = 0.01, SE = 0.004). This isn't surprising given that non-habitat in mountain environments is primarily composed of rock, snow and ice through which a bear would move faster given food sources are limited. In foothills environments the non-habitat class is composed primarily of barren landscape patches where vegetation is limited (e.g. mining sites).

Figure 6-21. Bar charts showing mean habitat proportion class results comparing slow moving vectors and fast traveling vectors for each individual bear.

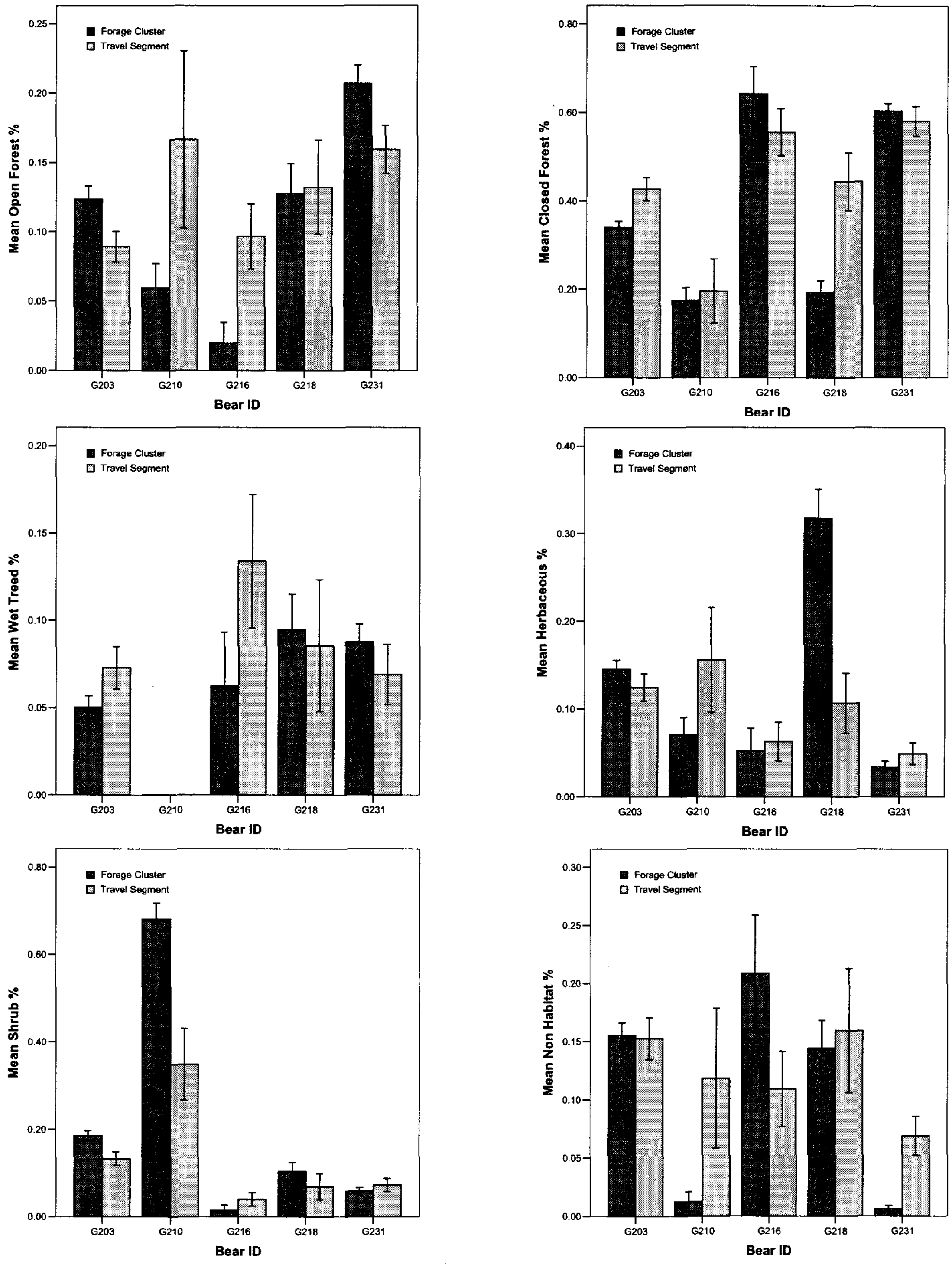
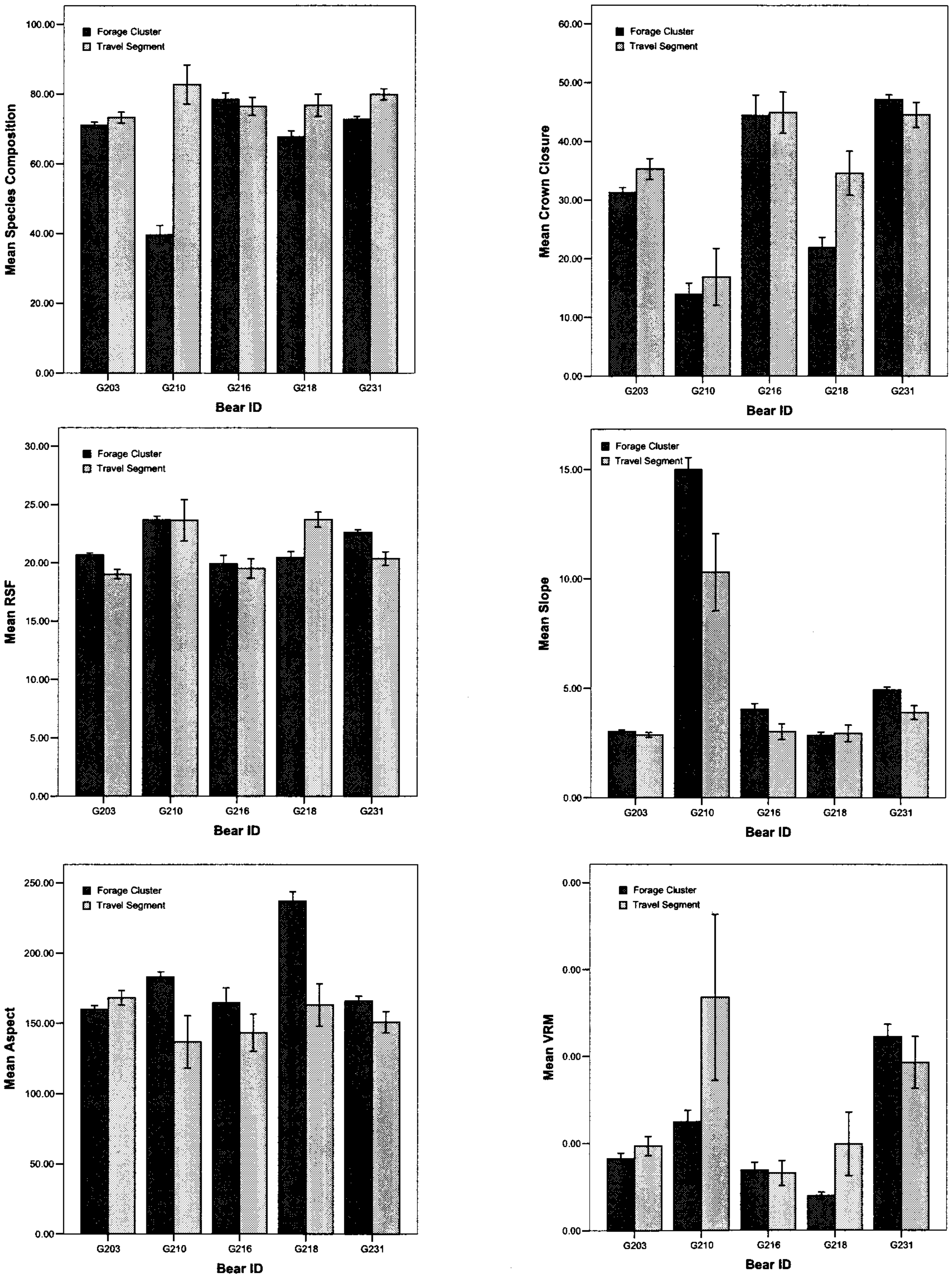


Figure 6-22. Bar charts showing mean landscape variables results comparing slow moving vectors and fast traveling vectors for each individual bear.

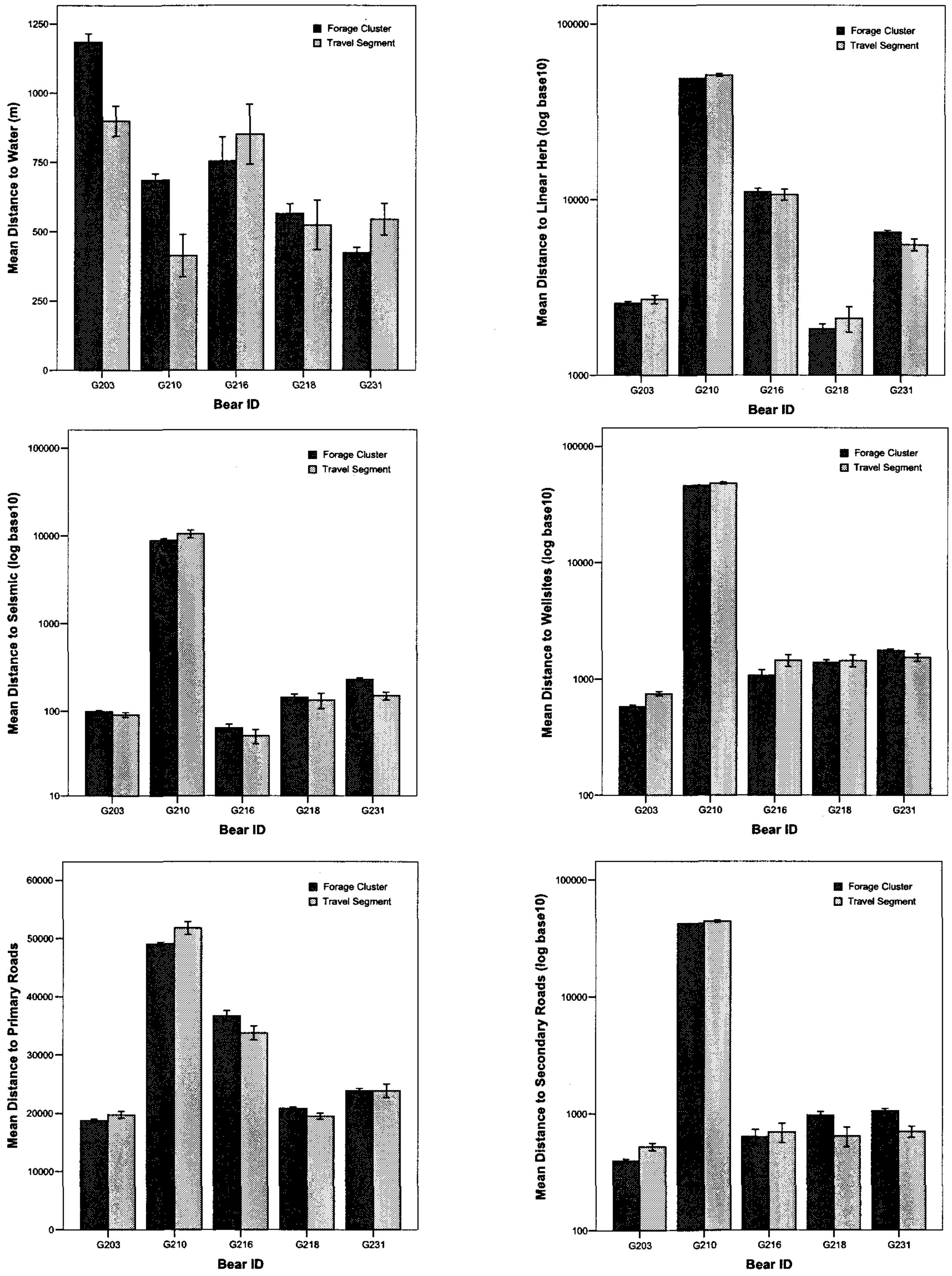


Two-class vector segmentation results were variable for species composition, crown closure, and RSF (Figure 6-22). Results for 3 out of 5 bears (G210, G218 and G231) demonstrated significantly higher mean species compositions for fast moving vectors over slow moving vectors. To reiterate, a higher species composition indicates a higher proportion of coniferous trees while a lower species composition indicates a higher proportion of deciduous trees. Mountain male G210 again demonstrated the largest differences between fast moving vectors (mean = 82.7, SE = 0.186) and slow moving vectors (mean = 39.5, SE = 1.37). Results for mean crown closures indicated that fast vectors had significantly higher crown closure percentages when compared to slow vectors for 3 out of 5 bears. Male G216 reported no significant differences ($P = 0.345$) while male G231 reported higher crown closure means associated with slow movement vector clusters. For Swan Hills female G203, mountain male G210, and foothills males G216 and G231, mean RSF values were significantly higher for slow moving vectors when compared to fast moving vectors. For foothills female G218, mean RSF values were significantly higher for fast moving vector segments over slow moving vector clusters.

Landscape variable comparisons included elevation, slope, aspect, and vector ruggedness (Figure 6-22). Mean elevation comparisons, while small significant differences were present between vector types, mainly provided a visual description of where grizzly bears resided on the landscape. All significant results for slope reported that slow movement vectors had higher slopes over fast movement vectors for both mountain and foothill bears. Again, the largest mean differences were reported for mountain bear G210. No significant differences were reported for individual grizzly bears G203 and G218 when examining slope. Mean aspect of fast moving vectors was also found to be significantly lower than slow moving vectors for all grizzly bears except Swan Hills female G203. Aspect differences were the greatest for foothills female G218. Finally, vector ruggedness was significantly higher for fast vectors over slow vectors for 3 out of

5 grizzly bears (G203, G210 and G218). No significant differences were found for foothills bear G216. Only individual G231 reported significantly higher vector ruggedness values for slow vectors over fast vectors.

Figure 6-23. Bar charts showing mean distance to features results comparing slow moving vectors and fast traveling vectors for each individual bear.



Results for distance to linear landscape and human use features are shown in Figure 6-23. For Swan Hills female G203 and mountain male G210, travel vectors were closer to water features than slow movement vectors. For foothills bears G216 and G231, slow movement vectors were closer (had smaller mean distances) to water features when compared to fast moving vectors. Distances to herbaceous linear features were not significant for 3 out of 5 grizzly bears (G203, G216, and G218). Only foothills male G231 highlighted fast travel vectors as occurring closer to herbaceous linear features when compared to slow vectors but these distances still ranged from 5.5 km to 6.5 km. Foothills individuals G216 and G231 reported mean distance to seismic lines to be lower for fast movement vectors over slow movement vectors. For example, G216 reported fast vectors were on average 51 m from seismic lines while slow vectors were on average 64 m from seismic lines. For G231, fast moving vector segments were approximately 150 m from seismic lines while slow moving clusters were 230 m from seismic lines. Significant results for distance to wellsites indicated that slow movement vectors were closer to wellsites when compared to fast movement vectors for individuals G203 and G216. Foothills bears G218 and G231 reported no significant differences when comparing distance to wellsites.

Mean distances to primary paved roads or major highways ranged from 19 km for Swan Hills bear G203 to 52 km for mountain bear G210. While significant differences were present for 4 out of 5 bears, overall distances were too large to really speculate any relationship between slow and fast vector classes. Of greater interest are the results for distance to secondary roads. Secondary roads included both 2-lane paved and gravel road types. Significant differences were only reported for Swan Hills female G203 and foothills male G231. Individual G203 reported lower mean distance to secondary roads for slow vector clusters (mean = 396.5, SE = 7.1) when compared to fast vector segments (mean = 521.8, SE = 19.26). As a corollary, individual G231 reported lower mean distance to secondary roads for travel vectors (mean = 703.4, SE = 38.7) when compared to slow movement clusters (mean = 1,056.7, SE = 25.2). Individuals G216 and

G218 reported no significant differences and mountain male G210 was too far away from all linear features including roads to legitimately consider.

Individual Landscape Discriminant Analysis Results

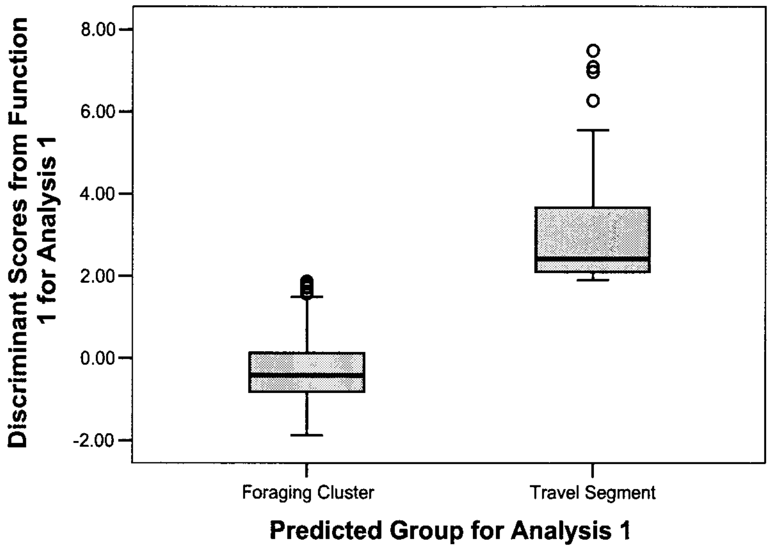
A multivariate step-wise discriminant function analysis (DFA) was used to determine the landscape characteristics which contributed most to discriminating between movement behaviors for each individual grizzly bear (Table 6-9, p. 263). Resulting eigenvalues for each DFA function were generally low indicating that landscape variables were not powerful in distinguishing between the two movement behaviors (slow clusters and fast travel segments). However, overall significant discriminant functions were obtained for each bear ($P < 0.001$). That being said, resulting structure matrices highlighted which landscape variables (loading cutoff > 0.30) did correlate with the DFA function. Mean discriminant scores differed significantly between movement classes. Only one (G203) of the five individual grizzly bears met the equal variance-covariance assumption. For the others, log determinants were similar. Of the five bears, mountain male G210 reported the best example of DFA model results.

G203 Discriminant Results **-** For individual G203, significant mean differences between slow movement clusters and fast travel segments were found for all landscape variables except herbaceous, non habitat, slope and vector ruggedness. For this bear, 14 of the possible 21 variables were entered into the DFA model using the stepwise procedure. The model reported a canonical correlation of 0.244 (6% explained variation). The five highest contributors as identified by the structure matrix were distance to wellsites (-0.545), distance to water features (0.448), RSF (0.428), and distance to secondary roads (-0.392) (Table 6-9). When broken down, the final two-movement cluster classification model correctly classified 99.8% of the slow movement vectors and only 4% of the fast travel segments used to develop the model. Resulting mean discriminant function scores were significantly different between movement classes ($t_{1092.9}$

= 17.805, $P < 0.001$), with higher mean scores reported for slow movement clusters (n = 4038, mean = 0.109, SE = 0.02) and lower mean scores reported for fast traveling segments (n = 764, mean = -0.578, SE = 0.04). For Swan Hills female G203, low proximity to wellsites, increased distance from water features, high RSF values, and close proximity to secondary roads discriminated between slow movement clusters and travel segments.

G210 Discriminant Results - For individual G210, significant differences between slow movement clusters and travel segments were found for all landscape variables except closed forest, crown closure, RSF, and elevation. For this bear, 12 of the possible 21 variables were entered into the DFA model. Model efficacy was reported at 38% (canonical correlation = 0.615). Wilk's lambda reported the unexplained variation at 0.622. Of the variables included, the structure matrix revealed that species composition (0.480), aspect (-0.364) and distance to water (-0.334) reported the largest correlations with the DFA function (Table 6-9). The final two-movement cluster classification model correctly classified 96% of the slow vectors and 62% of the fast vectors used to develop the model. Resulting mean discriminant function scores were significantly different between movement classes ($t_{61.0}$ = -10.359, $P < 0.001$), with lower mean scores reported for slow movement clusters (n = 610, mean = -0.244, SE = 0.03) and higher mean scores reported for traveling vectors (n = 60, mean = 2.48, SE = 0.26). Overall, travel segments were related to higher proportions of species composition (coniferous stands) and closer proximity to water features. Slow movement clusters were related to lower proportions of species composition (mixed to deciduous stands), south facing slopes, and were farther from water features.

Figure 6-24. Resulting box plot illustrating the distribution of discriminant scores for slow movement clusters and travel segments for individual grizzly bear G210.



G216 Discriminant Results - Individual G216 demonstrated significant mean differences between slow movement clusters and travel segments for open forest, wet treed, shrub, non habitat, distances to seismic, wellsites, primary roads, and slope and aspect variables. The stepwise model procedure entered 10 of the 21 possible variables. The resulting DFA model was able to explain only 29% of the variation (canonical correlation = 0.538). Wilk's lambda reported the unexplained variation at 0.71, yet the function was reported as significant ($P < 0.001$). The structure matrix reported open forest (-0.486) and distance to primary roads (0.316) as having the largest correlations with the DFA function (Table 6-9). The final model correctly classified 96.9% of the slow vectors and 58.1% of the fast vectors used to develop the model. Resulting mean discriminant function scores were significantly different between movement classes ($t_{174.26} = 10.372$, $P < 0.001$), with higher mean scores reported for slow movement clusters ($n = 225$, mean = 0.482, SE = 0.05) and lower mean scores reported for traveling vectors ($n = 129$, mean = -0.841, SE = 0.12). For male G216, results suggest that low proportions of open forest and increased distances from primary roads discriminated between slow movement clusters and travel segments. Travel segments generally had higher proportions of open forest and were found closer to primary roads.

G218 Discriminant Results - Female G218 reported significant mean differences between slow movement clusters and travel segments for closed forest, herbaceous, species composition, crown closure, RSF, distance to primary and secondary roads, elevation, aspect, and vector ruggedness variables. The stepwise procedure entered 11 variables into the DFA model. Again, the resulting model performed weakly explaining only 25% of the total variation (canonical correlation = 0.497). Although Wilk's lambda reported the function as significant ($P <$ 0.001), 75% of the variation remained unexplained. The resulting matrix reported aspect (0.489), closed forest (-0.402), and vector ruggedness (-0.369) as having the largest correlations with the resulting DFA function (Table 6-9). The final two-movement classification model correctly classified 96.5% of the slow moving vectors and 43.5% of the fast moving vectors used to develop the model. Resulting mean discriminant function scores were significantly different between movement classes ($t_{132.6} = 10.639$, $P < 0.001$), with higher mean scores reported for slow movement clusters ($n = 774$, mean = 0.229, SE = 0.03) and lower mean scores reported for traveling vectors ($n = 124$, mean = -1.429, SE = 0.15). For foothills female G218, larger (southwest) aspects, lower proportions of closed forest and lower vector ruggedness discriminated between slow movement clusters and travel segments.

G231 Discriminant Results – Individual male G231 reported significant mean differences between slow movement clusters and travel segments for open forest, non habitat, species composition, crown closure, RSF, distances to water, linear herbaceous, seismic lines, wellsite features, and secondary roads, as well as slope and aspect. The stepwise procedure entered 14 variables into the DFA model. The model reported a canonical correlation of 0.405 (16% explained variation). The highest contributor to the function as identified by the structure matrix was proportion of non habitat features (0.758) (Table 6-9). When broken down, the final two-movement classification model correctly classified 99.5% of slow vectors and 24.5% of fast vectors used to develop the model. Resulting mean discriminant function scores were significantly different between movement classes ($t_{391.7} = -12.957$, $P < 0.001$), with lower mean scores reported for slow movement clusters ($n = 2883$, mean = -0.160, SE = 0.014) and higher mean scores reported for traveling vectors ($n = 379$, mean = 1.22, SE = 0.11). Finally, results for foothills male G231 suggested that high proportion of non habitat was the only significant variable for predicting between slow movement clusters and travel segments. For this bear, travel segments had higher proportions of non habitat class than slow movement clusters.

Table 6-9. Discriminant analysis results for each individual bear showing overall explained variance with significant positive and negative contributing variables based on structure matrix results using a factor loading cut-off threshold of 0.3. Non significant variables were not listed.

		Variables Included in Analysis										
Bear ID	Model Variation Explained	Open Forest	Closed Forest	Non Hab	Species Comp	RSF	Dist to Water	Dist to Wellsites	Dist to Highways	Dist to Secondary	Aspect	VRM
G203	.06*					+.428	+.448	-.545		-.392		
G210	.38*				+.480		-.334				-.364	
G216	.29*	-.486							+.316			
G218	.25*		-.369								+.489	-.402
G231	.16*			+.758								

Note: * denotes significance $P < 0.001$

Sequential Movement Patterns and Mapping Results

Vector-based kernel density surfaces were created for each bear for each movement behavior (slow versus fast). It is important to note that the creation of each surface was completed using vector data rather than point data. This resulted in very different spatial movement patterns due to differing vector lengths and localized intensities (Figure 6-25 to Figure 6-29).

For all bears, resulting kernel surfaces suggested complex distributions of highly localized space use for slow movement clusters. Multiple centers or clusters of slow vectors were present for each bear weighted by duration of stay. For example, 50% kernel density outlines (dark green) highlighted slow movement clusters where individual bears either remained in the same region for longer than 8 hours (often including day and night classes) or revisited the same location more than once. While kernel overlap between the slow and fast travel surfaces was present for 95% outlines, 50% kernel overlap for slow movement clusters versus fast travel segments was considerably limited. In fact, centers for slow movement clusters and travel segments often emphasized different spatial regions within each home range.

Resulting fast travel surfaces visually provided a more comprehensive outline of the total movement path when compared to resulting slow movement surfaces. This is largely a function of travel segment vector length and distribution across the home range. Resulting slow movement vectors (short step lengths with higher turning angles) which tend to be more circular in nature generated focused areas of use. Travel segments (long directed step lengths) generated linear use surfaces similar to path buffers or home range approaches at the 95% level. However, centralized movement regions as indicated by 50% kernel outlines identified regions where individuals tended to travel frequently between slow movement clusters. The resulting example travel surfaces highlighted movement pathways or corridors separate from slow movement clusters.

Figure 6-25. Resulting fine-scale movement behavior kernel density maps for G203 showing slow movement clusters in green and travel segments in grey.

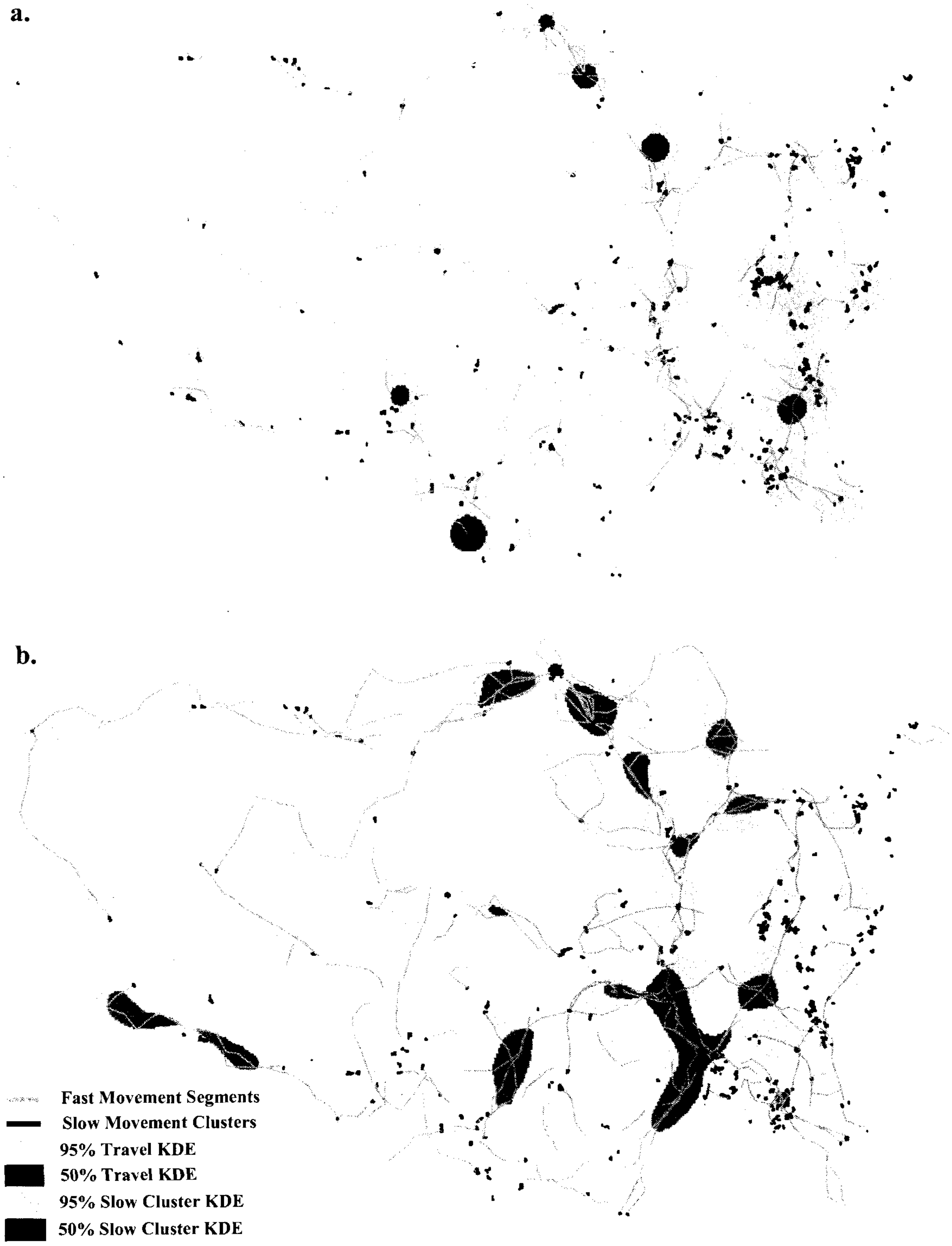


Figure 6-26. Resulting fine-scale movement behavior kernel density maps for G210 showing slow movement clusters in green and travel segments in grey.

Figure 6-27. Resulting fine-scale movement behavior kernel density maps for G216 showing slow movement clusters in green and travel segments in grey.

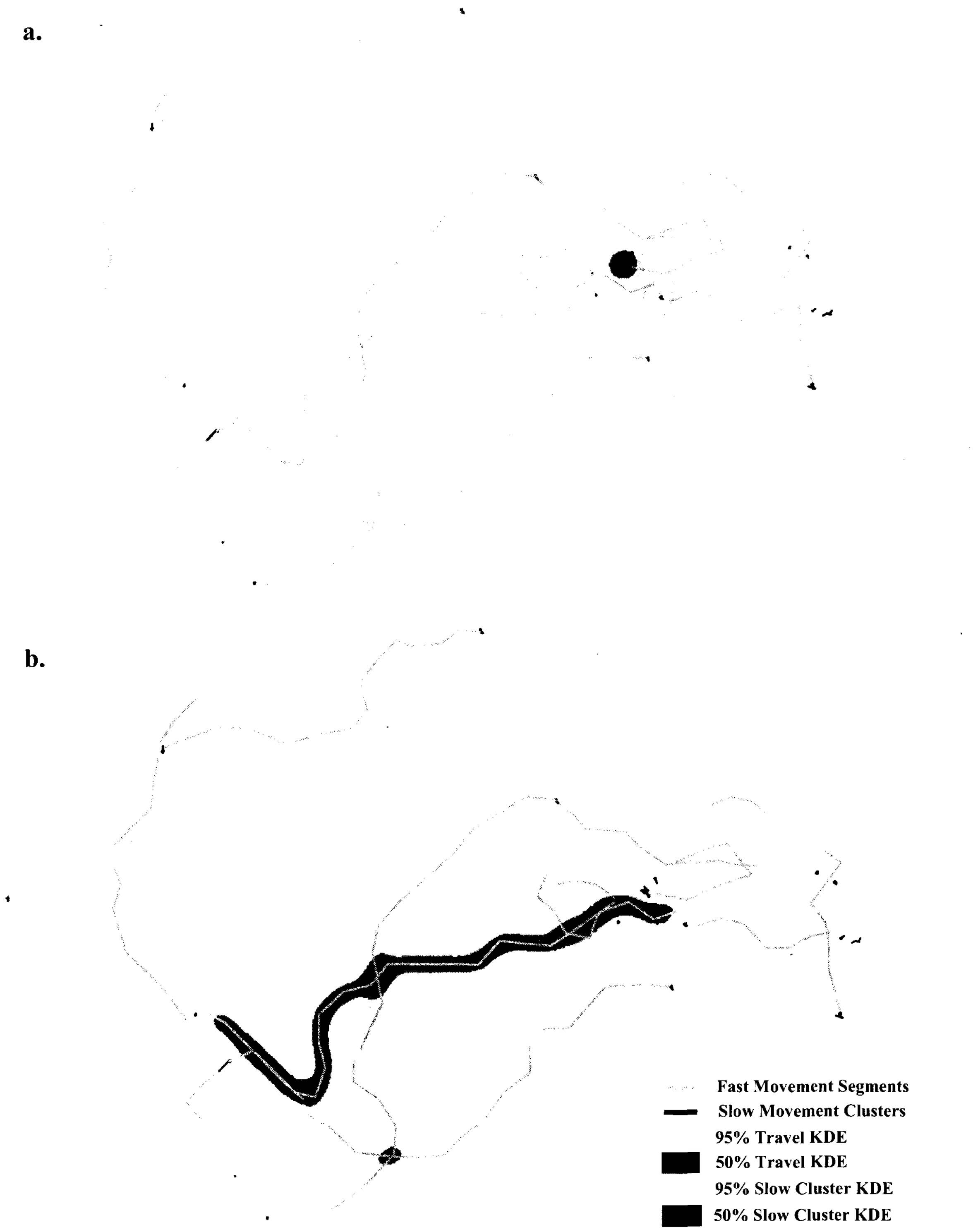


Figure 6-28. Resulting fine-scale movement behavior kernel density maps for G218 showing slow movement clusters in green and travel segments in grey.

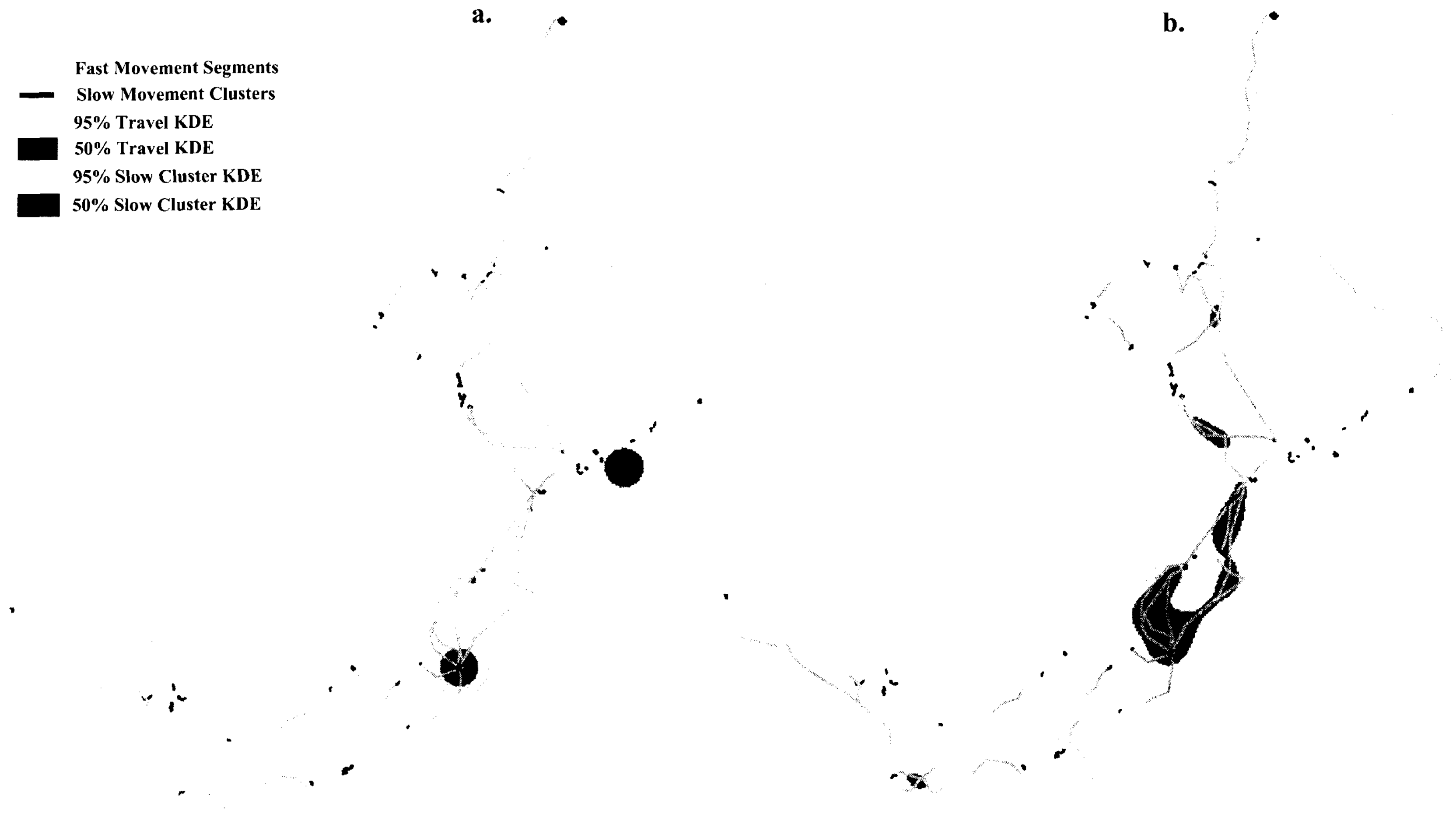
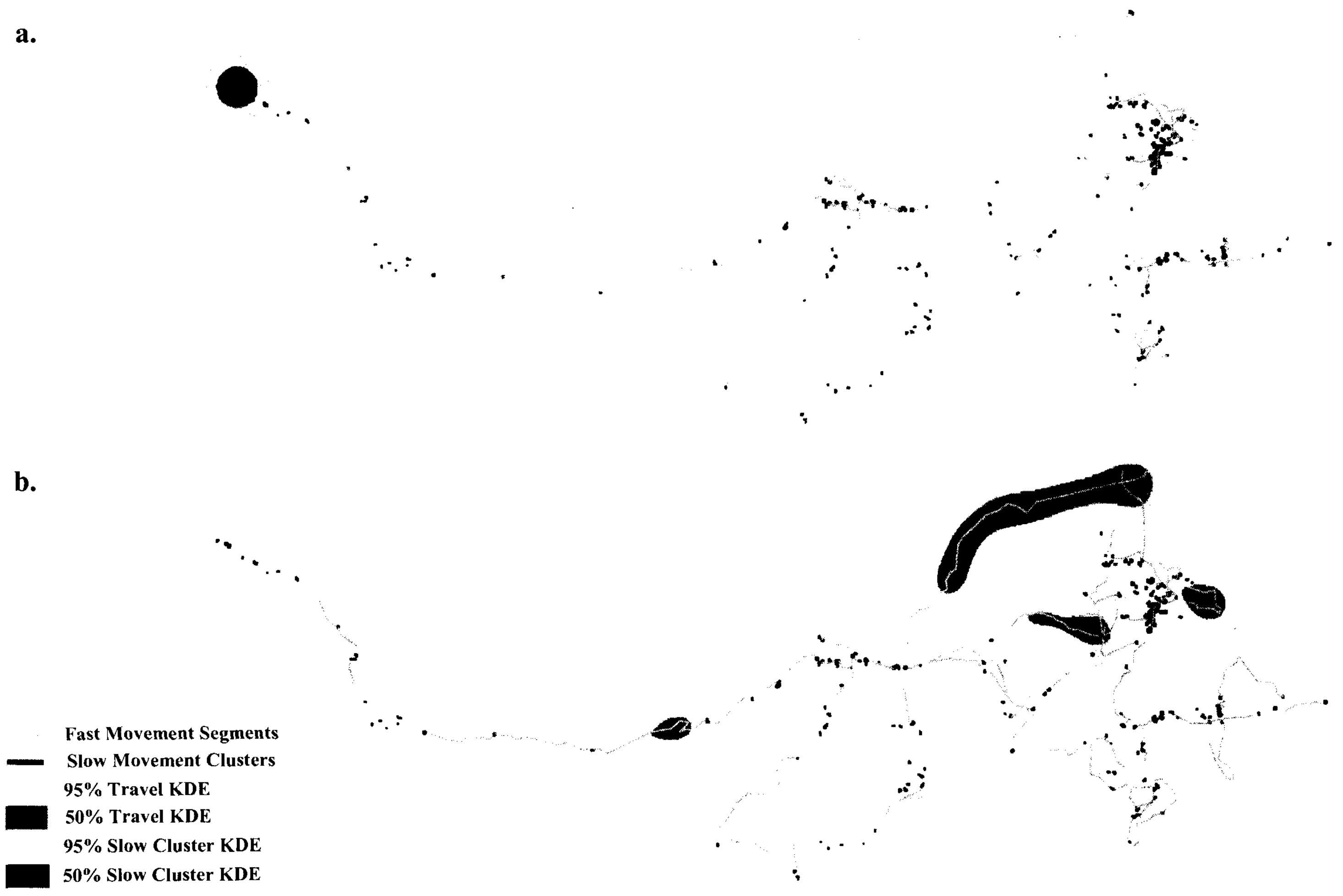


Figure 6-29. Resulting fine-scale movement behavior kernel density maps for G231 showing slow movement clusters in green and travel segments in grey.



6.5 Summary

This chapter promotes a novel, empirically-based approach in the study of animal movement that explicitly identifies the movement patterns of grizzly bears. By employing time series graphs in conjunction with vector movement patterns, individual movement behaviors can be identified. By decomposing the movement track into a dichotomous movement structure, we were able to group similar observations of slow movements and fast movements. This separation is necessary to understand the relationship between movement and the landscape (Martin et al. 2008). Regardless of individual variation, the separation of vectors into slow and fast movement behaviors was successful using the time series segmentation approach. Further, movement parameters thresholds defining behavior types could be established for this particular population of grizzly bears. Comparing movement parameters with underlying landscape properties has provided some insight into different movement behaviors in relation to varying landscape properties.

General movement segmentation results provided the baseline data required to proceed with the separation of movement behaviors at fine-scales. Data was screened for 5 individual grizzly bears and different movement types were identified. This research focused primarily on two types of movement, fast and slow. However, it has also been stated that to understand how animals perceive and react to landscape structure, we also need to identify the boundaries or transition locations of movement behaviors (Nams 2005) indicating the need to identify a third class. Previous attempts to generate a 3-process model to separate movement behaviors (foraging, transition, and fast movements) were generally unsuccessful and transition or middle-ground locations were often misclassified (Johnson et al. 2002, Hunter 2007). While transition vectors were identified here as a byproduct of segmenting fast and slow movements, they were excluded from subsequent analyses to make it easier to distinguish between the two movement classes. Therefore, some relationships may have been missed when conducting the comparisons.

However, as only sequential vectors were chosen chances are that if a landscape variable had an impact on prolonged movement behavior it would have been captured using this approach.

Beyond this, it has been suggested that two major concerns must be addressed when segmenting movement behaviors using a time series approach (Dettki and Ericsson 2006). This first concern is the definition of the appropriate cutoff or threshold value used to separate movement behaviors. The development of a cutoff threshold of 3 consecutive vectors was achieved after much trial and error. The second concern is specifically related to the choice of movement parameter used to represent vector movements. For grizzly bears, the use of normalized distance worked better than movement rate to reduce noise in the data while maintaining the overall characteristics of the data set. While general movement trends are consistent across bears, movement parameters such as movement rate, normalized distance and turning angle can vary significantly. As such, defining a single threshold for all individual segmentation graphs at this stage was inappropriate. Further, because movement data is largely skewed towards zero and non-normal in distribution, the use of one standard deviation threshold worked well to identify vectors with low or high normalized distances.

Previous studies have detailed the habitat-use of grizzly bears in Alberta (Nielsen et al. 2002, 2003, Nielsen et al. 2004a, Nielsen et al. 2004c, Munro et al. 2006). Resources important to grizzly bears are typically distributed heterogeneously in space. The general theory predicts that individual grizzly bears will spend more time in high quality habitats with abundant food sources resulting in shorter slower movements (Graves et al. 2007). Conversely, individual bears would reduce their time in regions with limited resources resulting in longer faster movement patterns. The advantage of separating movement into different classes provides researchers the opportunity of identifying movement parameters related to specific behaviors. By employing a sequential data threshold of three, researchers are able to examine movements where behaviors have occurred for more than one vector segment. This indicates a maintained or prolonged behavioral trend. For each individual grizzly bear, maintained movement behaviors varied. However, the most common movement pattern was one that alternated between periods of highly directed fast movements (also termed travel segment) and more tortuous slow movement (termed slow movement cluster).

At fine spatiotemporal scales, individual grizzly movement patterns were highly variable in both form and function, ranging from straight-lined movements to highly concentrated slow movement clusters (Figures 6-7 to 6-11). As is common with many studies, turn angle distributions for foraging vectors were more variable and concentrated around a bearing of 180°. In contrast, movement distributions had a concentrated range highly focused around zero which indicated movements occurred in a directed manner. For all bears, localized slow movement clusters and fast travel segments both increased during the months of June and September over July and August indicating seasonal variability within the vector structure. Improvements could potentially be made by relating monthly vector patterns to seasonal food models. Occasionally, individuals spent long periods of time in one spatial location. When an individual enters a profitable place, they typically intensify their space use (Phillips et al. 2004, Barraquand and Benhamou 2008). The largest slow movement cluster was recorded with > 130 consecutive vector events lasting just less than 2 days or 44 hours. Further, individuals were also found to travel long distances between slow movement cluster events. The longest occurring travel segment contained approximately 20 consecutive vectors which equals just over 6 hours of continuous fast movement.

The identification and separation of travel segments appeared to be less clean cut. With the exception of individual G216, sequential travel segments only made up 46% to 63% of classified moving vectors. This implies that while fast movements can be distinguished from slow movements, individual fast movement behavior is variable and not simply made up of consecutive travel segments. More specifically, fast movement behaviors on average do not last for 3 or more consecutive vectors implying that longer distance travels are less common and not the only type of movement process present when dealing with individual bears. In most cases, longer slow movement clusters were separated by more frequently occurring short periods of fast movements. The identification of slow movement clusters and travel segments coupled with sequential graph structures as presented here has proved to be a unique approach for examining consecutive vector movement data. While not statistically complex, it has provided a solid approach to movement separation, visualization and quantitative assessment. It further provided a base for additional exploration and statistical analysis. For example, time series graphs were additionally segmented to examine seasonal or daily differences.

Movement-landscape relationships were not easy to simplify and separate due to individual variation as well as the uncertainty of the relationship between the assumed vector and underlying landscape. It was the hope that when comparing mean landscape variables associated with two classes of vectors or movement types, results would be consistent across all bears and significant differences would exist between slow and fast vector classes. Unfortunately, results were highly individual and population-level inferences were difficult to make using a sample size of 5 individual bears. For example, for 3 out of 5 bears, travel segments occurred closer to water features when compared to slow movement clusters. For the other 2 individual bears (G216 and G231), slow movement clusters occurred closer to water features. Only one other study has examined movements related to landscape properties which produced results similar to the results presented here (Hunter 2007). Individual male G098 was found to travel through cooler areas (based on a solar index), closer to water, and areas that were barren with some green vegetation.

In this chapter, vectors were measured according to standard movement parameters. Based on the characteristics of vector distances, a model was produced to discriminate which landscape variables were identifiable using two movement behavior types. Overall models did not perform well, in that they did not produce large canonical correlations which resulted in small percentages of explained variation. However, for each individual bear, landscape variables were identified which did contribute to the discrimination of movement behavior type. Further, all functions were significant and direct comparisons of mean discriminant scores by movement type also differed significantly. Of the five individual analyses, mountain bear male G210 produced the best results when compared to the other bears. The poorest results were reported for Swan Hills female G203. It is possible that the ability to distinguish between movement behaviors is ultimately related to the landscape in which the bear resides and the sex of the bear. Further, resulting classifications preformed well when identifying slow movement clusters (> 90%) but performed poorly when identifying travel segments (< 62%).

The variables that did contribute to individual discriminant functions were distance to human features (e.g. wellsites and roads), distance to water, RSF, species composition, crown closure, aspect, vector ruggedness, and proportion of non-habitat. Generally, slow movement clusters were explained by south/southwest aspects, higher RSF values, lower percent species composition (deciduous/mixed forests), open forests, and higher vector ruggedness. Slow movement clusters were also found farther from water features, closer to wellsites, farther from primary roads but closer to secondary roads. Travel segments were explained by lower RSF values, conifer forests, closed forests or higher percentage cover, and low vector ruggedness. Travel segments were often closer to water features and primary roads, but further from secondary roads and wellsites features. Travel segments were also explained by high proportion of non habitat features. Variables that did not contribute and were often excluded from the analyses were habitat proportion classes (wet treed, herbaceous, and shrub), slope, distance to linear herbaceous (powerlines and pipelines), and distance to seismic lines.

While some general trends can be extracted, individual variation mitigates the opportunity to make any conclusive statements as indicated by direct individual mean comparisons. Given that grizzly bear movements result from both external and internal considerations, landscape variables alone are not likely enough to understand the movement behaviors of individual grizzly bears. The underlying surfaces used here may additionally not provide the information or variables needed to fully understand resulting spatial patterns. Influences not considered here may include social interaction with other bears, distribution of bear specific foods over seasons, response to human-bear encounters, and movements occurring during mating season. More specifically, the use of landscape classes does not contain information regarding food availability or the number of producing berry bushes.

Another possibility is that landscape variable extraction and vector-based movements may not occur at the same scale. That is, how can landscape properties be related to individual vectors at a meaningful scale? More specifically, the underlying process generating long travel segments or spatial response might not be captured within a grid-based surface (e.g. a human-bear interaction or flight response). Implementing such models is time-consuming, challenging and difficult to transfer to mapping environments.

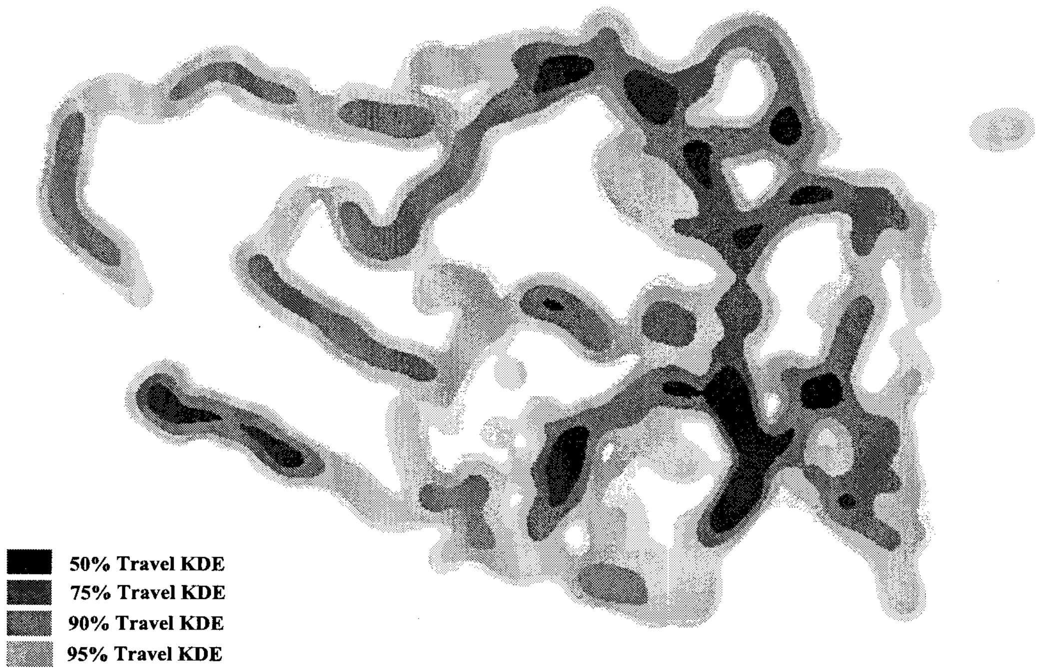
Beyond this, an additional limitation to the research conducted here was the lack of a process-based model approach. While the quantitative assessment was extensive, understanding the process generating the resulting spatial movement patterns was limited. An alternative approach would be to conduct a conditional logistic regression model where random movement steps would be compared to observed movement steps. This type of approach is typically used in resource selection function modeling (Nielsen et al. 2002, Nielsen 2005, Hunter 2007), or in the case of movement, a step selection function model (Fortin et al. 2005, Coulon et al. 2008).

However, to conduct a step selection function analysis a random step data set must be created from distributions of lengths and turning angles which was not part of this analysis.

Kernel density maps require more complex approaches than what was explored here. It is recognized that well developed kernel density models require additional programming and testing to truly be utilized for management purposes (Berland et al. 2008). However, it was important to emphasize the importance of developing different movement models specific to the movement behavior being studied. Results clearly demonstrated that resulting vector separations and thus movement behaviors create distinctly different localized home range delineations. Further, not only were these surfaces characterized by fast and slow moving vectors, they were also weighted according to the number of vectors assigned to each localized cluster event. In this way, the use of probability surfaces may provide an approach that may mitigate source error when working with straight-line vector segments (Horne et al. 2007). For example, a travel segment lasting longer in time and therefore space will be more heavily emphasized in the resulting surface than a travel segment lasting for only 3 consecutive segments.

By first segmenting vector data into two types of movement behavior, I was able to generate kernel estimation surfaces that were behavior specific. For example, specific localized travel regions or localized slow movement (feeding, bedding, resting, etc.) regions were more precisely identified. As demonstrated below (Figure 6-30), the creation of travel segment movement surfaces provided an opportunity to examine grizzly bear movement across more than one spatial scale. In Figure 6-30, the resulting kernel surface has been reclassified to emphasize the overall spatial movement pattern (e.g. a 95% vector movement home range). Beyond this, each surface can further be reclassified to emphasize the 50% localized travel regions or emphasize the 75% or 90% travel regions that fall somewhere in between. By determining regions of travel specific movements, the resulting outlines provide another approach for examining the influence of underlying landscape properties on varying spatial movement patterns. For example, the varying kernel density probabilities could emphasize zones of potential influence on grizzly bears travel specific movements. Further, one could examine travel movement hotspot landscape characteristics compared to the general or available movement landscape characteristics. The same could be completed with a slow movement cluster surface.

Figure 6-30. Probability surfaces of travel segments for individual grizzly bear G203 highlighting reclassifications showing varying levels of travel intensity weighted by travel segment duration and overlapping segments of travel (50%, 75%, 90% and 95% estimations).



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CHAPTER 7 – RESEARCH CONTRIBUTIONS AND RECOMMENDATIONS

7.1 Introduction

MacArthur and Wilson's influential theory of island biogeography recognized that habitat fragmentation eventually results in the creation of isolated 'island' populations as habitat connectivity decreased and linkages between habitats are broken. In an attempt to reduce the isolation of habitat fragments, numerous studies (Fahrig and Merriam 1985, Rosenberg et al. 1997, Beier and Noss 1998, Bunn et al. 2000) have recommended preserving landscape connectivity and thus the movement of individuals between habitat patches. For all species, including grizzly bears, connectivity is imperative for safe movement within home ranges (Noss et al. 1996) and across large landscapes for dispersal. However, before connectivity can even be considered, it is important that grizzly bear movements be studied and understood across multiple temporal and spatial scales as accomplished by this dissertation.

By understanding movement patterns and the processes underlying those patterns, it is possible to manage the landscape accordingly. Knowledge of grizzly bear movements is necessary to better understand space-use, landscape interactions, dispersal characteristics, and population distributions. The quantification of movements further provides information regarding when individuals are active, how fast they move, what physical areas they move through, and how much they vary in these traits. Finally, the separation of movement behavior into types can aid in the development of models which incorporate both the foraging and travel needs of grizzly bears within Alberta.

7.2 Research Contributions

Within this dissertation, I quantified and examined the movement ecology of grizzly bears in Alberta based primarily on GPS radiotelemetry data. The two primary objectives were to:

1) quantify grizzly bear movement rates, and 2) examine the relationship between grizzly bear spatial response and underlying landscape characteristics. As currently there has been no comprehensive review of the movement information generated by GPS radiotelemetry data, the majority of this research adopts a spatial and temporal exploratory nature. For example, at what spatial and temporal scales can movements be addressed? Also, is it possible to discern between travel oriented and slow movement behaviors for grizzly bears using GPS radiotelemetry data alone?

Working with GPS data sets further requires a solid understanding of the data assumptions, considerations and issues. The first issue which arises is generalizing a continuous process such as movement using discrete events in space and time. Secondly, within this dissertation straight-lined movements are assumed to occur between known GPS locations. Additionally, when working directly with fine-scale GPS radiotelemetry data, serial and spatial autocorrelation is inherent within the data structure. Finally, distinguishing between different movement behaviors or grizzly bear spatial response to underlying landscape variables is complex given both bear individuality and landscape complexity. In the following section, key findings and implications for management and research are summarized in order of chapter development.

Chapter 3 Summary

The primary goal of Chapter 3 was to examine the relationship between GPS radiotelemetry capture rate and resulting vector characteristics as indicated primarily by movement rate. Exploratory analysis was conducted at two spatial scales: global and local. Overall results reinforced the understanding that vector movement patterns vary spatially depending on the temporal scale of data collection. As the understanding of spatial patterns is reliant on exploratory data analysis, this chapter focused heavily on the quantification and comparisons of vector related movement characteristics as GPS radiotelemetry resolution decreased over time (20-min to 12-hr locations). Overall results emphasized the type of analysis and information available to researchers depends largely on the scale of data collection. Results indicated that data sampling has to be conducted at a rate or extent that is appropriate to detect the patterns or processes one is looking for. The most important finding of this chapter is the understanding of the relationship between temporal data scale and information available for analysis. Analysis should be conducted to the scale of data collection.

Overall, both global and local results demonstrated a significant decrease in information as temporal resolution decreased. For researchers interested in analyzing movement parameters, grouping GPS data across varying data collection schedules is possible. For example, no significant differences to movement rates were present between data collected at 1-hr, 2-hr, 4-hr, etc. intervals. However, it should be noted that movement rates calculated from data collected at 20-min intervals were significantly higher than all other collection intervals indicating the need for caution when conducting comparisons. Working with GPS radiotelemetry data collected at 20-min intervals provided a level of detail previously unattainable (e.g. the identification of internal vector clusters).

Results further demonstrated that spatial movement patterns and their relationship to underlying habitats will change considerably depending on the scale of data collection. For example, vector details are significantly reduced and data uncertainty is significantly increased when time between locations increases to 4-hr intervals. Researchers conducting vector-based movement analyses would need to buffer up to approximately 3.0 km (one side) or 6.0 km (total buffer width) to account for vector uncertainty when working with 4-hr data points. Another example of reduced accuracy is indicated by the change of habitat proportion along each vector. As vector resolution decreases, the ability to obtain accurate habitat information will also decrease. The use of vector contingency table analysis provided a more detailed understanding in relation to changing vector placement and habitat type. Results allowed for the quantification of error associated with data reduction.

Chapter 3 further demonstrated the presence of serial autocorrelation within sequential data structures. Serial autocorrelation varied by individual bear with data generally achieving independence at higher temporal lags. Further, the presence of serial autocorrelation in fine-scale data indicated the presence of prolonged movement behavior within the vector structure. The data segmentation required to eliminate serial autocorrelation also removes the data required to examine differences in movement behaviors or to identify spatial clusters within and across a movement trajectory.

Chapter 4 Summary

The main objective of Chapter 4 was to quantify and compare large-scale movement rate and home range size as related to population subgroup characteristics, spatial location, and temporal scale. The majority of large-scale movements for grizzly bears based upon GPS radiotelemetry data is programmed to record a location over large temporal intervals (e.g. 4 hours or 6 hours). Using the available data collected over a 7-year period, Chapter 4 empirically quantified and compared annual home ranges and movement rates for grizzly bears in Alberta.

Results emphasized that daily movement rates varied over large-scales due to both intra and extra-specific characteristics spatially and temporally. Significant differences to movement rates were found by sex and reproductive status, but not by year or age class. Results further demonstrated varying movement patterns between years, seasons, months and times of day. For this study, movements were also quantified and compared for mountain environments and foothills environments. Overall, grizzly bears residing in mountain environments were found to have significantly slower movement rates and smaller home ranges sizes when compared to grizzly bears residing in foothills environments. It is recognized that this is an extremely simplified understanding of where, how, and why grizzly bears are spatially distributed. However, movement rates were significantly different in each of the environments indicating the need for locally focused analyses. While overall movement rates were significantly faster in foothills landscapes over mountain landscapes, only subadult males demonstrated significant differences between the two. In addition to the intraspecific variation (e.g. reproductive status) reported here, bear interactions with other bears (e.g. male-female associations) will further complicate the understanding of movement patterns across large landscapes.

The quantitative results of movement rates and home range sizes reported here are important on two research fronts. First, the empirical assessment of GPS radiotelemetry data is the first of its kind completed for grizzly bear populations in the province of Alberta. As such, conservation and land-use managers will have a better understanding of grizzly bear home ranges and spatial movement across different temporal scales. Second, the detailed understanding of grizzly bear movement rates can be used to improve movement-based models, such as large-scale corridor or connectivity models. For example, simulation models which previously attempted to model movement corridors typically focused on the requirements and movement rates of female grizzly bears. However, given the extensive ranges and movement patterns of males or subadult males, either more than one model would be required, or movement parameters would have to be larger. Such fine-scale interactions are difficult to incorporate into large-scale movement models.

Chapter 5 Summary

The intent of Chapter 5 was to examine the relationship between grizzly bear home range size and underlying landscape characteristics. As the majority of grizzly bear radiotelemetry data is collected at 4-hr time intervals, comparisons were conducted at the home range level as indicated by results generated in Chapter 3. The relationship between home range size and landscape variables was best described according to landscape type. When separated, mountain bear home ranges sizes responded to three landscape classes: shrub, closed forest, and herbaceous. Foothills bear home ranges responded to seven landscape classes: linear herbaceous density, species composition, wellsite area, herbaceous, wet treed, shrub, and open forests. Overall models tended to respond the best when working with mountain bears over foothills bears suggesting that foothills landscapes have higher levels of complexity. Chapter 5 results indicated that exploring the relationship between landscape properties and movement rate could not be conducted and properly understood within the context of a grizzly bear's home range.

Results further explored the contribution of spatial autocorrelation in large-scale grizzly bear home range data. Overall explorations of global spatial autocorrelation indicated the presence of minimal positive spatial autocorrelation in home range size multiple regression model residuals when all bears were grouped. Subsequent model runs reported no significant global spatial autocorrelation in model residuals for both mountain home ranges and foothills home ranges. While autocorrelation was absent or limited at the global level, local analysis demonstrated the presence of limited spatial interaction between bear home ranges in the north-central portion of the study region. Localized positive spatial autocorrelation highlighted sub regions where the models performed poorly. These locations were either situated close to the boundary between mountain and foothills regions or near to a large disturbance site. Models could be improved by either selectively removing cases with significant autocorrelation or cases could be examined in more detail to determine why the model performed poorly in these regions.

Chapter 6 Summary

The focus of Chapter 6 was ultimately two-fold. First, the majority of the analysis focused on devising a method for differentiating between movement types. Second, to examine the relationship between the previously identified movement types and underlying landscape properties, a discriminant analysis was conducted. While large landscape differences were outlined in Chapter 5, approaches for dealing with fine-scale data were still needed. Therefore, this chapter endeavored to evaluate fine-scale movement patterns and their relationship to underlying landscape properties.

An important conclusion from the work completed in Chapter 6 is the separation of vector-based movements into movement behavior groups. Time series segmentation facilitated the breakdown of movement behaviors into slow movement clusters and fast movement travel segments by identifying sequential spatiotemporal clusters. This novel approach allowed for the analysis of movement while maintaining the sequential structure of the data itself. No other studies I'm aware of have conducted this type of examination for individual grizzly bears. This approach further provided a jumping-off point for additional statistical analyses, such as direct comparisons of movement behavior clusters. Resulting slow movement clusters and travel segments can be separated into specific movement behavior strategies for future movement models and home range analyses. From this perspective, the results presented here can aid in the development of better, more reliable movement models specific to grizzly bears. For example, we now recognize future movement models must be generated according to movement behavior.

The identification of locally homogeneous vectors or local stationarity within movement trajectories provided valuable insight into individual bear behaviors at fine-scales. The characterization of homogeneous slow movement and travel segment bouts allowed for additional analyses regarding cluster duration, cluster frequency and cluster characteristics (day versus night classes). Results demonstrated that slow movement clusters on average lasted longer than fast movement clusters for all bears. Further, both slow and fast clusters types were larger for June and September over July and August indicating seasonal differences within vector structures. By examining internal cluster characteristics, it is possible to infer additional information regarding the process generating them. For example, slow movement clusters with large mean residence times may indicate a profitable spatial location that should be examined in detail. For travel segments showing a large number of sequential fast movements, the next major question to be addressed is whether these segments represent a spatial response, flight, or simply the drive to acquire new resources. Unfortunately, this type of knowledge is exceptionally difficult to gather without direct observation of individual animals.

While some habitat-movement trends were reported according movement type, results were highly individual by bear. This made it difficult to draw population-level conclusions when working with such a small sample size. Further, of the five individuals with 20-min data available for analysis, one resided in the mountains, 3 in the foothills, and 1 in Swan Hills. The resulting discriminant analysis indicated the mountain DFA results were much improved over bears residing in the foothills. This result again supports the need for separate models according to landscape type.

7.3 Recommendations for Future Work

This dissertation has presented a solid understanding of grizzly bear movement ecology. Given the research completed, the most important recommendation that can be made is the need to recognize the limitations when working with GPS radiotelemetry data specific to movement analyses. Due to the complicated nature of the data, limitations exist on data processing as well as the type of analysis conducted. Of course with any research project, there always remains room for improvement. The priority of this dissertation was to empirically gather and assess movement data in a variety of ways. In this sense, the research has achieved its goals, yet new questions continually surfaced.

First, more research time needs to be spent investigating movement patterns and processes at finer spatial and temporal data scales. Right now, the best available data is collected at 20-min intervals. Comparisons to finer data collection levels, such as those gathered by Andrew Hunter, would allow for a better understanding of the inherent error when working with vector data structures. Unfortunately, working with finer-scales of GPS data comes with additional logistical and ethical considerations, such as battery life and impact of repetitive capture on grizzly bear health (Cattet et al. 2008).

Second, resulting movement parameters must be tested in the context of simulated movement modeling at larger-scales. Bridging the gap between empirical data and modeling approaches remains primarily unstudied for grizzly bears in Alberta. While Chapter 6 presents a robust technique for separating movement types, it has only been applied to 20-min data sets for five individual grizzly bears. The next step would be to ultimately test this approach using less frequently sampled data sets from a larger population of animals across the geographic area of interest. For example, applying the segmentation technique to a larger subpopulation of grizzly bears with 1-hr data, results may highlight population-level trends not achieved within the course of this study. With a larger data set, movement surfaces could be created that compliment foraging area or core area analysis.

Finally, no process-based approaches were conducted as part of this dissertation. As such, the ability to investigate the underlying mechanisms generating the GPS spatial movement patterns is limited. A next step would be to use the detailed movement results presented here to further parameterize movement models. For example, random walk models or step selection function models require the generation of random vector movements for comparison. These usually draw upon known movement parameter distributions to examine questions surrounding randomization. Further, linking movement parameters to underlying landscape properties requires more work across multiple scales.

Attempts to examine this relationship at the individual level were not as successful as needed to create functional movement models. While habitat-use models are well developed for the FRI project (Nielsen et al. 2002, 2003, Nielsen et al. 2004a, Nielsen et al. 2004c), movement-based models require more work. It is possible that movement behavior comparisons would be better understood using food-based surfaces rather than landscape classification surfaces. Again, future work should be conducted across more individuals to achieve a better understanding of the behavioral relationships between movement and underlying landscape properties. Currently, due to individual variability, drawing population-level conclusions is difficult. Understanding the overall spatial structure (pattern and process) of grizzly bear movements will significantly improve modeling efforts which attempt to replicate movement patterns across large-scale landscapes.

The potential exists to link the movement results presented here to other variables such as bear health and mortality rates. First, it would be interesting to examine the relationships of individual grizzly bears movement rates and health indicators (e.g. weight or stress) across the two primary landscape types. Second, by separating vector-based movements into slow movement clusters and travel segments for a larger population of grizzly bears, the resulting spatial pattern of mapped travel segments could provide additional information regarding movement behaviors across varying landscape types. For example, does the number of travel segments increase (occurrence or duration) in fragmented environments and what is the resulting spatial pattern? Alternatively, do slow movement clusters occurring for long periods of time indicate high-security habitat types or food patches high in resources? Understanding these relationships would help to identify landscapes or regions where focused management and conservation efforts are needed.

7.4 References

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