DEVELOPING LANDSCAPE-SCALED HABITAT SELECTION FUNCTIONS FOR FOREST WILDLIFE FROM LANDSAT DATA: JUDGING BLACK BEAR HABITAT QUALITY IN LOUISIANA

A Dissertation

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ABSTRACT

Understanding habitat needs of animal populations is critical for their effective management. In recent years, technological advances have increased the range of methods available to examine habitat selection patterns. However, available habitat data are often either limited to small geographic areas or are of coarse resolution, resulting in a gap in data to model habitat selection at landscape scales. I explored a method of processing Landsat data, the at-satellite reflectance tasseled cap, to address this data gap using black bears in south central Louisiana as a case study. As I showed, this case was particularly instructive because these bears occupy two very different habitat matrices. I examined the information content of resource measures derived from tasseled caps and determined that they contain substantially more information than is represented in coarse habitat maps such as available from the USGS GAP program. Additionally, this process could be applied over large areas and time frames, during different times of the year, and across sensors to produce consistent results that avoid the need to categorize land cover/habitats. I used logistic regression and the information theoretic approach to examine: the spatial scale at which habitat measures were derived, model complexity, and the relative value of groups of derived habitat measures. I grouped derived habitat measures to examine the information content in: images captured in two seasons, measures based on mean and standard deviation filters, and combinations of tasseled cap functions. My work suggests that researchers should consider multiple summary statistics derived over a range of scales, use multi-temporal data, and use all three tasseled cap functions to derive habitat measures. I calculated resource selection functions (RSF) for black bears in south central Louisiana and examined model

calibration and discrimination. Mahalanobis distance has been proposed as an alternative to RSF because it does not require delineation of available resources, although results from the two approaches have not been compared. In this study, habitat quality predictions from RFS models more accurately depicted bear habitat preference than those of Mahalanobis. I propose an alternative use of Mahalanobis distance to direct model extrapolation beyond the boundaries of modeled populations.

CHAPTER 1: INTRODUCTION

Effective management of wildlife populations is dependent on our understanding of the animal's habitat requirements. Habitat selection models have been used extensively in recent years to address management questions for species of interest, particularly important game species and species listed under the U.S. Endangered Species Act of 1972. Habitat quality has long been recognized as one of the primary influences in determining animal use and abundance in a given area, with habitat selection models as the primary tool for identifying those relationships. Aspects of habitat modeling, including the proper use of established methods, and criticism of perceived fatal flaws (White and Garrott 1990, Garshelis 2000) and limitations (Alldredge and Ratti 1986, White and Garrot 1990, Alldredge and Ratti 1992, Aebischer et al. 1993, Manly et al. 1993, Alldredge et al. 1998) have been the subject of much debate. However, in spite of their limitations, habitat models remain one of the most accepted tools for reserve selection and design, species management and recovery planning, environmental impact assessment, or other planning or management decisions that rely on evaluations of habitat suitability or quality.

The Louisiana black bear (*Ursus americanus luteolus*) is a federally listed threatened species with extant populations occurring within the Mississippi River alluvial plain. The U.S. Fish and Wildlife Service identified the development of a habitat model as a key element for recovery and management of the species (USFWS 1995, BBCC 1997). Rudis and Tansey (1995) developed a coarse black bear habitat model for the southeastern U.S., which includes the range of the Louisiana black bear, but the authors

of that study recommended finer scale modeling for management of specific subpopulations. Within the range of the Louisiana black bear, finer scale analyses are limited to Nyland's (1995) evaluation of habitat selection by bears occupying coastal Louisiana, and site-specific habitat evaluations using ad hoc methods. None of these analyses provide a mechanism to predict habitat suitability beyond the area considered. Finer scaled models evaluating the subspecies' extant range have yet to be developed. This is primarily due to the difficulty in developing a model (or models) that spans the diverse range of occupied habitats, and in selecting the appropriate analysis approach.

To assist resource managers with developing black bear recovery plans in Louisiana, I develop resource selection functions (RSF) for two isolated Louisiana black bear populations in South central Louisiana, identified as Coastal and Inland populations (Figure 1.1). A RSF is a function of characteristics measured on resource units such that its value for a unit is proportional to the probability of that unit being used (Manly et al. 1993). From the study area RSF models, I extrapolated model predictions beyond study area boundaries to a larger area being managed for recovery. I used readily available remote sensed data to develop habitat layers as the primary set of predictor variables using a new image processing technique, the at-satellite tasseled cap function. I examined the relative value of habitat variables derived from images captured during different seasons, and for individual and combinations of tasseled cap functions. I also examine the value of using multiple measures of habitat derived at different scales and based on different summary statistics. I critically examined the model building and hypothesis test strategy, and present methods that are compatible with current theory and recommendations.

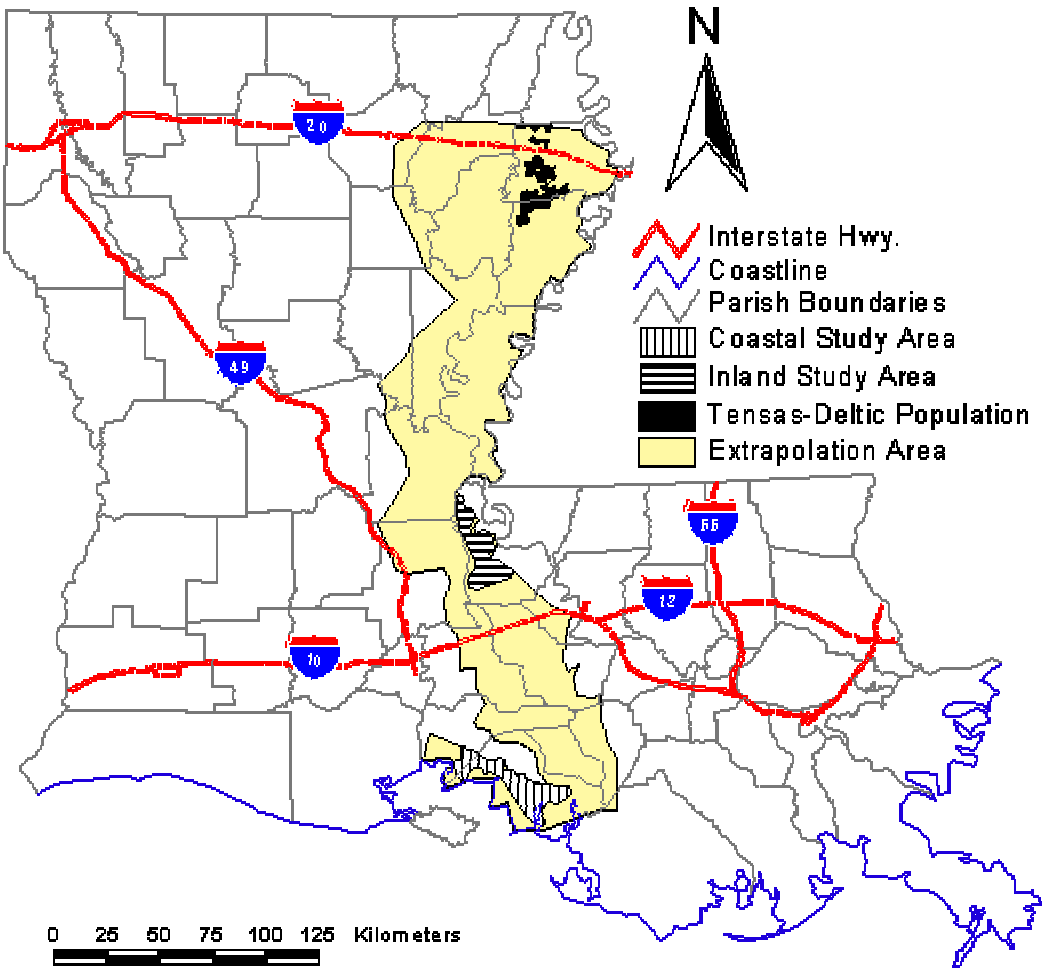


Figure 1.1. Location of extant black bear populations and telemetry study areas in southeastern Louisiana from which resource selections functions were developed. The resource selection function was extrapolated throughout the area indicated within the Mississippi River flood plain.

RESOURCE SELECTION CONCEPTS AND METHODS

Habitat has been defined as the type of place where an animal normally lives, specifically the collection of resources and conditions necessary for its survival. This definition has been extended, by common usage, to mean a set of specific environmental features, that for terrestrial animals, is often equated to a plant community or cover type

(Garshelis 2000). Habitat use is typically understood as the extent to which different vegetative associations or environmental features are used (Garshelis 2000). It is assumed that high quality resources will be selected more than low quality ones, that availability is not uniform, and that use may change with availability (Manly et al. 1993). When resources are used disproportionately, selection has taken place.

Resource selection occurs in a hierarchical fashion from the species' physical or geographic range (first order), to selection of individual home ranges within the geographic range (second order), to the animal's usage of features within its home range (third order), to selection of particular elements such as food items (Johnson 1980). Three designs for resource selection studies have been identified (Thomas and Taylor 1990; Manly et al. 1993), which differ in the level that resource use and availability are measured (population or individual animal). In design 1, measurements are made at the population level (individual animals are not identified), and used, unused or available resource units are sampled or censused. Design 1 studies assume a relationship between density and relative preference, an assumption that is violated if detectability of animals varies among habitats (Thomas and Taylor 1990). With design 2, individual animals are identified and use is measured for each, but availability is measured at the population level. With design 3, individuals are identified as in design 2, but both used and available (or used and unused) resources are sampled or censused for each animal. Inference from designs 1 and 2 are at the population level, or second order selection, where design 3 results in conclusions about selection within home ranges or feeding sites (Thomas and Taylor 1990). Aggregating results across many animals studied under design 3 can result in population level inference about the variability of third order selection among

individuals. However, design 3 does not address the critical question of why the home range was selected (Thomas and Taylor 1990), because the animal's home range represents some prior selection; that is, the animal has already selected a particular area (White and Garrot 1990).

Resource selection studies either categorize habitats or categorize locations (Alldredge et al. 1998). Design 1 studies use categorized habitats, which are typically specific vegetative communities. The challenge in defining discrete habitats is partitioning them into features that animals select, which may not be the ones researchers discern. Sufficient habitat categories must be delineated to ensure that the truly important types are not lumped with less important types that dilute discrimination, while at once avoiding too many types that diminish the power to discern selection (Garshelis 2000). Designs 2 and 3 use either categorized habitats or categorized locations. Categorized location studies use a multitude of habitat-related variables and attempt to identify those variables and their values that best characterize used sites. Landscape scale models have often been limited to a few simple habitat variables, such as land cover type or habitat type (i.e., categorized habitats), but wildlife-habitat relationships are multidimensional and are best studied with multivariate techniques (Morrison et al. 1992). Methods that categorize locations allow testing of hypotheses of habitat characteristics rather than habitat categories and have clearer biological meaning (Alldredge et al. 1998). Regression approaches have predictive capabilities but have additional constraints (Pendleton et al. 1998).

Methods that categorize habitats include Neu et al. (1974), Johnson (1980), Friedman's analysis of variance (Alldredge and Ratti 1986), and compositional analysis

(Aebisher et al. 1993). Methods that categorize locations include logistic regression, linear discriminate function analysis (LDFA), log-linear models, proportional hazard models, and ad hoc methods such as Mahalanobis distance (Manly et al. 1993). Alldredge et al. (1998) reviewed methods of resource selection and concluded that studies that characterize locations seem to require logistic regression, or more generally, resource selection functions (Manly et al. 1993), in which the probability of a resource unit being used is proportionate to the value of characteristics measured for the unit. Resource selection functions provide a model-based approach that is preferable to previously used ad hoc methods (Alldredge et al. 1998). Logistic regression allows exploratory analyses, provides information about the characteristics of habitats that are selected (Alldredge et al. 1998), and allows modeling of both discrete and continuous variables. Disadvantages include the difficulty of incorporating animals as sampling units (Pendleton et al. 1998), problems with highly correlated variables (collinearity), and greater complexity of model fitting relative to the more commonly used ad hoc goodness-of-fit test for categorical data. LDFA is also commonly used in studies that characterize locations. However, LDFA assumes multivariate normality and is limited to use with continuous variables, but it alleviates concerns of collinearity.

Logistic regression and LDFA require measurements of used and available (or unused) resources. The difficulty of defining "available" resources and the impacts on subsequent data analysis has been the subject of considerable discussion (Johnson 1980, White and Garrott 1990, Alldredge and Ratti 1992, Aebischer et al. 1993, Manly et al. 1993, McClean et al. 1998, Garshelis 2000). Including habitats that are unavailable to animals increases chances for Type I errors of resource selection, but excluding habitats

that are available to animals increases chances of Type II errors (McClean et al. 1998). To avoid the difficulty of defining availability, North and Reynolds (1996) used polytomous logistic regression by assigning locations to categories of use intensity. Rather than solving the problem, this approach leads to the question of how to properly define intensity of use, and then how to assign the continuous variable to multiple discrete categories.

In an effort to avoid the problem altogether, Clark et al. (1993) based their habitat model on Mahalanobis distance. The advantage of Mahalanobis distance over other techniques for categorizing locations is that only the set of used resources needs to be correctly defined, eliminating the problems in binary classification techniques caused by misclassification of available habitats (Clark et al. 1993). Mahalanobis distance is determined for a set of derived uncorrelated variables, thus eliminating problems of collinearity among variables found in multiple regression techniques. Multiple habitat configurations can have equal Mahalanobis distance, or dissimilarity to the mean habitat vector, allowing analysis of an infinite variety of habitat measures within a study area. However, Mahalanobis distance does not provide a mechanism for testing which explanatory variables should be included in the model, nor does it provide a mechanism for testing hypotheses about differences in selection among groups or among individuals. Model dependent variables must be selected using other statistical techniques, such as goodness-of-fit (GOF) tests (Clark et al. 1993). GOF testing requires conversion of continuous variables to discrete values, and each type of variable is analyzed separately (e.g., habitat type, distance class from roads). Multiple testing inflates type I error rates and fails to consider the multivariate nature of the selection process. In spite of these

limitations, Mahalanobis distance is an attractive method for developing GIS based habitat maps because it avoids the issue of defining availability and its comparatively easy to implement in GIS.

In addition to error sources previously discussed, measurement of habitat use and data processing may also introduce bias into the analysis. Measurement of habitat use can introduce bias into the analysis of habitat selection if differential detection probabilities exist among habitats (Neu et al. 1974, Schooley and McLaughlin 1992), or if radio-telemetry is used to obtain used locations, especially triangulation (White and Garrott 1986, 1990). Estimated animal locations must be precise relative to the scale of resource selection. As location error increases relative to the scale of selection, power to detect selection decreases (White and Garrott 1986). Further, if misclassification error rates are not constant among habitat types, both power and type I error rates are not predictable (Pace 1988). Several methods have been proposed to improve estimates of use from locations with telemetry errors (White and Garrott 1986, Nams 1989, Samuel and Kenow 1992). Waller and Mace (1998) accounted for telemetry error by reduced habitat complexity. They assigned the dominant cover type within a surrounding moving window equal to the size of the error. This process is easy to accomplish in GIS but can risk missing identification of small patches and linear features that may be very important to the animal.

Bias may also result from inappropriate data pooling during sampling or analytic procedures. The appropriate subjects of design 2 and 3 studies are the individual animals, not each location. Analysis involving more than one animal must allow for among-individual differences, assume that animals select resources similarly, or draw inferences

about average selection at the population level (Aebischer et al. 1993, Alldredge et al. 1998). Pooling data among animals may constitute pseudo-replication (Hurlbert 1984) and should be avoided if possibel. In cases where animals are unequally sampled, pooling data among animals could strongly affect results if all individuals did not make similar selections (White and Garrot 1990, Garshelis 2000). Problems with pooling across years (Schooley 1994) and seasons (Thomas and Taylor 1990) have also been reported.

In a review of methods for the study of resource selection, Alldredge et al. (1998) state, "the choice of a method is complex and sometimes controversial". The goal of this research project is to navigate these challenges and to produce a map of habitat selection for Louisiana black bears that will be useful in directing efforts to recover the species. I develop a resource selection function to estimate the relative probability of a habitat being selected based on observed use in the Coastal and Inland black bear populations using readily available data layers and landscape scale land cover data. Habitat was developed from Landsat imagery using methods that may be applied to other areas and time periods.

DISSERTATION ORGANIZATION

I have organized this dissertation into 6 Chapters as follows:

- Chapter 1 – (this chapter) provides an introduction to the concepts of resource selection function and describes overall study goals.
- Chapter 2 - describes the at-satellite tasseled-cap image processing technique used to develop the habitat variables that will be the primary predictive variables in all

subsequent analyses. Examples relating these unitless measures to tangible resources are provided.

- Chapter 3 – describes the conversion of the at-satellite tasseled cap functions to habitat variables, and examines the derived habitat variables for differences in available resources between the two study areas. Also examines differences in used resources between study areas and among individual bears and seasons.
- Chapter 4 – outlines the overall analysis process used to test a set of *a priori* hypothesis and to develop predictive resource selection function models. The "traditional" approach to model building is presented and critically examined, and an improved strategy is outlined that is consistent with current recommendations on model selection using the information theoretic approach (Burnham and Anderson 1998).
- Chapter 5 - examines a set of *a priori* hypotheses addressing questions of scale, model complexity, and the relative value of groups of habitat variables.
- Chapter 6 – describes development of predictive models that are used to extrapolate RSFs within the boundaries of each study areas, and I present a method to apply the study area-specific RSFs beyond study area boundaries. I also use the development of habitat selection predictions in south central Louisiana to explore issues of model calibration and validation for RSFs developed from used/available data. In addition to RSFs, I identified suitable resource units based on statistical distance (Mahalanobis distance) and compared those results with RSF predictions.

CHAPTER 2: THE TASSELED CAP FUNCTION AS A TOOL FOR WILDLIFE MANAGERS

INTRODUCTION

Wildlife managers frequently apply their craft to wildlife populations on multiple use lands where some uses compete for resources with managed populations. To effectively manage wildlife populations in multiple use settings, managers must have an understanding of habitat requirements and how changing resource availability will affect managed populations. Habitat selection models have been used extensively in recent years to address animal resource use/management questions for species of interest, particularly important game species and species listed under the U.S. Endangered Species Act of 1972. Increased computing power and advances in geographic information systems (GIS) and image processing have enhanced the ability of wildlife managers to expand their spatial-temporal scale when considering an animal's resource needs.

Remotely sensed data, such as satellite imagery, are available and can be used to investigate multi-temporal, landscape-scale animal resource questions but historically were expensive to acquire, required great skill and effort to process, and sensor data were used to create habitat category patch maps that had limited comparability from one project to the next as each researcher had their own processing methodology and land cover/habitat classification scheme. Additionally, researchers attempting to work with data from different time periods and over large areas had limited methods to remove the inherent differences resulting from satellite platform, drift in sensor calibration, season, and time of day (Huang et al. 2002a).

The recent formation of the Multi-Resolution Land Characteristics (MRLC) consortium, as well as advances in GIS technology and image processing method, overcame many of the limitations listed above. MRLC (http://www.epa.gov/mrlc/) is a cooperative effort among six federal agencies that began in 1992. The MRLC consortium makes standard geometrically and radiometrically corrected Landsat Thematic Mapper (TM) data for the conterminous U.S. available to state, local, and federal agencies and their affiliates at minimal costs (approximately $50-$100/scene [a scene covers an area about 180 km square, or 3.2 million hectares]). These data were the primary data source for GAP analysis (Loveland and Shaw 1996).

Landsat 4 and its successor satellites have been developed with radiometric sensors useful in discriminating landscape features at scales > 30 m^2. In particular an array of sensors collects 6 bands of data representing reflected/emitted electromagnetic energy from the visible, reflective-infrared, middle-infrared, and thermal-infrared regions of the spectrum. The at-satellite tasseled cap function, provides a standardized methodology to compress the six bands of Landsat Thematic Mapper (TM) data into 3 bands that explain the majority of variability in the data, are oriented along biologically interpretable axes, and are comparable in space and time (Huang et al. 2002a). Although the process to convert raw Landsat data to at-satellite tasseled cap functions requires a fairly sophisticated level of image processing skill, comparable to other classification techniques, the subjective art of extracting land cover/habitat categories is replaced with an objective, repeatable process, providing consistent results across large spatial and temporal extents and among researchers/managers. In this chapter, I provide some background information on the at-satellite reflectance tasseled cap function, and examine

the distribution of these data within the geographic range of black bears (*Ursus americanus*) in Louisiana as an example.

Tasseled Cap Function

Because of the complexity of displaying and extracting information from multi-spectral satellite data such as the six reflective TM bands, and the fact that the TM visible bands are highly correlated, it is desirable to compress those data into fewer meaningful variables. The tasseled cap transformations, so called because the shape of the transformed function in multivariate space resembles a tasseled cap, perform such a compression. The tasseled cap function is a linear transformation that rotates data into three new axes directly correlated to selected physical properties of vegetation, and captures 95% or more of the total data variability in bands 1-5 and 7 of Landsat TM scenes dominated by vegetation and soils (Crist et al. 1986). The three data dimensions or axes are referred to as brightness, greenness, and wetness, and are orthogonal to each other (Crist et al. 1986). Brightness is a weighted sum of all six bands, measures overall reflectance, and was originally used to differentiate light from dark soils. Greenness is a contrast between near-infrared and visible reflectance and serves as an index of vegetative cover density and vigor (i.e. biomass), similar to other, better known, vegetation indices such as NDVI. However, most of the other vegetation indices are based on only 2 rather than 6 TM bands. Wetness is a contrast between shortwave-infrared and visible/near-infrared reflectance, providing a measure of soil moisture content, vegetation density, and other scene characteristics (Crist et al. 1986).

The tasseled cap function was originally developed to understand important phenomenon of crop development in spectral space (Kauth and Thomas 1976), but has

the potential for identifying a number of other features (Figure 2.1). The tasseled cap contains sufficient information to identify key forest attributes such as species, age, and structure (Horler and Ahern 1986, Cohen et al. 1995, Hansen et al. 2001).

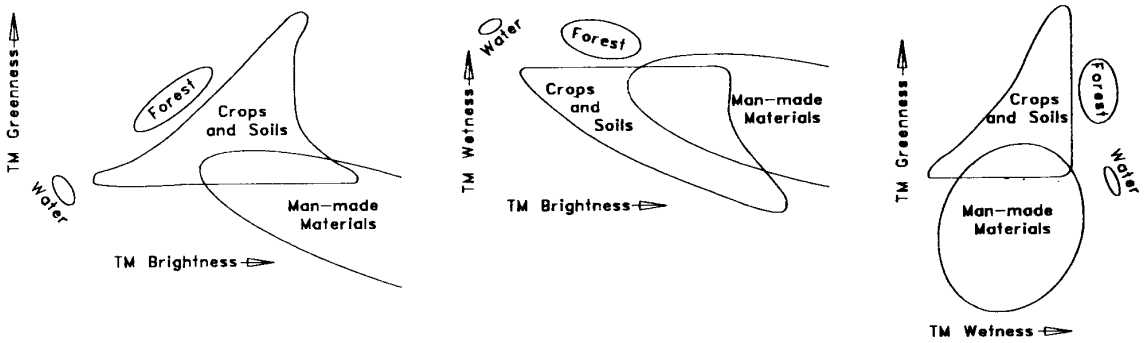


Figure 2.1. Approximate locations of important scene classes in TM tasseled cap feature space (source: Crist et al. 1986, with permission).

Something similar to the tasseled cap could be derived using Principal Components Analysis (PCA), a commonly used statistical technique to achieve data compression (Johnson and Wichern 1992). PCA creates new variables as weighted sums of the original data. Typically the first few components explain the majority of the variability in the data, with the first component explaining the largest fraction of the variability and each subsequent component explaining less than the preceding component (Johnson and Wichern 1992). PCA, like the tasseled cap transformation, transforms the data to a new coordinate system but unlike the tasseled cap function PCA axes are guaranteed to be orthogonal to one another. PCA was the inspiration for the tasseled cap, and brightness, greenness, and wetness roughly correspond to the first three principal components derived from TM data. However, the tasseled cap transformation has several

advantages over PCA. PCA is data dependent. That is, the weight coefficients that are applied to each TM band change from scene-to-scene, which makes consistent interpretation of PC images difficult. PCA is computationally expensive for large images or for many spectral bands. Although the tasseled cap is a linear transformation like PCA, the weight coefficients are fixed for a given sensor based on pre-defined characteristics.

Because of the intuitive appeal of tasseled cap functions and the fixed nature of the weight coefficients, several wildlife researchers have used tasseled cap functions in recent years as "pseudo-habitat" measures in lieu of the more traditional classified habitat maps to develop habitat selection models. For example, Mace et al. (1999), and Clevenger et al. (2002) have successfully used indices from the tasseled cap transformation to evaluate resource selection for bears. Most researchers that have used the tasseled cap transformation for resource selection studies have used greenness and wetness and ignored brightness, probably because its name implies a biological interpretation that is less straightforward. However, a large fraction of the variability in the TM data is incorporated into brightness. Relating the tasseled cap to PCA, this would be like discarding the first component, which contains the most information, and which might provide information important to partitioning spectral space into resource components important to the animal being studied. Few have explored the relative value of each tasseled cap function prior to selecting the components to be modeled, the seasonal variability in the information content of the tasseled caps, or the value of multitemporal data to identify resource selection.

At-satellite Reflectance Tasseled Cap

To use satellite imagery collected at different times, across mosaics of images (or scenes), or collected by different sensors, it is necessary to convert the Digital Numbers (DN) of commercially available satellite imagery to calibrated radiance values, and to obtain absolute reflectance levels of objects by normalizing solar angles and earth-sun distances by converting radiance to at-satellite reflectance. DNs are positive integers, typically calibrated to fit a range of values such as an 8-bit scale (0-255) by a linear transformation, and represent average brightness or radiance in a limited spectral range measured for a small area (30m x 30m for Landsat TM) on Earth; this value and its relative position are represented as a raster grid cell or pixel. DNs are transformed to radiance by removing the linear transformation, or stretch. To compare data collected at different times of the year, radiance must be further corrected for sun elevation and earth-sun distance. Images that are acquired under different solar illumination angles can be adjusted to one another based on the sun's angle from zenith (directly overhead). The earth-sun distance corrects for seasonal changes in the distance between the earth and sun. Substantial noise can be removed by converting DN to at-satellite reflectance, enhancing consistency of land cover characterization and increasing the temporal information contained in the images (Huang et al. Undated).

Huang et al. (2002a) developed a tasseled cap transformation using at-satellite reflectance values based on Landsat ETM+ (Enhanced Thematic Mapper Plus) data to allow for the use of multi-scene/temporal image sets. Landsat ETM+ data are collected by the Landsat 7 satellite, the most recent in a series of Landsat satellites, launched in 1999. Landsat 5 TM, launched in 1982, was the primary source of satellite imagery

available prior to the launch of Landsat 7. Voglemann et al. (2001) detailed a transformation of Landsat 7 ETM+ at-satellite reflectance values to Landsat 5 equivalents. Huang et al. (2002b) provided the reverse transformation, Landsat 5 TM values to Landsat 7 ETM+ equivalents based on Voglemann et al. (2001) coefficients.

Because the Louisiana bear data presented in this case study were collected during 1991-1995, and 1993 satellite imagery from Landsat 5 was used to investigate bear resource use, I discuss the steps to process Landsat 5 TM data to at-satellite reflectance below and compare the performance of at-satellite reflectance tasseled cap with expected values.

STUDY AREA

Bears in Louisiana are distributed among three isolated sub-populations located within the Mississippi River floodplain (U. S. Fish and Wildlife Service 1995). Bottomland hardwood forests that historically dominated the drier portions of the floodplain have for the most part been cleared for agriculture leaving forested islands and swamps that extant bear populations inhabit. The climate is warm and humid, with monthly average temperatures ranging from 10.8^{o} C (January) to 27.6^{o} C (July and August), and monthly precipitation averages from 8.4 cm (October) to 15.5 cm (August) (Evans et al. 1983).

Telemetry studies were conducted in 2 areas of south central Louisiana that are labeled Coastal and Inland (Figure 2.2). In spite of their close proximity, Coastal and Inland land cover differ greatly. Based on USDA Forest Service Forest Inventory and Analysis (FIA) data, 27% of Inland was un-forested, primarily cleared for cropland. Forest consisted of three types: 1) 64% sweetgum – Nuttall oak – willow oak

(*Liquidambar styraciflua – Quercus michauxii – Quercus phellos*), 27% sugarberry – American elm - green ash (*Celtis laevigata - Ulmus americanus - Fraxinus pennsylvanica*), and 3) 9% Cottonwood (*Populus deltoides*). Coastal was 65% un-forested. However, coastal marsh, scrub-shrub habitats, or other uncultivated vegetative cover of non-merchantable timber covered much of that area. Coastal forest types were baldcypress - water tupelo (*Taxodium distichum - Nyssa aquatica*)(43%), sweetbay - water tupelo - red maple (*Magnolia virginiana – Nyssa aquatica - Acer rubrum*) (29%), sugarberry – American elm - green ash (14%) and willow (*Salix* spp.) (14%).

Essentially two habitat types were available to Inland bears: seasonally flooded bottomland hardwood stands that varied in vegetation structure and composition according to harvest patterns and wetness, and agricultural crops, primarily corn and winter wheat. In Coastal, food and cover resources were disproportionately distributed among numerous habitat types (Nyland and Pace 1997) ranging from inundated swamps, scrub-shrub habitats and marshes to upland cover types on four salt domes that rise more than 30 m from the surrounding wetlands. The only Coastal agricultural crop was sugarcane, which was eaten by bears in fall.

METHODS

Data Development

Data development consisted of five steps: 1) identify available habitat, 2) establish random sample points within the available habitat, 3) identify forested patches within available habitat, 4) develop at-satellite reflectance tasseled cap functions to provide data coverage extending over both study areas, and 5) extract tasseled cap values

at sample points. I used 1993 TM satellite imagery obtained through the MRLC consortium for all image analyses described below.

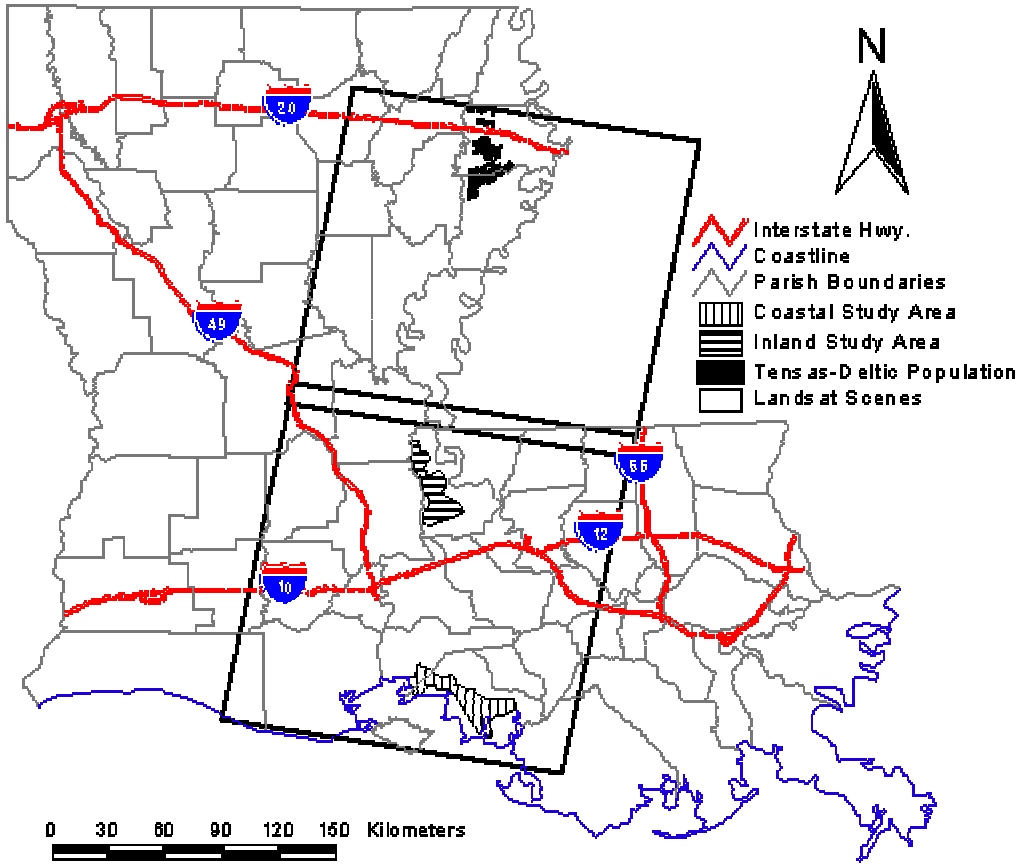


Figure 2.2. Location of the telemetry study areas in south central Louisiana and Landsat scene coverage. The northern image is 024/038 (row/path) and the southern image is 024/039.

Identify Available Habitat - I wanted to examine tasseled cap response within habitats occupied by bears in the two telemetry study areas. To limit my focus to areas known to be occupied by bears, I defined available habitat based on the distribution of capture and radio telemetry locations of bears. Beginning in December 1991 in Coastal, and in June

1992 in Inland, bears were located approximately weekly from aircraft (Wagner 1995). Locations were digitized from maps and stored as Universal Transverse Mercator (UTM) coordinates. These data were converted to GIS maps in ArcView 3.2. Between October 1991 through May 1995, 2,061 locations (capture locations and telemetry) were collected on 49 female bears. However, 28 females bears, 18 Coastal and 10 Inland, had 30 locations or more each, accounting for 1,915 of 2,061 (93%) locations. All locations were used in this analysis. To define a border area around these locations available to bears (available habitat), I delineated a composite buffer around telemetry locations for female black bears in each study area. The buffer radii around individual telemetry locations were based on the mean interlocation distance for female bears in each area (Wagner 1995; 1.06 km Coastal and 2.2 km Inland; average of spring-summer and fall interlocation distance means 1992-1994). This buffer represents a conservative estimate of the area that could have been used given the movement pattern (extent) observed by these animals, as nearly half the time animals move farther between locations than specified radii.

Establish Random Sample Points - Within the available area, defined above, separate samples equal to 1%, 3.5% and 5% of the available 30x30m pixels were obtained using systematic sampling with random point placement using the Sample extension to ArcView 3.2 (Quantitative Decisions, http://www.quantdec.com). Grids cells of approximately 300, 160, and 134 m square, representing 1%, 3.5% and 5% samples respectively, were established in each study area using a random starting point, and a pixel within each grid cell was selected at without replacement and with equal likelihood. A simple random sample of available habitat is often used to describe available resources

for habitat selection analysis with continuous data, although systematic (grid) samples are more effective than simple random or stratified random samples (Hirzel and Guisan 2002). Systematic grid placement with random point or pixel selection within grid cells achieves the superior spatial coverage provided by a purely systematic sampling scheme while maintaining an element of random selection (i.e., each pixel within each grid cell has equal probability of being selected).

Identification of Forested Areas - Black bears are forest dwelling animals (Kolenosky and Strathearn 1987). Accordingly, I was particularly interested in tasseled cap values in forested habitats. To isolate tasseled cap values from forested habitats for further examination, I used Louisiana GAP maps (http://sdms.nwrc.gov/gap/gap2.html). GAP maps were classified into 23 land cover categories using Landsat TM imagery collected between January and March 1993 with one November 1992 scene. Gap maps are a relatively coarse landscape land cover classification (Table 2.1) that I reclassified into either forested or unforested landcover. To eliminate numerous small streams ($\leq$ 30 m wide), classified in GAP data that create divisions in the forested patches and small (<2.2 hectares) isolated forested and unforested patches, I used a 210 m x 210 m (7 x 7 pixel) moving window mode filter. I overlaid major roads (identified as "Primary" and "SECOND" coverages on *Louisiana Oil Spill Contingency Plan Map CD, Version 1*, Louisiana Applied Oil Spill Research and Development Program, Louisiana State University, Baton Rouge, LA) into the forest layer to divide forested patches bisected by major roadways. I used IDRISI 32 (Clark Labs, Worcester, MA) for all raster image processing. I converted the raster image of forested patches to vector data for use in ArcView 3.2.

Table 2.1. Louisiana GAP original habitat categories (Hartley et al. 2000) and forest/unforested reclassification assignments.

Original Category Number	Original Category	New Category Number	New Category
1	Fresh Marsh	0	Un-forested
2	Intermediate Marsh		
3	Brackish Marsh		
4	Saline Marsh		
5	Wetland Forest – Deciduous	1	Forested
6	Wetland Forest – Evergreen		
7	Wetland Forest – Mixed		
8	Upland Forest – Deciduous		
9	Upland Forest – Evergreen		
10	Upland Forest – Mixed		
11	Dense Pine Thicket		
12	Wetland Scrub/Shrub – Deciduous	0	Un-forested
13	Wetland Scrub/Shrub – Evergreen		
14	Wetland Scrub/Shrub – Mixed		
15	Upland Scrub/Shrub – Deciduous		
16	Upland Scrub/Shrub – Evergreen		
17	Upland Scrub/Shrub - Mixed		
18	Agriculture – Cropland – Grassland		
19	Vegetated Urban		
20	Non-Vegetated Urban		
21	Wetland Barren		
22	Upland Barren		
23	Water		

Within the Coastal study area, 55% (2539 of 4654) of random locations were in forest, versus 76% of telemetry locations (963 of 1263). A similar association of telemetry locations with forest was observed in the Inland study area, with 42% (1744 of 4186) of random locations in forest, versus 88% of telemetry locations (710 of 806). This represents a clear association between bears in both areas and forested habitats (Coastal Pearson's Chi-square = 193.5, df = 1, $P < 0.01$; Inland Pearson's Chi-square = 582.9, df = 1, $P < 0.01$).

Tasseled Cap Development - I acquired geo-referenced, terrain corrected Landsat TM satellite imagery (30m resolution) from the U.S. Geological Survey, EROS Data Center (Sioux Falls, South Dakota, USA) for 2 scenes covering the study area (Path/Row 023/038 and 023/039) for the fall (29 September) and spring (22 April), 1993. I purchased the raw 7-band imagery made available through the Multi-Resolution Land Characterization (MRLC) consortium (Loveland and Shaw 1996). I selected these images because the dates of image capture were comparable to the time span over which the telemetry data were collected and the imagery was an exceptional value ($50 U.S./scene/season). These data were collected using the Landsat 5 satellite.

To facilitate comparison among scenes/seasons, I used at-satellite reflectance tasseled cap transformation based on a combination of methods similar to those currently being used by MRLC[1] (Huang et al. 2002b, Huang pers. comm.). The steps in the process are outlined in Figure 2.3, and include the steps to produce at-satellite tasseled cap functions for Landsat 7 ETM+ data. I transformed Landsat 5 TM raw DN (DN5) to Landsat 7 equivalents (DN7hat), based on a process developed by Vogelmann et al. (2001), and the alternative formulation presented in Huang et al. (2002b). The transformation uses the following equation:

$$\hat{DN7}_{\lambda} = (DN5_{\lambda} \times slope_{\lambda}) + intercept_{\lambda}$$

where λ represents TM band number 1-5 and 7. The coefficients used to transform DN5 to DN7hat are provided in Table 2.2.

[1] For Landsat 5 TM data collected after May 5, 2003, see also Chander and Markham (undated).

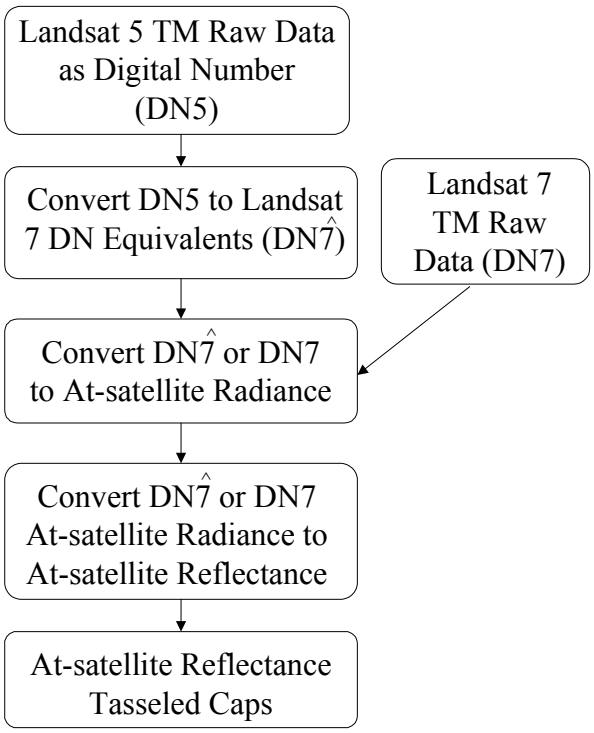


Figure 2.3. Process to convert Landsat data to at-satellite reflectance tasseled caps.

DN7hat for each band was transformed to at-satellite reflectance by converting DN7hat to at-satellite radiance and then adjusting for solar angle and earth-sun distance using the following formula:

$$L_\lambda = (Gain_\lambda * DN_\lambda) + Bias_\lambda$$

$$\rho_\lambda = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN_\lambda \cdot \sin(\theta)}$$

where:

λ = ETM + /TM band number

L = at-satellite radiance

gain = an element of band specific adjustment of DN to radiance from Table 2.3

bias = an element of band specific adjustment of DN to radiance from Table 2.3

ρ = at-satellite reflectance, unitless

d = Earth-Sun distance in astronomical unit, derived by interpolation of Table 2.4.

ESUN = Mean solar exoatmospheric irradiance from Table 2.5 (Irish 2000).

θ = Sun elevation angle, provided in the scene's header file.

Table 2.2. Coefficients to transform Landsat 5 DN to Landsat 7 ETM+ equivalents. (Source: Huang et al. 2002b).

Band # (λ)	Slope	Intercept
1	0.9398	4.2934
2	1.7731	4.7289
3	1.5348	3.9796
4	1.4239	7.0320
5	0.9828	7.0185
7	1.3017	7.6568

Table 2.3. Gain and bias values to convert DN7hat to at-satellite radiance. (Source: Huang et al. 2002b).

Band#	Gain	Bias
1	0.7756863	-6.1999969
2	0.7956862	-6.3999939
3	0.6192157	-5.0000000
4	0.6372549	-5.1000061
5	0.1257255	-0.9999981
7	0.0437255	-0.3500004

Table 2.4. Earth-sun distance in astronomical units. (Source: Irish 2000)

Julian Day	Distance	Julian Day	Distance	Julian Day	Distance	Julian Day	Distance	Julian Day	Distance
1	0.9832	74	0.9945	152	1.0140	227	1.0128	305	0.9925
15	0.9836	91	0.9993	166	1.0158	242	1.0092	319	0.9892
32	0.9853	106	1.0033	182	1.0167	258	1.0057	335	0.9860
46	0.9878	121	1.0076	196	1.0165	274	1.0011	349	0.9843
60	0.9909	135	1.0109	213	1.0149	288	0.9972	365	0.9833

Table 2. 5. ETM+ solar spectral irradiances, or *ESUN*, to convert at-satellite radiance to at-satellite reflectance. (Source: Irish 2000)

Band#	watts/(meter squared * μm)
1	1969.000
2	1840.000
3	1551.000
4	1044.000
5	225.700
7	82.070
8	1368.000

After calculating at-satellite reflectance, I validated that image processing worked as expected. Within seasons, in the area of scene overlap, I cropped pairs of sample images of matching areas from each scene-band, and regressed one image on the other. If image processing worked as expected, an intercept of 0 and a slope of 1 would be observed. I also selected a sample of pseudo-invariant objects, such as large parking lots and deep water (Huang et al. Undated), to compare across seasons. If image processing worked as expected, pseudo invariant objects would be expected to have the same value across seasons. Intercept and slope values for 023/038 fall and 023/039 fall were close to expected values, but 023/038 spring versus 023/039 spring were not (Table 2.6). Further investigation into differences in pseudo-invariant objects indicated that the problem was with 023/039 spring image. The selected sample of pseudo-invariant objects averaged 97% agreement between 023/038 spring and fall scenes, but only 82% between 023/039 spring and fall scenes. Communications with C. Huang, USGS, confirmed that this level of variability was much greater than expected. Discussions with EROS Data Center confirmed that the problem was with that image and that they were unable to reprocess the image to correct the problem, and that a substitute image was not available from MRLC. Accordingly, to remove the processing error, I modeled the relationship between

023/038 spring and 023/039 spring (the problem image) by extracting three matching pairs of images from the area of overlap and regressing 023/038 spring on 023/039 spring for each band. I attempted to capture the range of values in each band in each overlap sample. The results of the three separate regressions for each band were averaged and then were applied to 023/039 spring to obtain 023/038 spring equivalents (C. Huang pers. comm.).

Table 2.6. Results of regressing matching pairs of images extracted within seasons, in the area of scene overlap, from each scene-band.

023/038 Fall vs. 023/039 Fall

Band#	Intercept	Slope	r
1	0.000835	0.974537	0.99
2	0.000898	0.970757	0.99
3	0.000267	0.977798	1.00
4	-0.000028	0.983251	1.00
5	-0.000294	0.984549	1.00
7	0.000042	0.981375	1.00
Average	0.0002867	0.978711	0.99
Expected	0	1	1.00

023/038 Spring vs. 023/039 Spring

Band#	Intercept	Slope	r
1	0.009423	1.148190	0.98
2	0.007182	1.121899	0.98
3	0.003997	1.274987	0.99
4	0.003989	1.117046	0.99
5	0.002785	1.122103	0.99
7	0.001556	1.176051	0.99
Average	0.004822	1.160046	0.99
Expected	0	1	1.00

Following adjustment of 023/039 spring, the at-satellite reflectance tasseled cap function was calculated for each image using weight coefficients in Table 2.7 (Huang et

al. 2002a and 2002b). Images were then cropped to an area surrounding the study areas and mosaics were created for each season. I used Idrisi32 v.I32.22 (Clark Labs, Clark University, Worchester, Massachusetts, USA) for all image processing.

Analysis

Effect of sample size - I extracted the value for each tasseled cap for each of the three sets of random points (1%, 3.5% and 5% samples), and their distributions were compared visually using Loess smoothed empirical density functions (EDF). Because smaller sample sizes require less computer overhead, their use would be advantageous provided that the smaller sample sizes did not eliminate low frequency values or alter the shape of the EDF.

Table 2.7. Coefficients to convert at-satellite reflectance to tasseled caps. (Source: Huang et al. 2002a).

	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.35612057	0.39722874	0.39040367	0.69658643	0.22862755	0.15959082
Greenness	0.33438846	0.35444216	0.45557981	0.69660177	0.02421353	0.26298637
Wetness	0.26261884	0.21406704	0.09260517	0.06560172	0.76286850	0.53884970

Assessment of At-satellite Tasseled Cap - To access how well the at-satellite tasseled cap normalized image noise, I compared each tasseled cap in the area of overlap visually. Any differences would be obvious at the seam where the overlapping images were joined (Huang et al. Undated). I also assessed between scene differences by regressing matching pairs of images extracted within seasons, in the area of scene overlap, from each tasseled cap, and by comparing pseudo-invariant objects between seasons and across images. If image processing worked as expected, an intercept of 0 and a slope of 1 would

be observed, and pseudo-invariant objects would be expected to have the same value across seasons. Images of each tasseled cap in each study area are presented in the Appendix.

To gain insight into the information contained in each at-satellite tasseled cap, and to compare its performance with the theoretical performance of the tasseled cap as presented by Crist et al. (1986), I selected the following land cover features: water, developed (industrial sites or large paved areas), agricultural areas ("Ag"), coastal marsh, dry forest, and wet forest. Dry forest and wet forest are relative terms, and separate the more upland from more inundated forest in the study area. I sampled between 10 and 30 locations for each feature throughout the combined images and determined "typical" values (an informal median) for each feature in both seasons and graphed them using tasseled cap combinations comparable to those presented in Figure 2.1.

To examine the information content of the at-satellite tasseled cap function, I generated EDFs for each study area as a whole and for their forested areas only. Using the random locations within the forested portions of each study area, I determined the linear relationship among the at-satellite tasseled cap components using Pearson's correlation coefficients and developed separate correlation matrices for each area.

RESULTS

The Coastal and Inland study areas contain 42,057 and 37,644 hectares of land, respectively and all is assumed potentially available for bears to use. The 1% random sample consisted of 4,654 Coastal and 4,186 Inland locations. Comparison of EDFs among the 1%, 3.5% and 5% samples for each area-season-tasseled cap component were

virtually indistinguishable, so to lessen the demands on computer resources, the 1% sample data were used in all subsequent analyses using the random locations.

I compared each tasseled cap visually at the seam where the overlapping images were joined to access how well the at-satellite tasseled cap normalized image noise, and if the adjustment of the 023/039 spring image was successful. The seams created by the overlapping spring images and the overlapping fall images were undetectable indicating that there was little noise between the scenes and successful adjustment of the 023/039 spring image. The results of regressing matching pairs of images extracted within seasons, in the area of scene overlap, from each tasseled cap also indicated a successful tasseled cap transformation (Table 2.8), and pseudo-invariant objects between seasons and across images were comparable.

Table 2.8. Results of regressing matching pairs of images extracted within seasons, from scene overlap for each tasseled cap.

023/038 Vs. 023/039 Fall

Tasseled Cap	Intercept	Slope	r
Brightness	0.003	0.973	0.989
Greenness	0.000	0.975	0.992
Wetness	-0.000	0.981	0.996

023/038 Vs. 023/039 Spring – Post Correction

Tasseled Cap	Intercept	Slope	r
Brightness	0.013	0.957	0.991
Greenness	0.004	0.955	0.990
Wetness	-0.002	0.978	0.992

Figure 2.4 plots the value of pairs of at-satellite tasseled caps for selected land cover features in each season. The format of the graphs is the same axis layout as used by Crist et al. (1986) to facilitate comparison with Figure 2.1 above. Figures 2.5 and 2.6

present EDFs for each study area as a whole and for forested areas only. The EDFs show the distribution of the data, allowing visual comparison with statistical distributions, and shows how the distribution of the data change seasonally and when only forested areas are considered. Table 2.9 presents the correlation matrices for each area, which indicates the direction and strength of the linear relationship between pairs of tasseled cap components, both within and across seasons.

a.

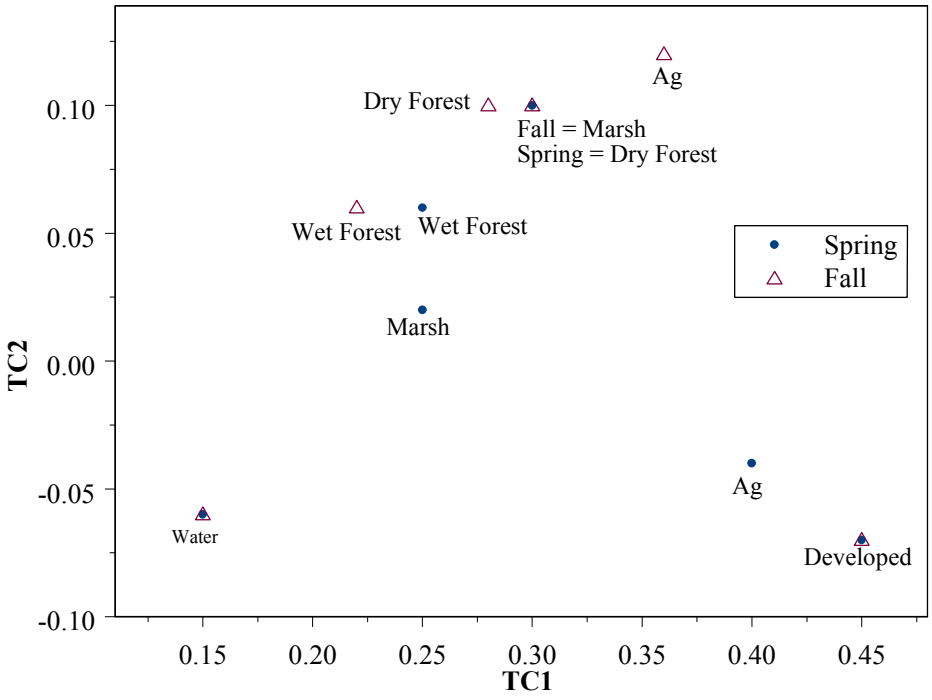
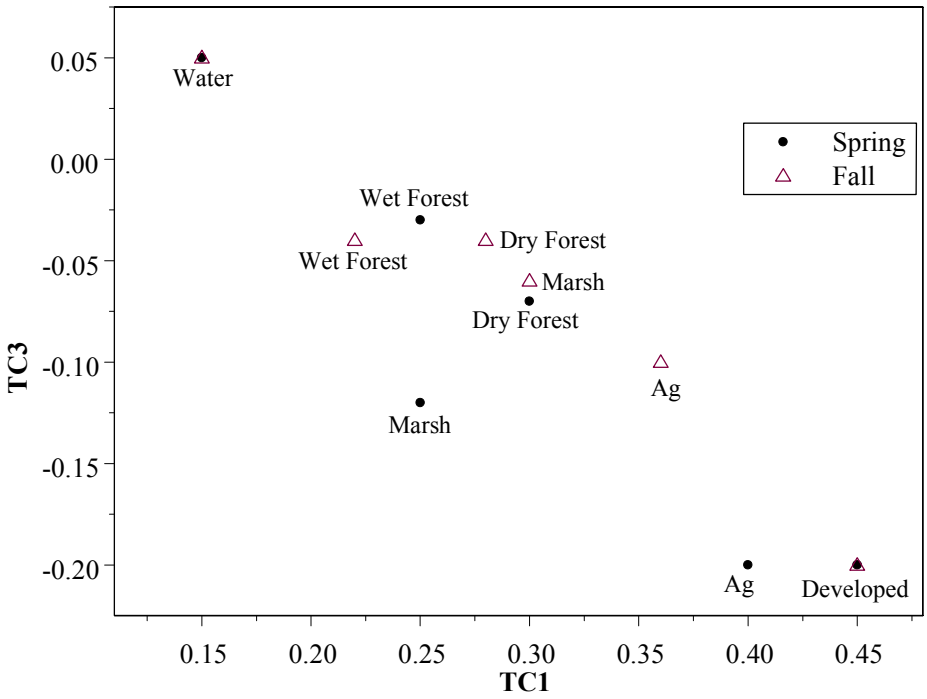


Figure 2.4. Typical tasseled cap values of selected land cover features in scenes 023/038 and 023/039 captured in spring (April 22) and fall (September 29), 1993.

b.



c.

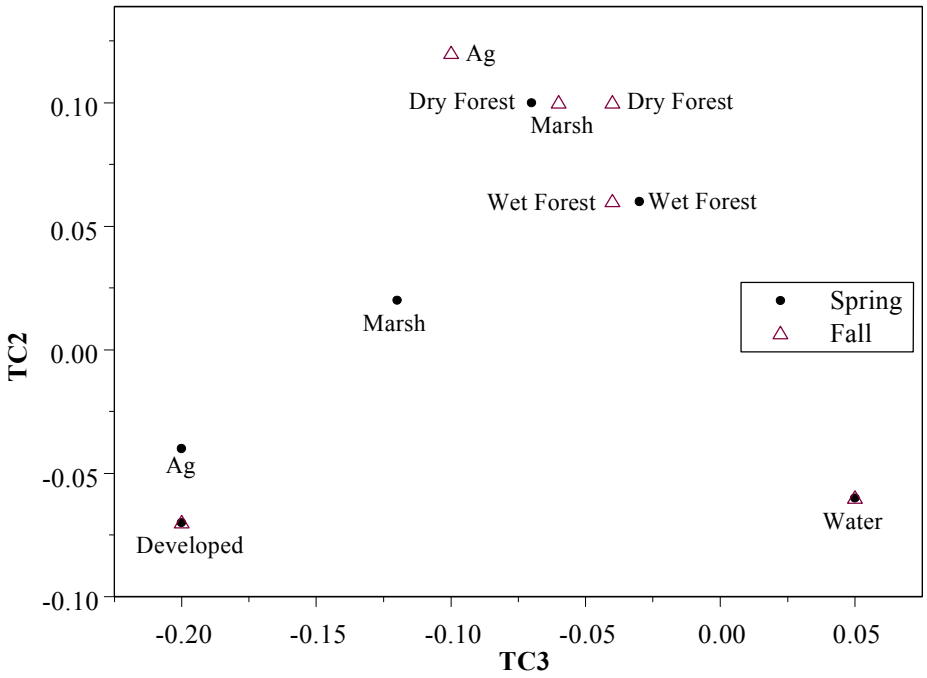
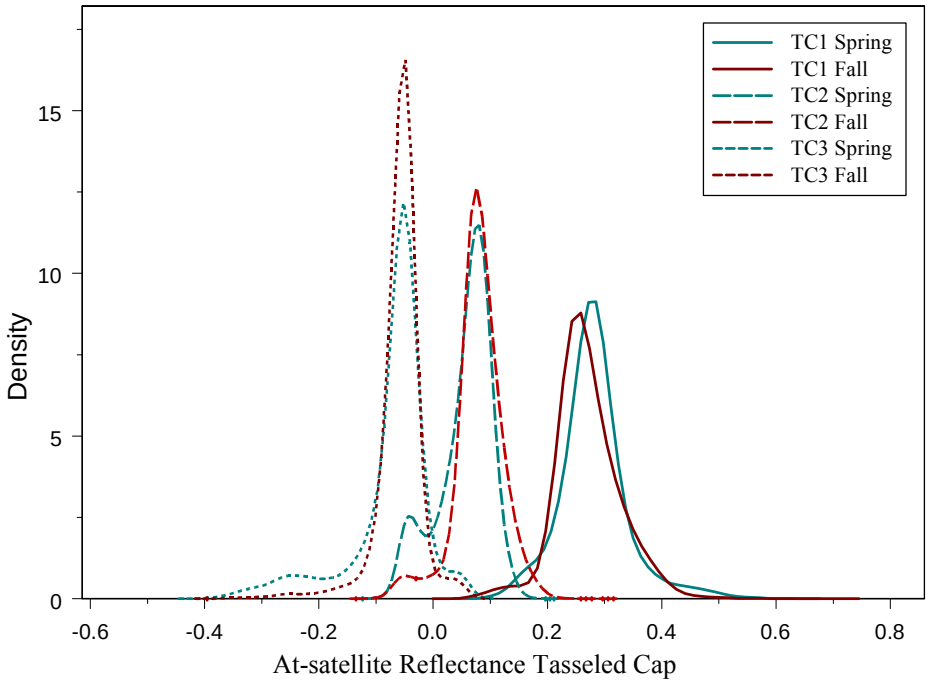


Figure 2.4. Continued.

a.



b.

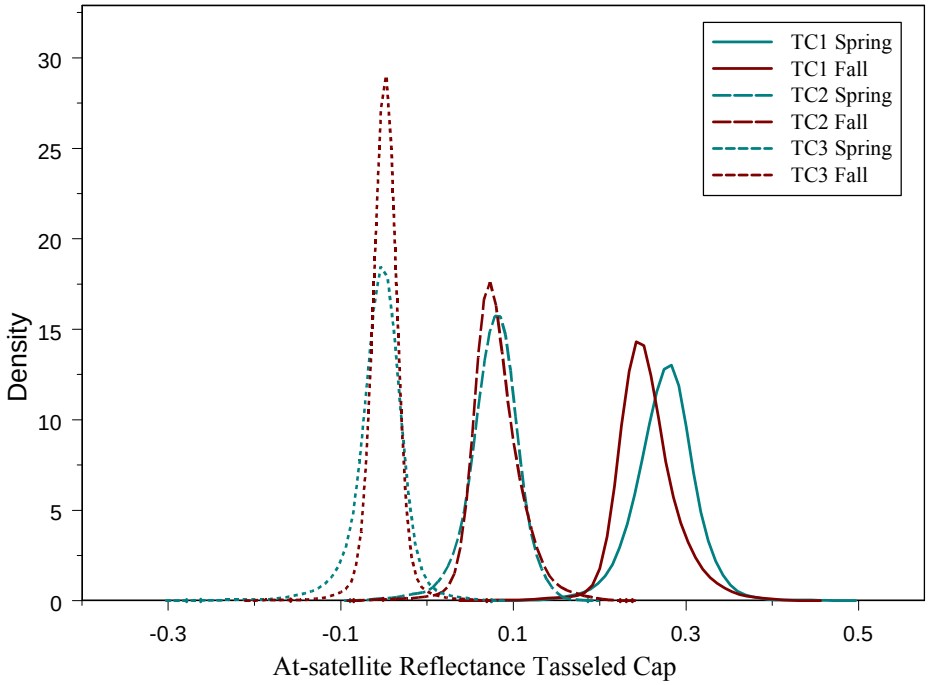
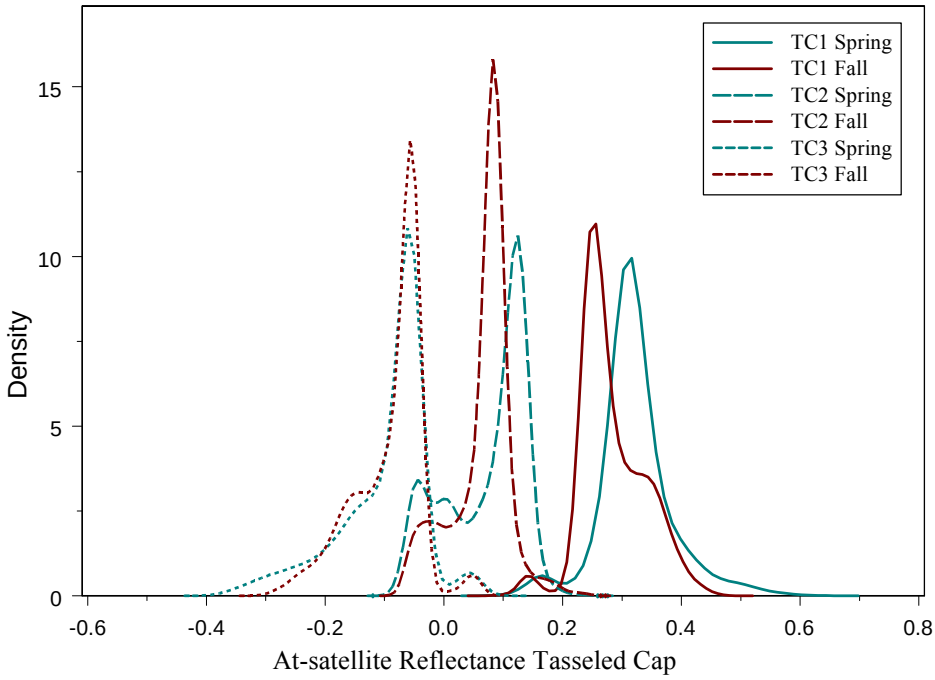


Figure 2.5. Comparison of spring and fall tasseled cap Loess smoothed empirical density functions within the Coastal study area's available habitat a) throughout the area, and b) in forested portions only.

a.



b.

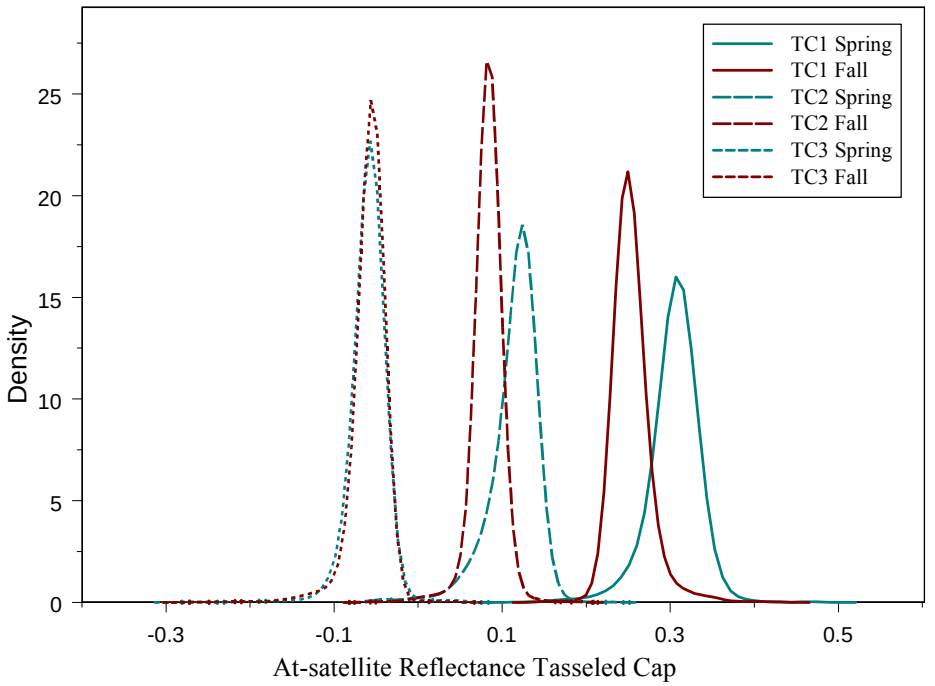


Figure 2.6. Comparison of spring and fall tasseled cap Loess smoothed empirical density functions within the Inland study area's available habitat a) throughout the area, and b) in forested portions only.

Table 2.9. Correlation matrices of tasseled caps in Coastal, and Inland study areas. TC1-3 represents Brightness, Greenness, and Wetness respectively, and S and F represent Spring and Fall respectively.

Coastal

	TC1S	TC2S	TC3S	TC1F	TC2F	TC3F
TC1S	1.00	0.77	-0.72	0.51	0.46	-0.47
TC2S	0.77	1.00	-0.25	0.28	0.42	-0.18
TC3S	-0.72	-0.25	1.00	-0.57	-0.44	0.66
TC1F	0.51	0.28	-0.57	1.00	0.87	-0.64
TC2F	0.46	0.42	-0.44	0.87	1.00	-0.33
TC3F	-0.47	-0.18	0.66	-0.64	-0.33	1.00

Inland

	TC1S	TC2S	TC3S	TC1F	TC2F	TC3F
TC1S	1.00	0.74	-0.52	0.17	0.09	-0.20
TC2S	0.74	1.00	0.07	-0.21	0.20	0.23
TC3S	-0.52	0.07	1.00	-0.39	0.06	0.53
TC1F	0.17	-0.21	-0.39	1.00	0.44	-0.65
TC2F	0.09	0.20	0.06	0.44	1.00	0.29
TC3F	-0.20	0.23	0.53	-0.65	0.29	1.00

DISCUSSION

The at-satellite tasseled cap produced results that were consistent across scenes and seasons. Additionally, selected land cover features were oriented along tasseled cap component axes consistent with expected relationships, and the results were easily interpretable. These results also suggest that use of all three tasseled cap components rather than use of single or dual components, as has been typically used by wildlife researchers, improves the ability to separate land cover/habitat features evidenced by the above biplots (Figure 2.4) and correlation matrices. This analysis also suggests that the use of multi-temporal datasets may improve information content and be useful in identifying selection of certain important resources or separation of overlapping features such as marsh and forest. These hypotheses will be formally tested in Chapter 5. The correlation matrices suggest that some variability in correlations among tasseled cap

components differs by habitat, as evidenced by 1/3 of the correlations changing slope direction (sign of the correlation coefficient) between the two areas. Correlations among tasseled cap components between image seasons were generally less than within seasons also indicating that additional information can be gained by using multi-temporal data.

The EDFs show that each tasseled cap component is from a unimodal, relatively Gaussian distribution, which becomes increasing normal, although leptokurtic, when restricted to data from the forested areas. Accordingly, use of parametric statistics, such as mean and standard deviation to smooth or aggregate values over larger areas or to examine variability among pixels will perform adequately.

The at-satellite tasseled cap offers several advantages over other image processing techniques: it compresses all of the available data into 3 orthogonal components, which explain 95% of the variability in the data, with axes rotated along environmentally interpretable gradients. The process can be applied over large areas and time frames, during different times of the year, and across sensors to produce consistent results that avoid the use or the need to categorize land cover/habitats. The MRLC consortium is making at-satellite tasseled cap image commercially available for a limited number of scenes and plans to increase availability of this product in the future. Researchers and wildlife managers attempting to model animal resource use at landscape scales should consider these data in the place of a course habitat map.

CHAPTER 3: DEVELOPMENT AND PRELIMINARY EXAMINATION OF HABITAT VARIABLES

INTRODUCTION

One of the primary goals of this study was to develop models of habitat selection that could be applied beyond study area boundaries to predict habitat suitability throughout the region, across a range of habitat types, using habitat variables derived from the at-satellite reflectance tasseled caps described in Chapter 2. Because habitat selection is normally implied from the disproportionate use of habitat relative to its availability (Neu et al. 1974, White and Garrott 1990), changes in the availability of resources will usually result in differences in model coefficients and selection. Thus, I wanted to examine the extent of differences between available resources in the 2 study areas. However, I wanted to conduct that analysis in such a way as not to examine the habitat variable's relationship between used and available resources. To do so would compromise the development of *a priori* models and subsequent estimates of variability and test statistic values on the estimates of selection (Burnham and Anderson 1998, Harrell, 2001).

As part of the habitat model development process, I needed to identify the geographic scale at which apparent selection patterns are consistent (i.e., does modeled selection change in response to changing the scale at which habitat variables are measured?) so that I could develop a reasonable set of *a priori* models of habitat selection. I found no published accounts describing how habitat variables derived from satellite imagery change in response to changes in measurement scale. To examine the

scale aspect, I derived at-satellite reflectance tasseled cap means and standard deviations using a range of "moving window" sizes.

In addition to examining issues of scale, I needed to evaluate the adequacy of habitat variables derived from at-satellite reflectance tasseled caps for describing bear habitat use. To evaluate the adequacy of the habitat's specificity (ability to identify resource units selected by the species) and resolution (measurement scale or smallest mappable unit), I examined the extent of differences in used resources between the two study areas, and among seasons and individual bears. I expected some differences in habitat variables if they have adequate resolution and specificity. If I fail to detect differences among habitat variables at used locations, then either the resolution or specificity (or both) is inadequate, or no differences truly exist. I thought the latter hypothesis doubtful, given the observed differences in habitat occupied by individual bears, so if differences are detected, resolution and specificity will be assumed to be adequate for further analysis to develop models of selection.

METHODS

Data Development

Data development consisted of four steps: 1) identify used habitat, 2) identify available habitat, 3) sample the available habitat, 4) develop habitat variables from at-satellite reflectance tasseled cap functions at a range of spatial scales, and extract habitat values at used and available locations. Each of these steps is explained in detail below.

Identify Used Habitat - Beginning in December 1991 in Coastal, and in June 1992 in Inland, fellow graduate students and I located radio-tagged bears approximately weekly from aircraft (Wagner 1995). I assumed temporally adjacent locations were not serially

correlated because intervals between consecutive locations averaged 8.6 days (SD=6.6) (Swihart and Slade 1985). All aerial locations were obtained during daylight hours using methods adopted from Gilmer et al. (1981). While in flight, we plotted locations directly onto 1:24,000 USGS quadrangle maps. I digitized the aerial locations from the flight maps and stored them as Universal Transverse Mercator (UTM) coordinates. These data were converted to GIS maps in ArcView 3.2 (ESRI, Redlands, CA, USA). I assessed aerial location precision by comparing global positioning system (GPS) locations (receiving uncorrected 32 fix average position estimates) of den sites, recovered collars and dummy transmitters (blind to tracker) placed at a set of test locations, to digitized aerial locations. Median location error was 281 m (147 m inner quartile, 417 m outer quartile, n=106).

Between October 1991 and May 1995, we collected 2,061 locations (capture and telemetry locations) of 49 female bears. We recorded 30 or more locations for 28 bears (18 Coastal and 10 Inland), accounting for 1,915 of 2,061 (93%) locations (1151 Coastal locations and 764 Inland locations). Bear locations were distributed across three bear seasons, which I defined based on plant phenology and bear biology as: winter (1 Dec. - 31 Mar.), spring-summer (1 April - 31 July), and fall (1 Aug. - 30 Nov.) (Wagner 1995). Because differences among bears and seasonal use were of interest in this analysis, only those bears with 30 or more locations, with location distributed among all seasons (minimum number of locations in any season was 7) were retained in the set of used locations.

Identify Available Habitat and Establish Random Sample Points - The methods that I used to identify available habitat and to select random sample points are described in

Chapter 2. The same available habitat and random sample point used in Chapter 2 are used in this chapter.

Develop Habitat Measures - I calculated at-satellite reflectance tasseled cap brightness, greenness, and wetness values for Landsat scenes 023/038 and 023/039, captured in fall and spring of 1992, using methods adopted from Huang et al. (2002b, pers. comm.), and described in Chapter 2. I cropped the images to include only the study areas and immediate vicinity, and mosaiced the tasseled cap function – season – scene images into single images for each tasseled cap function - season (6 mosaiced images).

To address issues of scale, define meaningful habitat units and reduce the effects of location error, I smoothed the 6 mosaiced images by assigning each pixel the mean and standard deviation of tasseled cap values calculated within a moving window centered on the pixel. I used seven window sizes, 90 m x 90 m (0.8 hectares), 210 m x 210 m (4.4 hectares), 510 m x 510 m (26.0 hectares), 495 m radius (77.0 hectares), 990 m x 990 m (98.0 hectares), 1005 m radius (317.3 hectares) and 2010 m x 2010 m (404.0 hectares), to examine the sensitivity of modeled selection to changing the scale over which these habitat variables were measured. I selected these window sizes because I believed they represented a reasonable range over which to examine this effect. By using the moving window mean, the effect of location errors in measured habitat values was reduced compared with values extracted from a single, possibly erroneous, location (Erickson et al. 1998, Waller and Mace 1998), as are minor location and reflectance errors in the satellite data. The standard deviation describes the variability of tasseled cap values within the window, which could be important in modeling bear habitat selection. Low standard deviations would indicate homogenous conditions and high values would

indicate that the window consists of divergent values (e.g., a large patch of mature forest would be expected to have a low standard deviation, where a pixel near a forest-agricultural transition may have a similar mean but would have a much higher standard deviation). I used IDRISI32 v.I32.22 (Clark Labs, Clark University, Worchester, Massachusetts, USA) for all image processing and to derive window means and standard deviations, collectively referred to as the habitat variables, for used and available locations. I converted the IDRISI data files to ArcView grids and used the ArcView 3.2 script SampleGrid.ave (available from http://www.commenspace.org/resources/tools.html) to extract habitat variables for each used and available location. I similarly extracted GAP habitat categories for available locations for comparison of my habitat variables with the coarse but relatively precise GAP maps.

Statistical Analysis

Statistical analyses consisted of two steps: 1) I tested for differences between study areas among habitat variables measured at available locations at each scale and examined differences graphically, and 2) I tested for differences between study areas, and among seasons and bears and their interactions among habitat variables extracted from used habitat at each scale and examined differences graphically. Each of these steps is explained in detail below. I examined available and used resources separately in this chapter so as not to compromise results of hypotheses test examining resource selection presented in Chapter 4. All statistical analyses were conducted using S-Plus, version 6.1 (Insightful Corp. 2002).

Examination of Available Habitat - For each of the seven window sizes, I conducted a MANOVA to test whether or not study area differences explained significant amounts of the variability in response vectors consisting of the twelve habitat variables (moving window mean and standard deviation for spring and fall tasseled caps 1-3) measured at available locations. Model significance was compared based on approximated F-statistics, estimated from Wilks' lambda. The assumptions of MANOVA are: 1) response variables are a random, independent sample from each population; 2) they have a common covariance structure; and 3) each population is multivariate normal. As others have pointed out (Manly et al. 1993, Harrell 2001), environmental variables often do not meet these criteria. However, because my sample sizes were large, the assumption of multivariate normality can be relaxed by appealing to the central limit theorem (Venables and Ripley 1999). If the MANOVA was significant ($\alpha = 0.05$), then I examined univariate tests for each habitat variable. I calculated area specific means and standard deviations for each habitat variable and examined graphs of the relationship between each habitat variable, study area, and scale.

Examination of Used Habitat - For each of the seven window sizes, I also conducted a MANOVA to test whether or not the following predictor variables explained significant amounts of the variability in the response vectors, which consisted of the twelve habitat variables extracted from used locations: 1) study area, 2) bear seasons (spring-summer, fall, and winter), 3) interaction between study area and bear seasons, 4) bears within study areas, and 5) interaction between bears within study areas and bears seasons. Model significance was compared based on approximated F-statistics, estimated from Wilks' lambda. If the MANOVA was significant ($\alpha = 0.05$), then I examined the

univariate tests for each variable. I examined graphs of the response of bears by season and area to each habitat variable over the range of spatial scales considered.

RESULTS

Habitat Measures

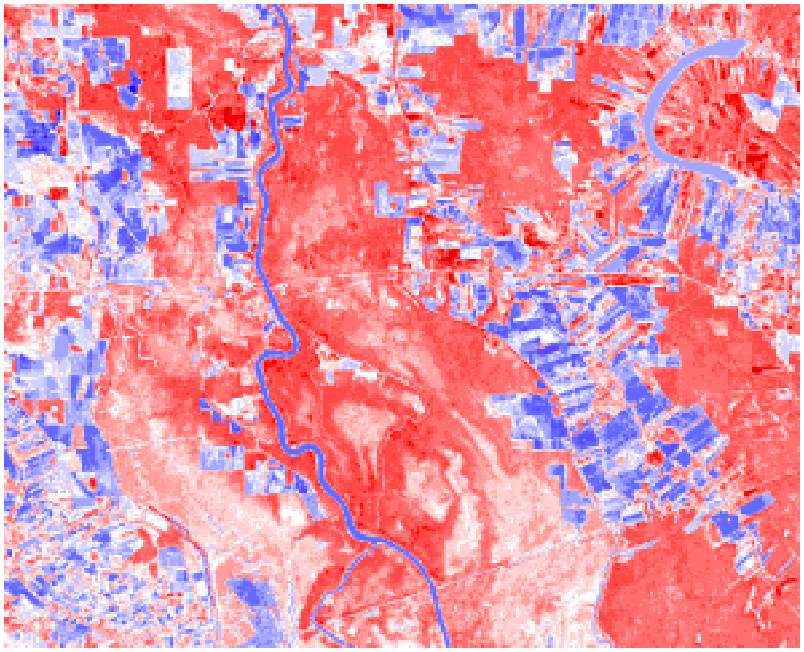
Calculating a mean and standard deviation of each of the three tasseled caps in two seasons (fall and spring) at seven spatial scales, produced 84 habitat variables (Table 3.1). Images based on these variables showed distinct changes with changing scale (Figure 3.1).

Table 3.1. List of habitat variables developed from at-satellite reflectance tasseled cap function. Each of the below list habitat variables were developed at each of seven scales, or moving window sizes: 90x90m, 210x210m, 510x510m, 495m radius, 990x990m, 1005m radius, and 2010x2010m, resulting in a total of 84 variables.

Tasseled Cap Function	Tasseled Cap	Season of Image Capture[1]	Statistic[2]	Habitat ID
Brightness	TC1	S	M	TC1.S.M
			SD	TC1.S.SD
		F	M	TC1.F.M
			SD	TC1.F.SD
Greenness	TC2	S	M	TC2.S.M
			SD	TC2.S.SD
		F	M	TC2.F.M
			SD	TC2.F.SD
Wetness	TC3	S	M	TC3.S.M
			SD	TC3.S.SD
		F	M	TC3.F.M
			SD	TC3.F.SD

Notes: [1] S = Spring, F = Fall; [2] M = Mean, SD = Standard deviation.

90x90m Mean



510x510m Mean

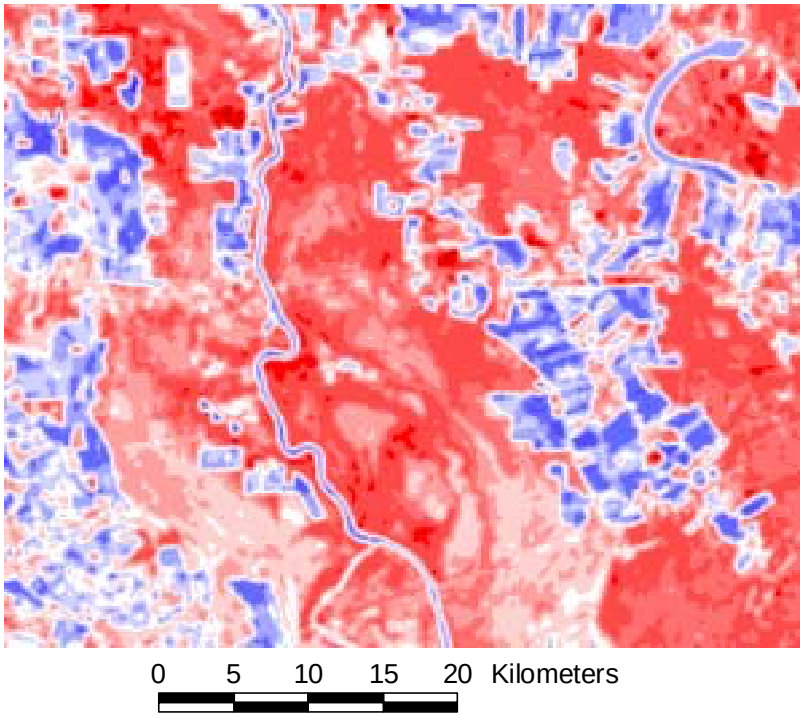
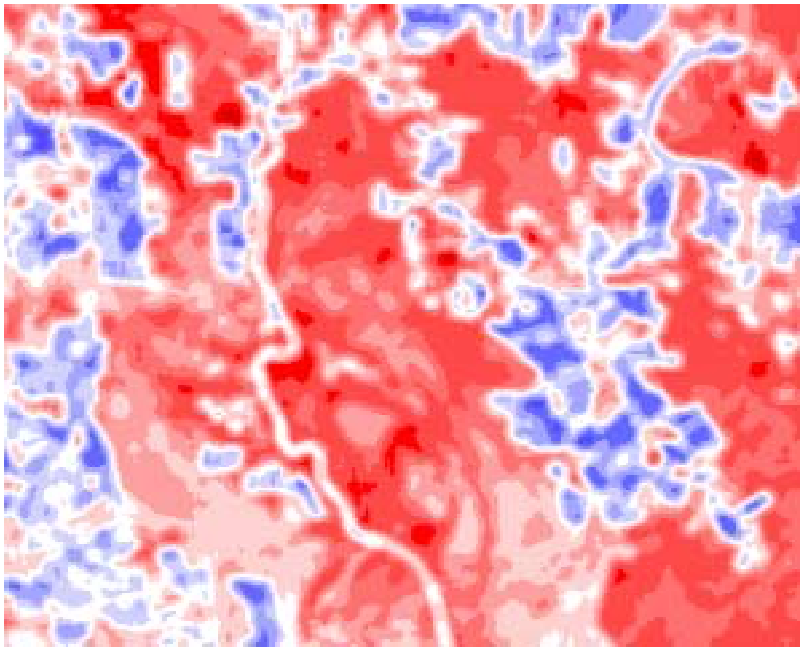


Figure 3.1. Example images of spring greenness (TC2) means and standard deviations at moving window sizes of 90x90m, 510x510m, 990x990m, and 2010x2010m. In the images, dark red represents high values, to white in the mid range, to dark blue for the lowest values.

990x990m Mean



2010x2010m Mean

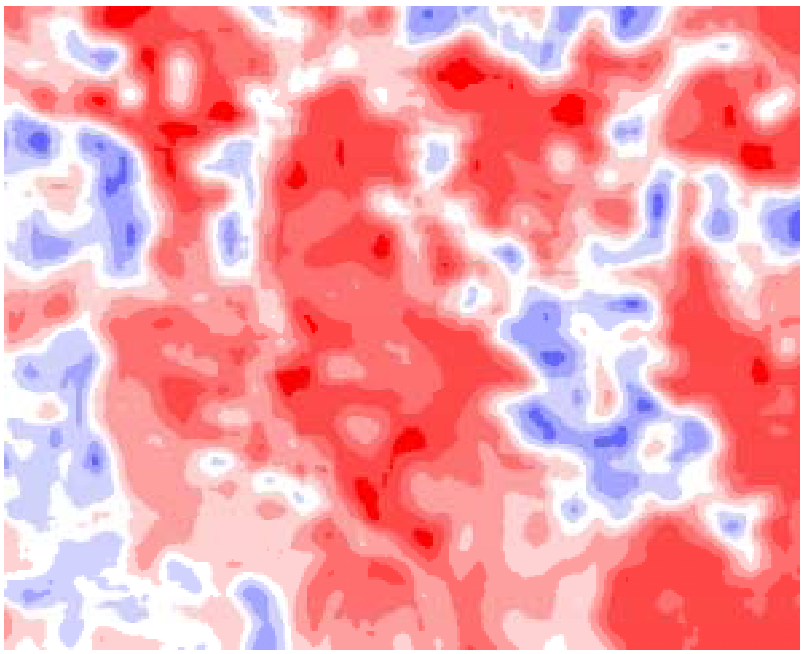
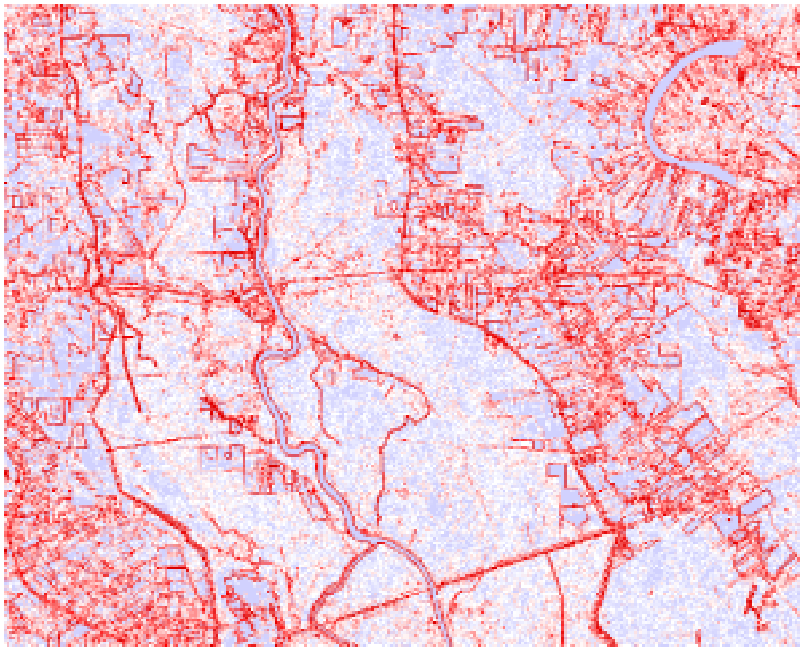


Figure 3.1 continued.

90x90m Standard Deviation



510x510m Standard Deviation

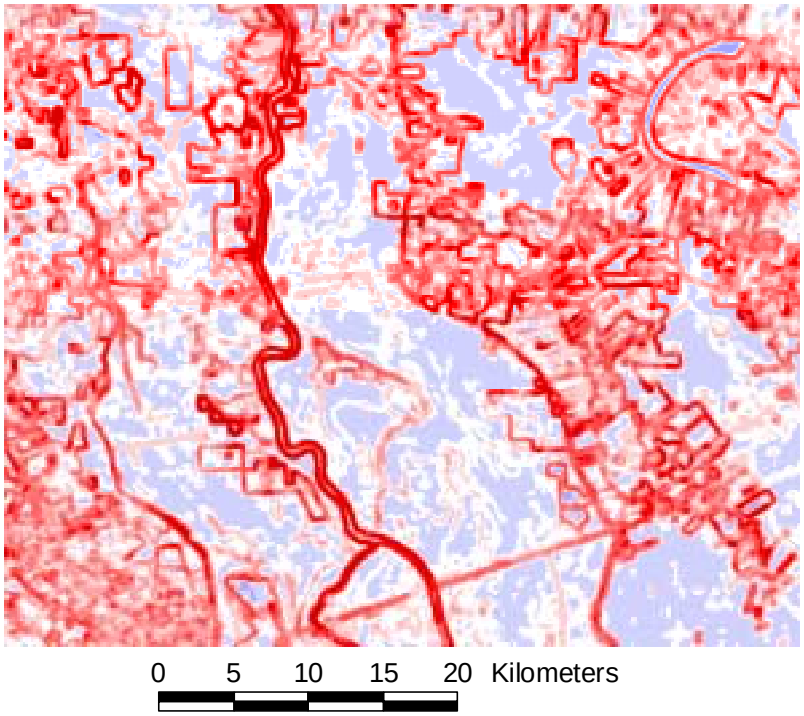
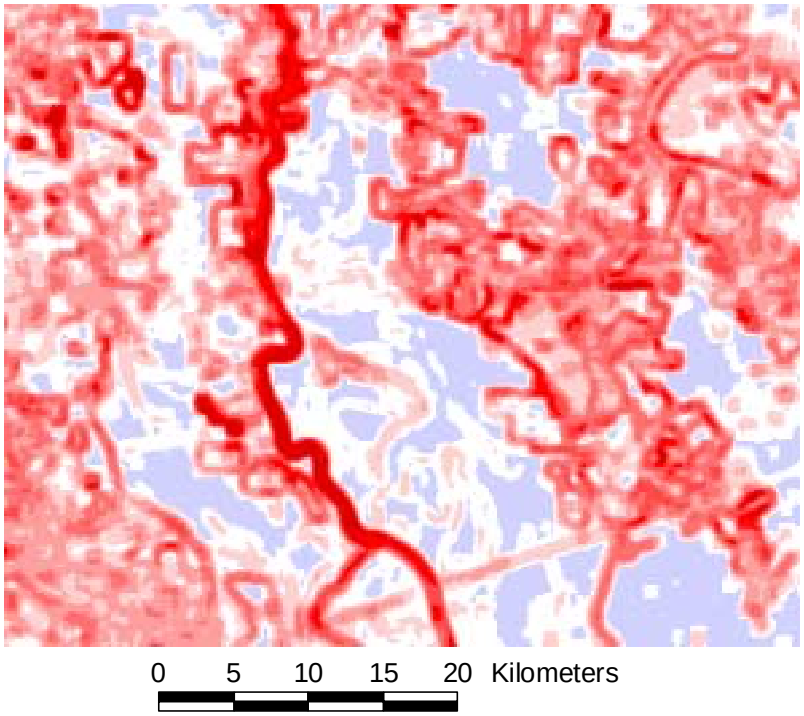


Figure 3.1 continued.

990x990m Standard Deviation



2010x2010m Standard Deviation

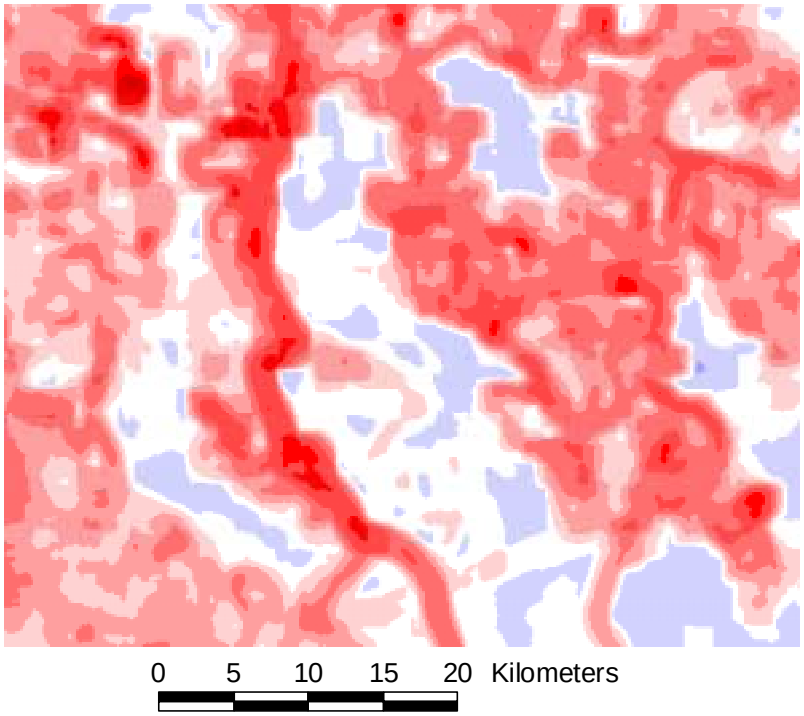


Figure 3.1 continued.

Examination of Available Habitat

MANOVA results indicated that the available habitats in the two study areas, as measured by the habitat variables, differed ($P < 0.0001$ for all overall tests) at all scales (Table 3.2). Univariate analyses suggest:

- Study area means for habitat variables derived from moving window means were relatively unaffected by scale, with similar values across all scales, maintaining a constant relationship between Coastal and Inland values (Figure 3.2a).
- Comparing study area means for habitat variables derived from moving window means (Figure 3.2a), Inland had greater spring and fall brightness, greater mean spring greenness, lower fall greenness and lower spring and fall wetness than Coastal, reflecting a larger fraction of the Inland study area in dryer forested and agricultural conditions compared with the wetter forest and coastal marsh in the Coastal study area.
- Study area means for habitat variables derived from moving window standard deviations increased with increasing scale. Differences between study area values also increased with scale, except fall brightness, indicating interaction between study area and scale.
- Inland study area means for habitat variables derived from moving window standard deviations were greater than for Coastal for spring brightness, spring greenness, and spring and fall wetness. Coastal fall brightness was greater than for Inland at 90m x90m, 210m x 210m, and 510m x510m scales, but not different at scales greater than 510m x 510m. Coastal fall greenness was greater than for

Inland at scales less than 510m x 510m, and less than for Coastal at 510m x 510m and larger.

- Study area standard deviations for habitat variables derived from moving window means decreased with increasing scale, with the relationship between study area and scale relatively constant for about half of such variables and interaction was apparent for the remaining half (Figure 3.2b).
- Study area standard deviations for habitat variables derived from moving window standard deviations increased with increasing window size to intermediate scales and then either leveled off or decreased slightly. Interaction between study area and scale was apparent for these variables.
- Overall, study area standard deviations for habitat variables derived from moving window standard deviations for Inland were greater than for Coastal.

Graphs of the distribution of the habitat variables within GAP habitat categories (Figure 3.3) also show differences between study areas in many of the GAP habitat categories that occur in both areas. The variability of the habitat variables within GAP habitat categories also shows that there is considerable information in the habitat variables beyond the coarse categories represented in the GAP maps.

Examination of Used Habitat

MANOVA results for each of the seven window sizes provide strong evidence (P <0.0001 for all tests) that the response vector of the twelve habitat variables for used locations differed between study areas (Coastal n = 1,151; Inland n = 764), among bear seasons (all bears observed in all seasons), and among bears within areas (18 Coastal

bears, 10 Inland bears), but seasonal habitat use differences were inconsistent between areas (area*season interaction), and differences among bears were also inconsistent among seasons (bear*season interaction) at each scale (Table 3.3). Scale differences were also apparent in the results of univariate tests (Table 3.4), and through examination of plots of habitat variables by bear and season (Figure 3.4).

Table 3.2. MANOVA results testing for differences in twelve derived tasseled-cap values between study areas (Coastal [n = 4,654] and Inland [n = 4,186]) at random locations in available habitat. *F*-values were based on Wilk's lambda, with numerator and denominator degrees of freedom shown in parenthesis. $P < 0.0001$ for overall test at all scales. Results for univariate test follow MANOVA results. For tests with results with $P < 0.05$, the relationship between inland and coastal are provided and "++" indicates $P \leq 0.001$, "+" indicates $P > 0.001$ and ≤ 0.01, "0" indicates $P > 0.01$ and ≤ 0.05, "-" indicates $P > 0.05$.

Window Size	**90m x 90m**	**210m x 210m**	**510m x 510m**	**495m radius**	**990m x 990m**	**1005m radius**	**2010m x 2010m**
			MANOVA Results				
$F_{(12, 8827)}$	260	339	540	824	930	1579	1805
			Results of Univariate Tests				
TC1.S.M	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC1.F.M	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC2.S.M	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC2.F.M	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$
TC3.S.M	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$
TC3.F.M	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$	$C>I_{++}$
TC1.S.SD	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC1.F.SD	$C>I_{++}$	$C>I_{++}$	$C>I_{+}$	-	-	-	-
TC2.S.SD	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC2.F.SD	$C>I_{++}$	-	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC3.S.SD	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$
TC3.F.SD	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$	$I>C_{++}$

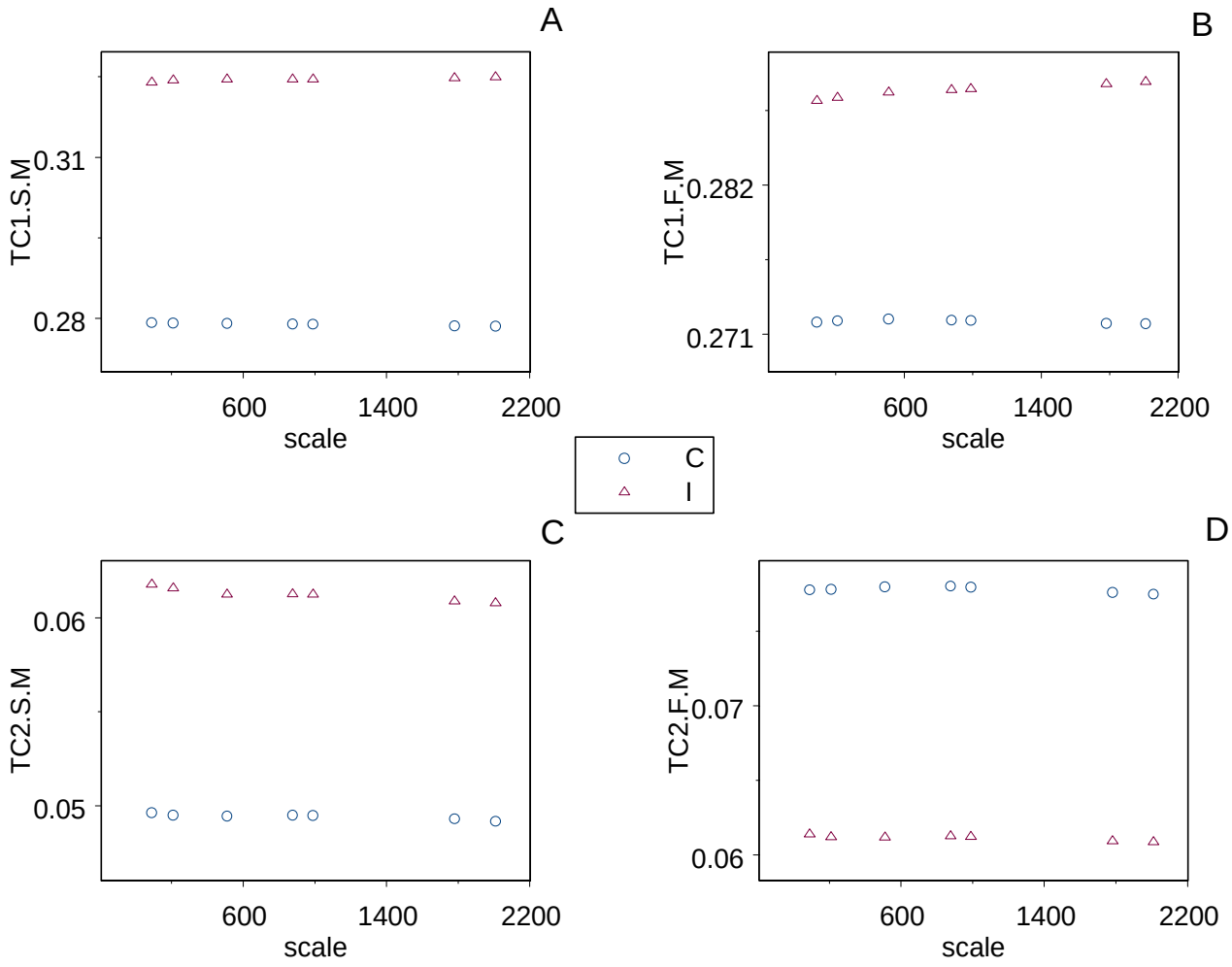


Figure 3.2a. Observed means of 12 habitat variables between study area (○ – Coastal, △ – Inland) and across seven scales. Scale is defined as the area (m^2) of the moving windows considered (90x90m, 210x210m, 510x510m, 495m radius, 990x990m, 1005m radius, 2010x2010m). Habitat variable names appear on the y-axis and are structured as TCn.i.s, where "TCn" identifies tasseled-cap 1-3 (brightness, greenness, and wetness), "i" indicates the season of image capture (S=spring, F=fall), and "s" indicates the window statistic, either window mean or standard deviation.

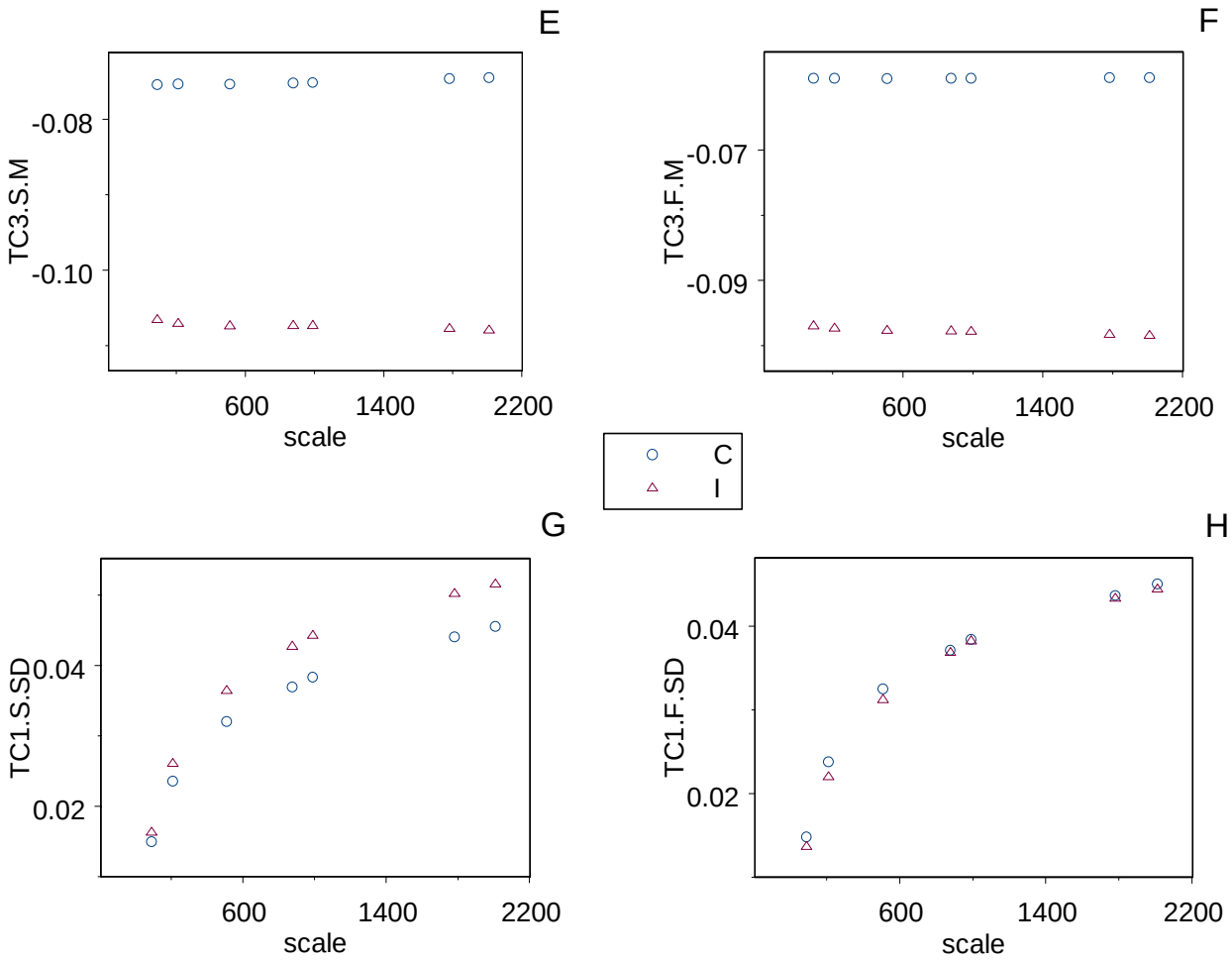


Figure 3.2a continued.

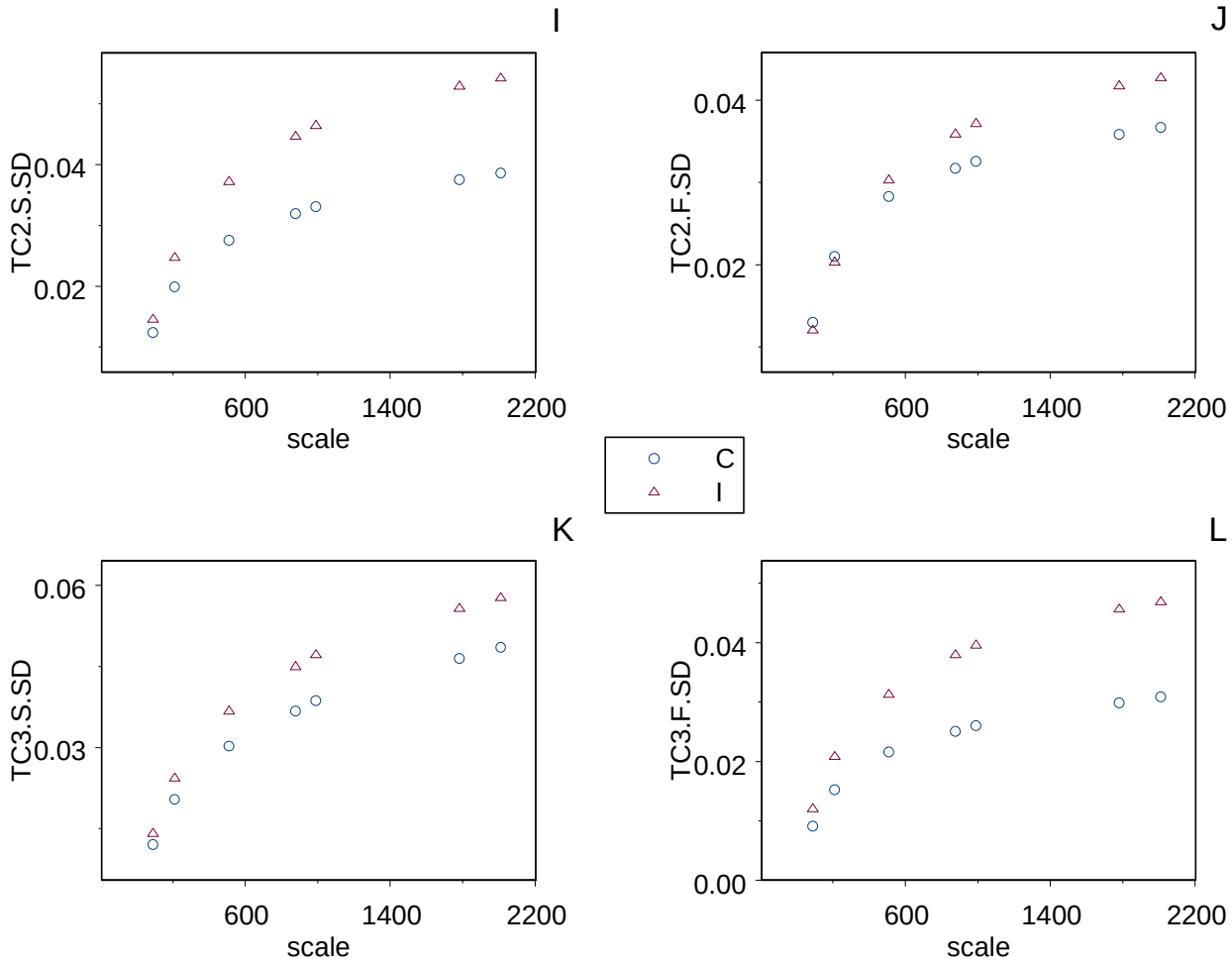


Figure 3.2a continued.

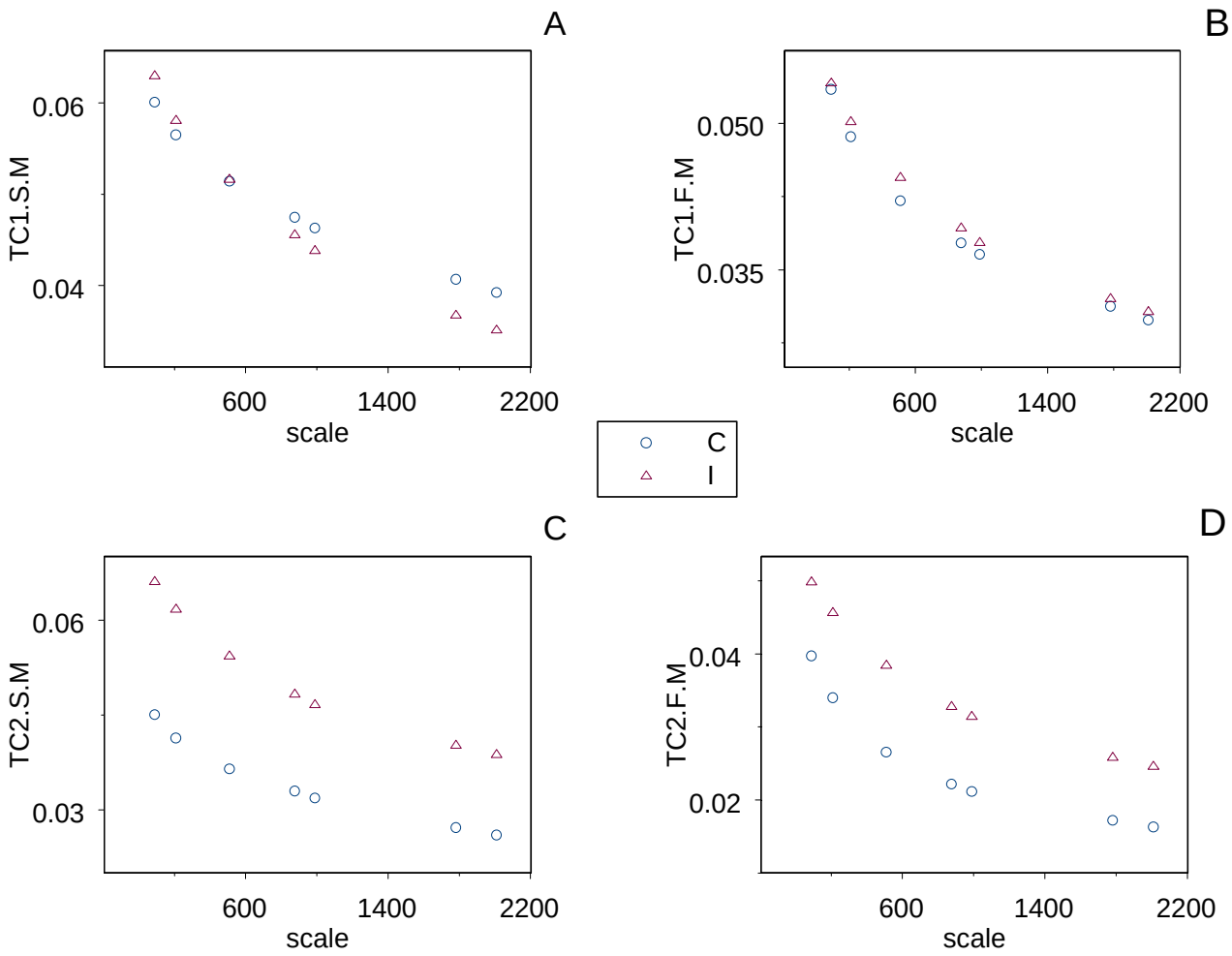


Figure 3.2b. Variability (in units of standard deviation) of 12 habitat variables between study area (○ – Coastal, △ – Inland) and across seven scales. Scale is defined as the area (m^2) of the moving windows considered (90x90m, 210x210m, 510x510m, 495m radius, 990x990m, 1005m radius, 2010x2010m). Habitat variable names appear on the y-axis and are structured as TCn.i.s, where "TCn" identifies tasseled-cap 1-3 (brightness, greenness, and wetness), "i" indicates the season of image capture (S=spring, F=fall), and "s" indicates the window statistic, either window mean or standard deviation.

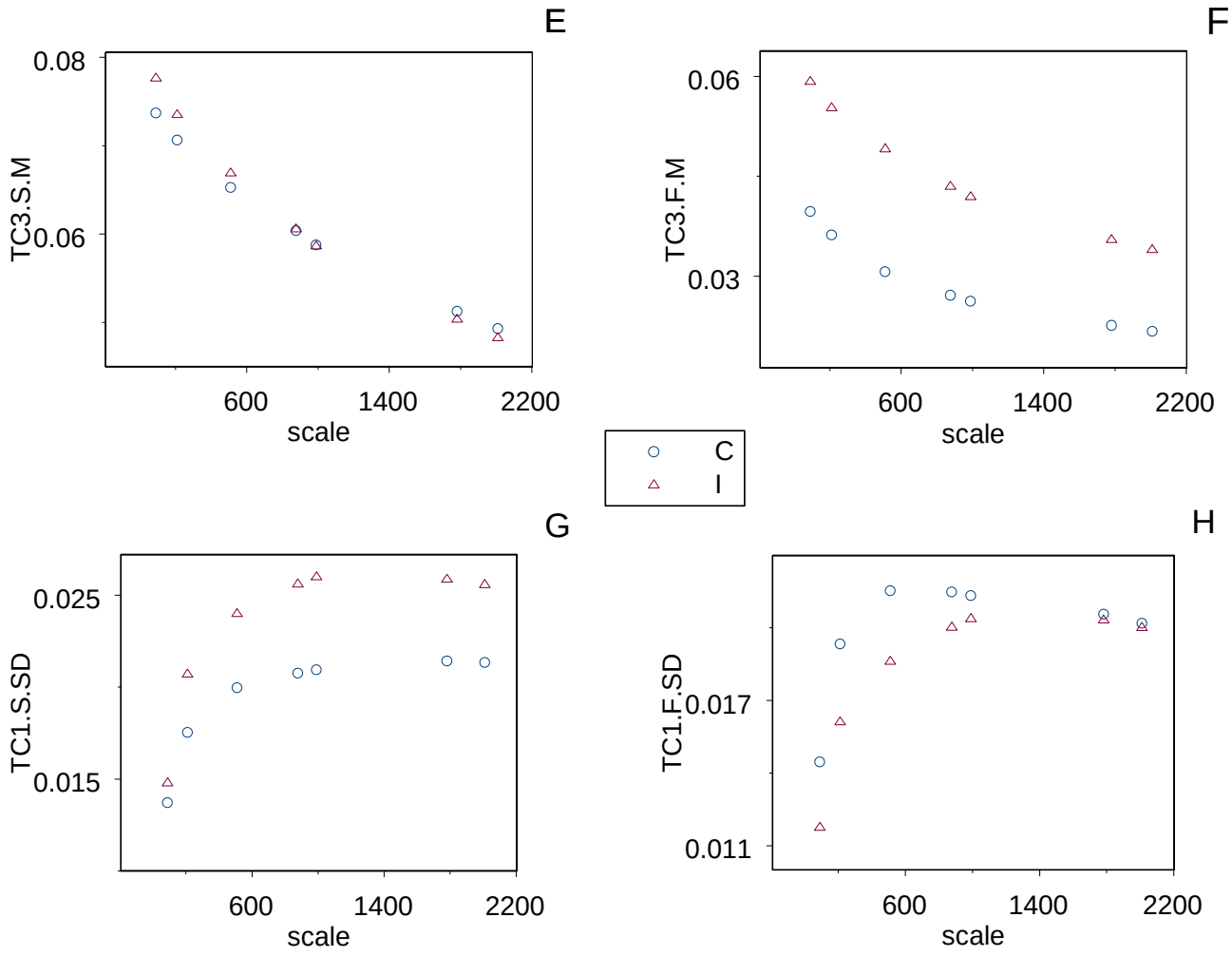


Figure 3.2b continued.

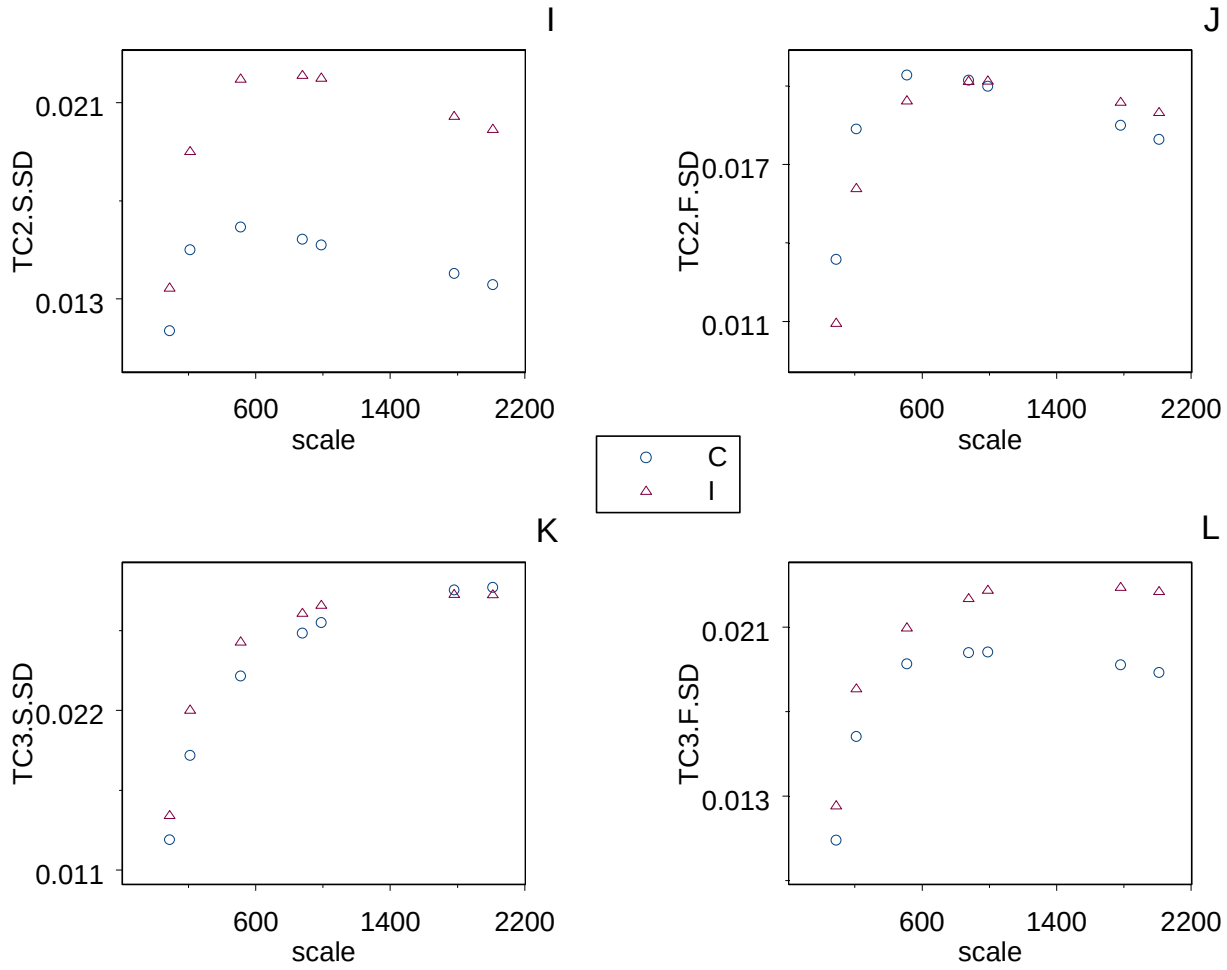


Figure 3.2b continued.

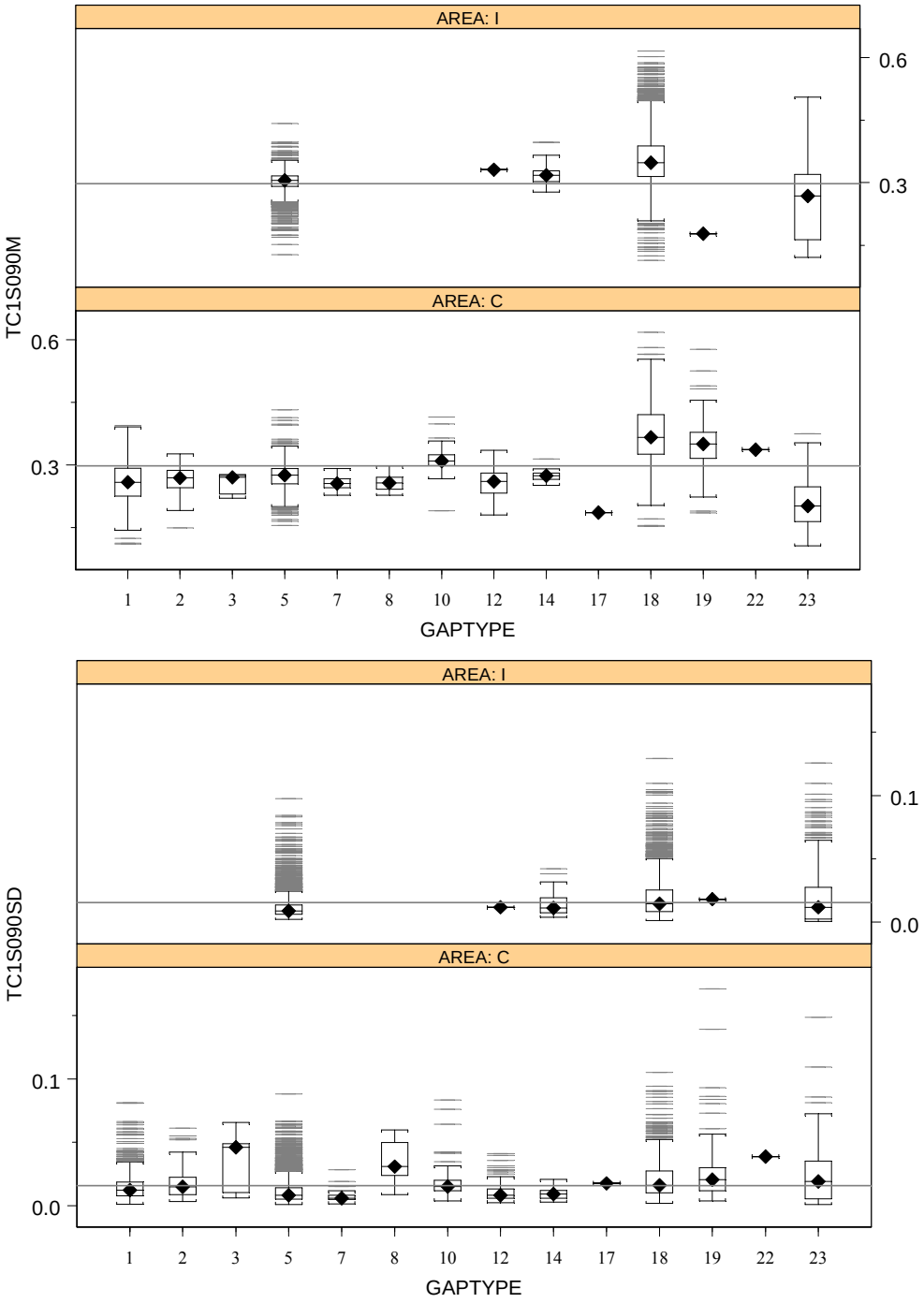


Figure 3.3. Range of the habitat variable, specified on the y-axis, within each GAP habitat category based on the available sample for the Coastal and Inland study areas. Data for two scales are presented: 90m x 90m and 2010m x 2010m. Grey reference lines represent the grand mean of the habitat variable. Gap categories are: 1 fresh marsh, 2 intermediate marsh, 3 brackish marsh, 5 wetland forest–deciduous, 7 wetland forest–mixed, 8 upland forest-deciduous, 10 upland forest–mixed, 12 wetland scrub/shrub–deciduous, 14 wetland scrub/shrub–mixed, 17 upland scrub/shrub-mixed, 18 agriculture-cropland–grassland, 19 vegetated urban, 22 upland barren, and 23 water.

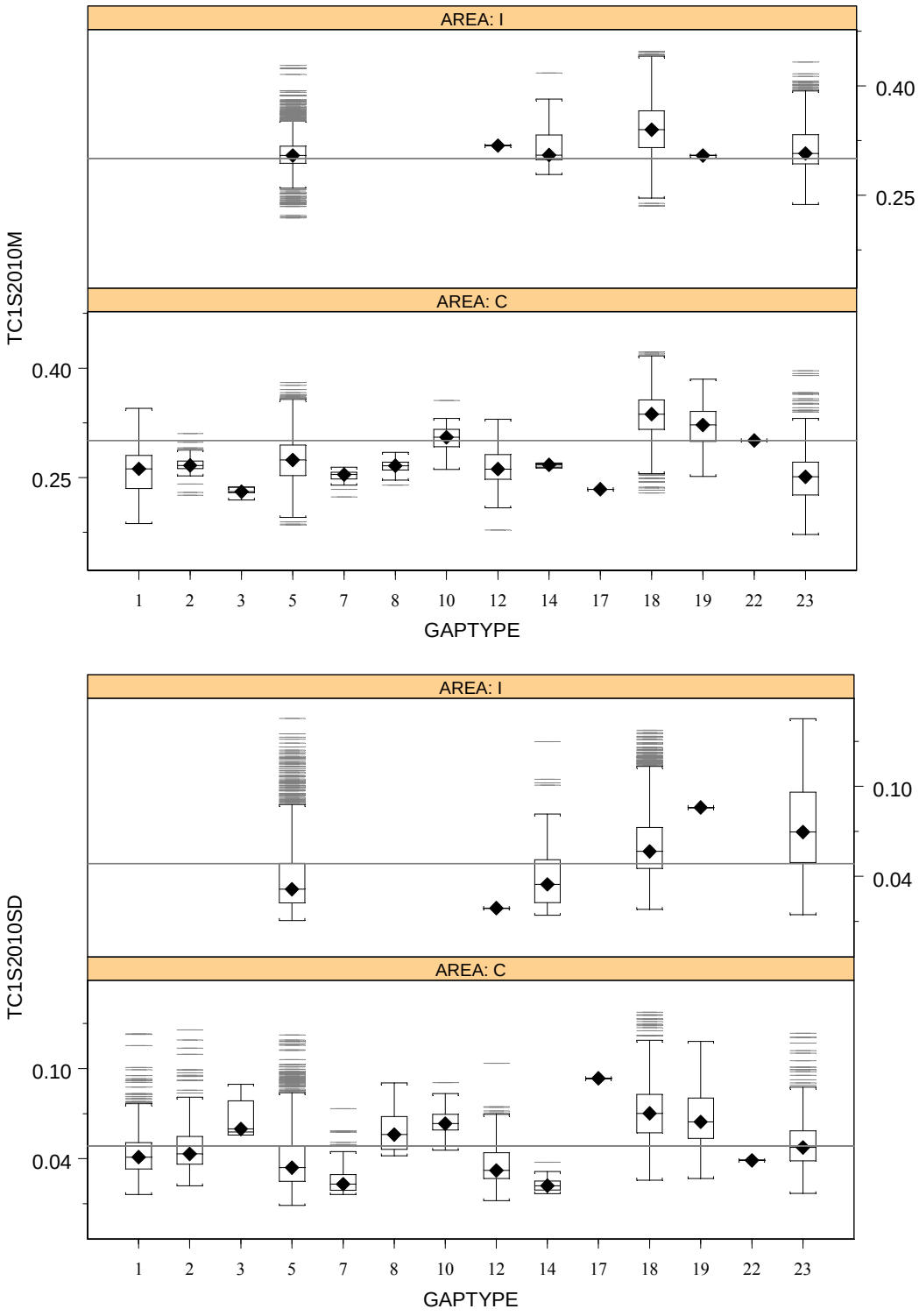


Figure 3.3. Continued.

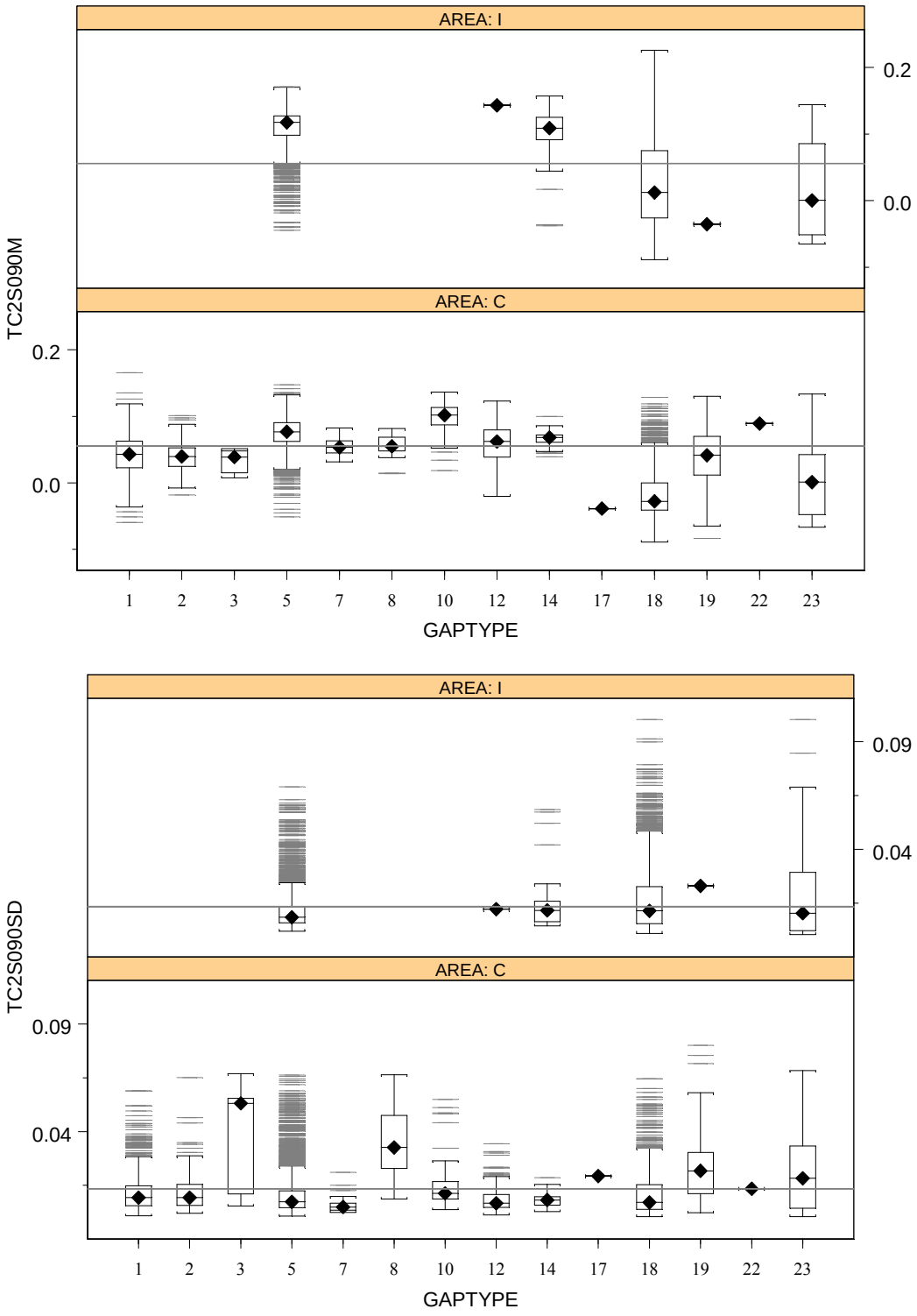


Figure 3.3. Continued.

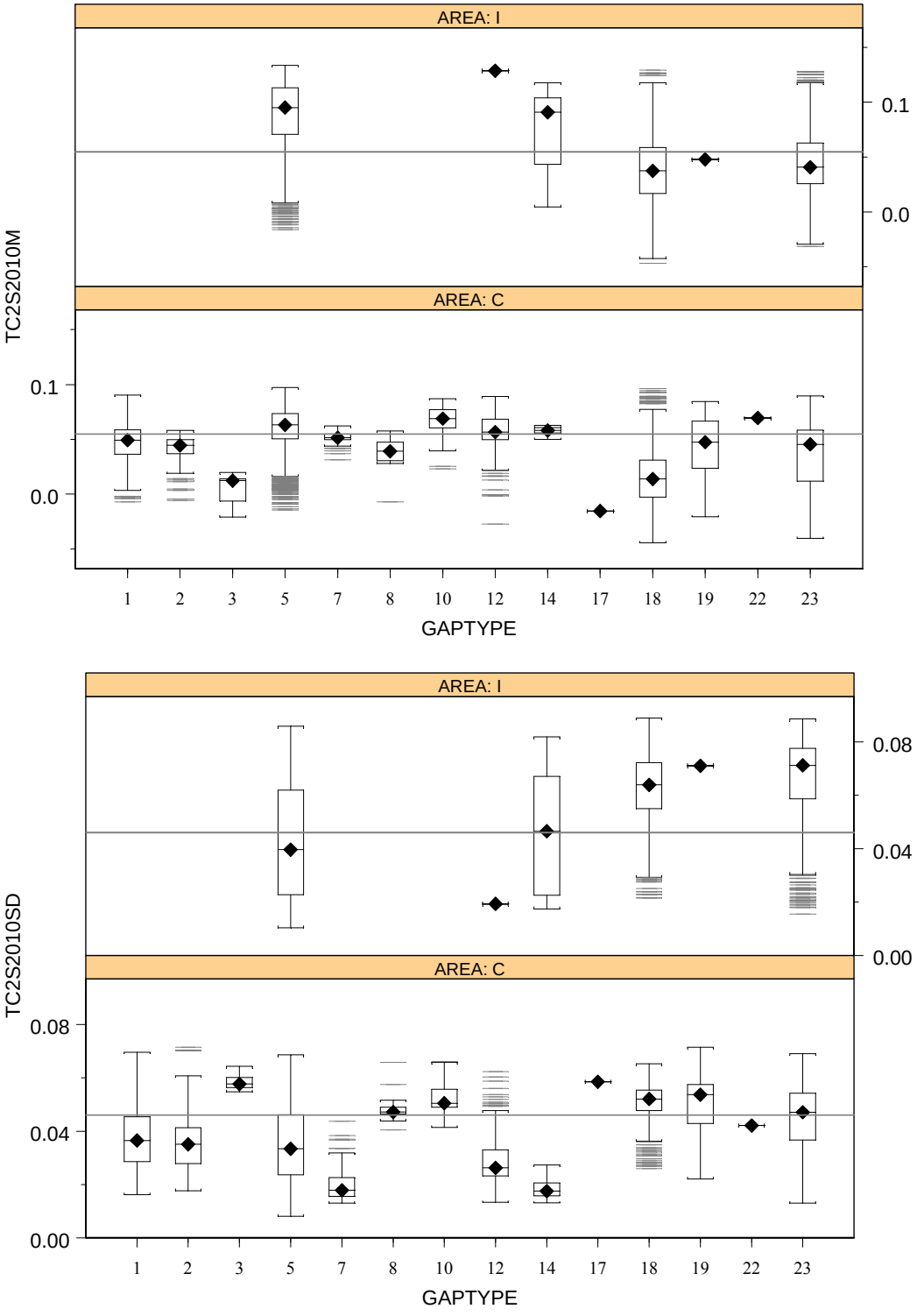


Figure 3.3. Continued.

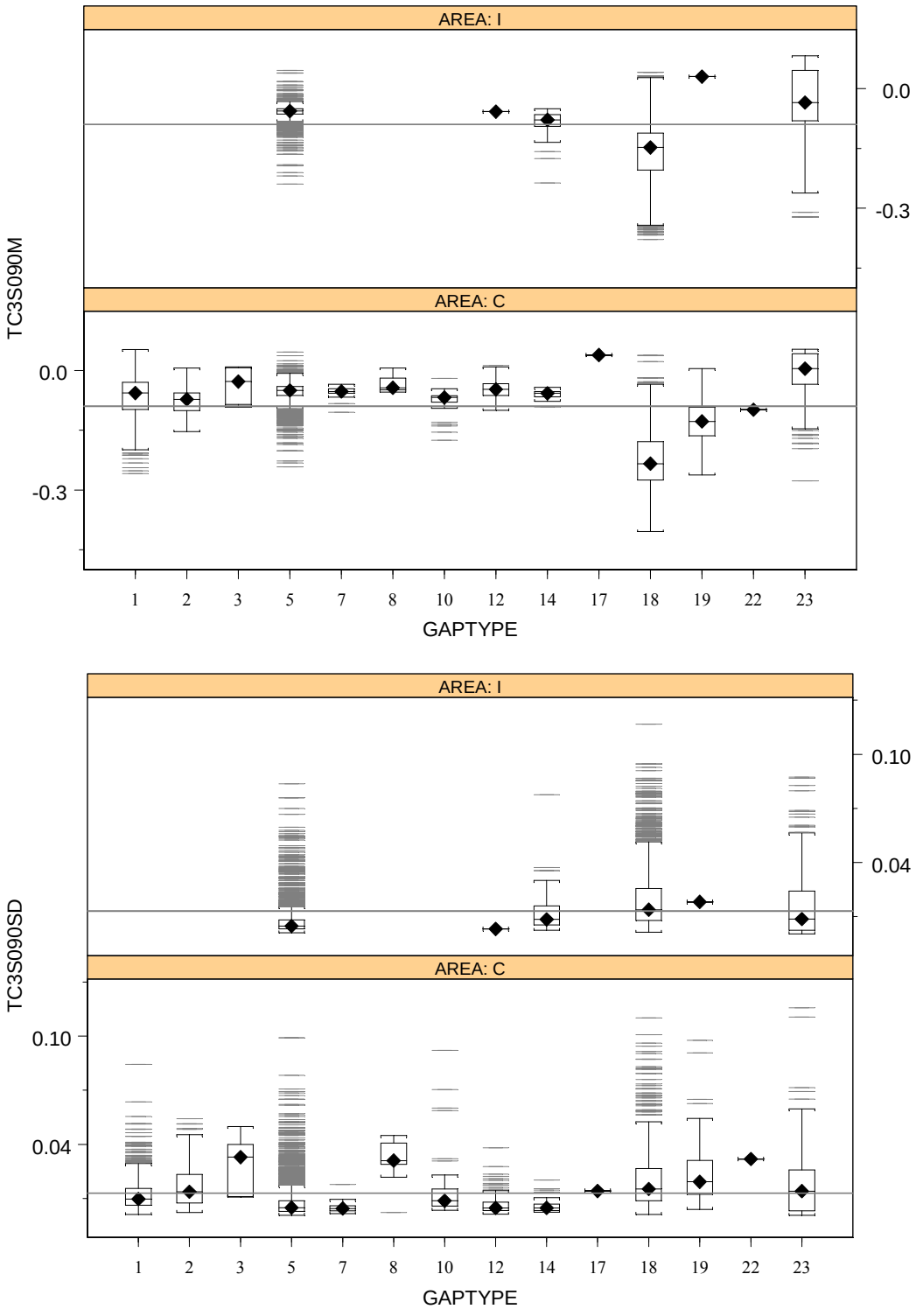


Figure 3.3. Continued.

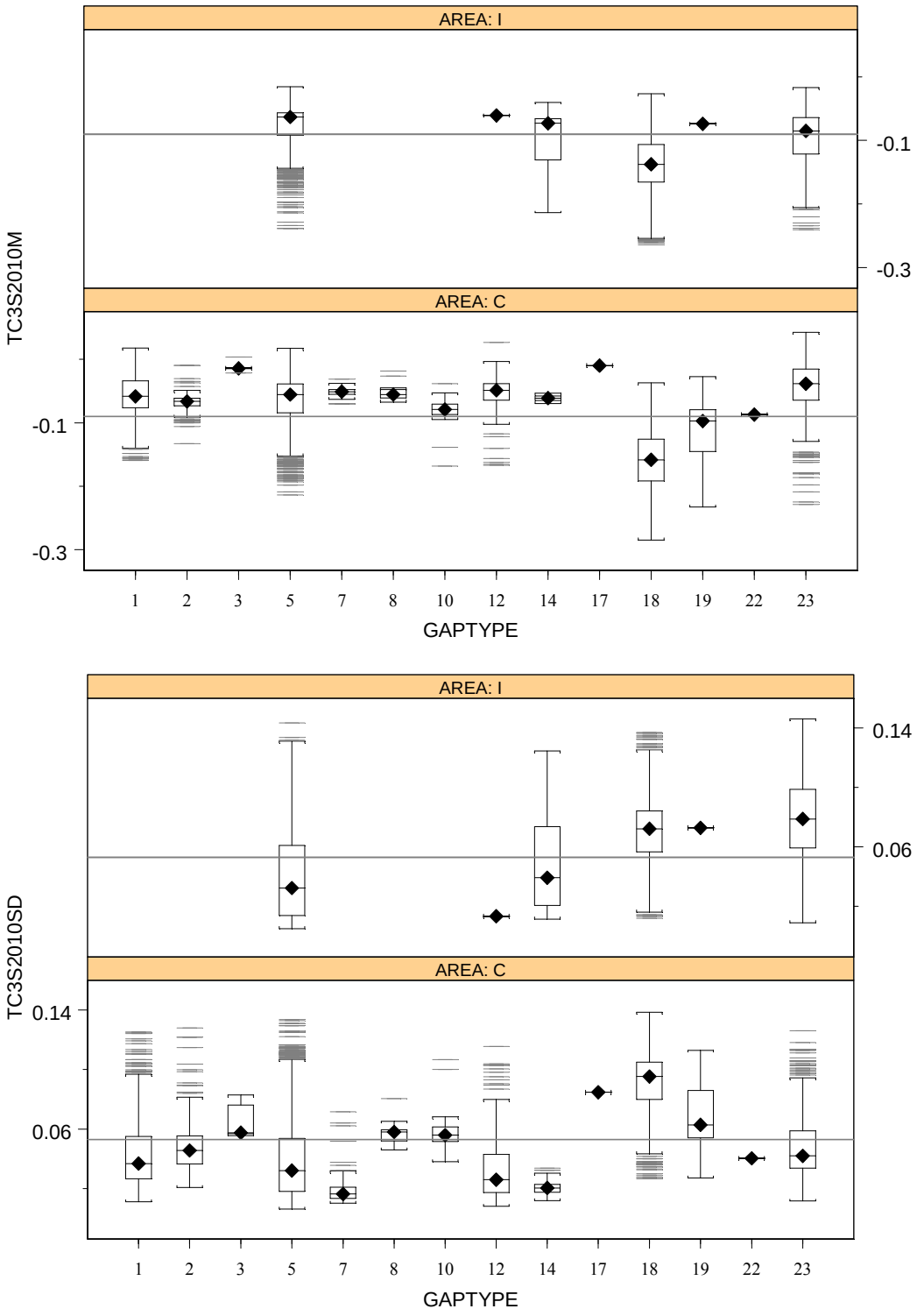


Figure 3.3. Continued.

Table 3.3. MANOVA results testing for differences in the twelve habitat variables between areas (Coastal and Inland). *F*-values presented in the table are based on Wilk's lambda, with numerator and denominator degrees of freedom shown in parenthesis. *P* <0.0001 for all tests.

	Area (1 df)	**Season (2 df)**	**Area * Season (2 df)**	**Bears w/in Area (26 df)**	**Bear * Season (52 df)**
Window Size	$F_{(12, 1820)}$	$F_{(24, 3640)}$	$F_{(24, 3640)}$	$F_{(312, 19926)}$	$F_{(624, 21345)}$
90m x 90m	217.3	5.3	2.4	9.0	1.7
210m x 210m	314.5	7.0	4.1	13.1	2.8
510m x 510m	594.4	10.8	5.9	20.6	3.1
495m radius	885.0	13.0	7.8	26.5	3.7
990m x 990m	973.9	13.1	8.6	28.3	3.8
1005m radius	1628.6	13.2	9.5	42.4	4.7
2010m x 2010m	1908.7	13.6	10.1	47.7	5.0

DISCUSSION

As I expected, increasing scale (moving window size) smoothed window means, and increased window standard deviation as larger spatial extents were considered, as is evident in Figure 3.1. Figure 3.1 also provides insight into why F-values increased with increasing scale for both available and used samples. F-values increased with increasing scale because 1) differences between study area means for each habitat variable either increased slightly with increasing scale, as in the case of window means, or increased substantially as in the case of window standard deviations, while 2) study area standard deviations, or variation among moving window values assigned to each pixel, decreased for window means with increasing scale, at finer scales increased to a maximum among window standard deviations at intermediate scales, and then decreased at coarser scales. Interaction between study area and scale was apparent (Figure 3.1), in that the rate of change for many of the habitat variables with increasing scale differed between study areas.

Based on the results presented in this chapter, available and used habitat, as measured by the habitat variables, differed between study areas, and used locations differed among seasons and bears. These results are not surprising given the large differences in the available habitat composition of the two study areas, as measured by the coarse GAP habitat categories, which contain less information than the habitat variables developed in this chapter (Figure 3.3). Large differences in used habitat resulted from the differences in available resources, as many of the habitat types available to bears in the Coastal study area were not available to Inland bears, some of which were highly preferred, such as GAP category 10, "upland forest – mixed", the dominate cover type on Weeks Island.

The apparent information content in the habitat variables developed in this chapter suggest that they have adequate resolution and specificity to examine habitat selection for black bears in the study areas, but that development of a single model that can be applied to both study areas and extrapolated beyond study area boundaries is doubtful. I explore this hypothesis further in Chapters 5 and 6.

Table 3.4. Results of univariate tests following MANOVA, testing used location for differences in habitat variables at each scale between study areas, among seasons, area*season interaction, among bears, and bear*season interaction. For tests with results with $P < 0.05$, the relationship between Inland and Coastal are provided and "++" indicates $P \leq 0.001$, "+" indicates $P > 0.001$ and ≤ 0.01, "0" indicates $P > 0.01$ and ≤ 0.05, "-" indicates $P > 0.05$.

	Window Size						
Study Area	**90x 90**	**210x 210**	**510x 510**	**495 Radius**	**990x 990**	**1005 Radius**	**2010x 2010**
TC1.S.M	++	++	++	++	++	++	++
TC1.F.M	-	-	-	-	+	++	++
TC2.S.M	++	++	++	++	++	++	++
TC2.F.M	0	+	++	++	++	++	++
TC3.S.M	+	+	++	++	++	++	++
TC3.F.M	++	++	++	++	++	++	++
TC1.S.SD	++	++	++	++	++	++	++
TC1.F.SD	++	++	++	++	++	++	++
TC2.S.SD	-	-	0	++	++	++	++
TC2.F.SD	++	++	++	++	+	-	0
TC3.S.SD	++	++	++	++	+	-	-
TC3.F.SD	-	0	++	++	++	++	++

Season	**90x 90**	**210x 210**	**510x 510**	**495 Radius**	**990x 990**	**1005 Radius**	**2010x 2010**
TC1.S.M	++	++	++	++	++	++	++
TC1.F.M	++	++	++	++	++	++	++
TC2.S.M	++	++	++	++	++	++	++
TC2.F.M	-	-	0	++	++	++	++
TC3.S.M	++	++	++	++	++	++	++
TC3.F.M	++	++	++	++	++	++	++
TC1.S.SD	-	++	++	++	++	++	++
TC1.F.SD	0	++	++	++	++	++	++
TC2.S.SD	+	++	++	++	++	++	++
TC2.F.SD	+	++	++	++	++	++	++
TC3.S.SD	++	++	++	++	++	++	++
TC3.F.SD	++	++	++	++	++	++	++

Area * Season	**90x 90**	**210x 210**	**510x 510**	**495 Radius**	**990x 990**	**1005 Radius**	**2010x 2010**
TC1.S.M	-	0	0	-	-	-	-
TC1.F.M	0	+	++	++	++	++	++
TC2.S.M	++	++	0	-	-	-	-

Table 3.4. Continued.

TC2.F.M	++	++	++	++	++	++	++
TC3.S.M	-	-	-	-	-	+	+
TC3.F.M	-	-	-	-	-	-	-
TC1.S.SD	-	-	-	+	++	++	++
TC1.F.SD	-	-	-	++	++	++	++
TC2.S.SD	0	-	-	-	0	+	0
TC2.F.SD	0	-	-	++	++	++	++
TC3.S.SD	-	-	0	++	++	++	++
TC3.F.SD	-	-	-	+	++	++	++

Bear	**90x 90**	**210x 210**	**510x 510**	**495 Radius**	**990x 990**	**1005 Radius**	**2010x 2010**
TC1.S.M	++	++	++	++	++	++	++
TC1.F.M	++	++	++	++	++	++	++
TC2.S.M	++	++	++	++	++	++	++
TC2.F.M	++	++	++	++	++	++	++
TC3.S.M	++	++	++	++	++	++	++
TC3.F.M	++	++	++	++	++	++	++
TC1.S.SD	++	++	++	++	++	++	++
TC1.F.SD	++	++	++	++	++	++	++
TC2.S.SD	++	++	++	++	++	++	++
TC2.F.SD	++	++	++	++	++	++	++
TC3.S.SD	++	++	++	++	++	++	++
TC3.F.SD	++	++	++	++	++	++	++

Bear * Season	**90x 90**	**210x 210**	**510x 510**	**495 Radius**	**990x 990**	**1005 Radius**	**2010x 2010**
TC1.S.M	++	++	++	++	++	++	++
TC1.F.M	++	++	++	++	++	++	++
TC2.S.M	++	++	++	++	++	++	++
TC2.F.M	-	++	++	++	++	++	++
TC3.S.M	++	++	++	++	++	++	++
TC3.F.M	++	++	++	++	++	++	++
TC1.S.SD	+	++	++	++	++	++	++
TC1.F.SD	++	++	++	++	++	++	++
TC2.S.SD	0	++	++	++	++	++	++
TC2.F.SD	+	++	++	++	++	++	++
TC3.S.SD	+	++	++	++	++	++	++
TC3.F.SD	++	++	++	++	++	++	++

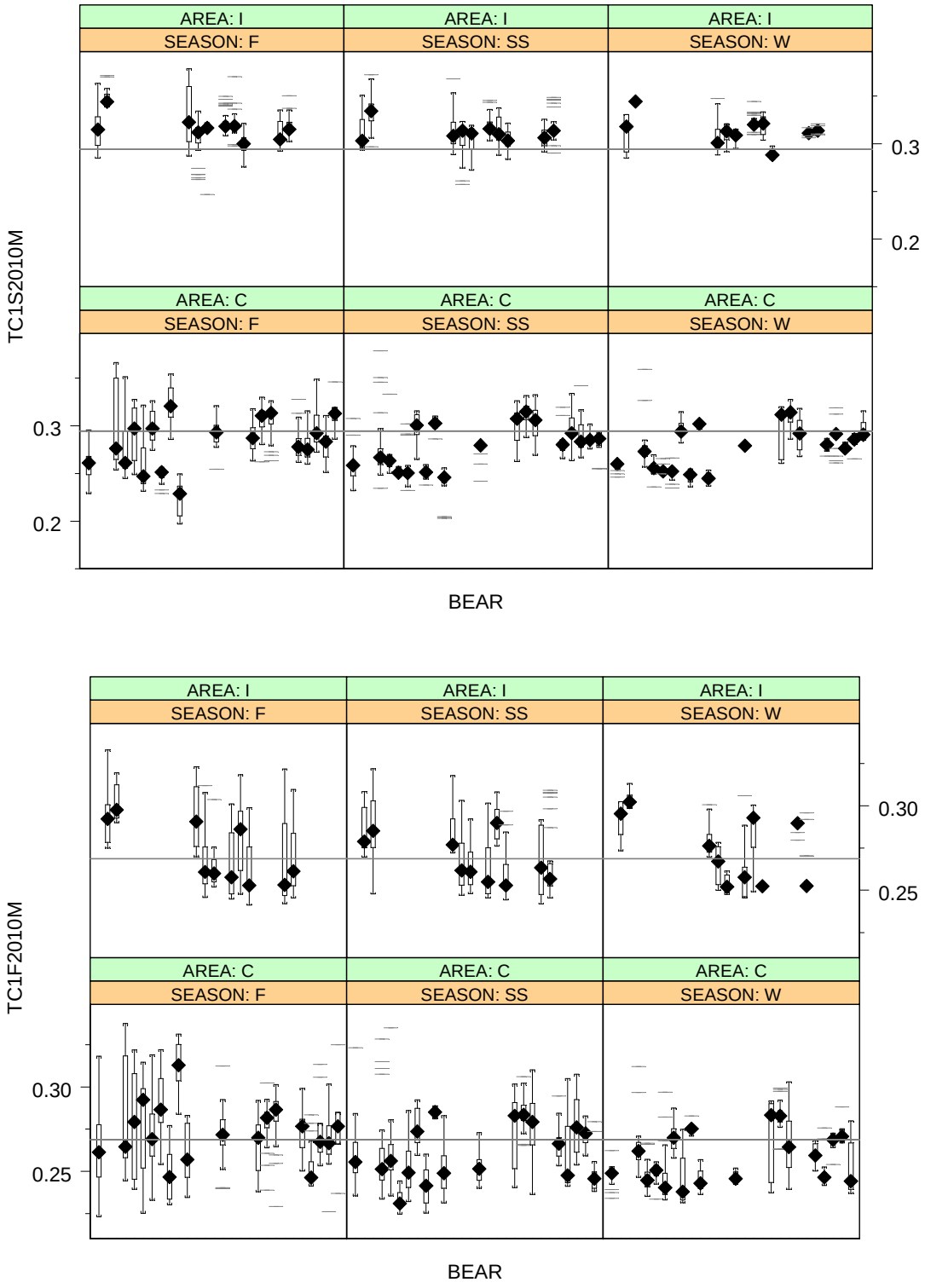


Figure 3.4. Box plots show the range of each habitat variable used by each bear in each season, at the largest spatial scale considered (2010m x 2010m moving window). Reference lines, representing the mean of all used locations for the habitat variable, are shown in grey.

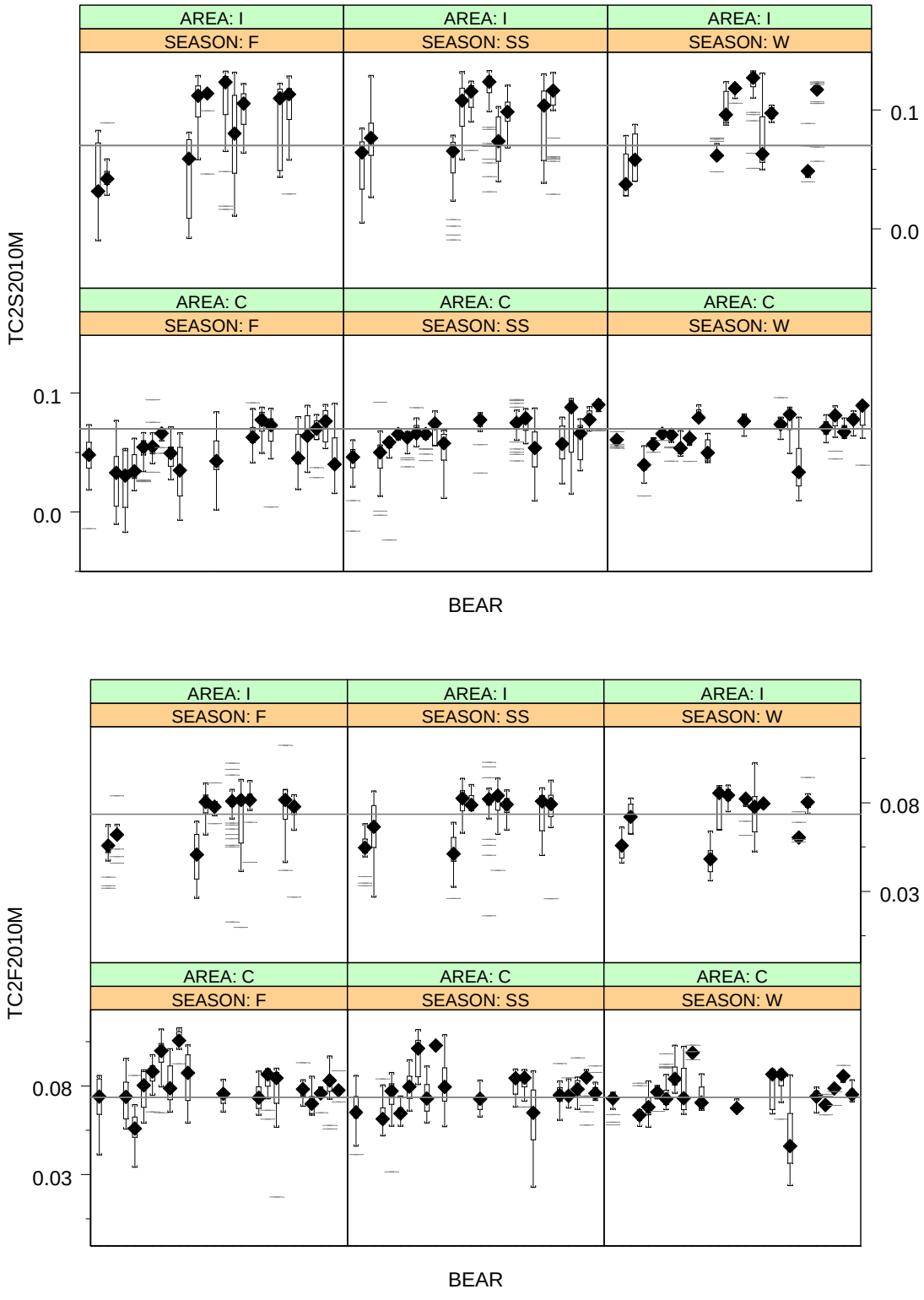


Figure 3.4. Continued.

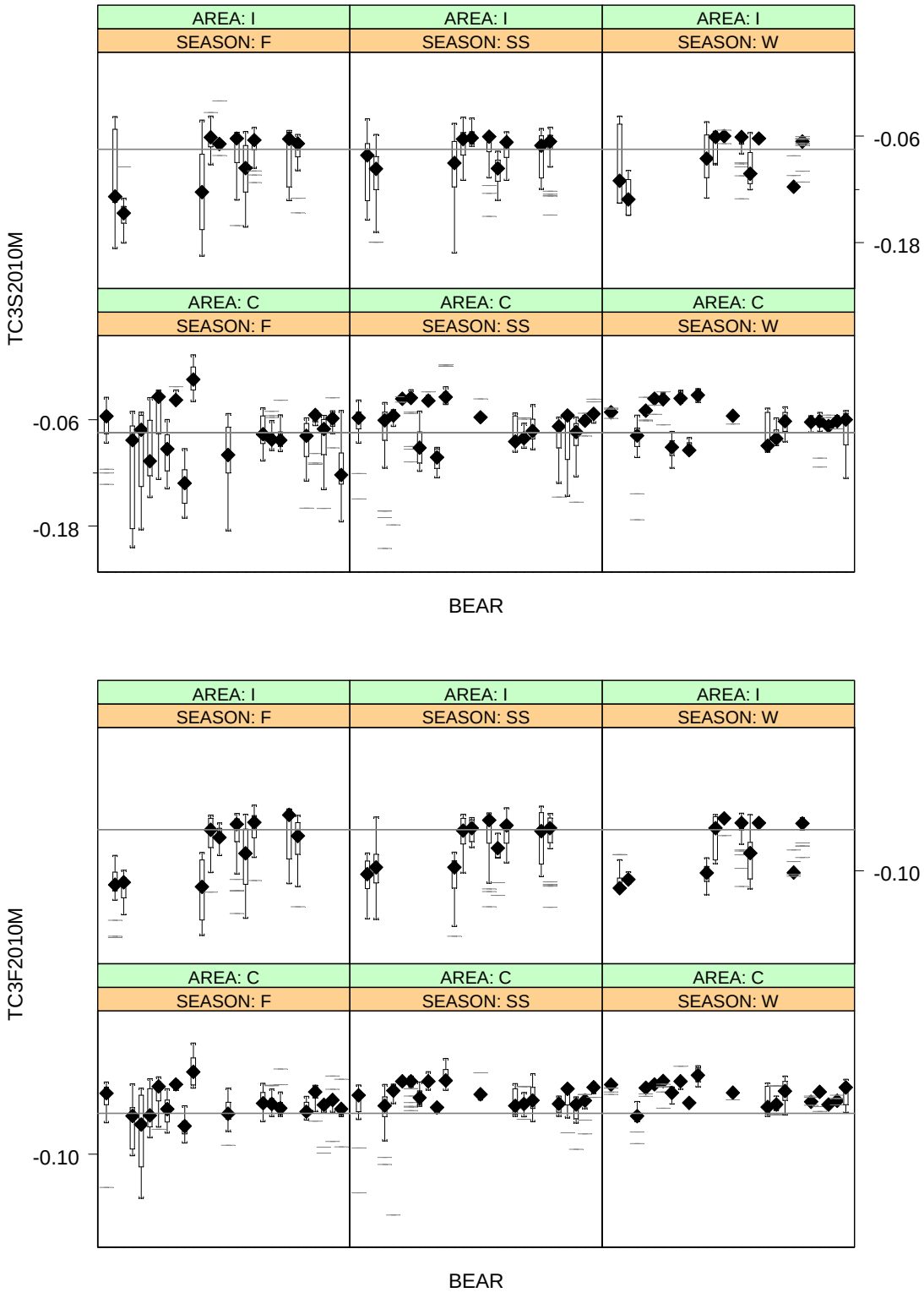


Figure 3.4. Continued.

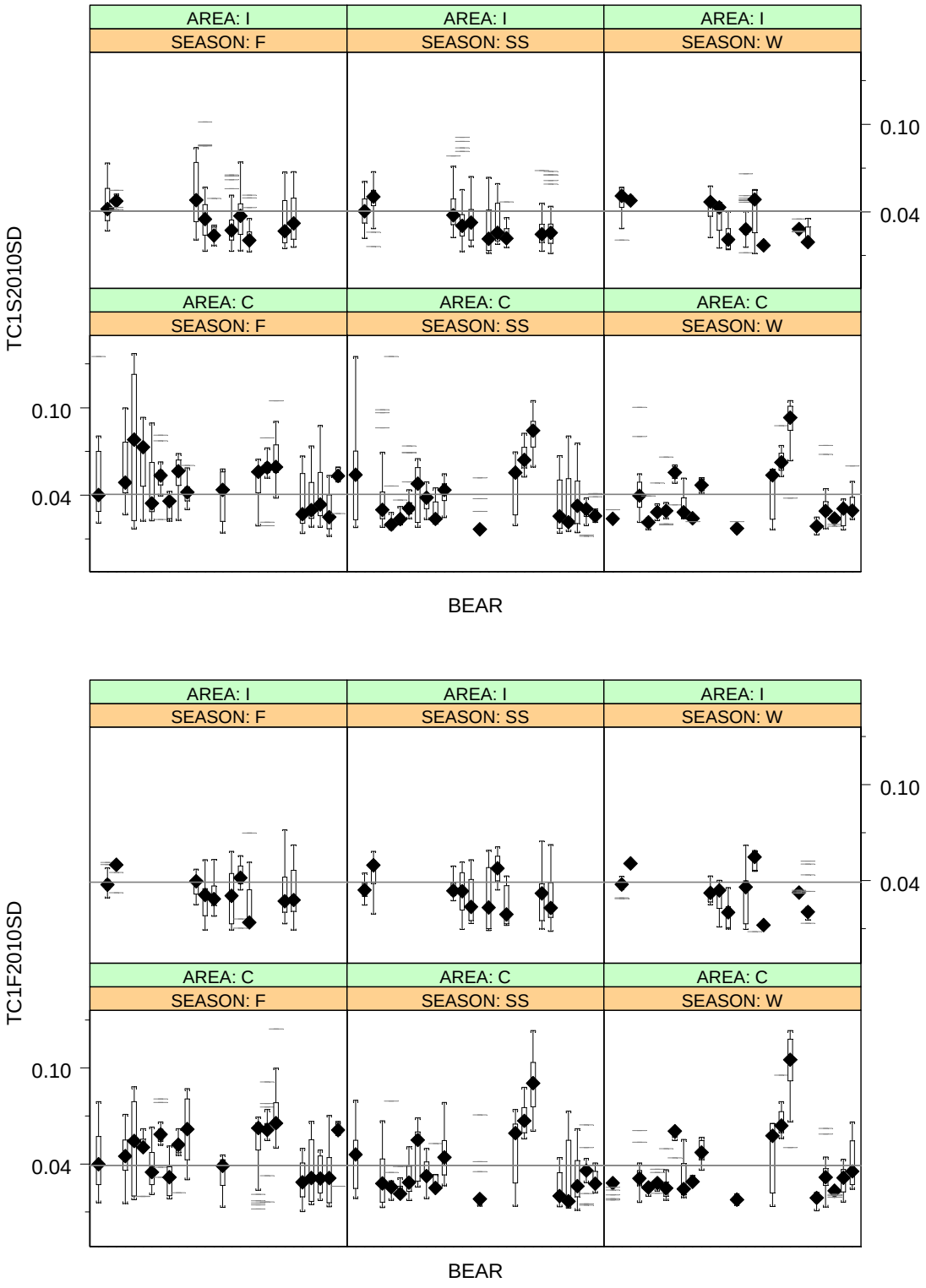


Figure 3.4. Continued.

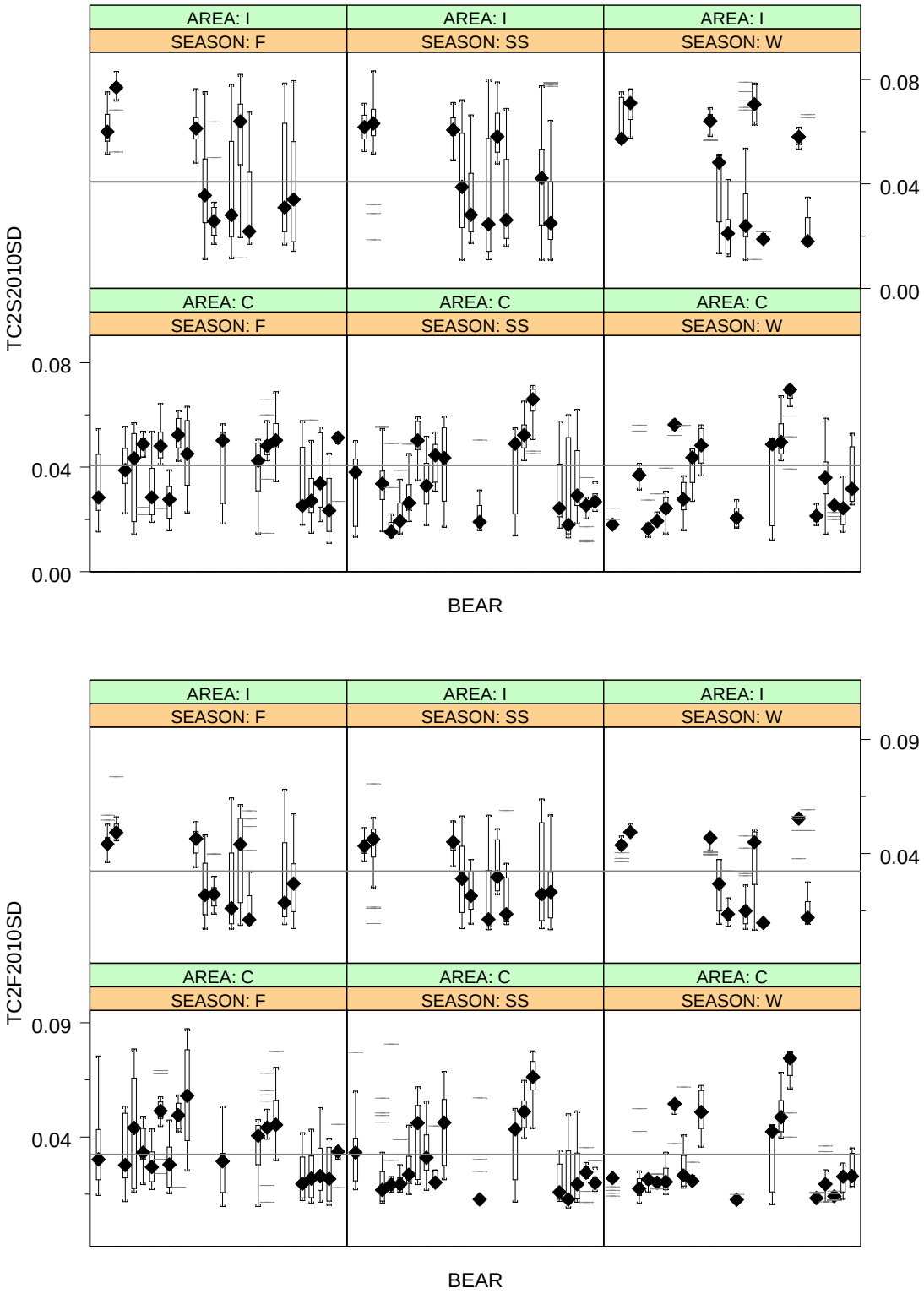


Figure 3.4. Continued.

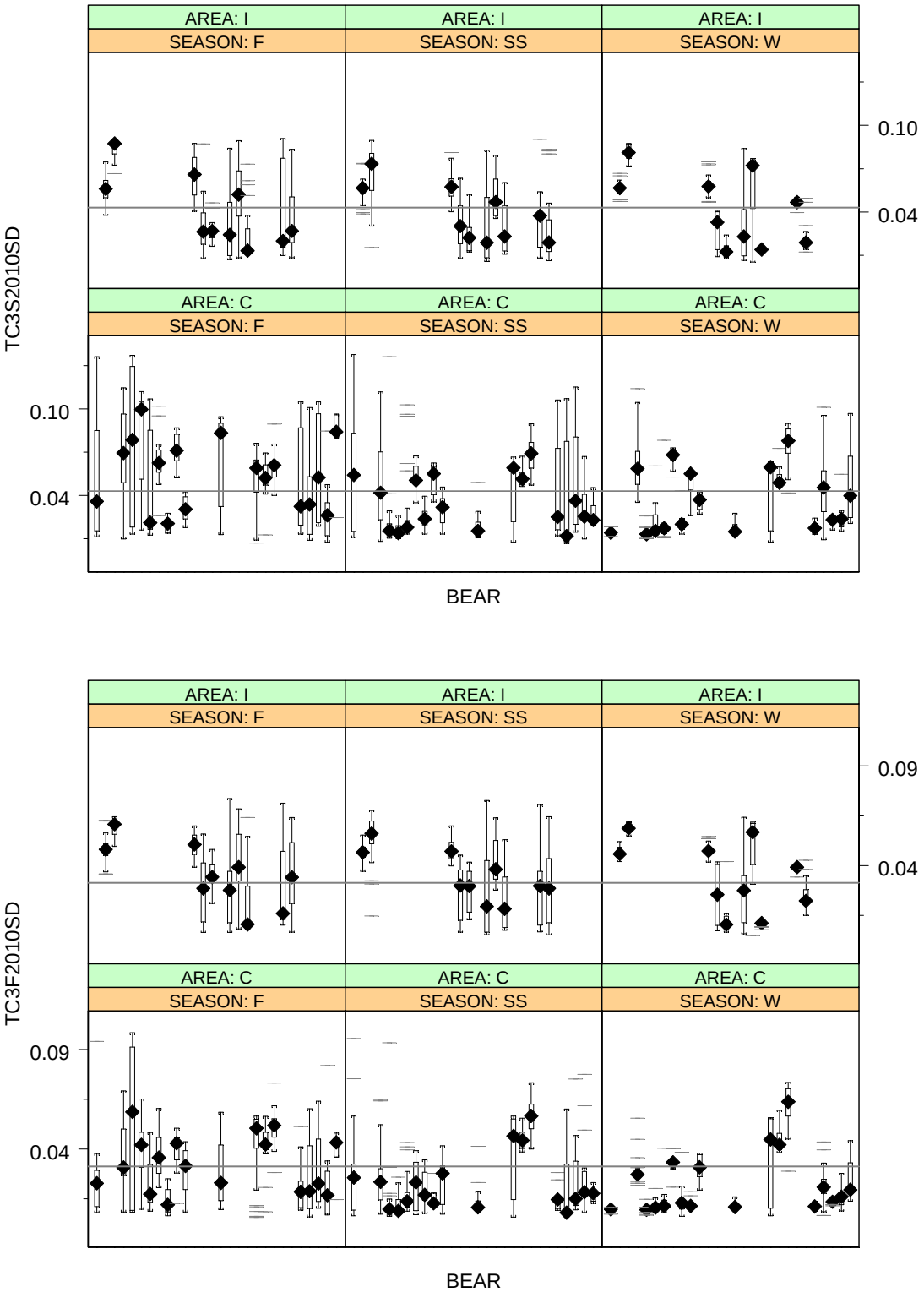


Figure 3.4. Continued.

CHAPTER 4: SELECTION OF AN APPROPRIATE MODEL BUILDING APPROACH

INTRODUCTION

As discussed in Chapters 1 and 2, there is considerable interest among natural resource managers in developing landscape scale habitat models for wildlife species. In order to develop a landscape scale habitat model, measures of the value of resources available to the species of concern and methods to quantify animal resource use across the landscape must be identified. In previous chapters, I described my analyses for selecting measures of available resources, the use of the tasseled cap function to derive habitat variables, methods to quantify resource use, and a regression-based resource selection function for development of a habitat model for Louisiana black bears.

In order to test my hypotheses regarding black bear resource selection and develop a predictive habitat model, a structured modeling process was required. The traditional approach for model building and hypothesis testing relies on null hypothesis significance tests, with frequent selection and examination of individual predictor variables. This approach has been criticized by a number of ecological researchers in recent years (Yoccoz 1991, Cherry 1998, Johnson 1999, Anderson et al. 2000, Boyce 2001, and Harrell 2001). In this chapter, I outline the traditional modeling process, identify deficiencies in the process based on current recommendations from the literature, and outline an alternative modeling approach based on Harrell (2001), which incorporates the use of the information theoretic approach advocated by Burnham and Anderson (1998) and provides clear guidance for the use of logistic regression for developing models for prediction and hypothesis testing.

SUMMARY OF THE TRADITIONAL APPROACH TO LOGISTIC REGRESSION MODELING

The traditional approach for development of logistic regression models is characterized by reliance on significance levels (p-values), null hypothesis testing, and "data dredging". Hosmer and Lemeshow's (1989, 2000) *Applied Logistic Regression* has been widely cited as the authoritative reference for logistic regression, with over 1,000 citations in many fields appearing since the book's first printing (Hosmer and Lemeshow 2000). In section 4.2 (pages 92-104) of *Applied Logistic Regression*, Hosmer and Lemeshow (2000) provide detailed guidelines for logistic regressions and methods for model building strategies. Their modeling process is patterned in the traditional hypothesis testing approach and is summarized below.

Initial Variable Evaluation (Step 1)

Univariable analysis is performed on each candidate variable to obtain estimates of variable significance (i.e., p-values) using one of the following methods:

1. Contingency tables of binomial response or outcomes (y=0,1) versus the k levels of the independent nominal or ordinal variable, or continuous variable with limited integer responses.
2. For continuous variables, univariable logistic regression, or alternatively, two-sample t-tests, are used and supplemented with examination of smoothed or scatter plots of the logit, or fitted values, versus the variable under consideration.

Select Variables for Multivariable Analysis (Step 2)

Hosmer and Lemeshow (2000) proposed two methods for constructing a multivariable model and further reducing the variable set considered. The method used

depends on the amount of data available relative to the number of variables being considered.

1. Construct a multivariable model using all variables with p-value <0.25 in univariable tests in step 1, along with all variables of known importance.
2. Alternatively, if sample size (the numbers of outcomes in each group) is adequate relative to the total number of candidate variables then include all scientifically relevant variables in a multivariable model regardless of the outcome of the univariable tests performed in step 1 above. Use a best subsets technique, which will construct all possible models from the full set of candidate variables and rank the models using a specified estimate of model fit such as the coefficient of determination (R^2) or deviance, to identify the "best" set of candidate models for further analysis. Stepwise variable selection techniques could be used instead of the best subsets method.

Refine Multivariable Model (Step 3)

Assess importance of each variable in the multivariable model selected in step 2 above using the Wald statistic and examination of the model coefficients, and eliminate variables that do not contribute to the model. Compare the new reduced model to the original multivariable model using the likelihood ratio test to determine if significant information was lost as a result of dropping the variable from the model. This process of deleting, refitting and verifying continues until all unimportant variables are eliminated. Then, any variables not included in the original multivariable model (i.e., variables dropped from consideration in step 2) are added to the reduced model that resulted from the deleting and refitting procedures to identify variables that alone are not significantly

related to the outcome, but, when combined with other variables in the model, make an important contribution. All variables that significantly contribute are retained.

Test Assumptions of Linearity for Continuous Variables (Step 4)

Check the assumption of linearity of the logit for continuous variables by examining graphs of the observed values versus the response. If the function is not linear, then determine the most logical parametric shape of the relationship between the variable and the response (e.g., quadratic, cubic, or higher order polynomial) and include additional variables in the model to account for the nonlinearity. Hosmer and Lemeshow (2000) refer to this model as the *main effects model*. Fractional polynomials and generalized additive models are proposed as more analytic approaches to assess the assumption of linearity for continuous variables.

Test for Interactions (Step 5)

Based on prior knowledge, identify plausible interactions among variables in the main effects model and test for them by adding each interaction to the main effects model one at a time and testing for changes in model fit using a likelihood ratio test. Retain all interactions that significantly improve model fit. The model containing all of the main effects and significant interactions, the "preliminary final model", must be checked for adequacy and fit prior to being used for inferences.

Assess Model Fit (Step 6)

To assess model fit or calibration (i.e., how effectively the model describes the response), Hosmer and Lemeshow (2000) recommend using the Hosmer-Lemeshow goodness-of-fit test, which is a Pearson chi-square statistic computed from observed and expected frequencies (Hosmer and Lemeshow 2000, p. 147), followed by an analysis of

residuals. An assessment of model discrimination, the model's ability to discriminate between those subjects that experience the outcome of interest versus those that do not, must also be performed, and Hosmer and Lemeshow (2000) recommend using the area under the receiver operating character (ROC) curve. Both calibration and discrimination are important.

Model Validation (Step 7)

Validate the model with out-of-sample data, either a hold out set (i.e., a set of observations selected at random and removed from the dataset prior to initiating model development) or, if possible, a different data set.

CRITIQUE OF TRADITIONAL APPROACH FOR LOGISTIC REGRESSION MODELING

The methods for initial variable evaluation, the selection of variables for multivariable analysis, and the refinement of the multivariable model (Steps 1-5) under the traditional approach encourage, if not depend on, data dredging through initial univariable screening, iterative variable examination, and the use of stepwise selection procedures. Harrell (2001, p. 56-58) outlines a number of problems with stepwise selection and concludes that "stepwise variable selection has been a very popular technique for many years, but if this procedure had just been proposed as a statistical method, it would most likely be rejected because it violates every principle of statistical estimation and hypothesis testing". Univariable screening and stepwise variable selection allow researchers to avoid the real thinking that is required to construct a set of *a priori* models, based on best available scientific information or informed opinion, to which testing will be limited. Univariable screening to identify "significant" variables to be entered into a subsequent multivariable model is just forward stepwise selection in which

the variables removed in the screening process are not reanalyzed in later steps. This is even worse than stepwise modeling as it can miss important variables that are only important after adjusting for other variables, and can cause severe biases in the resulting multivariable model fits while losing valuable predictive information from deleting marginally significant variables (Harrell 2001, p. 60).

Additionally, there are no procedures recommended in the traditional approach for determining the number of variables that may be considered given the amount of data available. The number of candidate variables considered in the modeling process, including all candidate variables screened for association with the response, nonlinear terms, and interactions, should not exceed the amount of information in the dataset, which is a function of sample size. When too many free parameters are included in a model for the amount of information in the data, over-fitting has occurred and the estimated worth of the model (e.g. R^2) will be overstated and future observations will not agree with predicted values (Harrell 2001, p. 60). Over-fitting incorporates noise and results in finding spurious associations between X and Y. For binary responses, a rule of thumb to avoid over-fitting is to limit the number of parameters, p, in the model from m/10 to m/20, where m is the smaller of the number of observed binary outcomes (Harrell 2001, p. 61). Variable screening and stepwise selection also does not solve the problem of too many variables for too little data.

Step 4 recommends the use of scatter plots to assess the assumption of linearity of the logit, and, if the response is judged to be nonlinear, to decide a "logical parametric shape" and include the additional terms in the model to account for the nonlinearity. However, in the vast majority of studies, the assumption of linearity of non-binary

predictors is probably unreasonable (Harrell 2001, p. 53), and the only reason to assume linearity is that there is insufficient information in the sample to allow reliable fit of nonlinear terms. The recommended approach typically results in an adequately fitting model, but estimates of model fit will be overstated because the degrees of freedom that are consumed during the subjective assessments are not accounted for in the computation of those estimates (Harrell 2001, p. 53).

In step 5, each "plausible" interaction is added one at a time and assessed for significance. As with steps 1-4, this additional iterative testing further overstates estimates of model fit resulting from the failure to account for the additional phantom degrees of freedom. To avoid this problem, only interactions specified in the *a priori* set of candidate models should be considered.

In Step 6, the traditional approach recommends the use of a global goodness-of-fit test to determine if the model is adequate. However, it has been demonstrated that the recommended Hosmer-Lemeshow goodness-of-fit test has limited power and is fairly dependent on how predictions are grouped. Also, a large goodness-of-fit statistic simply indicates that there is some lack of fit, but provides no insight into its nature. More power for detecting lack of fit is expected from testing specific alternatives to the model (Harrell 2001, p. 231). If a more complex model does not provide a better fit, then this provides some assurance that the fitted model is reasonable (Agresti 1996, p. 114). A plot of observed responses against predicted responses (a calibration plot), can also be examined to determine the extent of the lack of fit. A calibration plot graphically depicts that fraction of p events predicted with probability p that actually occur (i.e., are observed). A calibration plot clearly identifies in which prediction intervals the model

performs poorly, allowing the analyst to assess the consequences of the differences. For example, a model may fail the global goodness of fit because of over prediction p in the upper decile. This over prediction may be acceptable because it represents only 10% of the observations and the predictions are ranked correctly, even though the magnitude of the predicted value is overstated.

If the model is to be used for prediction, a model having poor calibration can be dismissed outright. Given two models that have similar calibration, discrimination should be examined. Discrimination can be quantified by the use of rank measures such as Somer's D_{xy}, Spearman's ρ, and area under ROC curve or probability of concordance (c index). Probability of concordance, the c index, is a unitless index of the strength of the rank correlation between predicted probability of responses and actual responses – a measure of model's predictive discrimination. It is derived from the Wilcoxon-Mann-Whitney two-sample rank test, computed by taking all possible pairs of observations such that one responded and one did not. The c index represents the proportion of such pairs with the responder having a higher predicted probability than the nonresponders. The c index is identical to the area under the ROC curve, which is a widely used measure of discrimination. A c value of 0.5 indicates random predictions (we might as well flip a coin), 0.7-0.8, acceptable discrimination, 0.8-0.9, excellent discrimination and >0.9 outstanding discrimination (Hosmer and Lemeshow 2000, p. 162). The c index is also related to Somer's D_{xy} rank correlation between predicted probabilities and observed responses where

$$D_{xy} = 2(c - 0.5) \qquad \text{(Eq. 1)}$$

D_{xy} value of 0 indicates that the model is making random predictions, where a value of 1 indicates perfect discrimination. *Dxy* and c have the advantage of being insensitive to the prevalence of positive responses.

Other measures of discrimination not based on ranks include Brier's score and Nagelkerke's generalized R^2. Brier's score (eq. 2) is frequently used in judging meteorological forecasts.

$$B = \frac{1}{n} \sum_{i=1}^{n} (Pi - Yi)^2 \qquad \text{(Eq. 2)}$$

where *Pi* is the predicted probability and *Yi* is the corresponding observed response for the i^{th} observation. However, discrimination may be estimated more directly and with greater sensitivity with model X^2 and Nagelkerke's generalized R^2 (eq. 3) (Harrell 2001, p. 78)

$$R^2 = (1\text{-}\exp(\text{-}LR/n)) \,/\, (1\text{-}\exp(\text{-}L^0/n) \qquad \text{(Eq. 3)}$$

where *LR* is the global log likelihood ratio statistic for testing the importance of all predictors in the model; L^0 is the –2 log likelihood for the null model. Evaluation of several of these measures described above will provide greater insight into the model's discrimination ability than if only one of the measures is considered.

Additionally, models used for prediction should be validated to estimate how well the model will predict future observations and to ensure that the model is not over-fitted or is otherwise inaccurate. The simplest validation method is a one time splitting of the dataset into training and test samples, which are used for model development and model validation respectively. This splitting must occur before model development begins. Following model development using the training sample, calibration and discrimination are validated on the test sample. There are several disadvantages of this approach,

however, these can be overcome by using bootstrap resampling to obtain nearly unbiased estimates of future model performance (Lachenbruch and Mickey 1968, Verbyla and Litvaitis 1989, Harrell 2001). Boyce et al. (2002) provide a nice review of evaluating resource selection functions derived using logistic regression and points out the additional challenges in validating models based on presence/available (use-vs.-availability) designs.

Calibration plots developed from bootstrap resample estimates will have a slope near 1 and an intercept near 0 if well calibrated. When parameter estimates are derived from one dataset and then applied to predict outcomes on an independent dataset, overfitting will cause the slope of the calibration plot to be less than 1 (the shrinkage factor), typically with low predictions too low and high predictions too high. "Apparent" calibration accuracy can be estimated using a nonparametric smoother relating predicted p to observed. The nonparametric estimate can be evaluated at a sequence of p levels, and the distances from the 45˚ line (perfect fit) can be compared with the differences when the model developed from the current bootstrap sample is compared back on the whole sample. Averaged over many replications, the level specific differences are subtracted form the apparent calibration to estimate over optimism in calibration (Harrell 2001, p. 262). Bootstrap validation should also be used to compute over optimism in measures of discrimination. Proper bootstrap validation must repeat any variable selection steps for each resample (Harrell 2001).

THE MODERN APPROACH FOR MODEL DEVELOPMENT

The modeling strategy recommended by Harrell (2001) overcomes the above-identified shortcomings of the traditional approach. Harrell's approach begins with a

decision on the number of degrees of freedom that can be spent to avoid problems of overfitting, followed by a decision on where they should be spent and a commitment to spending them. Later reconsideration of how those degrees of freedom have been spent is not recommended if statistical tests or confidence limits are to be considered. A strategy for developing predictive models is outlined below, followed by an outline of developing models for hypothesis testing (adapted from Harrell 2001, pages 79-83).

Development of Predictive Models

1. Formulate good *a priori* models based on as much pertinent data as possible over a wide distribution of predictor values that lead to good hypotheses of relevant candidate variables and their possible interactions. Do not examine Y in developing this list.
2. Specify the degree of nonlinearity that should be allowed for each candidate variable based on prior knowledge where possible. If prior knowledge cannot be used to specify the degree of nonlinearity, the number of degrees of freedom devoted to the variable should be based on its perceived importance in predicting Y, and on sample size. If the number of terms specified in the *a priori* models is too large in comparison to the number of outcomes in the sample, use data reduction, ignoring Y, until the number of model terms is acceptable, based on an estimate of likely overfitting or shrinkage. Overfitting can be assessed by the m/10 to m/20 rule or by the van Houwelingen-Le Cessie heuristic shrinkage estimate (Eq. 4), which quantifies the amount of overfitting present:

$$\gamma = \frac{\text{model}\chi^2 - p}{\text{model}\chi^2} \qquad \text{(Eq. 4)}$$

where p is the total degrees of freedom for the predictors and model X^2 is the likelihood for testing the joint influence of all predictors simultaneously (the global test statistic).

This process avoids the assumptions of linearity in the traditional modeling process by including nonlinear terms in the *a priori* models. The simplest nonlinear model is a quadratic (i.e., adding an X^2 term), which will account for a parabolic relationship. Model complexity can be increased to handle more complex relationships; however, polynomials have some undesirable qualities. Polynomials can have undesirable peaks and valleys, and fitting the data in one region of X can greatly affect the fit in other regions and will not adequately fit many functional forms (Harrell 2001, p. 18). When there are several predictors, the restricted cubic spline function is better for estimating the true relationship between X and logit {Y = 1} for continuous variables without assuming linearity (Harrell 2001, p. 233). Spline functions are piecewise polynomials that can accommodate a variety of functions. Splines divide the *x*-axis into intervals at endpoints called knots, and polynomials are fit to the intervals between the knots. Increasing function complexity can be accommodated by increasing k, the number of knots, with k limited by the amount of available data. Restricted cubic splines (Harrell 2001, p. 20) use cubic polynomials between knots to achieve a smooth function, but constrain the function to be linear in the tails. Restricted cubic splines have an added advantage in that only k – 1 parameters are estimated, as opposed to unrestricted cubic spline models that require k + 3 knots. Knots are typically established at fixed quantiles (percentiles) of a predictor's marginal distribution, with the quantiles being a function of the number of

knots. For example, if k=3, knots are established at 0.10, 0.50 and 0.90 quantiles, where 4 knot model use 0.05, 0.35, 0.65, and 0.95. The principle factor in choosing an appropriate k is sample size. Use of more than 5 knots is seldom required, so the decision is then between k = 3, 4, or 5.

3. Use the entire sample in model development. If the following steps are too difficult to repeat for each bootstrap of cross-validation sample, hold out test data from the following model development steps for validation of the final model.
4. Conduct structured tests of model complexity to simplify the model with limited need to penalize the final model. For example, make all continuous predictors have the same number of knots, varying k from 0 (linear) to the most complex *a priori* model and choose the value of k that optimizes Akaike's information criteria (AIC) as a data-based choice of the best model complexity "for the money".
5. Check linearity assumptions by comparing to more complex models or retain the complexity that was prespecified in step 2. Retaining the prespecified complexity is attractive if the model will be used for prediction and thus must be validated. If model complexity is altered as a result of this examination, confidence limits and other statistics will not be correct.
6. Check additivity assumptions by testing interaction terms specified in the *a priori* models, based on a global test for additivity. If the global test of additivity is decisive (e.g. P > 0.3), then all interactions terms can be eliminated; otherwise all interaction terms should be retained.
7. Determine that there are no overly influential observations. Overly influential observations can be detected using statistical measures that apply to a variety of

regression models such as leverage, DFBETAS, DFFIT, and DFFITS, which are described in most texts on linear models.

8. Do limited backwards step-down selection if parsimony is more important than accuracy, as when developing predictive models. The backwards step-down method is preferred because:
    a. It usually performs better than forward stepwise methods, especially when collinearity is present.
    b. It forces consideration of the full model, which is the only fit providing accurate standard errors, error mean square and P-values.
    c. It is very efficient, which is an important attribute if the procedure is included in the validation process.

    If step-down selection is used, the variable selection process must be included in the resampling procedure to validate the model or to compute confidence limits and other measure of model fit. This is the "final model".
9. Interpret the final model graphically by examining predicted values and significance tests. Collinear predictors should be assessed using pooled tests of association to avoid misleading impressions of their significance. However, in general, collinearity is not a large problem compared to nonlinearity and overfitting (Harrell 2001, p. 244).
10. Validate the final model for calibration and discrimination ability using bootstrapping techniques. Repeat steps 5 through 8 for each bootstrap cycle.

Development of Models for Hypothesis Testing

The strategy for developing models for hypothesis testing follows the process outline above for developing predictive models, with the following modifications.

1. Parsimony is of little concern for hypothesis testing because the full model, including insignificant variables, will result in more accurate P-values for testing models of interest.
2. Consideration of interactions is still a major concern for hypothesis testing. Each *a priori* defined interactions should be evaluated with a combined main effect + interaction test.
3. Conserving degrees of freedom devoted to predictor variables is of little concern. The degrees of freedom allowed for each variable should be based on prior beliefs, while considering the tradeoff between bias and power.
4. Model validation is not necessary, although it can be used to quantify the degree of over-fitting.

CONCLUSIONS

The traditional modeling approach has a number of shortcomings when compared with current statistical recommendations. I have identified these deficiencies and outlined a modeling strategy based on the recommendations presented by Harrell (2001), which overcomes them.

I use the modern modeling strategy in Chapter 5 to test a set of *a priori* models examining hypotheses about selection scale, required model complexity, and the relative value of combinations of predictor variables. This strategy is extended to develop predictive models in Chapter 6, where the "best" models identified in the hypotheses testing phase are further examined for parsimony and calibration and are validated. The validation process is discussed further in Chapter 6, including the additional challenges to

validate models constructed from presence/absence (use-vs.-availability) designs compared with the typical presence/absence design.

CHAPTER 5: HYPOTHESES TESTING

INTRODUCTION

As discussed in Chapter 1, wildlife habitat models are valuable tools to manage wildlife resources and are increasingly being used to manage species of concern. Of particular interest to conservation planners are habitat models developed on a landscape scale that might be useful for predicting habitat quality outside the locale in which they were developed. However, acquiring adequate landscape scale habitat data is often a limiting factor in model development. The use of habitat variables derived from tasseled cap functions as predictive variables in habitat models have shown some promise; however, no critical examination of the relative value of the function's components has been reported.

In this chapter, I will examine the effect of measurement scale and season of image capture on discriminating habitat use patterns of black bears in south central Louisiana, and investigate the relative ability of tasseled cap derived habitat variables, both alone and in combination, to detect perceived patterns of bear habitat selection. I will use the results of those analyses in Chapter 6 to develop a resource selection function that can be used to predict bear habitat selection within two study areas in south central Louisiana, and explore the potential to extrapolate predictions beyond the study area boundaries.

METHODS

Data Development

In addition to the "Forest" variable developed from GAP data to separate forested from unforested areas as explained in Chapter 2, and 84 habitat variables described in Chapter 3, I was also interested in road density as a predictive variable because roads have been an influential predictor in other models of black bear habitat selection (Mykytka and Pelton 1989, Clark et al. 1993, Hellgren et al. 1991, Rudis and Tansey 1995, van Manen and Pelton 1997). To determine road density, I first merged all primary, secondary and tertiary roads (identified as "Primary", "SECOND" and "Tertiary" coverages on Louisiana Oil Spill Contingency Plan Map CD, Version 1, Louisiana Applied Oil Spill Research and Development Program, Louisiana State University, Baton Rouge, LA), excluding tertiary roads identified as trails, into a single data layer. Next, I developed a raster data layer of 30m x 30m pixels and calculated road density (km of road/km^2) for each pixel using a 1005m-radius moving window filter. I used IDRISI 32 (Clark Labs, Worcester, MA) for all raster image processing. As with the other raster data layers described in previous chapters, I used ArcView 3.2. script SampleGrid.Ave (available from http://www.commenspace.org/resources/tools.html) to extract road density for used and available locations

Used and Available Habitat

Between October 1991 and May 1995, we collected 2,061 locations (capture locations and telemetry) on 49 female bears. I dropped 15 bears (8 Coastal and 7 Inland), each with less than 5 locations, from all analyses in this and subsequent chapters, which resulted in a loss of 26 used locations. I retained 2,035 (1,249 Coastal, 786 Inland)

locations of 34 female bears (23 Coastal, 11 Inland). I described the selection of 8,840 (4,654 Coastal, 4,186 Inland) available habitat sample locations in Chapters 2 and 3. The boundaries of available habitat were unaffected by the elimination of bears with less than five locations.

Statistical Analysis

Following the "modern" approach to model building and hypothesis testing outlined in Chapter 4, I first constructed a set of *a priori* hypotheses and then developed logistic regression models to test those hypotheses. I relied on the information theoretic approach, as presented by Burnham and Anderson (1998), using delta AIC and Akaike weights rather than null hypothesis tests with a pre-specified type I error rate (α level). Akaike weight, w_i, is the weight of evidence in favor of model *i* being the "best" model given the data at hand and the models considered (Burnham and Anderson 1998, p. 125).

My hypotheses or research questions are listed hierarchically below.

- Can a single "robust" model (ignoring area effects) adequately describe black bear habitat selection in both the Coastal and Inland study areas? To determine if a single robust model that did not include study area differences was adequate, I developed a logistic regression model containing all variables of interest (Table 5.1) for each scale of interest. Habitat variables and their interactions with study area were modeled using five-knot restricted cubic splines. I used the scale model with the greatest Akaike weight to determine if the effects of study area were additive or, if there was evidence of study area by habitat measure interaction. The presence of study area effects would indicate that a single robust model would not be possible, and that either a combined model with area effects or

separate models for each study area would be required. If there is evidence that a single robust model is not adequate, then I will develop separate models for each study area and determine which scale contains the most information for each area using AIC weight as for the single model test for scale. Development of separate models for each area would allow me to identify and compare the "best" modeling scales in each area to determine if the apparent interaction between study areas and scale observed in Chapter 3 was reflected in model selection. If there was interaction between scale and study area, then the best scales at which selection is detected will be different between the two areas. I will plot the relationship between Delta AIC and scale to examine how model information content changes with scale for the single and separate study area models.

- Is the *a priori* habitat model complexity (i.e., five-knot restricted cubic splines) required? Using the "best" scale single robust model if adequate, or alternatively, the "best" scale models for each study area, I will determine if the *a priori* model complexity is required or if a more parsimonious model is adequate. As discussed in Chapter 4, in the vast majority of studies, the assumption of linearity of non-binary predictors is probably unreasonable, and the only reason to assume linearity is that there is insufficient information in the sample to allow reliable fit of nonlinear terms. In this study, I anticipated that bears would select: intermediate values of most habitat variables, with selection being curvilinear around an optimal range. Accordingly, to avoid the assumption of linearity, I fit models using the restricted cubic spline function. With no prior knowledge of the degree of nonlinearity of habitat variables, I chose a model complexity of five-

knots (see discussion in Chapter 4). To avoid over-fitting, I limited the maximum number parameters, p, in any of the models considered to meet the m/10 to m/20 rule. I conducted structured tests of model complexity to compare the *a priori* model complexity with simpler models. The five-knot restricted cubic spline (RCS) model was compared to four-knot, and three-knot RCS models, and cubic and quadratic polynomials, and linear models. Information on the appropriate model complexity will be used in Chapter 6 to develop predictive models.

- What is the relative importance of each group of predictive variables? To examine the relative importance of each group of predictor variables given above, I developed new models by dropping variable groups from the full model of "best" scale (Table 5.1) for the single model if adequate, or alternatively, for each area, and compared all models using AIC weights. I selected groups of predictor variables for testing that others have identified as important predictors of bear habitat use, or groups of predictor variables that I believed might have value and my initial examination supported further consideration (Chapters 2 and 3).
    - Predictive values that have been identified by others as predictive of black bear habitat use that I considered were Forest and road density (Mykytka and Pelton 1989, Clark et al. 1993, Hellgren et al. 1991, Rudis and Tansey 1995, van Manen and Pelton 1997).
    - I believed that the habitat variables, described in Chapter 3, would be predictive of bear habitat use because 1) others have successfully used tasseled cap derived habitat variables (Mace et al. 1999 used greenness; Clevenger et al. 2002 used greenness and wetness) to model bear habitat

selection, 2) as described in Chapter 2, greenness is roughly equivalent to the second of the first three principle components represented by the tasseled cap function, and 3) as discussed in Chapter 2, it was logical to use all three components. Habitat variables were grouped to examine the relative contribution of each group of variables to explain the differences between used and available locations as follows:

- All habitat variables derived from window means.
- All habitat variables derived from window standard deviations.
- All habitat variables derived from spring images.
- All habitat variables derived from fall images.
- All habitat variables derived from combinations of tasseled cap (1&2, 1&3, 2&3).
- All habitat variables derived from each tasseled caps (1, 2, and 3).

Table 5.1. List of *a priori* models examined.

Combined Study Area Models (Variables in Full Single Model: Study Area, Forest, road density, all habitat variables at model scale [12 variables/scale], and all Habitat Variables*Study Area interactions – Model Complexity: 5-knot restricted cubic spline [RCS])
Models Examining Scale
Full Combined Model 90m x 90m
Full Combined Model 210m x 210m
Full Combined Model 510m x 510m
Full Combined Model 495m radius
Full Combined Model 990m x 990m
Full Combined Model 1005m radius
Full Combined Model 2010m x 2010m
Models Examining Study Area Effects
Full Combined Model – Best Scale
Drop Study Area*Habitat Variable Interaction
Drop study area effects (no interaction or additivity)

Table 5.1. Continued.

Study Area Specific Models (Variables in Full Study Area Specific Model: Forest, road density, and all habitat variables at model scale [12 variables per scale] – Model Complexity: 5-knot RCS)

Models Examining Scale

Full Coastal model 90m x 90m	Full Inland model 90m x 90m
Full Coastal model 210m x 210m	Full Inland model 210m x 210m
Full Coastal model 510m x 510m	Full Inland model 510m x 510m
Full Coastal model 495m radius	Full Inland model 495m radius
Full Coastal model 990m x 990m	Full Inland model 990m x 990m
Full Coastal model 1005m radius	Full Inland model 1005m radius
Full Coastal model 2010m x 2010m	Full Inland model 2010m x 2010m

Combined or Study Area Specific Models – Best Scale (Variables in Single or Study Area Specific Full Models)

Models Examining Model Complexity

Full Model – 5 knot RCS
Full Model – 4 knot RCS
Full Model – 3 knot RCS
Full Model – Cubic polynomial
Full Model – Quadratic polynomial
Full Model – Linear

Models Examining Variable Groups (Model Complexity: 5-knot RCS)

Full Model
- Drop Forest[1]
- Drop Road Density[1]
- Drop all habitat variables derived from window standard deviation[1]
- Drop all habitat variables derived from window means[1]

All habitat variables from spring images, Forest, and road density
All habitat variables from fall images, Forest, and road density
All habitat variables from tasseled caps 1 and 2 + Forest + road density
All habitat variables from tasseled caps 1 and 3 + Forest + road density
All habitat variables from tasseled caps 2 and 3 + Forest + road density
All habitat variables from tasseled cap 1 + Forest + road density
All habitat variables from tasseled cap 2 + Forest + road density
All habitat variables from tasseled cap 3 + Forest + road density

Note: [1] All other full model variables retained.

RESULTS

The "best" modeling scale for single combined study area models was 2010m x 2010m, with the weight of evidence for the model increasing (smaller delta AIC values) with increasing scale (Table 5.2, Figure 5.1). Comparison of models with and without study area effects and study area by habitat measure interactions at the 2010m x 2010m scale, strongly suggest that, as suspected based on the findings in Chapter 3, habitat selection differs between the two study areas, and that the differences are not additive (Table 5.3). Accordingly, study area cannot be ignored in the modeling process, and separate models for each study area were required.

Table 5.2. Model selection statistics examining scale with study areas combined in a single model. The "best" model is in bold and null model values are presented for comparison. Full model predictive variables include all habitat variables within each scale, Forest, road density, study area, and study area by habitat variable interaction. The models avoid the assumption of linearity by using the restricted cubic spline function with 5-knots.

Model	Deviance	k*	AIC	Delta AIC	w_i
Full combined model 90m x 90m	8682.03	90	8862.03	589.29	0.000
Full combined model 210m x 210m	8443.17	96	8635.17	362.43	0.000
Full combined model 510m x 510m	8221.70	98	8417.70	144.96	0.000
Full combined model 495m radius	8157.42	102	8361.42	88.69	0.000
Full combined model 990m x 990m	8134.14	102	8338.14	65.41	0.000
Full combined model 1005m radius	8091.11	102	8295.11	22.37	0.000
Full combined model 2010m x 2010m	**8068.74**	**102**	**8272.74**	**0.00**	**1.000**
Null model	10484.14				

*For models with k < 102, model did not converge because of singular information matrix. Model convergence was obtained by iteratively reducing model complexity on offending variables, reducing complexity by one knot at a time until model converged.

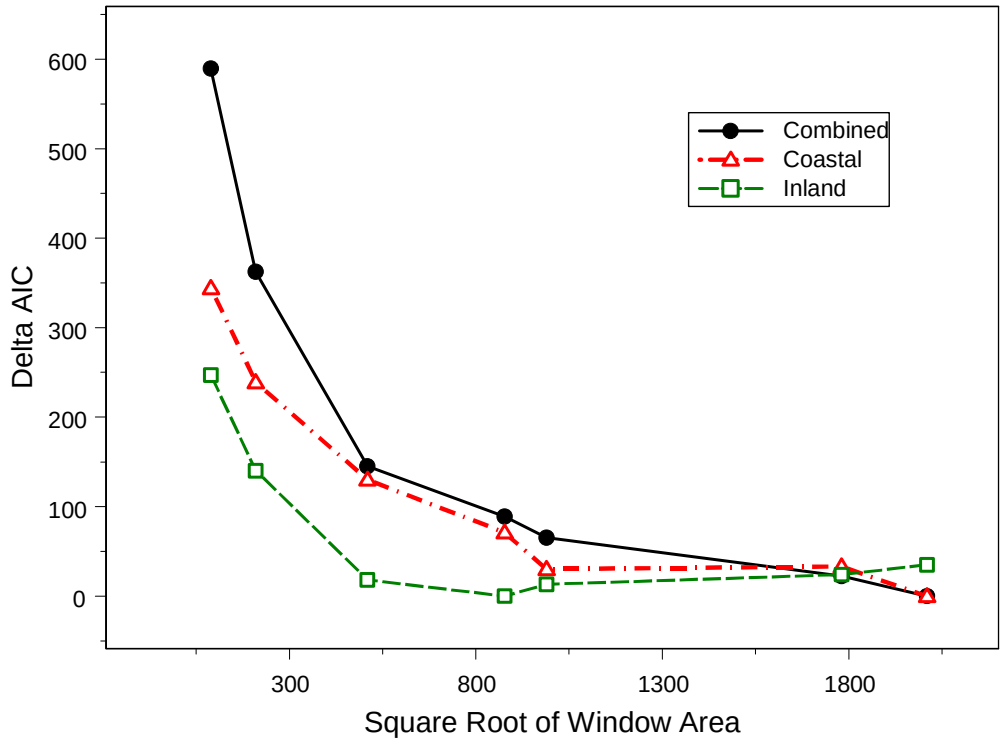


Figure 5.1. Relationship between delta AIC and scale. Delta AIC is calculated for a set of logistic regression models examining the relationship between black bear habitat use in Louisiana and predictive variables. Scale is presented as the square root of moving window area. Moving window sizes considered are 90m x90m, 210m x201m, 495m radius, 510m x 510m, 990m x 990m, 1005m radius, and 2010m x 2010m.

Table 5.3. Model selection statistics examining study area effects (interaction and additivity) for the best scale combined study area model. The "best" *a priori* model is in bold and null model values are presented for comparison. Full model predictive variables include all habitat variables within best scale, Forest, road density, study area, and study area by habitat variable interaction. The models avoid the assumption of linearity by using the restricted cubic spline function with 5-knots.

Model	**Deviance**	*k*	**AIC**	**Delta AIC**	w_i
Full combined model 2010m x 2010m	**8068.74**	**102**	**8272.74**	**0.00**	**1.000**
No Study Area*Habitat Variable Interaction	8591.62	52	8695.62	422.88	0.000
No study area effects (no interaction or additivity)	8746.46	51	8848.46	575.73	0.000

Comparison of study area specific models across scales suggested that the "best" modeling scales differed between areas (Table 5.4), confirming the apparent interaction between study areas and scale observed in Chapter 3. The "best" modeling scales were 2010m X 2010m and 495m radius in the Coastal and Inland areas, respectively (Figure 5.1). Because of these differences, all subsequent hypotheses were examined using study area specific "best" scale models.

Table 5.4. Model selection statistics examining scale separately for each study area. The "best" *a priori* model in each area is in bold and null model values are presented for comparison. Full model predictive variables include all habitat variables within each scale, Forest, and road density. The models avoid the assumption of linearity by using the restricted cubic spline function with 5 knots. Models are ranked based on delta AIC.

Model	Deviance	k*	AIC	Delta AIC	w_i	Rank
Full Coastal model 90m x 90m	5526.65	49	5624.65	344.18	0.000	7
Full Coastal model 210m x 210m	5421.62	49	5519.62	239.15	0.000	6
Full Coastal model 510m x 510m	5308.14	51	5410.14	129.67	0.000	5
Full Coastal model 495m radius	5249.05	51	5351.05	70.58	0.000	4
Full Coastal model 990m x 990m	5208.48	51	5310.48	30.01	0.000	2
Full Coastal model 1005m radius	5211.49	51	5313.49	33.02	0.000	3
Full Coastal model 2010m x 2010m	**5178.47**	**51**	**5280.47**	**0.00**	**1.000**	**1**
Null model	6092.51					
Full Inland model 90m x 90m	3121.04	49	3219.04	246.88	0.000	7
Full Inland model 210m x 210m	3012.64	50	3112.64	140.48	0.000	6
Full Inland model 510m x 510m	2887.98	51	2989.98	17.82	0.000	3
Full Inland model 495m radius	**2870.16**	**51**	**2972.16**	**0.00**	**0.998**	**1**
Full Inland model 990m x 990m	2883.04	51	2985.04	12.88	0.002	2
Full Inland model 1005m radius	2894.32	51	2996.32	24.16	0.000	4
Full Inland model 2010m x 2010m	2905.19	51	3007.19	35.03	0.000	5
Null model	4340.37					

*For models with k < 51, model did not converge because of singular information matrix. Model convergence was obtained by iteratively reducing model complexity on offending variables, reducing complexity by one knot at a time until model converged.

Tests of the model complexity suggested that the 5-knot restricted cubic spline models provided the best fit (Tables 5.5 and 5.6). Model ranks based on model

complexity in the two study areas were identical, suggesting that the ability of the specified model complexities to fit the data was similar across study areas. All variable groups were important in modeling black bear habitat selection in the Inland area, and all but road density were important in the Coastal area (Tables 5.5, 5.6).

Table 5.5. Model selection statistics examining study model complexity and variable groups for the best scale Coastal study area model. The "best" *a priori* model is in bold. Full model predictive variables included all habitat variables at the best area specific scale, Forest, and road density. Models examining variable groups used the restricted cubic spline function with 5 knots. Models are ranked based on delta AIC.

Model	*Deviance*	**k**	**AIC**	**Delta AIC**	w_i	**Rank**
Models Examining Model Complexity						
Full Coastal model – 5 knot RCS	**5178.47**	**51**	**5280.47**	**0.00**	**1.000**	**1**
Full Coastal model – 4 knot RCS	5262.70	39	5340.70	60.23	0.000	2
Full Coastal model – 3 knot RCS	5338.26	27	5392.26	111.79	0.000	4
Full Coastal model – cubic polynomial	5273.08	39	5351.08	70.61	0.000	3
Full Coastal model – quadratic polynomial	5346.41	27	5400.41	119.94	0.000	5
Full Coastal model – linear	5562.88	15	5592.88	312.41	0.000	6
Models Examining Variable Groups						
Full Coastal model	5178.47	51	5280.47	0.66	0.418	2
Drop Forest	5212.35	50	5312.35	32.54	0.000	3
Drop Road Density	**5179.81**	**50**	**5279.81**	**0.00**	**0.582**	**1**
Drop all habitat variables derived from window st. dev.	5454.60	27	5508.60	228.79	0.000	11
Drop all habitat variables derived from window means	5387.62	27	5441.62	161.81	0.000	6
Habitat variables from spring images*	5423.27	27	5477.27	197.46	0.000	10
Habitat variables from fall images*	5402.07	27	5456.07	176.26	0.000	7
Habitat variables from tasseled caps 1and 2*	5284.66	35	5354.66	74.85	0.000	5
Habitat variables from tasseled caps 1 and 3*	5280.26	35	5350.26	70.45	0.000	4
Habitat variables from tasseled caps 2 and 3*	5394.69	35	5464.69	184.88	0.000	8
Habitat variables from tasseled caps.1*	5431.83	19	5469.83	190.02	0.000	9
Habitat variables from tasseled cap 2*	5535.56	19	5573.56	293.75	0.000	13
Habitat variables from tasseled cap 3*	5516.23	19	5554.23	274.42	0.000	12

Note: "*" indicates that in addition to the predictive variables listed, Forest and road density are included.

Table 5.6. Model selection statistics examining study model complexity and variable groups for the best scale inland study area model. The "best" *a priori* model is in bold. Full model predictive variables included all habitat variables at the best area specific scale, Forest, and road density. Models examining variable groups used the restricted cubic spline function with 5 knots. Models are ranked based on delta AIC.

Model	Residual Deviance	k	AIC	Delta AIC	w_i	Rank
Models Examining Model Complexity						
Full Inland model – 5 knot RCS	**2870.16**	**51**	**2972.16**	**0.00**	**1.000**	**1**
Full Inland model – 4 knot RCS	2933.668	39	3011.67	39.51	0.000	2
Full Inland model – 3 knot RCS	3006.905	27	3060.91	88.74	0.000	4
Full Inland model – cubic polynomial	2972.205	39	3050.20	78.04	0.000	3
Full Inland model – quadratic polynomial	3012.658	27	3066.66	94.50	0.000	5
Full Inland model – linear	3157.954	15	3187.95	215.79	0.000	6
Models Examining Variable Groups						
Full Inland model	**2870.16**	**51**	**2972.16**	**0.00**	**1.000**	**1**
Drop Forest	2925.34	50	3025.34	53.18	0.000	2
Drop Road Density	2967.92	50	3067.92	95.76	0.000	4
Drop all habitat terms derived from window st. dev.	3010.84	27	3064.84	92.68	0.000	3
Drop all habitat terms derived from window means	3163.61	27	3217.61	245.45	0.000	11
Habitat variables from spring images*	3037.21	27	3091.21	119.05	0.000	7
Habitat variables from fall images*	3097.04	27	3151.04	178.88	0.000	10
Habitat variables from tasseled caps 1and 2*	3006.59	35	3076.59	104.43	0.000	5
Habitat variables from tasseled caps 1 and 3*	3006.69	35	3076.69	104.53	0.000	6
Habitat variables from tasseled caps 2 and 3*	3022.44	35	3092.44	120.28	0.000	8
Habitat variables from tasseled caps.1*	3081.99	19	3119.99	147.83	0.000	9
Habitat variables from tasseled cap 2*	3215.99	19	3253.99	281.83	0.000	12
Habitat variables from tasseled cap 3*	3217.57	19	3255.57	283.41	0.000	13

Note: "*" indicates that in addition to the predictive variables listed, Forest and road density are included.

DISCUSSION

Combined and area specific models exhibited similar overall patterns in their relationship of model information content, as measured by delta AIC, to increasing scale, and appear to reach an asymptote near the 1km window scale. This provides some evidence that the range of scales considered was adequate. However, I found strong evidence that the best scale for modeling habitat selection differed between the Coastal and Inland study areas, as I suspected based on the results presented in Chapter 3. As a

consequence of the study area by scale interaction, coupled with interactions among the study areas and habitat variables, development of a single model spanning both study areas and potentially suitable for extrapolation outside the study area boundaries was not possible. However, development of study area specific models was possible and provided valuable insight into required model complexity and the relative value of variable groups.

The model complexity of study area specific models strongly supported my *a priori* hypothesis that the bears' response to the habitat variables was best modeled as a nonlinear function. Five-knot restricted cubic spline models provided the best fit to the data overall, and model fit statistics (i.e., AIC and w_i) provide useful information into the relative amount of information lost by simplifying the model. In some circumstances, the use of a simpler model may be warranted, such as predicting habitat suitability using a GIS. For example, use of restricted cubic splines models for prediction in a typical GIS environment would be difficult, however, cubic polynomial models can be easily used. Model selection statistics allow an informed choice of an appropriate model complexity for the situation at hand.

In addition to scale, the relative importance of road density also differed between study areas. Road density accounted for a sizable fraction of the variability in the Inland study area, but was about as likely to contribute to model fit as not in the Coastal study area. The relative value of Forest is comparable in both study areas, and although an important variable to be included in the model if available, may not be worthy of extensive effort to develop otherwise.

Moving window means and standard deviations (i.e., habitat variables) were important in modeling bear habitat use, and although their relative value differed between study areas, the best models for each area included both measures. Similarly, habitat variables derived from spring and fall images differed in relative importance between study areas (spring imagery was more informative in Inland, fall imagery was more informative in Coastal), but the best models included variables derived from both seasons. Habitat variables derived from tasseled cap 1, brightness, were more informative than habitat variables derived from the other two tasseled caps in both areas. The relative value of habitat variables derived from tasseled caps 2 and 3, greenness and wetness, differed between study areas, with habitat variables derived from greenness and wetness of equal value in the Inland study area, but habitat variables derived from wetness more informative than those derived from greenness in the Coastal study area. This finding is also consistent with my *a priori* expectations, as I thought that the extent of inundated land in the Coastal area was a factor limiting bear distribution.

In summary, the conclusions from these analyses are:

- Scale matters. Habitat variables derived from tasseled cap functions using different sized moving window filters produced measures of varying information content. Researchers attempting to develop habitat models from remote sensed data should explore a range of scales rather than using the raw 30m data.
- Consider multiple summary statistics. The best models for both study areas included both habitat derived summary statistics – the moving window mean and standard deviation. Little effort is required to calculate multiple summary

statistics from processed imagery, and they should be considered if the statistic can be justified *a priori*.

- Use multi-temporal data if available. In this study, habitat variables derived from imagery captured during spring and fall improved model information content. In each study area, the relative amount of information available from the imagery of each season differed. I suspect that this situation is not unique and finding a rational for selecting imagery from one season over another would be difficult.
- Use all of the information available in the tasseled cap function. The tasseled cap function produces three commonly used measures, brightness, greenness, and wetness. As discussed in Chapter 2, the tasseled cap function is similar to a principle-components analysis, typically with decreasing amount of information in each subsequent measure. However, each measure includes different information, with the potential for each measure to be more important in one situation than another. If justified by *a priori* hypotheses, all of the data should be considered before being discarded.

CHAPTER 6: RESOURCE SELECTION MODELS FOR PREDICTION

The development of bear resource selection models began in Chapter 5 with the identification of the bear habitat selection model for each study area that had the lowest AIC. Those models were used for hypothesis testing; however, as described in Chapter 4, a refinement of those models to identify the most parsimonious model was required for prediction of bear resource selection within the study areas.

In addition to model refinement, examination of model calibration, discrimination and validation were required. Examination of model calibration and discrimination are often lacking in published RSF models, and validation is not typically conducted despite the clear need to do so before such models are used for management (Fielding and Bell 1997, Verbyla and Litvatis 1989). No model should be used for prediction unless it has been determined that the model effectively describes the response (calibration), adequately discriminates between those subjects that experience the outcome of interest versus those that do not (discrimination), and has acceptable capabilities to correctly predict future observations.

In this chapter, I refine the "best" models from Chapter 5 to make predictions of bear resource selection in each study area and present a method to apply the study area-specific RSFs beyond study area boundaries. I also use the development of habitat selection predictions in south central Louisiana to explore issues of model calibration and validation for RSFs developed from used/available data where separate samples of used and available resources are taken as opposed to using a census or single sample in which subjects either exhibit a response or not (e.g., used and unused resources).

I also consider an alternative method to RSFs for identifying suitable resource units based on statistical distance, known as Mahalanobis distance. As discussed in Chapter 1, logistic regression requires measurements of used and available (or unused) resources. The difficulty of defining "available" resources and the impacts on subsequent data analysis has been the subject of considerable discussion (Johnson 1980, White and Garrott 1990, Alldredge and Ratti 1992, Aebischer et al. 1993, Manly et al. 1993, McClean et al. 1998, Garshelis 2000). The advantage of Mahalanobis distance over logistic regression is that only the set of used resources needs to be correctly defined, eliminating the problems caused by misclassification of available habitats (Clark et al. 1993). However, Mahalanobis distance assumes multivariate normality, which is typically not valid for most habitat data (Manly et al. 1993, Harrell 2001), and users of Mahalanobis distance interested in evaluating model variables or hypothesis testing must rely on other statistical techniques. In spite of these limitations, Mahalanobis distance is an attractive method for developing GIS-based habitat maps because it avoids the issue of defining availability and it's comparatively easy to implement in GIS. I explore the use of Mahalanobis distance to identify resource selection in my study areas and compare those results with RSF results. I also explore a new use of Mahalanobis distance to evaluate the similarity of the available resources in potential bear habitat beyond my study area boundaries to identify areas where study-area specific models of bear resource selection may be reasonably applied. Based on those findings, I will generate bear habitat selection maps for areas outside of my study areas, but within Louisiana's Mississippi River Alluvial Plain.

METHODS

The model building process used in this chapter follows that outlined in Chapter 4. All statistical analyses were performed with S-Plus, version 6.1.

The Resource Selection Function

Manly et al. (2002; p. 13) defined the resource selection function (RSF) as a function of characteristics measured on resource units such that its value for a unit is proportional to the probability of that unit being used. When a resource selection function is derived from a census or single sample of used and unused resource units, the RSF is referred to as a resource selection probability function (RSPF), and the function gives the expected probability of use for the observed resource units. For RSPFs developed from used/unused data using logistic regression, expected values estimated by the logistic regression model (equations 6.1 or 6.2) are the probability of observing the response (i.e., $Y = 1$), given the values of the matrix of predictors, $\boldsymbol{X}$, and $\boldsymbol{\beta}$, and the vector of estimated regression coefficients $\beta_0 - \beta_k$.

In matrix terms, the logistic function is

$$\text{Prob}\{Y = 1|X\} = [1 + \exp(-\boldsymbol{X\beta})]^{-1} \tag{6.1}$$

or equivalently,

$$\text{Prob}\{Y = 1 \mid X\} = \frac{\exp(\beta_0 + \beta_1 X_1 + \ldots \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \ldots \beta_k X_k)} \tag{6.2}$$

To model used/unused data using logistic regression, the bounds of the study area are delineated and resource units to be censused or sampled are identified. The resource units are then observed to determine whether or not they are used; used units are coded as 1 and unused units are coded as 0. *A priori* predictor variables that are known or hypothesized to be associated with resource use are then measured on each unit.

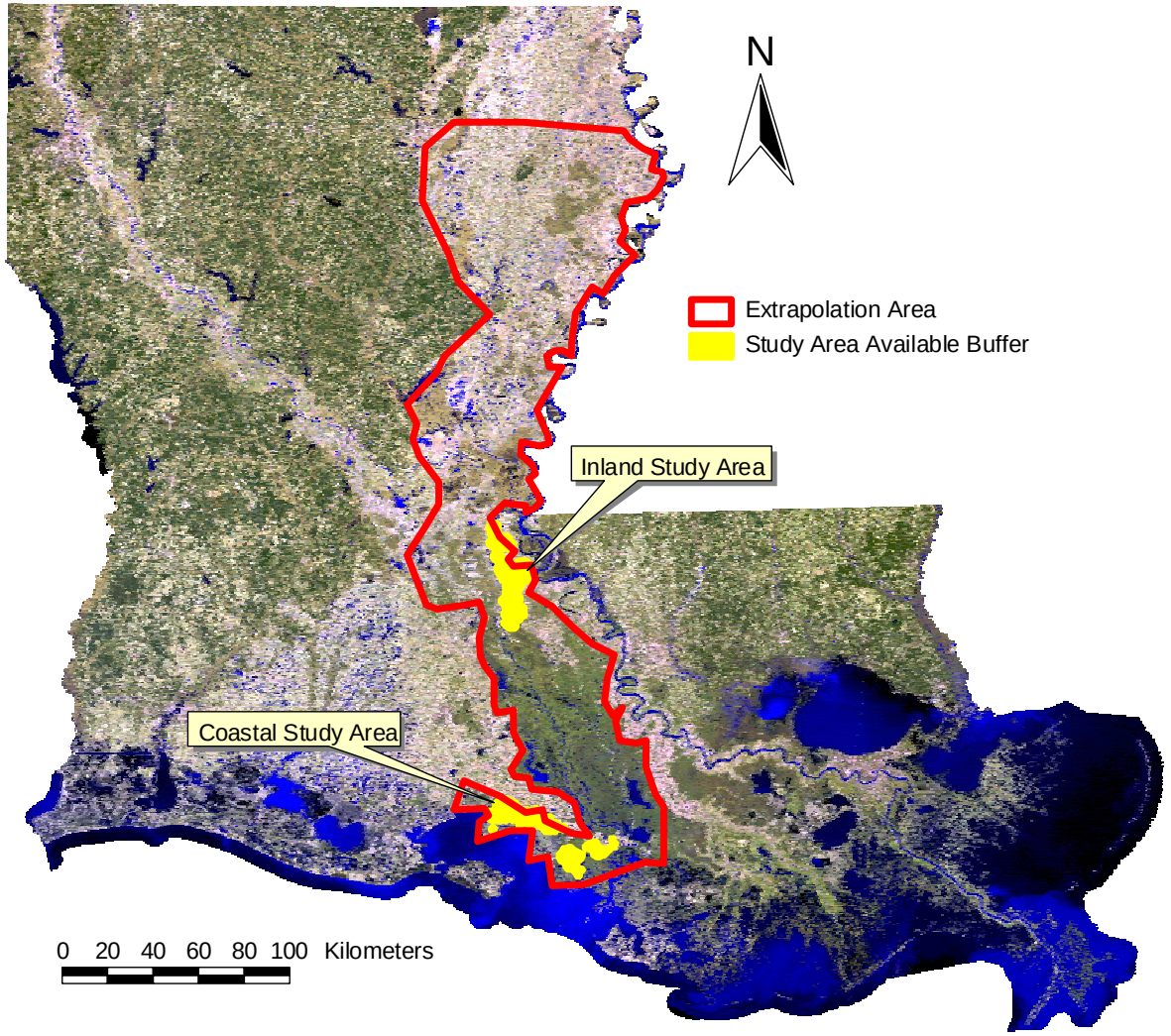


Figure 6.1. Study areas in south Central Louisiana and extrapolation area within Mississippi Alluvial Floodplain.

Regression coefficients are estimated by of maximum likelihood, and the model can then be used to estimate, or predict, the probability of use for each unit.

However, when separate independent samples are taken of used and available sites (used/available data), the estimated Prob$\{Y = 1|X\}$ can be considered a RSPF only if P_a, the probability of sampling an available resource unit, and P_u, the probability that the resource unit was used given that it was sampled, are known (Manly et al. 1993). In this situation, the model intercept, β_0 in equation 6.2, is modified to $\log_e[(1-P_a)P_u/P_a]+\beta_0$ to allow available and used resource units to be sampled with different probabilities. The resource selection function can then be estimated by substituting $\beta_0 - \log_e[(1-P_a)P_u/P_a]$ for β_0 in equation 6.2. If P_u or P_a is unknown, Manly et al. (1993) state that the RSF can still be estimated using equation 6.3, but the model predictions must be considered an index of use rather than interpreted as the true probability of use.

$$w(x) = \exp(\beta_1 X_1 + \ldots \beta_k X_k) \qquad (6.3)$$

where $\beta_1 - \beta_k$ are derived from logistic regression (eq. 6.1 or 6.2).

I recorded radio-collared bear locations (i.e., used resource units) and randomly selected available resource units within each study area using GIS. As was the case for my study, when a sample of available resource units are selected from GIS data, such as satellite imagery or other raster data, P_a can be defined as the ratio of the number of pixels in the sample to the total number of pixels in the study area. However, P_u cannot be determined from typical telemetry data because the sampling proportion of used units is unknown. Therefore, I was unable to develop a RSPF for bear resource use in my study areas and I had to develop a RSF.

Interpreting the RSF developed from used/available data as if it were a RSPF derived from used/unused data is inappropriate because of the sensitivity of predicted probabilities to changes in the sampling proportions of used and available resource units. In my study, including more or fewer pixels in the sample would alter the sampling proportion of available resources, and, similarly, increasing or decreasing the relocation interval could have changed the sampling proportion of used units. As these sampling proportions change, altering the relative fraction of used to available units in the sample, so does the range of predicted values within each category. Classification is sensitive to the relative size of the two component groups (i.e., used and available) and always shifts the range of predicted values for both groups towards the larger group. This fact is independent of model fit (Hosmer and Lemeshow 2000, p. 157). This effect is depicted graphically in Figure 6.2, which I constructed by treating the samples of used and available resources for the Inland study area as if they were a census of used/unused resource units, sampling the used and available resources at different probabilities, and predicting the RSF using the model with the lowest AIC for the Inland study area from Chapter 5 for each sampling proportion. It is evident that decreasing the probability of used locations in the sample skews the distribution of Prob{Y = 1|X} towards 0, and increasing the probability of used locations skews the distribution towards 1. So, interpreting logistic regression model predictions from used/available data as though they were used/unused data is clearly inappropriate. To eliminate this problem, many researchers bin, or group, RSF predicted values estimated using equation 6.3 in quantiles from which inference and maps are made. However, ranks, and thus quantiles, of predicted values from equations 6.2 and 6.3, with and without elimination of the model

intercept, $\beta_{0,}$ are identical, and thus the predicted values form standard statistical packages, based on equation 6.2, can be used directly avoiding the need to calculate values using equation 6.3. This fact is important in that many statistical packages have procedures to assess model calibration and discrimination based on predicted values from equation 6.2. This fact also suggests that measures of model discrimination based on ranks should be valid, which is discussed further below. Accordingly, for all analyses in this chapter I used model predictions from equation 6.2 as the estimated RSF.

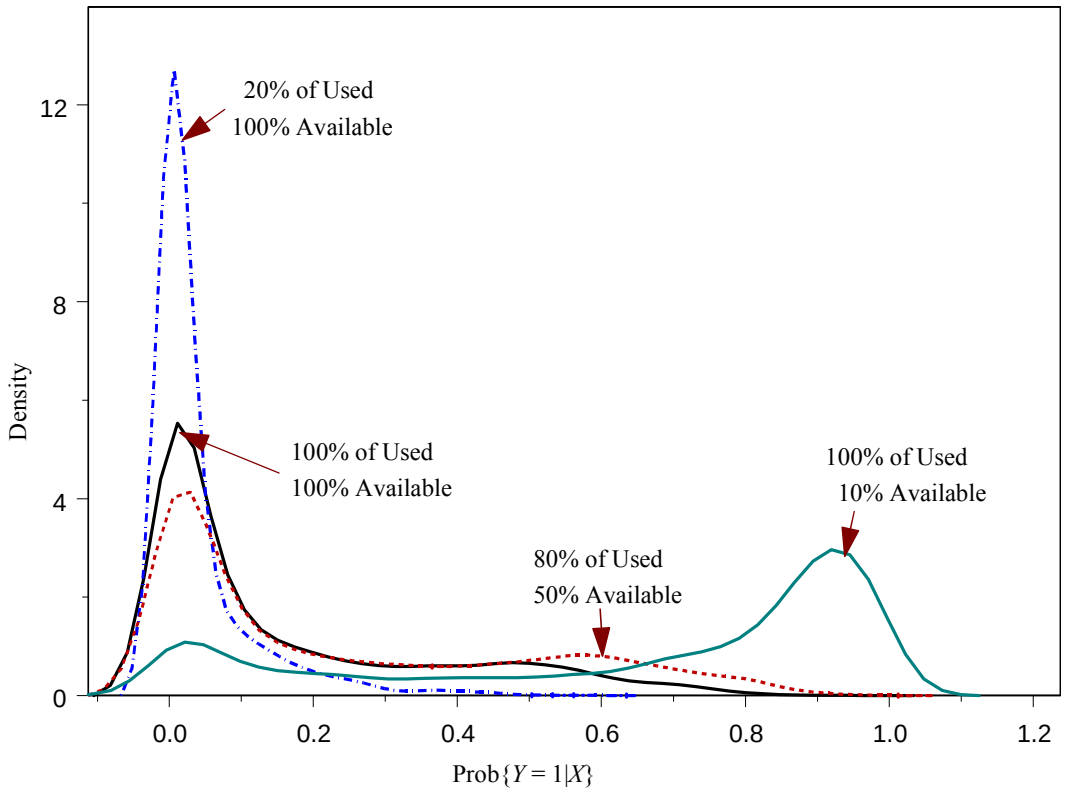


Figure 6.2. Distribution of Prob$\{Y = 1|X\}$ for different sampling probabilities of used and available units. Lines are kernel smoothed densities of Prob$\{Y = 1|X\}$. Inland study area data were used for this example. The dataset included 4,186 available units and 786 used units.

Final Model Development, Model Calibration, Validation, and Refinement

To find the most parsimonious "final" model for each study area, I first examined DFBETAS and DFFITS (Harrell 2001, p. 245 and 261) to determine that there were no overly influential observations, and then performed limited backwards selection (see Chapter 4 and below) on the "best" full model for each area identified in Chapter 5 (i.e., Full Coastal model 2010 m x 2010 m, Full Inland model 495 m radius). As discussed in Chapter 4, models used for prediction should be examined to determine model adequacy (calibration), and they should be validated before being used for management decisions. To assess over optimism in the final models' estimated calibration and discrimination, I used bootstrapping methods described by Harrell (2001). In this process, a new sample (the bootstrap sample) of size *n* is drawn with replacement from the original *X* and *Y* sample of size *n*. A model based on the bootstrap sample is derived and applied without change to the original sample, and the accuracy indices from the bootstrap sample minus the index computed on the original sample is an estimate of optimism. The process is repeated for j bootstrap replications to obtain an average optimism for the accuracy indices. Each of the 200 bootstrap iterations included the limited backward selection process used to derive the "final" model. In this process, each predictor variable was dropped from the "best" full model, and AIC was calculated for the reduced model. If the reduced model resulted in an increase in AIC > 2, then the variable was eliminated, else the variable was retained, and the process was repeated with the next variable in the model until each variable in the model was evaluated. Factors requiring multiple degrees of freedom were retained or dropped as a group, so any higher order terms accounting for nonlinearity of a variable were dropped with the predictive variable as a group. Variable

selection for each bootstrap iteration was recorded and summarized, and over optimism in measures of discrimination were calculated and reported. I also used the results of these analyses to adjust the "final" model for predictions in each study area. If predictor variables included in "final" model were frequently included in the bootstrap models, then those variables would be added back into the "final" model, and vice-a-versa, if a predictor variable was included in the "final" model but rarely included in the bootstrap models, then it was eliminated from the "final" model. Calibration was assessed using calibration plots, as discussed in Chapter 4, and the Hosmer-Lemeshow GOF test.

Based on my previous examination of important sources of variation (see Chapter 3), I expected differences among bears to dominate variability among used locations. The bootstrapping procedure estimating how well the model for each study area would be expected to perform on a new random sample drawn from the same population as a whole, but provided little insight into how well the models would be expected to perform on a new bear from the study area. Therefore, I also wanted to: 1) estimate how well the models would be expected to perform on a new bear from the study area, 2) gain insight into the range of variability in habitat selection among individual bears within each study area, and 3) gauge the relative influence of bears with large numbers of used locations on model selection. I used a modified "jackknife" procedure to perform these assessments. For all bears with > 50 locations (bears $j - n$), I removed the j^{th} bear's used locations from the study area's original dataset, and developed the j^{th} training set model. The j^{th} training set model was then used to predict the probability of use for each location observed for the j^{th} bear. These were compared with the similar predictions for the j^{th} bear's locations based on the final model using Spearman ρ^2.

Further, I considered the model assessment method proposed by Boyce et al. (2002), which I refer to as the Boyce test. The Boyce test is a k-fold cross validation for evaluating "prediction success", based on the correlation between RSF ranks and area-adjusted frequencies for a withheld sub-sample of data. Calculation of the Boyce test requires extrapolation of model predictions to determine the area in ad-hoc bins of used location predictions. Boyce et al. (2002) argued that many methods for evaluating logistic regression models are inappropriate for used/available data because the distribution of used sites is not drawn directly from available sites, so neither category is exclusive as in the usual application of logistic regression, as discussed above.

Commonly, in used/available designs modeling continuous variables, samples of available resource units are larger than those of used units, favoring classification into the larger group, independent of model fit. Researchers unaware of this phenomenon may get the impression that their models are poor when in fact that may not be the case. Boyce at al. (2002) asserted that ROC (which is the same as c-index; see Chapter 4) and similar measures are flawed when used with used/available data, but provide no evidence to support that position. Because the Boyce test lacks a well developed theoretical basis, and like the Hosmer-Lemeshow GOF test, would be sensitive to how data are binned, I believe that the rank based methods to assess the model's discriminatory ability (e.g., Somer's D_{xy} and c-index), discussed in Chapter 4 and used in this chapter, perform adequately on used/available data. To assess the validity of this hypothesis, I compared the c-index for each of the variable probability samples used to create Figure 6.2 for the Inland study area, and evaluated similar datasets for the Coastal study area.

Extrapolate RSF Predictions Within Study Area Boundaries

I used the final model to predict the RSF for all available and used locations in the original datasets for each study area. I plotted those predictions using GIS to create maps of predicted habitat selection. Model predictions were binned into 20% quantiles (i.e., $\leq$ 20th percentile, > 20th percentile and $\leq$ 40th percentile, > 40th percentile and $\leq$ 80th percentile, and > 80th percentile).

Compare RSF Results With Mahalanobis Distance Within Study Area Boundaries

Some researchers have used Mahalanobis distance as an alternative to RSFs because it is relatively easy to implement in a GIS and avoids the problems associated with defining availability. Mahalanobis distance is the dimensionless statistical distance of a set of variables from a multivariate centroid, adjusted for variance in each dimension of the multivariate set. Small distances indicate similarity to the centroid, which in this case is the multivariate mean of the set of measured habitat characteristics. Mahalanobis distance is calculated as

$$M = (\mathbf{x} - \hat{\boldsymbol{\mu}})' \hat{\boldsymbol{\Sigma}}^{-1} (\mathbf{x} - \hat{\boldsymbol{\mu}}) \qquad (6.4)$$

where $\mathbf{x}$ is the p-dimensional matrix of observed habitat characteristic variables (x_1, x_2, … x_p), $\hat{\boldsymbol{\mu}}$ is the mean vector of habitat characteristics estimated from the used locations and $\hat{\boldsymbol{\Sigma}}$ is the estimated covariance matrix from the used locations. Assuming multivariate normality, Mahalanobis distances are approximately distributed as a chi-squared with p-1 df. Some authors have plotted significance levels (p-values) and others have plotted scaled distances, or binned distances into quantiles, avoiding the usually questionable assumption of multivariate normality (Knick and Rotenberry 1998).

Mahalanobis distance has been proposed as an alternative to RSF (Clark et al. 1993), but I was unable to locate any studies that compared the two approaches on the same data. Therefore, I calculated $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ for used locations in each study area and determined Mahalanobis distances for used and available sample locations combined based on those values. Mahalanobis distances of used locations were binned into 20% quantiles (i.e., $\leq 20^{th}$ percentile, $> 20^{th}$ percentile and $\leq 40^{th}$ percentile, $> 40^{th}$ percentile and $\leq 80^{th}$ percentile, and $> 80^{th}$ percentile), and available locations were binned using the used binned distances. For example, if the first bin ($\leq 20^{th}$ percentile) for used Mahalanobis distances was 0-7, then the first bin for the combined locations would be based on this same distance interval. I compared Mahalanobis distances for combined used and available sample locations with RSF results for each study area using Spearman's ρ^2.

Extrapolate RSF Predictions and Mahalanobis Distances Beyond Study Area Boundaries

To identify blocks of potentially suitable habitat beyond study area boundaries, I needed a sample of available habitat in the extrapolation area. I used the Sample extension to ArcView 3.2 (Quantitative Decisions, http://www.quantdec.com) to generate 1-km grid with a random starting point and orientation angle in order to systematically sample the extrapolation area (Figure 6.1). As with the other raster data layers described in previous chapters, I used ArcView 3.2 script SampleGrid.Ave (available from http://www.commenspace.org/resources/tools.html) to extract all model predictor variables for the extrapolation sample.

Because RSFs are a function of used units relative to what is available to the animal, application of RSFs to areas other than where they were developed is suspect

unless the available resources are comparable in the original and extrapolation areas. I used Mahalanobis distance to evaluate the similarity between the available resources in each study area and those available throughout the extrapolation area. I calculated $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ for available locations in each study area and determined Mahalanobis distances for the available sample locations, which were then binned into 20% quantiles. I then calculated Mahalanobis distance for the extrapolation sample using $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ for available locations in each study area, and binned the extrapolation locations using the available binned distances, providing a measure of similarity to the available resource units in each study area. RSF predictions beyond study area boundaries should only be applied to areas where availability was comparable. I produced maps depicting the similarity throughout the extrapolation area to each study area.

I extrapolated RSF using the final model for each study area to the extrapolation sample, and binned the extrapolation area's predicted values using the same bin intervals developed for the predictions within the study areas. This allowed comparison of selection relative to the selection within the study area (bin intervals would be much wider based on comparable extrapolation quantiles). I produced maps of RSF based on each study area.

I also produced maps depicting similarity throughout the extrapolation area to the used location in each study area. I calculated Mahalanobis distance for the extrapolation sample using $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ for used locations in each study area, and binned the extrapolation sample distances into the same bin intervals developed from the used samples.

RESULTS

Model Calibration, Validation, and Refinement

The "best" (lowest AIC) Coastal and Inland full models identified in Chapter 5 were the "Full Coastal model 2010m x 2010m" and "Full Inland model 495m radius" models. These models included Forest, road density, and 12 habitat variables at the specified model scale. Five-knot RCS functions were required to provide adequate model complexity.

Bootstrapped limited backwards selection on the full models for each study area, performed in conjunction with calibration and validation, confirmed that the "best" model for the Inland study retained all model variables for the majority of resamples and thus should be used as the Final Inland model (Tables 6.1, 6.2). However, those results suggested that road density should be dropped from the Final Coastal model because it was more likely to be excluded from the "best" model for the 200 bootstrap resamples than not. All Coastal and Inland Final model variables, excluding some nonlinear terms, were highly significant (Table 6.3), except TC3F2010M in the Coastal model, which was marginally significant but was retained because it was more likely to be retained than not in the bootstrap validation process.

The Hosmer-Lemeshow global goodness-of-fit test suggested that the fit of the Final Coastal model was poor (P=0.0003). However, the bootstrap estimates of calibration errors were small (mean absolute error=0.019, 0.9 quantile of absolute error=0.037), and the source of the lack of fit is evident in the calibration plot (Fig. 6.3). That is, model predictions in the range of 0.2-0.4 (~0.65-0.85 quantiles of predicted values) are overestimated, and predicted values > 0.5 (the upper 0.9 quantile of predicted

Table 6.1. The number/fraction of bootstrap resamples in which *k* variables were retained using limited backward selection on the "best" full Coastal and Inland study area models identified in Chapter 5.

	Coastal		Inland	
k	# of Bootstrap Iterations with k Variables	Fraction of Bootstrap Iterations with k variables	# of Bootstrap Iterations with k Variables	Fraction of Bootstrap Iterations with k variables
9	1	< 1%	0	0%
10	0	0%	2	1%
11	21	11%	9	5%
12	86	43%	34	17%
13	76	38%	61	31%
14	16	8%	94	47%

Table 6.2. The number/fraction of bootstrap resamples in which each variable was retained using limited backward selection on the "best" full Coastal and Inland models identified in Chapter 5.

	Coastal		Inland	
Factor	# of Bootstrap Iterations Factor Retained	Fraction of Iterations Factor Retained	# of Bootstrap Iterations Factor Retained	Fraction of Iterations Factor Retained
TC1.F.M	200	100%	200	100%
TC1.F.SD	200	100%	185	93%
TC1.S.M	197	99%	200	100%
TC1.S.SD	200	100%	133	67%
TC2.F.M	199	100%	199	100%
TC2.F.SD	200	100%	147	74%
TC2.S.M	198	99%	187	94%
TC2.S.SD	172	86%	200	100%
TC3.F.M	101	51%	200	100%
TC3.F.SD	190	95%	197	99%
TC3.S.M	200	100%	188	94%
TC3.S.SD	200	100%	200	100%
Forest	200	100%	200	100%
Road Density	27	14%	200	100%

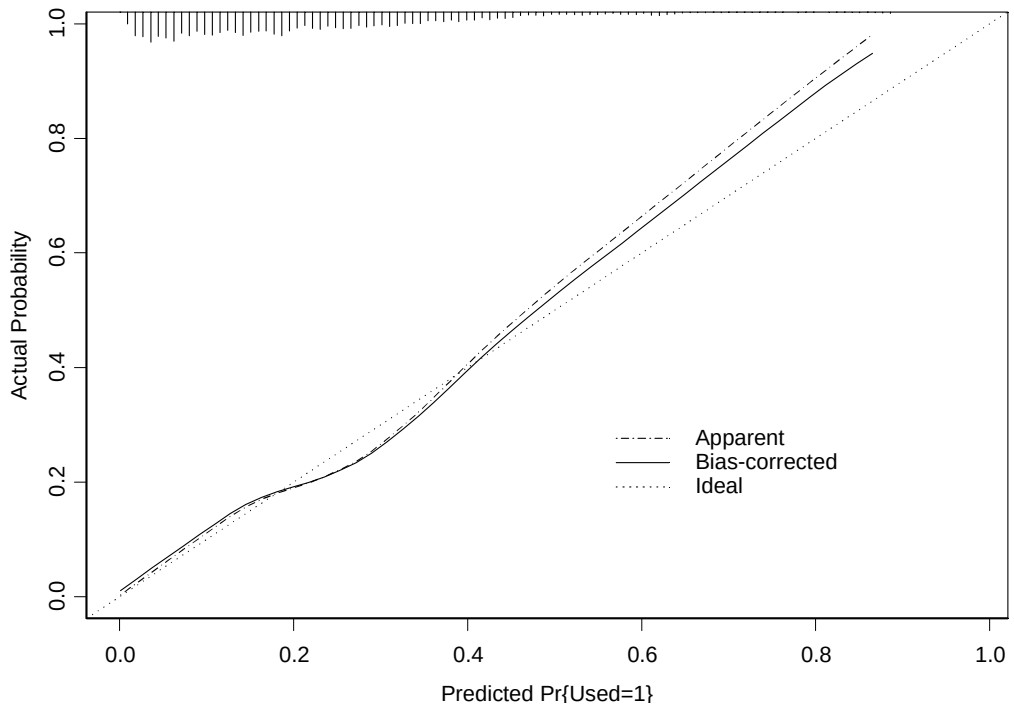
Table 6.3. ANOVA table of Final Coastal and Inland models. Chi-square and P-values were based on Wald statistic.

Final Coastal Model				Final Inland Model			
Factor	Chi-Square	d.f.	P	Factor	Chi-Square	d.f.	P
TC1F2010M	56.05	4	<.0001	TC1F495rM	44.24	4	<.0001
Nonlinear	25.81	3	<.0001	Nonlinear	14.5	3	0.0023
TC1F2010SD	36.41	4	<.0001	TC1F495rSD	17.47	4	0.0016
Nonlinear	36.05	3	<.0001	Nonlinear	5.69	3	0.1275
TC1S2010M	39.34	4	<.0001	TC1S495rM	49.91	4	<.0001
Nonlinear	35.36	3	<.0001	Nonlinear	25.71	3	<.0001
TC1S2010SD	95.55	4	<.0001	TC1S495rSD	10.78	4	0.0291
Nonlinear	10.6	3	0.0141	Nonlinear	4.15	3	0.2458
TC2F2010M	28.96	4	<.0001	TC2F495rM	39.46	4	<.0001
Nonlinear	11.15	3	0.0109	Nonlinear	9.01	3	0.0292
TC2F2010SD	51.66	4	<.0001	TC2F495rSD	12.02	4	0.0172
Nonlinear	20.38	3	0.0001	Nonlinear	11.59	3	0.0089
TC2S2010M	26.69	4	<.0001	TC2S495rM	22.87	4	0.0001
Nonlinear	20.37	3	0.0001	Nonlinear	5.36	3	0.1473
TC2S2010SD	17.48	4	0.0016	TC2S495rSD	52.8	4	<.0001
Nonlinear	15.35	3	0.0015	Nonlinear	19.79	3	0.0002
TC3F2010M	7.6	4	0.1073	TC3F495rM	51.18	4	<.0001
Nonlinear	2.08	3	0.5559	Nonlinear	18.19	3	0.0004
TC3F2010SD	21.61	4	0.0002	TC3F495rSD	28.77	4	<.0001
Nonlinear	2	3	0.5729	Nonlinear	21.88	3	0.0001
TC3S2010M	26.14	4	<.0001	TC3S495rM	21.51	4	0.0003
Nonlinear	25.84	3	<.0001	Nonlinear	10.88	3	0.0124
TC3S2010SD	48.99	4	<.0001	TC3S495rSD	34.17	4	<.0001
Nonlinear	7.85	3	0.0493	Nonlinear	22.45	3	0.0001
Forest	33.73	1	<.0001	Forest	51.25	1	<.0001
				Road Density	74.64	1	<.0001
TOTAL				TOTAL			
NONLINEAR	333.04	36	<.0001	NONLINEAR	199.77	36	<.0001
TOTAL	648.54	49	<.0001	TOTAL	668	50	<.0001

values) are underestimated. This lack of fit does not however, diminish the utility of the model because the predicted values are used as a RSF representing the relative probability of use. The Hosmer-Lemeshow global goodness-of-fit test provides no evidence of a lack of fit of the Inland Final model (P=0.51), calibration errors were small (mean absolute error=0.008, 0.9 quantile of absolute error=0.019), and the calibration plot fit well (Fig. 6.3), except for model predictions > 0.5 (the upper 0.9 quantile of predicted values), which were overestimated. It is important to note that calibration was relatively consistent among bootstrap resample estimates for both the Coastal and Inland Final models as evidenced by the close agreement between the apparent and bias-corrected calibration curves.

Final model validation statistics based on the jackknife by bear procedure suggested that the discriminatory ability of both the Coastal and Inland Final models was acceptable (Table 6.4). The Final Coastal model had a *c* index value (ROC) of 0.76, which is considered acceptable discrimination (Hosmer and Lemeshow 2000), and the Final Inland model had a *c* index value of 0.89, which is considered excellent discrimination. Bootstrap validation results indicated over-optimism in D_{xy} of 0.025 for the Coastal model and 0.018 for Inland, which resulted in bias-corrected estimates of D_{xy} of 0.485 for Coastal and 0.755 for Inland, and translates to bias-corrected *c* index values of 0.74 and 0.88 for Coastal and Inland respectively. The bias-corrected measures of discrimination provided a good estimate of what would be obtained by a future independent validation. Briers score, another measure of discrimination, also suggested that the discriminatory ability of both study area models was acceptable with bias-corrected estimates of 0.14 and 0.09 for the Coastal and Inland areas, respectively.

a.



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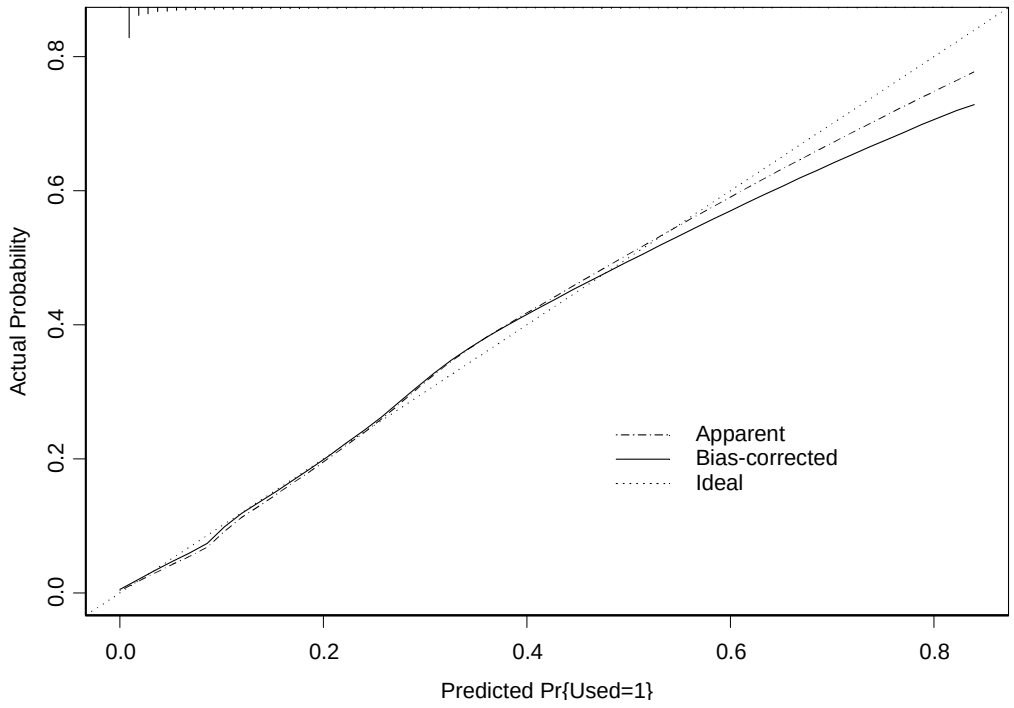

Figure 6.3. Bootstrap calibration curve using a loess smoother examining the Final Coastal (a) and Inland (b) model fit, and a rug plot of the predicted value distribution.

Table 6.4. Final model discrimination statistics and jackknife results.

Coastal Study Area

	n obs	c	D_{xy}	R^2	Brier	
Final Model	5903	0.76	0.512	0.22	0.14	
		Jackknife Model Discrimination				**Comparison of Jackknife to Final Model**
Bear ID	**n. bear obs**	**c**	**D_{xy}**	**R^2**	**Brier**	**ρ2**
001	63	0.76	0.52	0.23	0.14	0.91
011	106	0.78	0.55	0.25	0.13	0.12
012	69	0.76	0.51	0.22	0.13	0.73
015	119	0.78	0.55	0.25	0.13	0.87
021	52	0.76	0.52	0.23	0.14	0.94
026	52	0.77	0.54	0.25	0.13	0.85
039	100	0.75	0.50	0.21	0.14	0.86
041	104	0.74	0.48	0.19	0.14	0.70
043	93	0.74	0.49	0.19	0.14	0.56
049	54	0.76	0.52	0.23	0.14	0.95
050	67	0.75	0.50	0.22	0.14	0.70
mean		0.76	0.52	0.22	0.13	0.74
st. dev.		0.012	0.024	0.021	0.003	0.241

Inland Study Area

	n. obs	c	D_{xy}	R^2	Brier	
Final Model	4972	0.89	0.77	0.44	0.09	
		Jackknife Model Discrimination				**Comparison of Jackknife to Final Model**
Bear ID	**n. bear obs**	**c**	**D_{xy}**	**R^2**	**Brier**	**ρ2**
005	97	0.88	0.76	0.41	0.09	0.71
009	58	0.89	0.78	0.44	0.09	0.67
027	123	0.89	0.78	0.43	0.08	0.91
029	103	0.89	0.77	0.43	0.08	0.58
034	123	0.89	0.77	0.42	0.08	0.74
036	76	0.90	0.80	0.46	0.08	0.61
045	74	0.89	0.77	0.43	0.09	0.82
mean		0.89	0.78	0.43	0.09	0.72
st. dev.		0.006	0.011	0.016	0.002	0.116

Bias-corrected R^2 estimates of 0.20 and 0.41 for Coastal and Inland, respectively, suggested that the models fit the data reasonably well.

Results of the jackknife procedure indicated that training set models were relatively stable to the removal of individual bears, as evidenced by the low variance in training set model concordance *(c)* and Somer's D_{xy} values. Jackknife results also suggested that on average, the final model fits individual bears reasonably well (mean of jackknifed $\rho^2 = 0.74$ for Coastal and 0.72 for Inland), and provided no evidence that the number of locations for individual bears influenced model discrimination or fit. Through the jackknife process, I identified one bear, Coastal bear 011, that was using resources that differed from those selected by other bears. Bear 011 was the only bear with the majority of locations along a boundary between fresh marsh and cypress swamp.

Because I relied on rank based methods to assess final model discriminatory ability (i.e., c/Dxy), and the claim of Boyce et al. (2002) that ROC is unsuitable to assess discrimination for use/available designs, I examined whether those measures were compromised when estimated for the set of variable probability samples. My findings were consistent with the assertion that rank-based indexes are insensitive to the prevalence of positive responses (Harrell 2001, p. 248; Table 6.5), and provide further evidence that model discrimination can be appropriately assessed using these measures on data collected under used/available designs.

Extrapolate RSF Predictions Within Study Area Boundaries

I mapped the Coastal RSF values, which I calculated for each used and available resource unit within the Coastal available resource buffer (Fig. 6.4) using the Final Coastal model, by binning the values into 20% quantiles (Fig. 6.5). Similarly, I mapped the Inland available resource buffer (Fig. 6.6) and RSF values (Fig. 6.7).

Table 6.5. Model discrimination measured by *c* (or Somer's D_{xy}) for different sampling probabilities of used and available units. The full dataset included 4,186 available units and 786 used units.

Proportion of Used Sampled	**Proportion of Available Sampled**	**Coastal *c***	**Inland *c***
100	100	0.756	0.886
20	100	0.780	0.893
80	50	0.758	0.884
100	10	0.767	0.897

Compare RSF Results With Mahalanobis Distance Within Study Area Boundaries

I calculated Mahalanobis distances for used locations in each study area and binned them into 20% quantiles. I then assigned all used and available sample locations within the respective study areas into one of the used location quantiles and produced a map of the classified sample locations for each study area (Fig. 6.8 and 6.9). Comparing Figure 6.5 with 6.8, and Figure 6.7 with 6.9, I noted obvious differences in the relative value of resources estimated by these two approaches in both study areas. For example, some areas that were heavily used by bears, such as Weeks Island in the western most portion of the Coastal study area, were mapped as having high relative selection probability (high RSF values) as expected, but the same area fell into mixed Mahalanobis distance quantile intervals. However, caution should be used when attempting to interpret differences between RSF and Mahalanobis distances because the two measures are not directly comparable. The RSF quantiles are the relative probability of use, with the fraction of used locations increasing with increasing RSF quantiles. This is not the

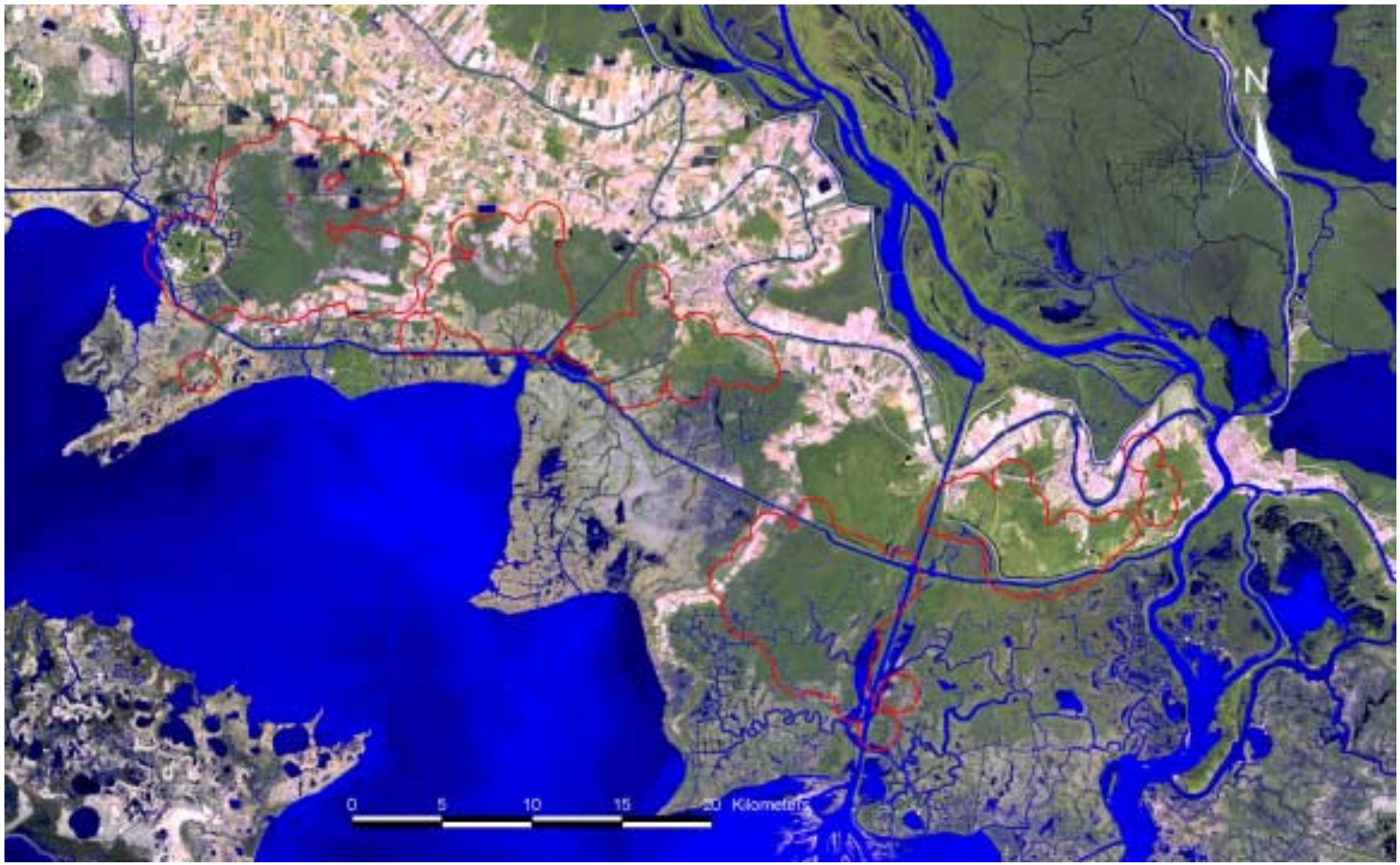

Figure 6.4. Coastal study area available buffer boundary, outlined in red. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

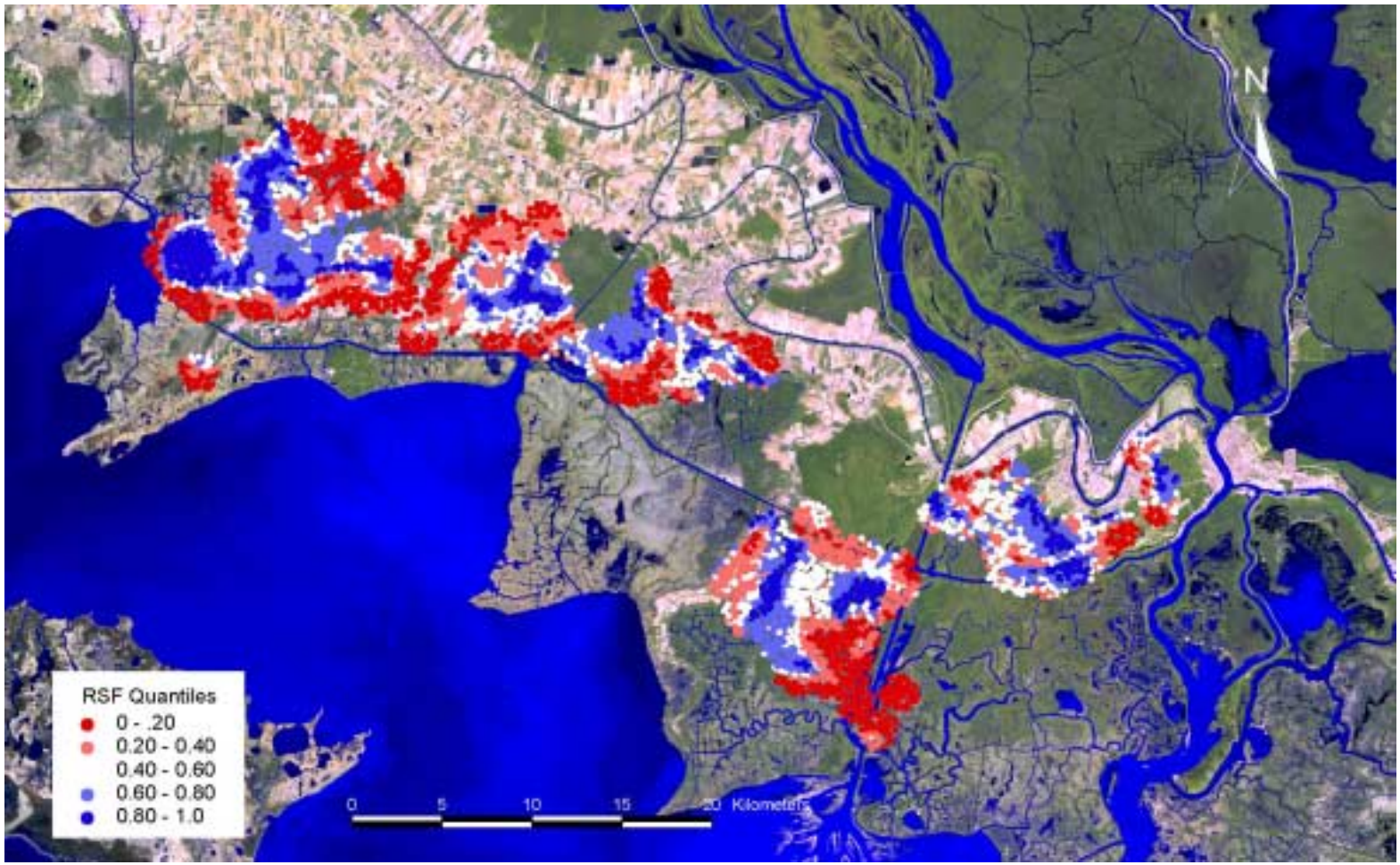

Figure 6.5. Coastal study area resource selection function (RSF) predictions. Increasing quantiles indicate increasing selection. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

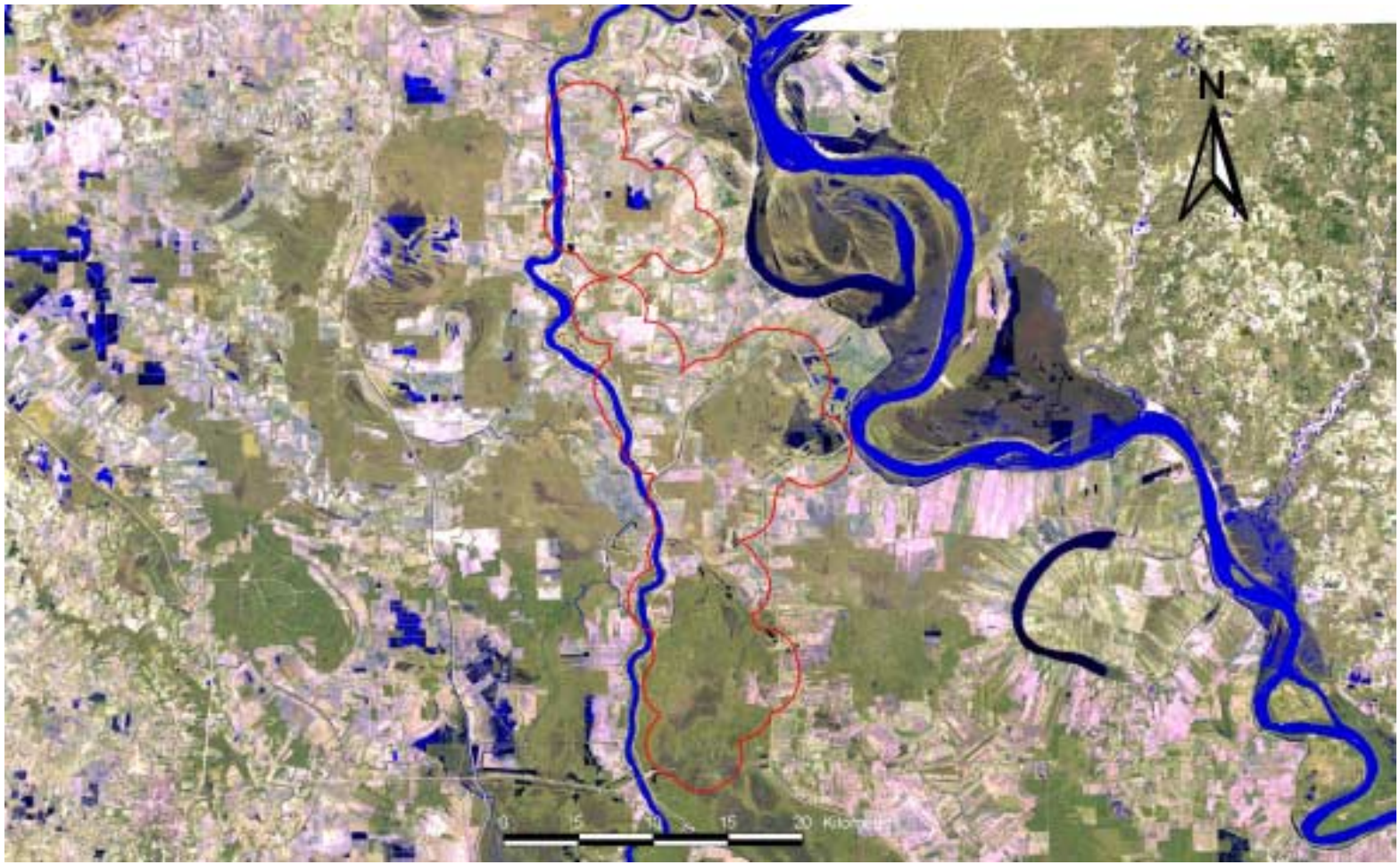

Figure 6.6. Inland study area available buffer boundary, outlined in red. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

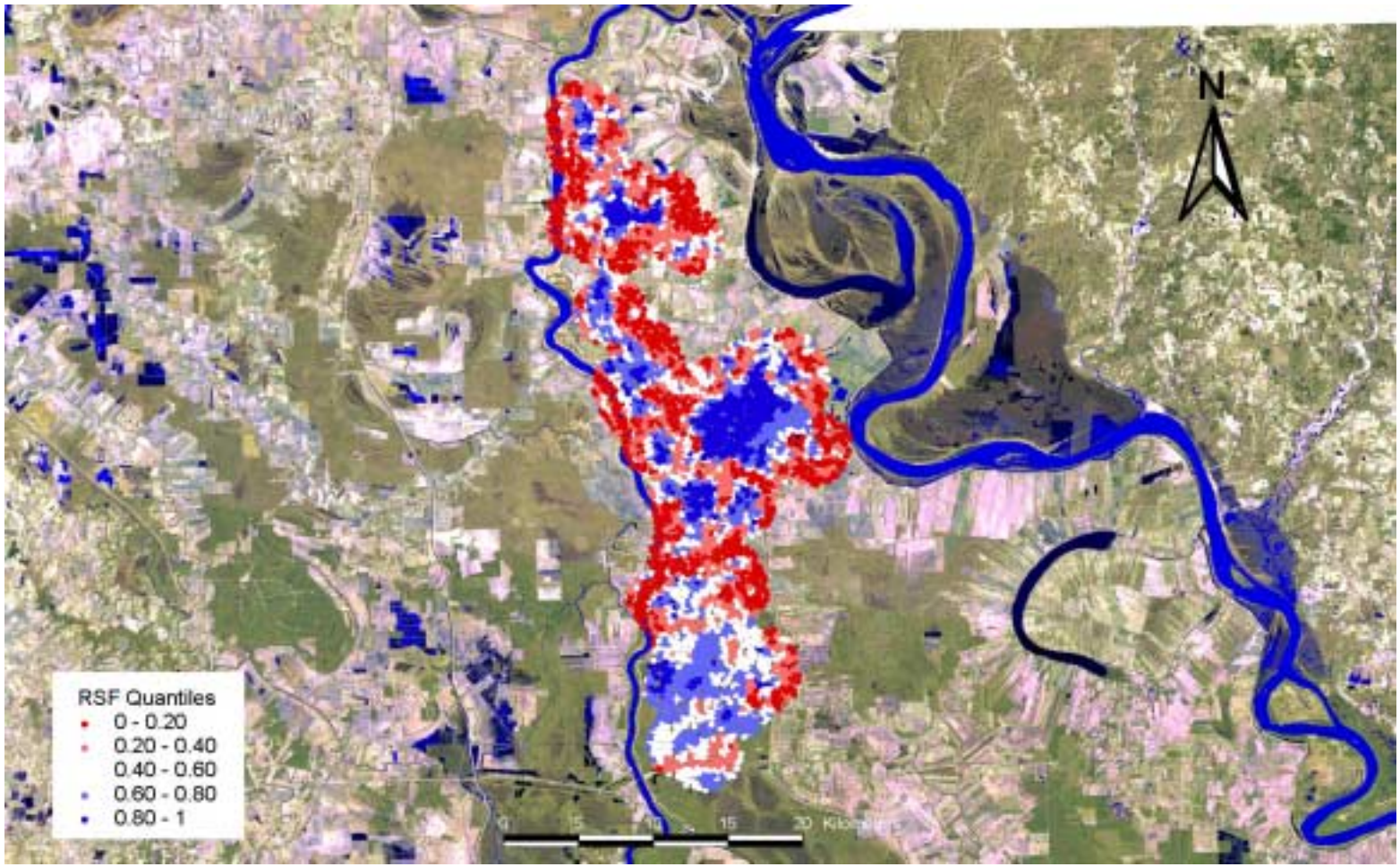

Figure 6.7. Inland study area resource selection function (RSF) predictions. Increasing quantiles indicate increasing selection. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

case with Mahalanobis distance, where increasing quantiles indicate increasing dissimilarity from the multivariate centroid of the predictor variables for used locations and each quantile contains 20% of the used locations. To quantitatively assess the relationship between RSF estimates and Mahalanobis distance, I compared ranked RSF with ranked Mahalanobis distances for each area using Spearman's ρ^2. In the Coastal study area, the rank correlation between RSF and Mahalanobis distances was weak (Spearman's $\rho^2 = 0.28$; Figure 6.10). The rank correlation between RSF and Mahalanobis distances in the Inland study area was greater than in the Coastal study area, but still not strong (Spearman's $\rho^2 = 0.58$; Figure 6.11).

Extrapolate RSF Predictions and Mahalanobis Distances Beyond Study Area Boundaries

RSFs identify the relationship of used units relative to what is available to the subject species, and should not be applied to areas with a different set of available resources. As one of my goals was to predict habitat selection throughout the extrapolation area, I used Mahalanobis distance to identify areas within the extrapolation area that were similar to each study area (Fig. 6.12 and 6.13). As the similarity of a prospective area to the study area decreases (increasing Mahalanobis distance), the applicability of the RSF developed to the prospective area decreases. Based on Mahalanobis distances of study area available resources, very little of the extrapolation area was similar to the Coastal area, and thus the applicability of the Coastal RSF model predictions (Figure 6.14) outside of the Coastal study area was limited. However, large portions of the extrapolation area were very similar to the Inland study area. Thus, Inland RSF model predictions (Figure 6.15) may be applicable to those areas. An example of

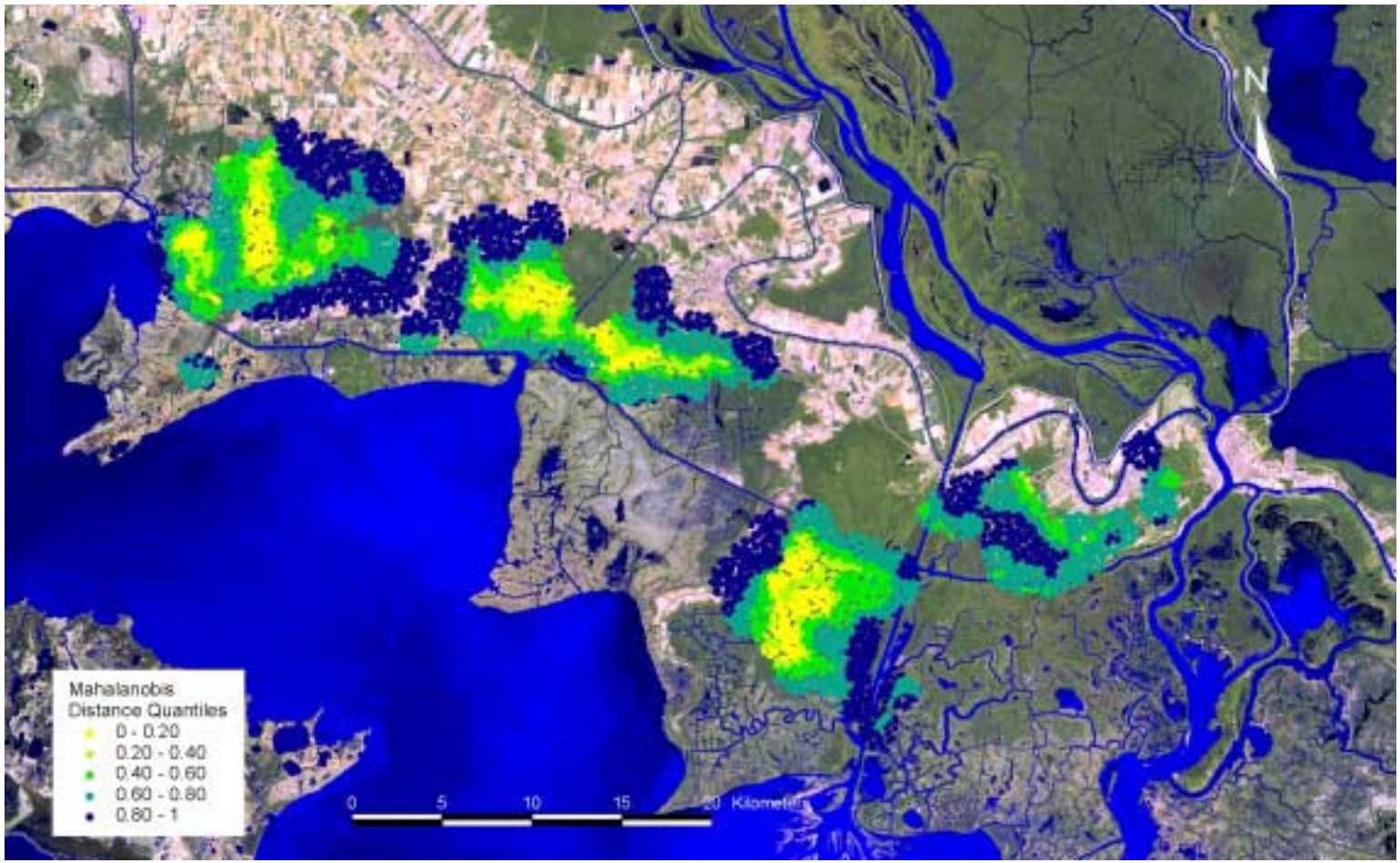

Figure 6.8. Coastal study area Mahalanobis distances based on Coastal used locations. Increasing quantiles indicate decreasing similarity to used locations. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

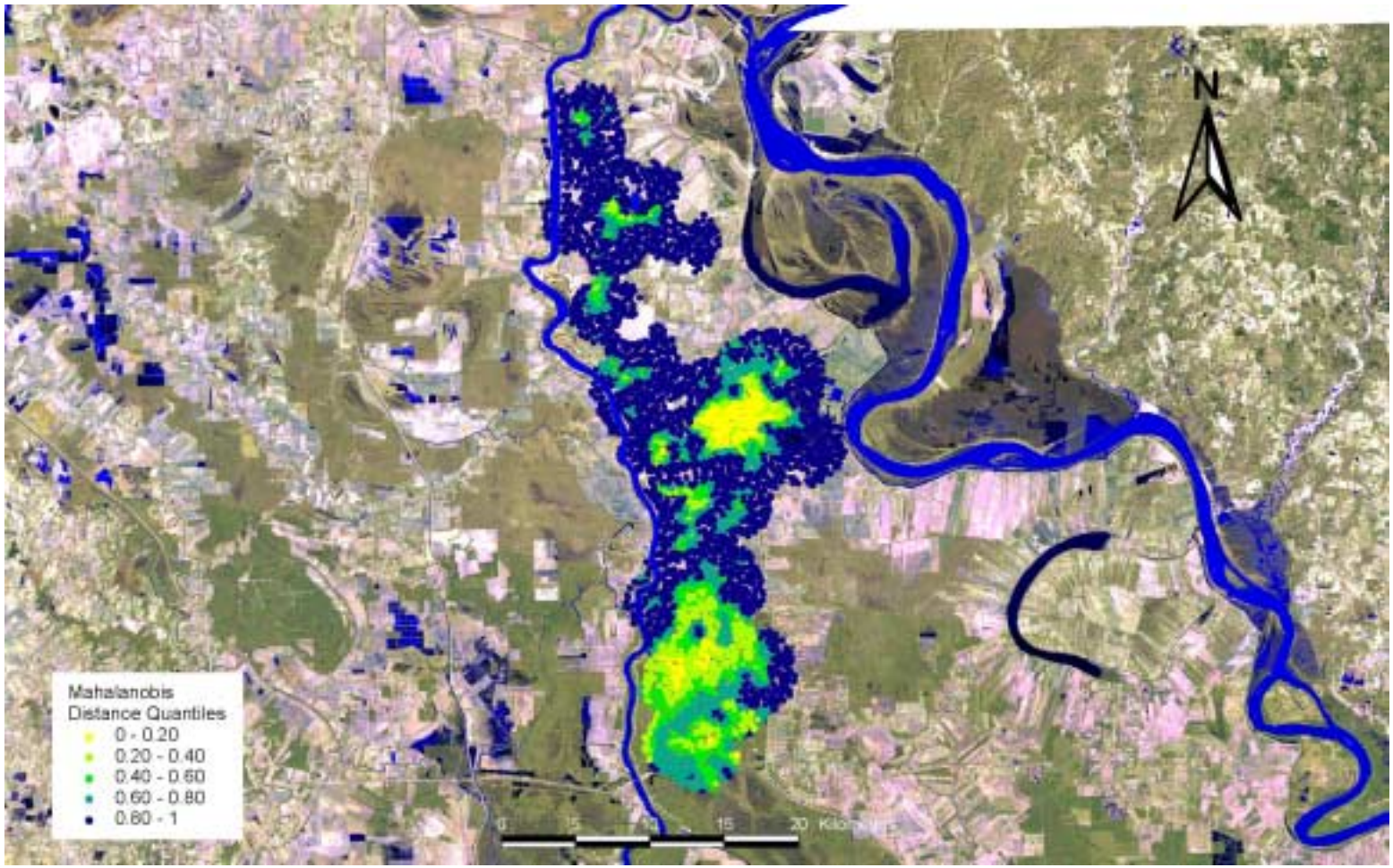

Figure 6.9. Inland study area Mahalanobis distances based on Inland used locations. Increasing quantiles indicate decreasing similarity to used locations. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

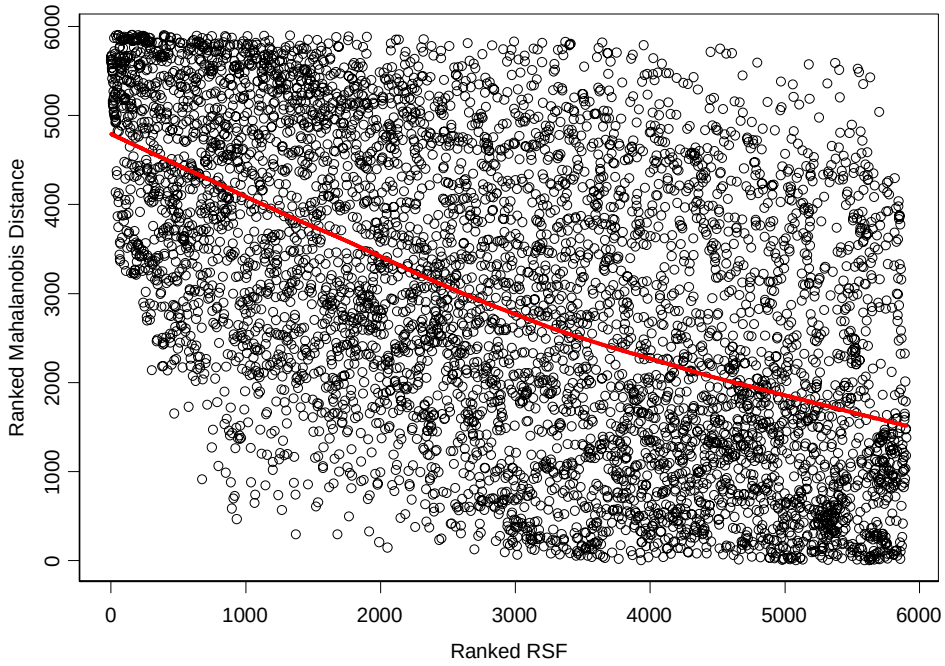

Figure 6.10. Ranked RSF versus ranked Mahalanobis distances for the Coastal study area, with a loess line (red line). The expected relationship is high ranked RSF (high probability of use) would have low Mahalanobis distances (similar to used locations).

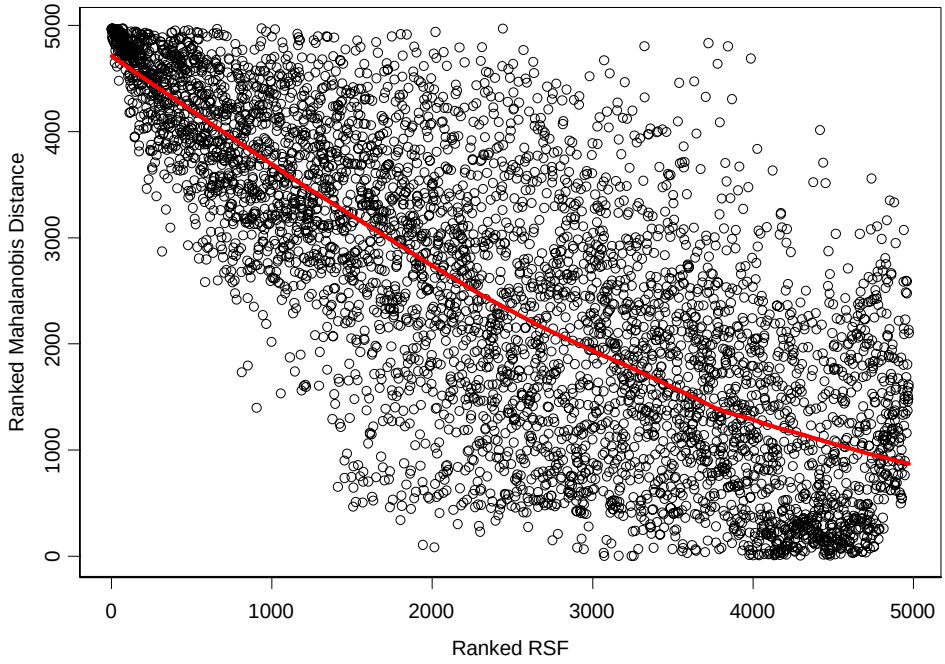

Figure 6.11. Ranked RSF versus ranked Mahalanobis distances for the Inland study area, with a loess line (red line). The expected relationship is high ranked RSF (high probability of use) would have low Mahalanobis distances (similar to used locations).

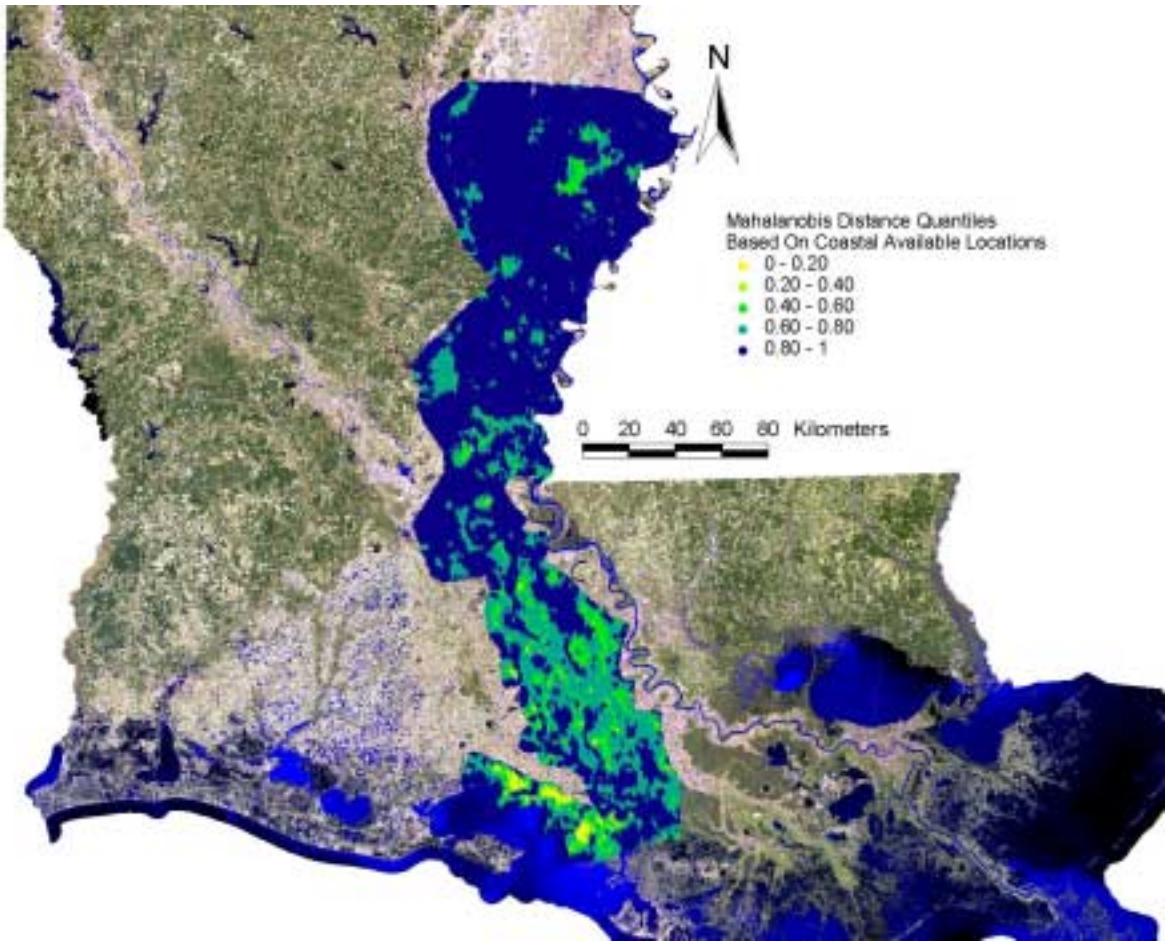

Figure 6.12. Extrapolation area Mahalanobis distances based on Coastal available locations. Increasing quantiles indicate decreasing similarity to available locations. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

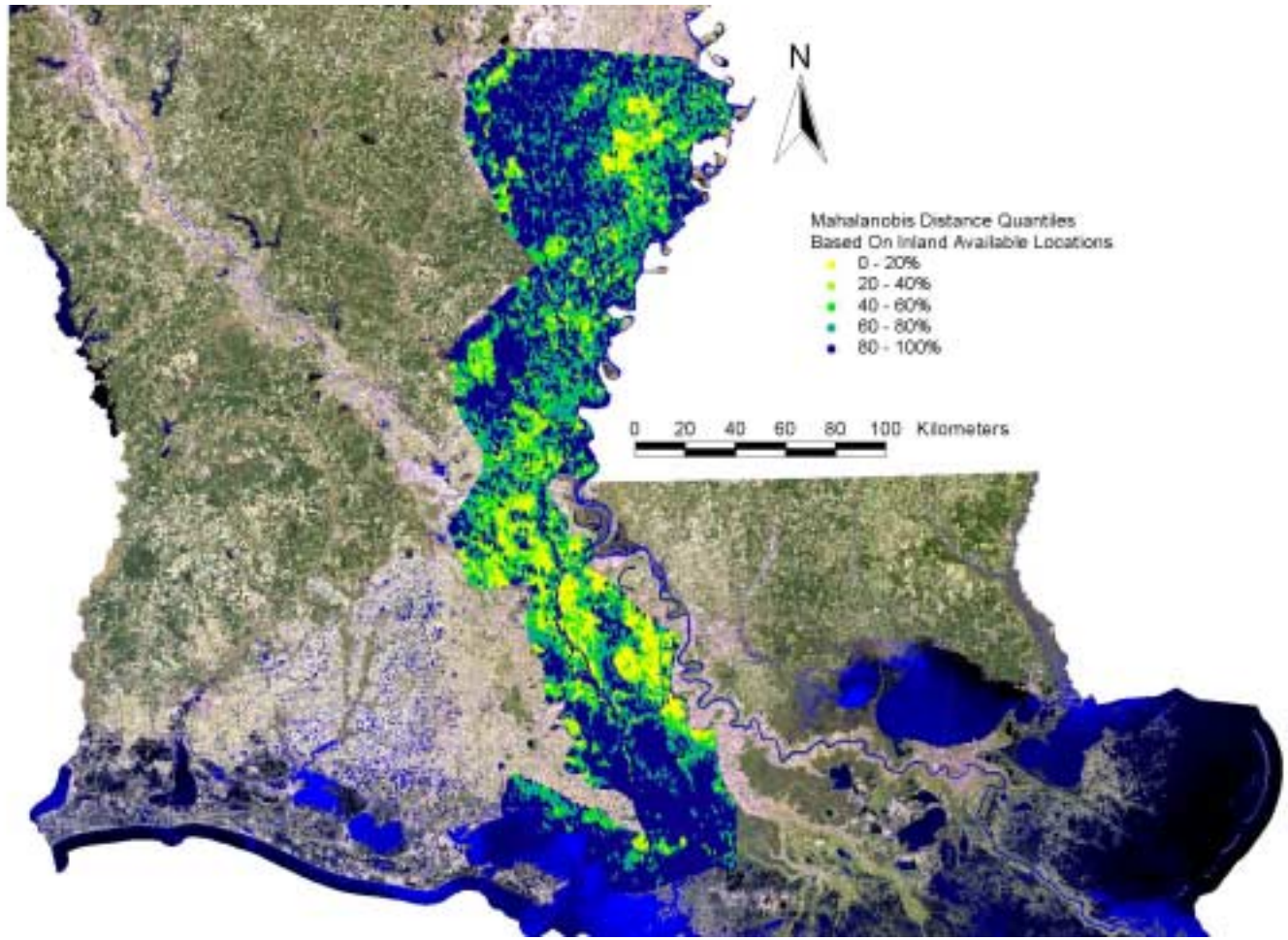

Figure 6.13. Extrapolation area Mahalanobis distances based on Inland available locations. Increasing quantiles indicate decreasing similarity to available locations. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

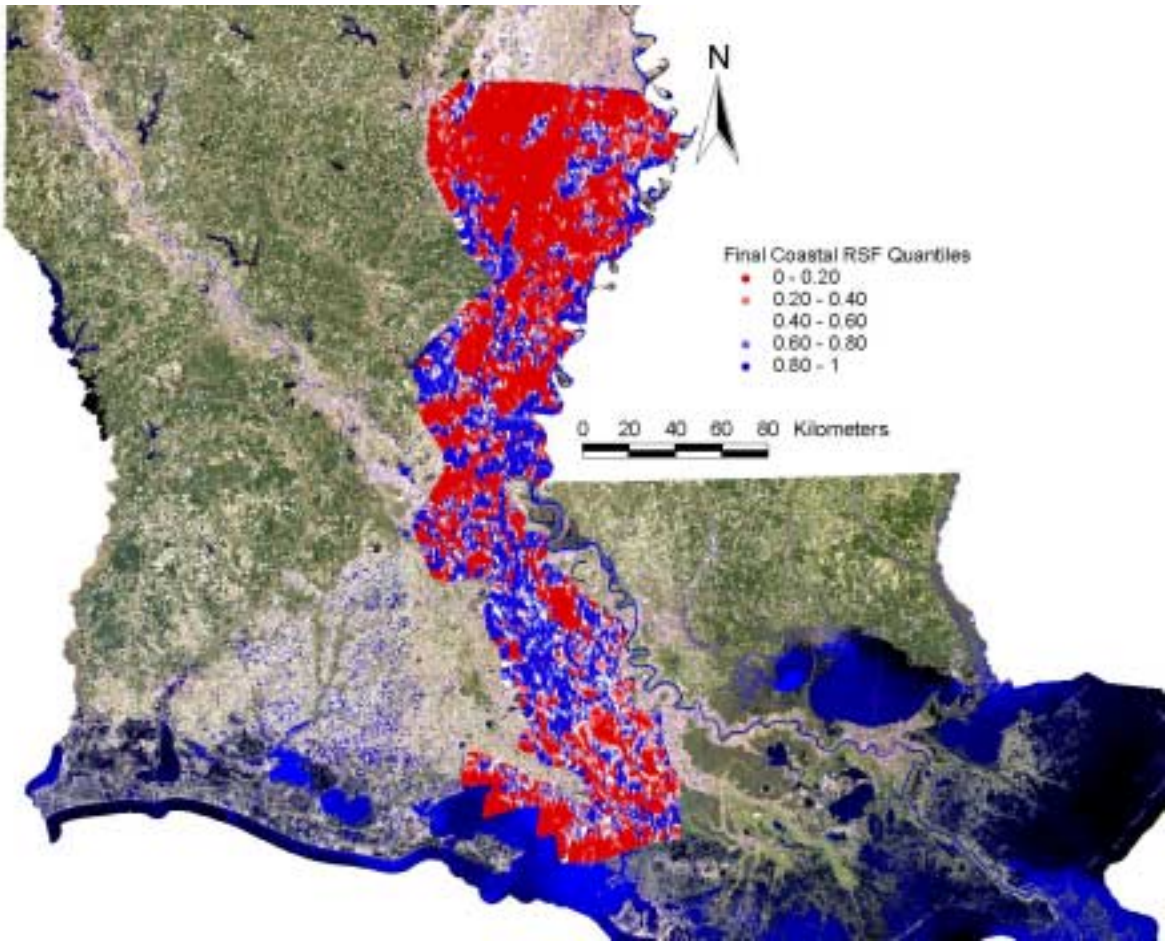

Figure 6.14. Extrapolation area resource selection function (RSF) predictions from Final Coastal model. Increasing quantiles indicate increasing selection. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

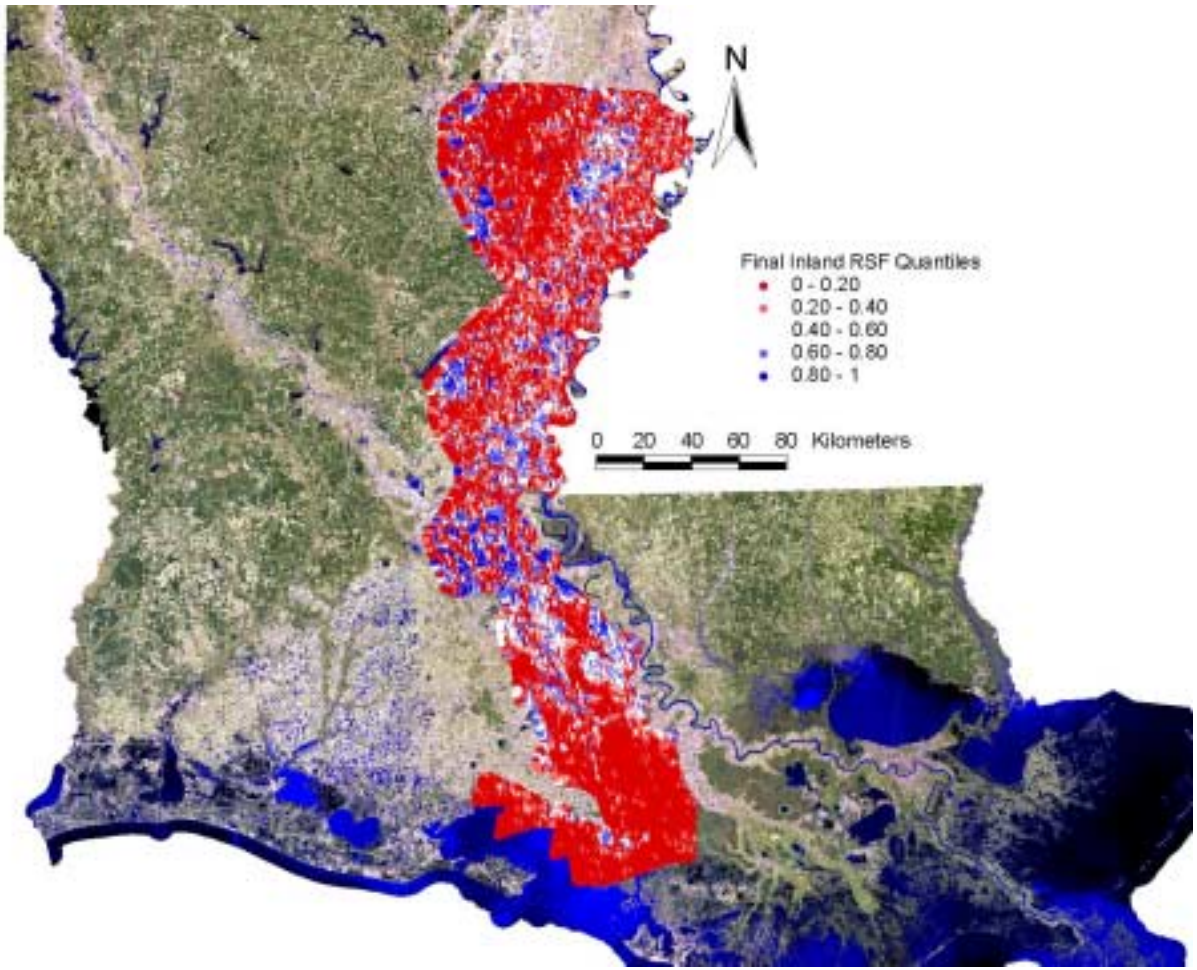

Figure 6.15. Extrapolation area resource selection function (RSF) predictions from Final Inland model. Increasing quantiles indicate increasing selection. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

the use of this model is a more careful examination an area known as three rivers (including Three Rivers, Grassy Lake, and Red Rivers Wildlife Management Areas) (Fig 6.16 and 6.17), which is of particular interest to agencies committing resources to the repatriation of bears.

DISCUSSION

Rigorous assessment of model calibration, discrimination and validation has been recognized as a necessary step that must be completed before habitat models are used for management decisions. I outlined the issues associated with assessing calibration, discrimination, and validation on used/available data, and provided a rational for using proven methods that make use of standard logistic regression model predictions rather than $w(x)$ (based on eq. 6.3). Although measures of calibration may be compromised as a result of used/available sampling designs, calibration curves were useful for assessing the magnitude and potential consequences of any lack-of-fit. Because I specified a set of a priori candidate models and based model selection on AIC, there were four possible sources for any lack-of-fit: failure to include an unknown but important predictor variable, failure to specify an unknown but important interaction, over-fitting, or failure of the assumption of linearity of the logit. I incorporated steps to avoid over-fitting and the assumption of linearity of the logit into the modeling process, so I was assured of selecting the model with the best fit to the data from my a priori universe of "reasonable" models by selecting the model with the lowest AIC.

I agree with Boyce et al. (2002) that methods related to classification tables (e.g., confusion matrices and Kappa statistics) are flawed, but the flaws in the use of those methods apply equally to the typical logistic regression situation based on used/unused,

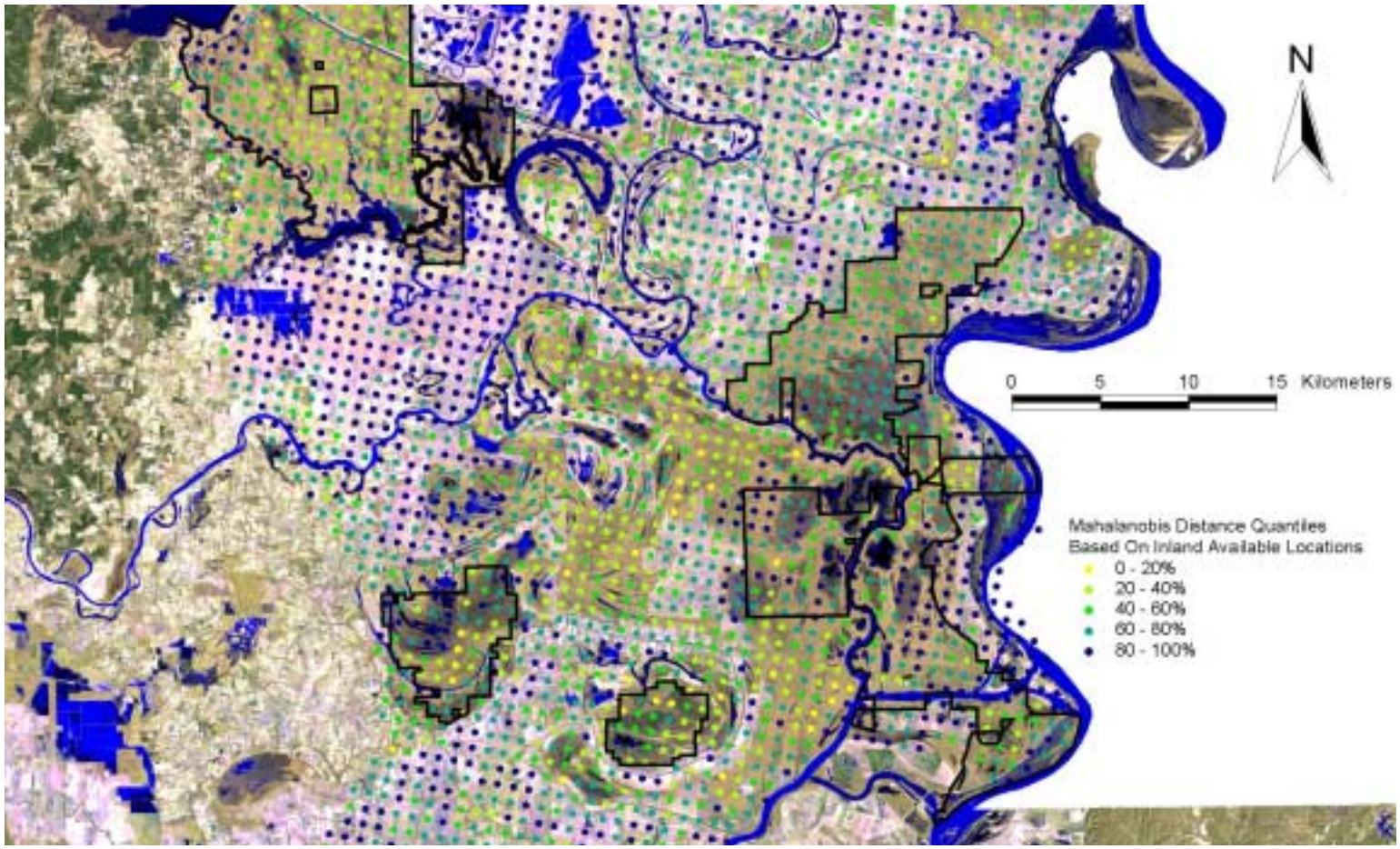

Figure 6.16. Mahalanobis distances based on Inland available locations to Three Rivers, Grassy Lake, and Red River Wildlife Management Areas (WMA boundaries in black). Increasing quantiles indicate decreasing similarity to available locations. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

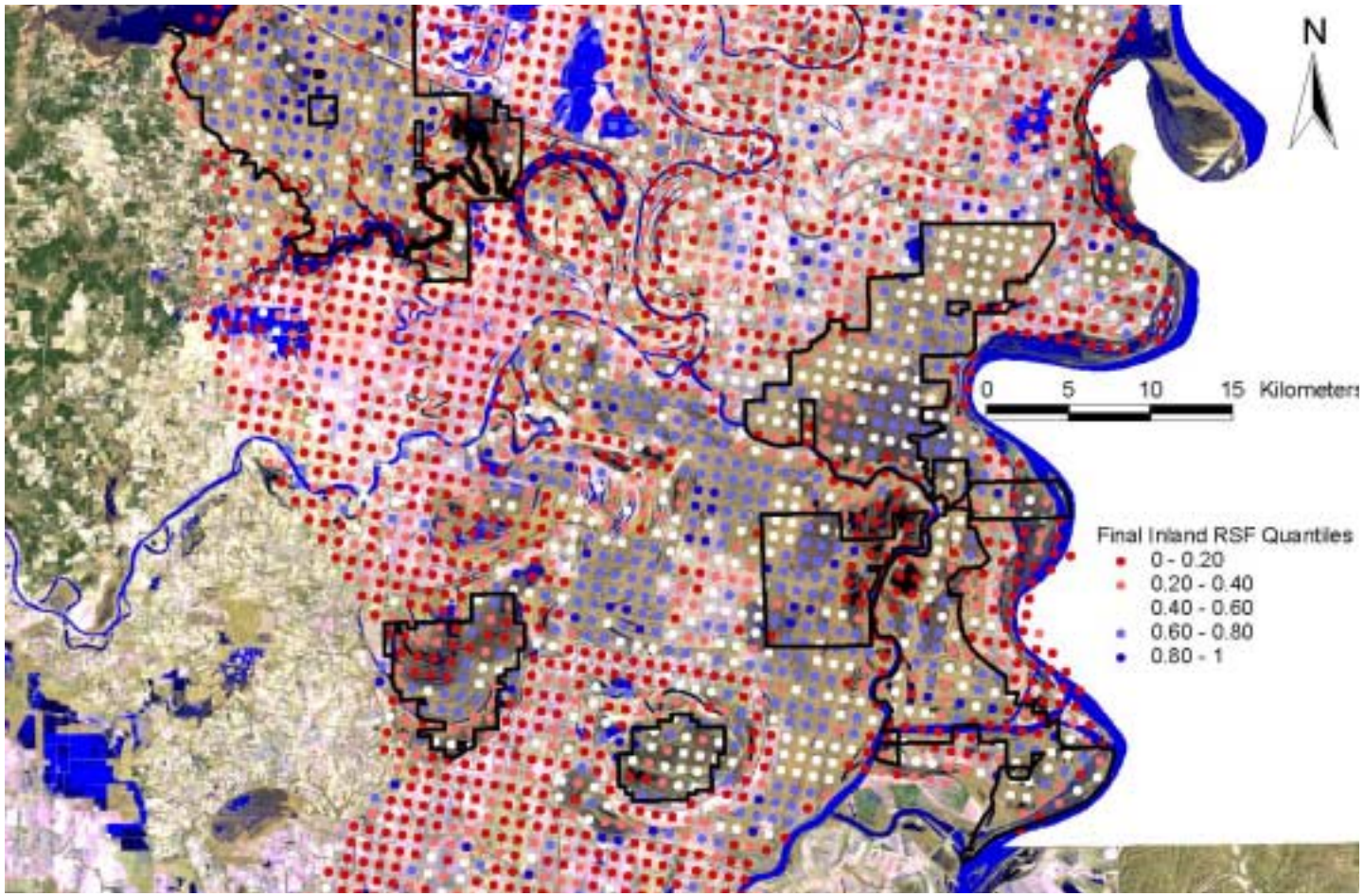

Figure 6.17. Resource selection function (RSF) predictions from Final Inland model to Three Rivers, Grassy Lake, and Red River Wildlife Management Areas (WMA boundaries in black). Increasing quantiles indicate increasing selection. The background image is a 1992-1993 Landsat color composite (RGB – 7, 5, 3); image source: LOSCO Environmental Baseline Inventory Dataset 'Thematic Mapper Image of Louisiana, UTM15 NAD83, LOSCO (1999) [la_north & la_south].

or other mutually exclusive dichotomous data (Hosmer and Lemeshow 2000, Harrell 2001). In the case of used/available models, Boyce et al. (2002) failed to distinguish the two aspects for evaluating logistic regression models, calibration and discrimination. Poorly fitting models (poor calibration) may still have good discrimination (Hosmer and Lemeshow 2000, pp. 162-163). Accordingly, models should be assessed by considering both calibration and discrimination. I was unable to determine whether the Boyce test is actually measuring calibration, discrimination, or a combination of both.

Theoretically, the discrimination measures c/D_{xy} should be stable regardless of the number of used and available points included in the sample when ranked based measures of resource selection are used. My results were consistent with that theory. Thus, contrary to the claims of Boyce et al. (2002), I found no reason to doubt the applicability of c/D_{xy} to assess discrimination for used/available designs. Accordingly, I used bootstrap validation procedures, which are superior to other validation methods (Efron 1983, Verbyla and Litvaitis 1989) and should be used to validate RSF models based on logistic regression for either used/unused or used/available designs, for my RSF models. The discrimination of the Final Coastal and Inland RSF models was good and excellent, respectively, indicating that the models readily discriminated between used and available sample points, and that the models were robust to changes in sample composition. However, the bootstrapping validation procedure provided no insight into the variability of model performance for individual animals.

The difficulty of incorporating animals as sampling units in the analysis, and thus to assess the extent of variability in individual resource selection (Pendleton et al. 1998), has been one of the criticisms of using logistic regression to develop RSFs.. Analyses

involving more than one animal must either allow for among-individual differences, assume that animals select resources similarly, or draw inferences about average selection at the population level (Aebischer et al. 1993, Alldredge et al. 1998). I wanted to develop models of average selection at the population level, so my results were not compromised by my inability to model individual bears. However, based on MANOVA results presented in Chapter 3, differences among bears was a large source of explained variability. Consequently, the Final Coastal and Inland models would be expected to exhibit superior validation on a random sample of used and unused locations, as in the case of the bootstrap validation, than on samples that excluded entire portions of a study area (Manly pers. com.), or individual bears. The jackknife procedure provided a rational for partitioning the study area into discrete spatial units for validation, as each bear uses a different spatial area within the study area, and incorporated differences in individual selection into the validation process. Jackknifing on bears also allowed me to estimate how well the models would be expected to perform on a new bear from the study area, to gain insight into the range of variability in habitat selection among individual bears within each study area, and gauge the relative influence on the model of bears with the most used locations in each study area. In cases where animals are unequally sampled, pooling data among animals could strongly affect results if all individuals did not make similar selections (White and Garrot 1990, Garshelis 2000).

Aebischer et al. (1993) expressed an additional concern resulting from the inability to include individual animals in the model. They suggested that pooling data among animals, as was the case in this study, constitutes pseudo-replication (Hurlbert 1984). However, in this study, predictor variables used to develop RSFs typically varied

as much or more among relocations within bears than among bears within areas, suggesting that concerns for pseudo-replication in this study would be overstated.

Mahalanobis distance has been proposed as an alternative to logistic regression to map resource selection using GIS. Advocates of this method argue that it avoids the problems associated with defining available resources and that it is easy to implement in GIS. As typically used to model habitat selection, Mahalanobis distance is calculated for used locations to produce a map of habitat similarity, with decreasing similarity assumed to infer decreasing probability of use. However, the essential component inherent in the RSF, but missing from Mahalanobis distance is the ability to rank resource units by their relative probability of use (Manly et al. 2002). For Mahalanobis distance to be comparable to RSF, similarity must correlate with probability of use. To fulfill this requirement, the probability that a particular habitat configuration will be used must be a function of statistical distance from the multivariate centroid of used locations, with equal statistical distances having equal probabilities of use. This assumption would only be valid in rare cases where 1) the matrix of predictor variables are multivariate normal, 2) the multivariate centroids represent a singular optimal resource configuration, and 3) the probability of use diminishes as a symmetrical parabolic function, at least along the major axes of the multivariate space, with increasing distance from the centroid (i.e., the probability of use decreasing equally with equal statistical distance). It is unlikely that these three conditions will be met with real data. Mahalanobis distance was only weakly correlated with RSF values in the more diverse habitats of the Coastal study area. The correlations in the Inland area were stronger than those in the Coastal area, but still should only be considered moderate. Although many of the predictor variables in my

study were approximately multivariate normal, roughly meeting condition 1, conditions 2 and 3 were clearly not met. In a similar example, Knick and Rotenberry (1998), examined the potential of using Mahalanobis distance to predict habitat quality in a simulated landscape, and found that any deviation from the original habitat mean vector, even in a biological meaningful direction such as habitat improvement, resulted in a greater Mahalanobis distance, due to the failure of condition 3. In that case, an increase in shrublands was expected to result in an increase in jackrabbit habitat suitability but because habitat suitability increases logistically rather than parabolically, Mahalanobis distance failed.

Although resource selection studies are conducted for a variety of reasons (Manly et al. 1993), the overall goal of most of these studies is to identify those habitat features that are at a minimum correlated or indicative of what is "prized" by the species. RSFs are clearly superior to Mahalanobis distance in this regard. Additionally, statistically sound model building process exists to develop RSFs using logistic regression. In this chapter, I developed Mahalanobis distances based on the results of variables selected by the logistic regression modeling process, but most authors that have used Mahalanobis distance have relied on a combination of statistical procedures which have many of the shortcomings discussed in Chapter 4.

Availability matters. Advocates of Mahalanobis distance attempt to escape this reality, but use must be judged relative to availability. I suggest that a better use of Mahalanobis distance is to assess the similarity of available habitats to assess where RSF models might reasonably be applied outside of the areas in which they are developed. Using this process, a RSF could be developed using a statistically sound model building

process, Mahalanobis distance calculated for those variables from the set of available locations and then extrapolated to other areas of interest, and RSF predictions extended to those areas with similar available resources. This process provides a rationale to select areas where the RSF can be applied, and where applicable, provides a metric with the desired properties of increasing values correlated with increasing probability of use. Although violations of multivariate normality would limit the applicability of Mahalanobis distance to assess similarity of available habitats, the other two assumptions required to interpret Mahalanobis distance based on used locations as a RSF do not apply.

In addition to the more process-based considerations that I have addressed, the results of this study have the potential for practical application to address a number of management questions for black bears in Louisiana. Within each of the study areas, RSF model predictions quantify the relative value of the landscape for bears. However, it is important to recognize that these results are based on habitat measures taken in 1993, and should only be applied to areas that are relatively unchanged since that time. This same caveat applies to predictions of habitat similarity and RSF beyond the study area boundaries, which may be useful to identify blocks of potentially suitable but unoccupied habitat, potential corridors, and lands for acquisition of conservation easements. The image processing methods that I used should allow application of the RSF models developed from 1993 data to similarly processed current image data, although this process has not been tested.

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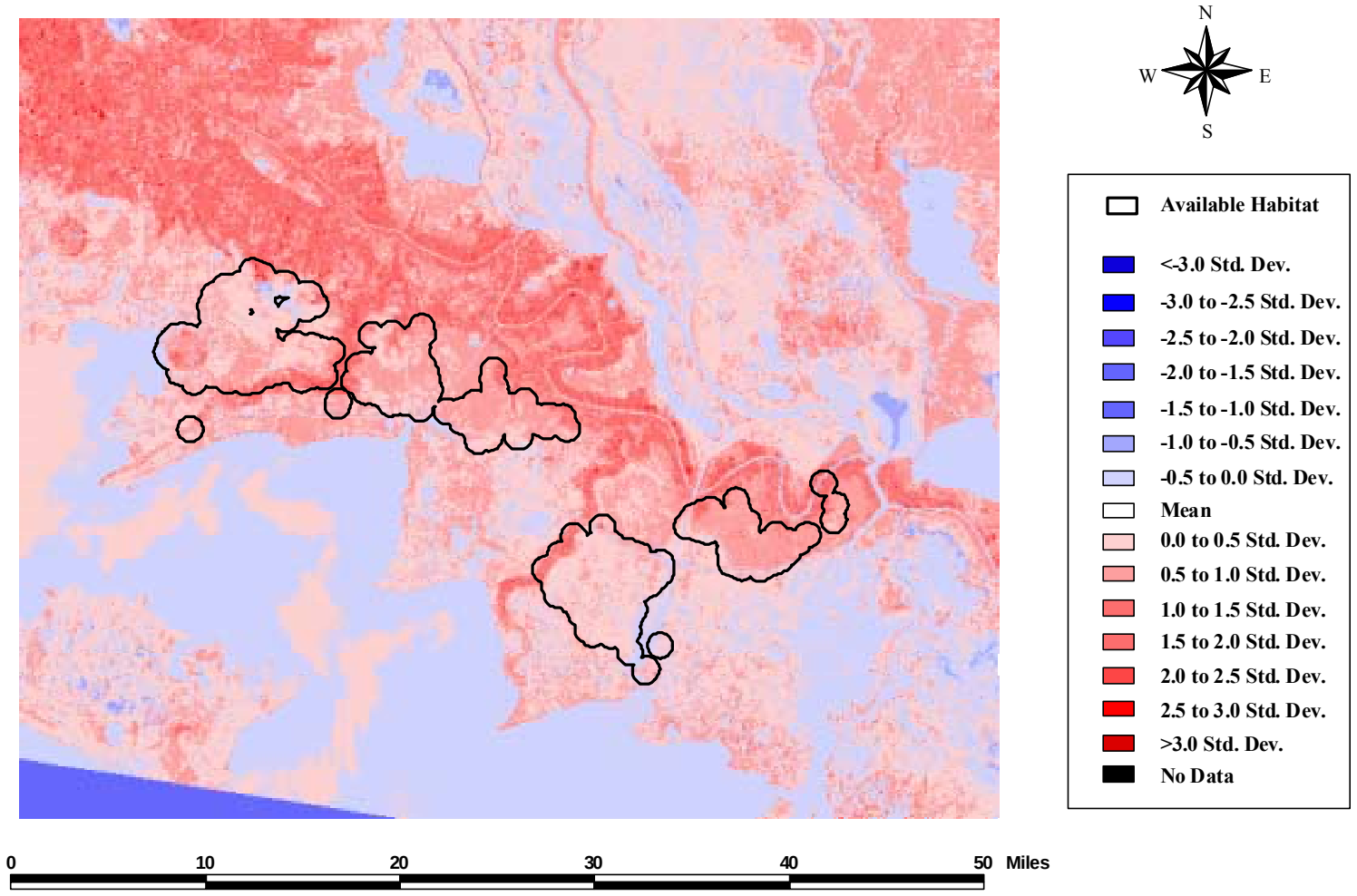
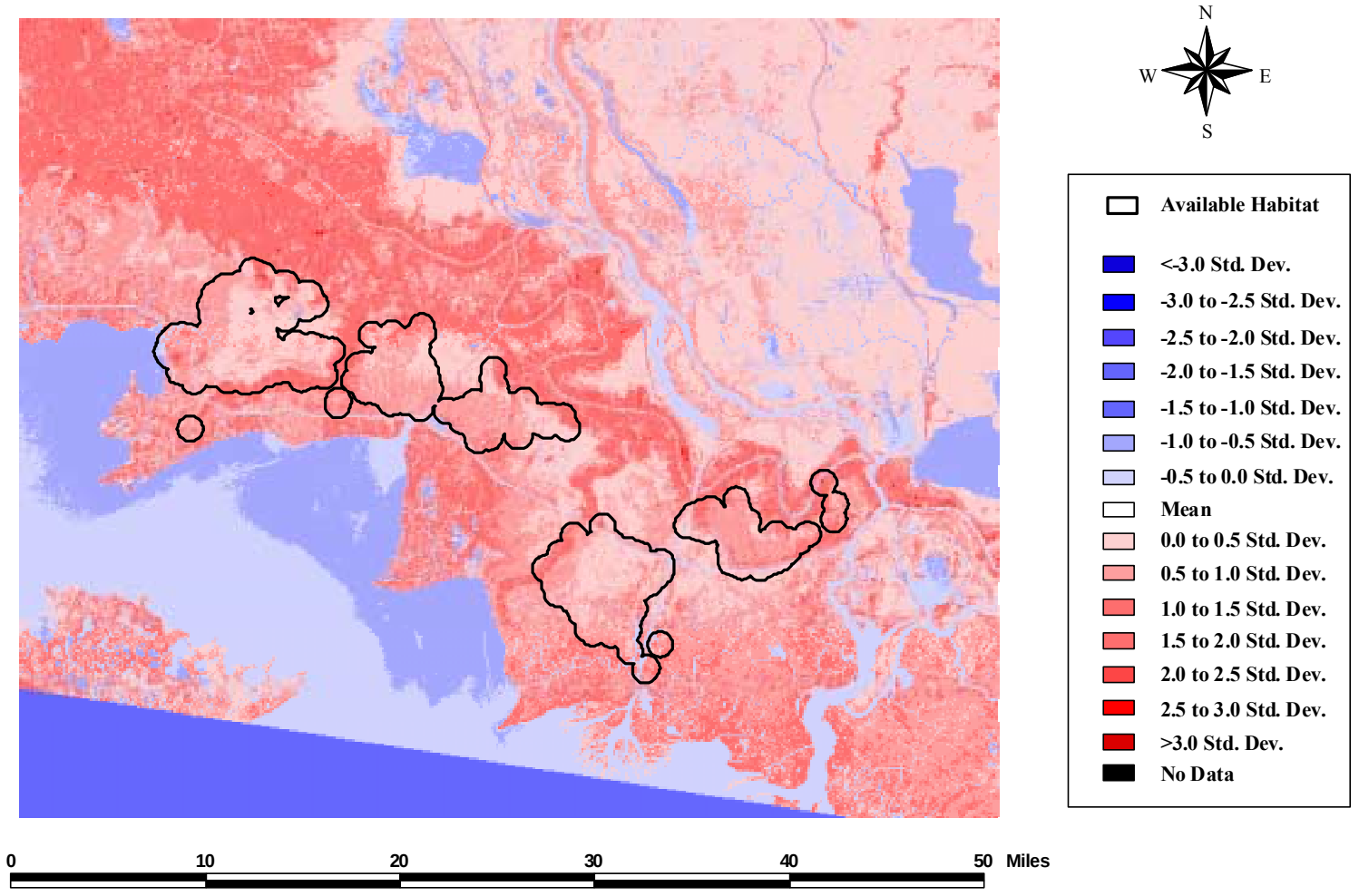
APPENDIX: TASSELED CAP IMAGES



A1. At-satellite reflectance tasseled cap 1, brightness, based on data collected April 1993 in the Coastal study area.



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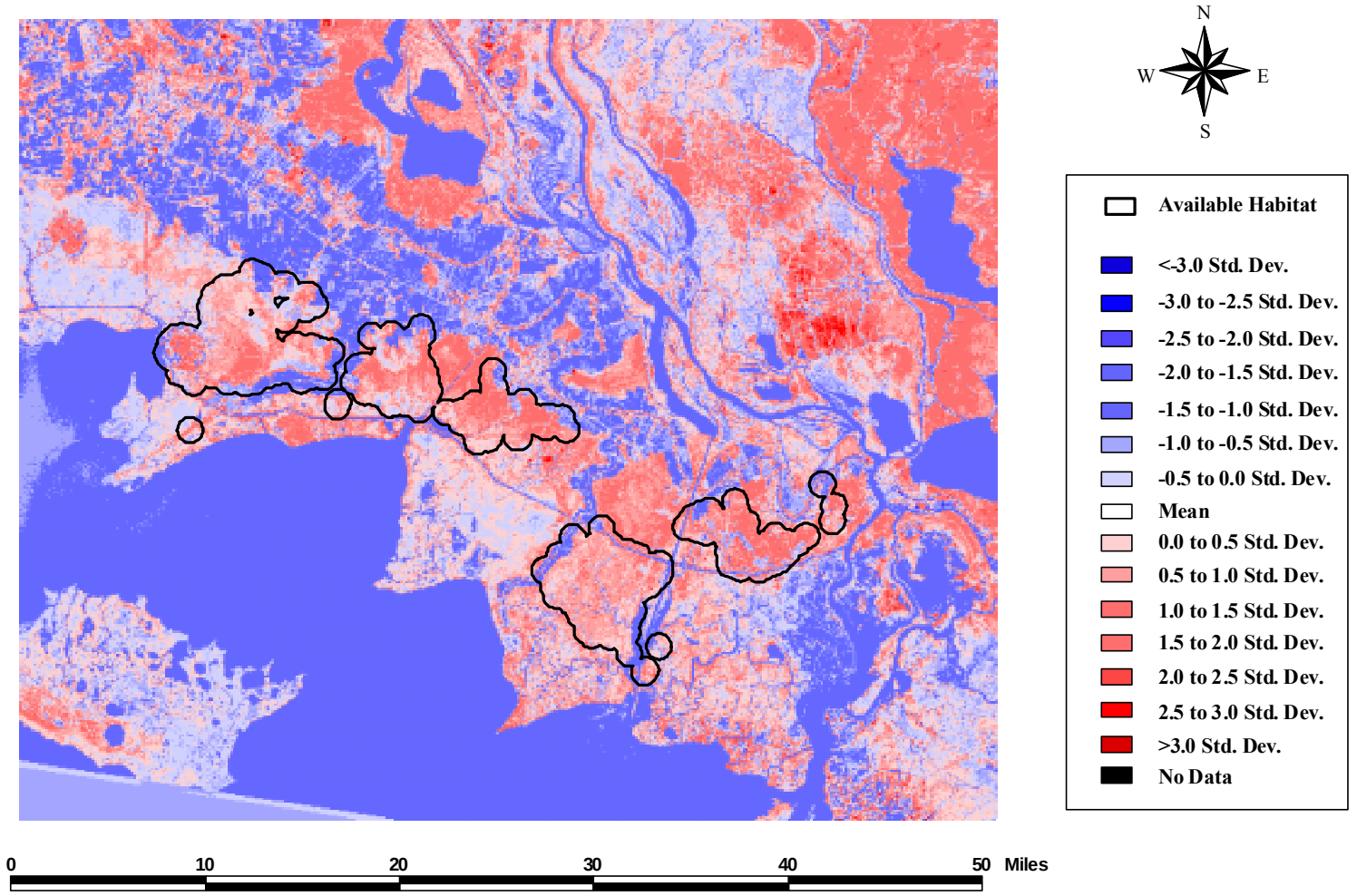
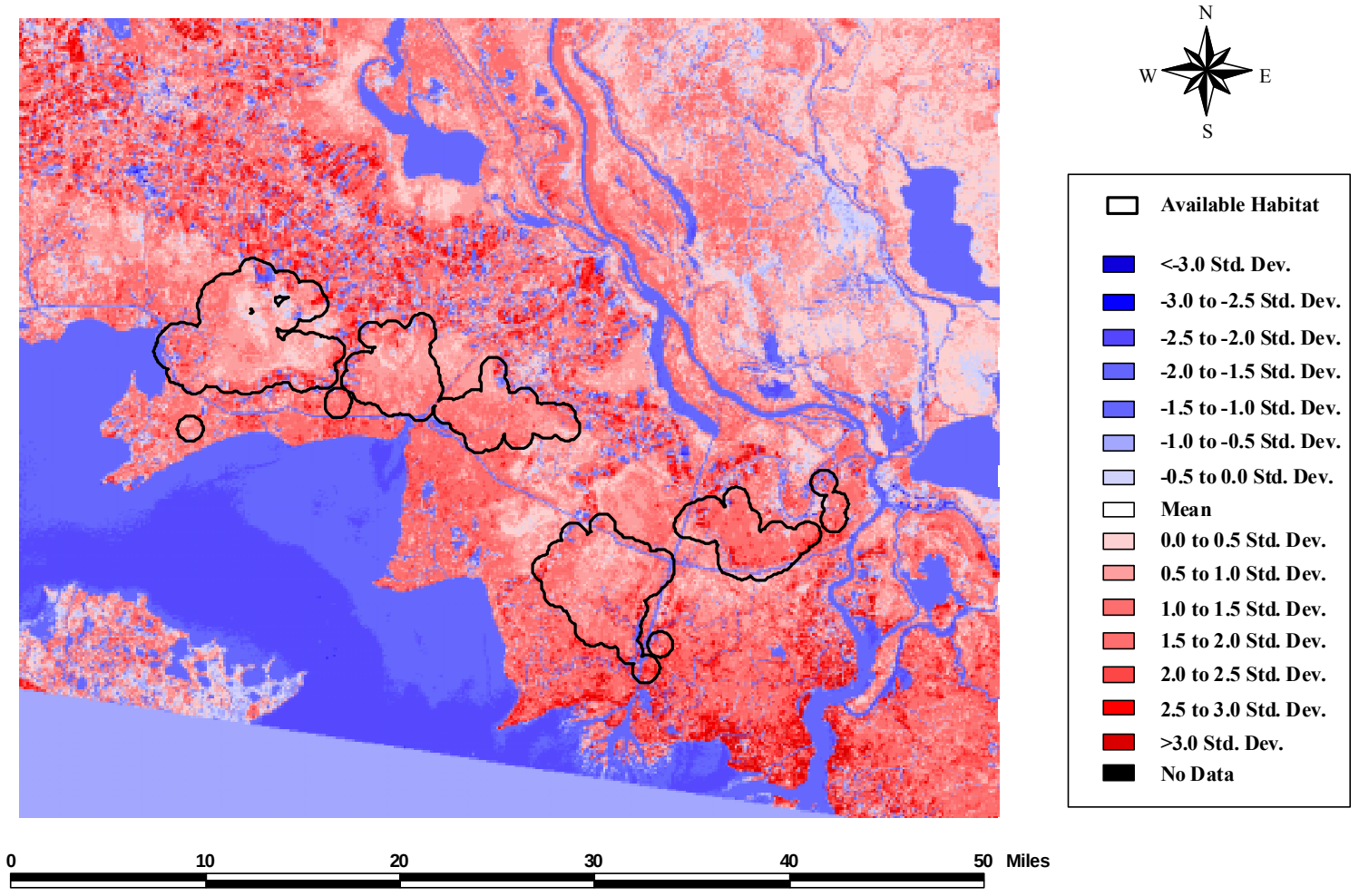


A3. At-satellite reflectance tasseled cap 2, greenness, based on data collected April 1993 in the Coastal study area.



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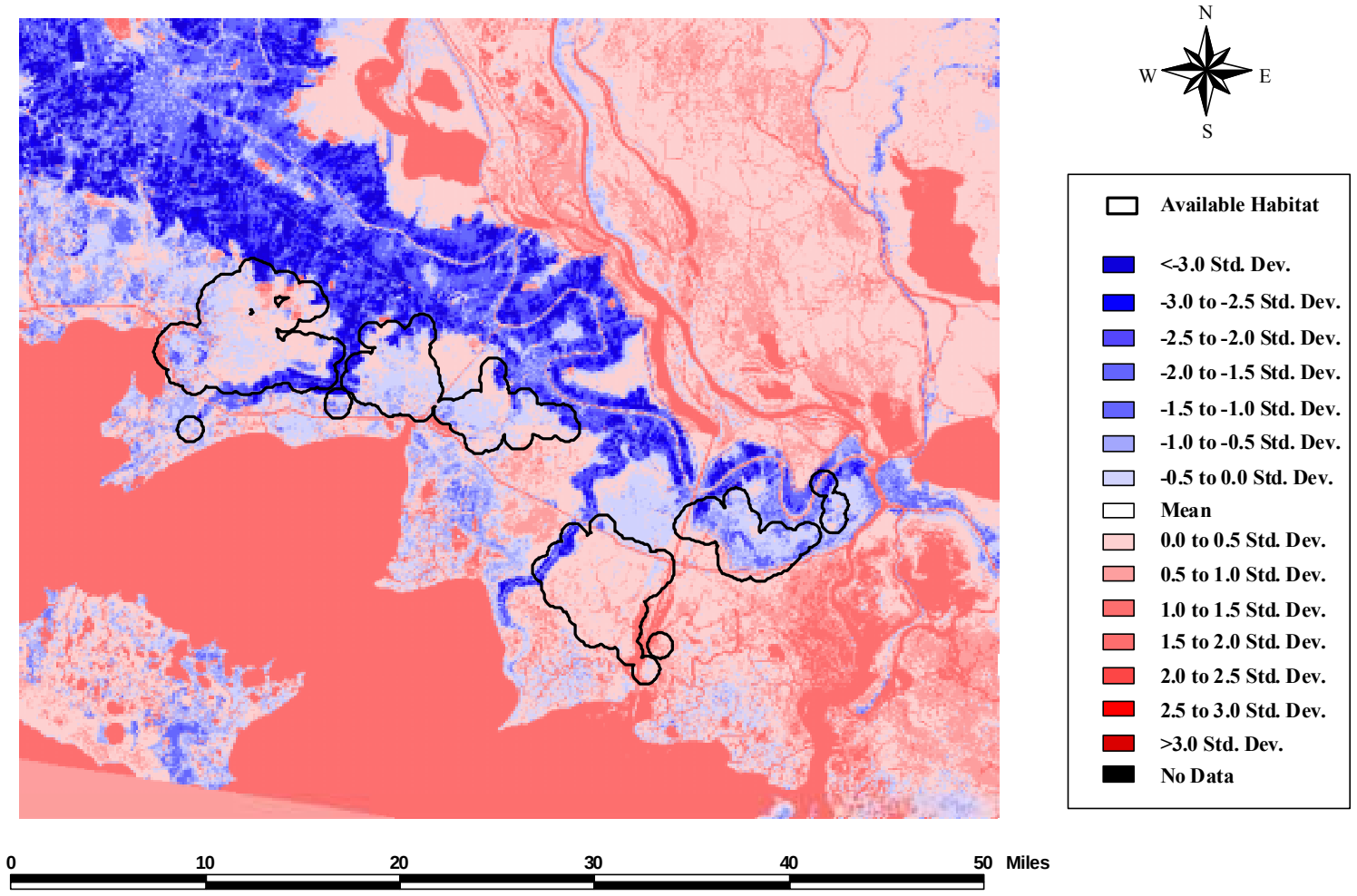
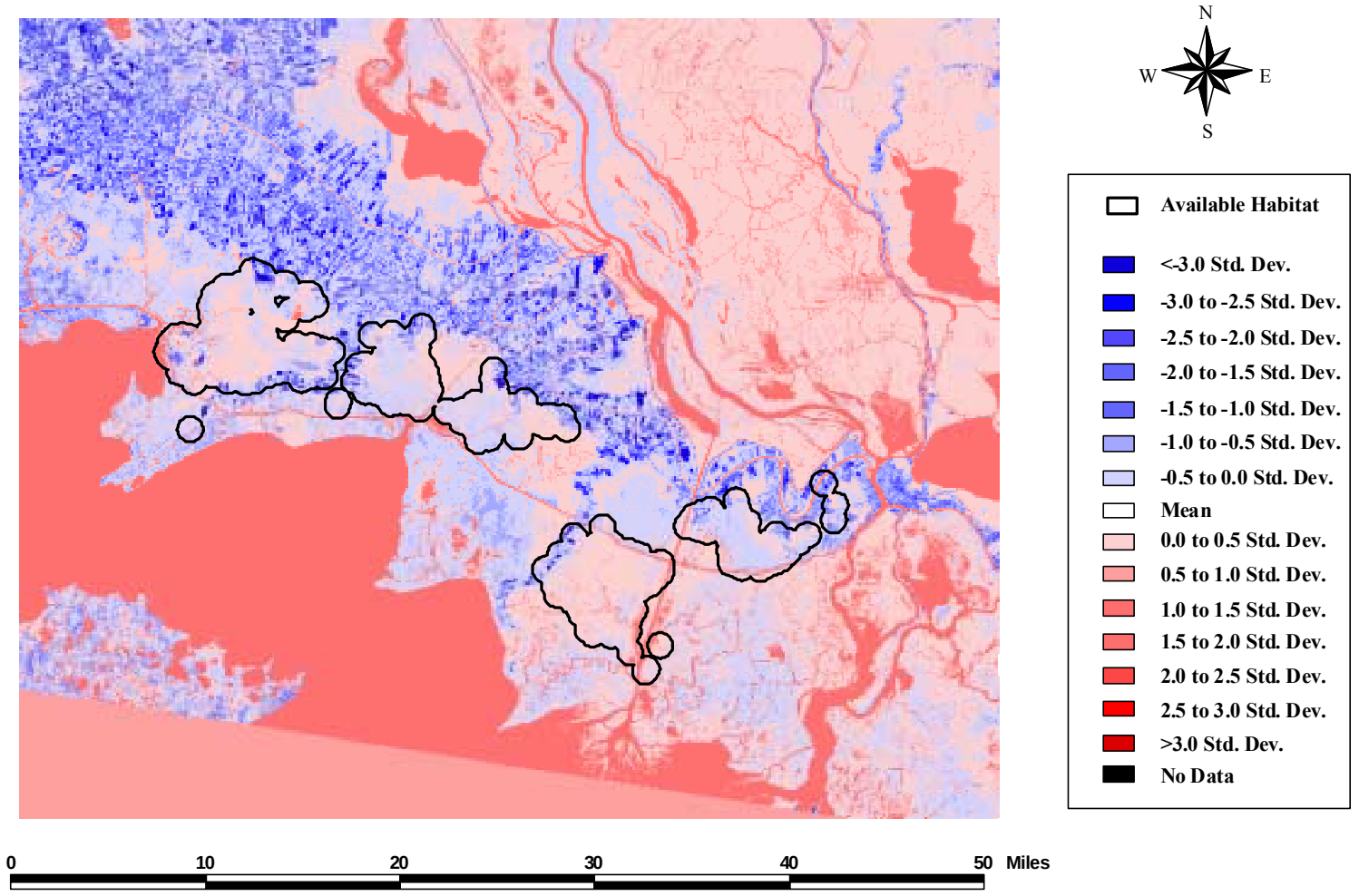
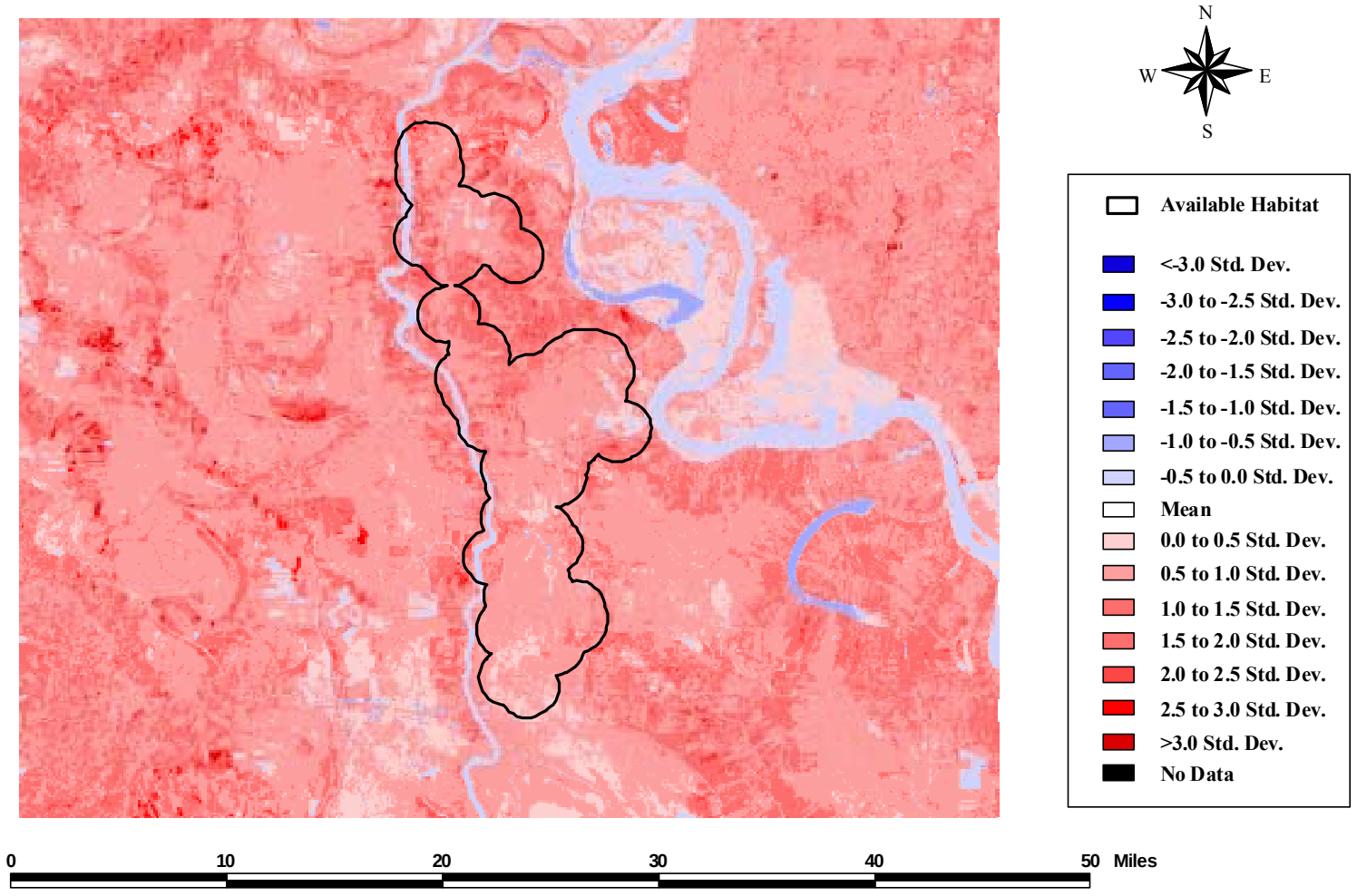


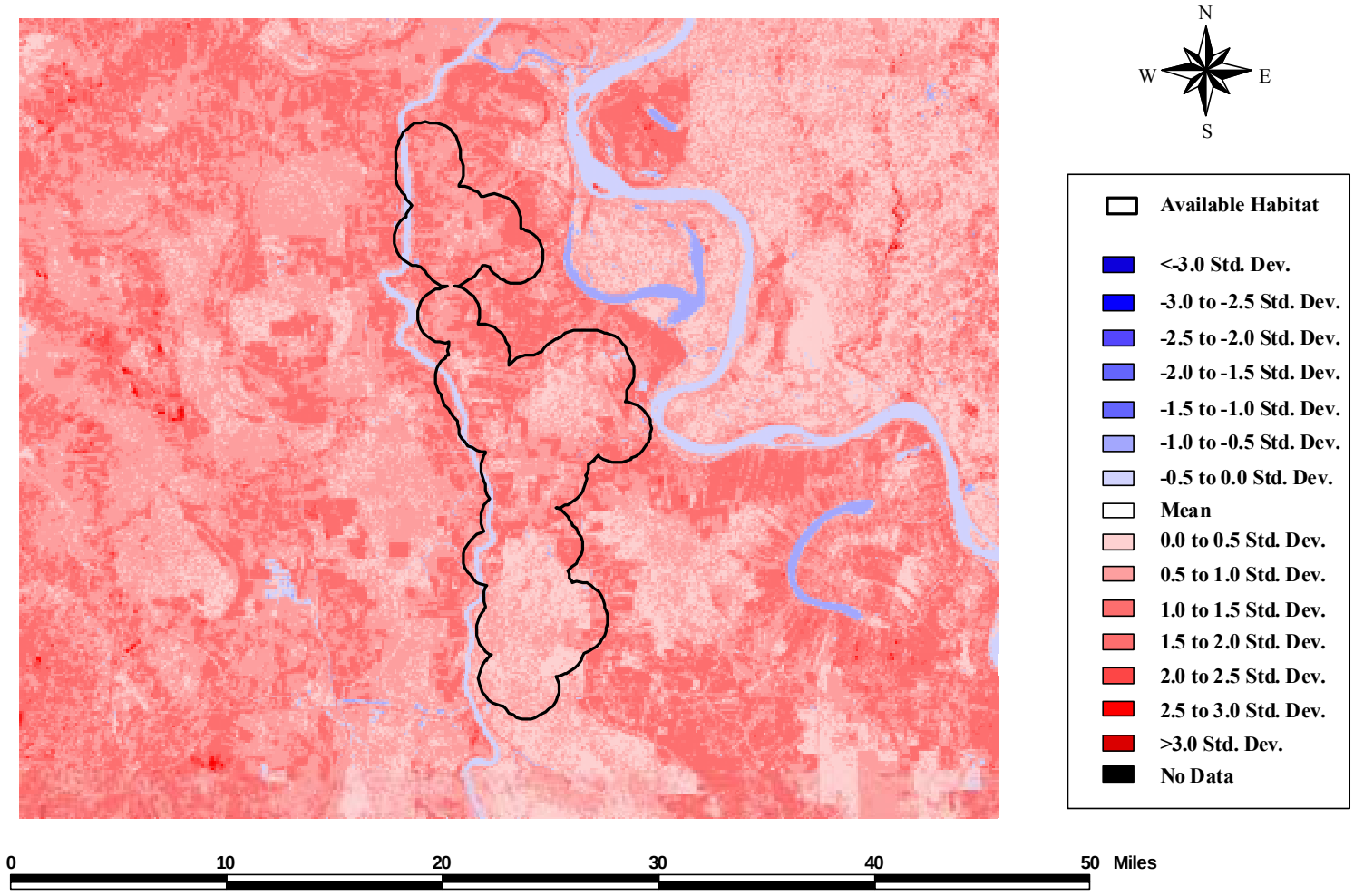
A5. At-satellite reflectance tasseled cap 3, wetness, based on data collected April 1993 in the Coastal study area.



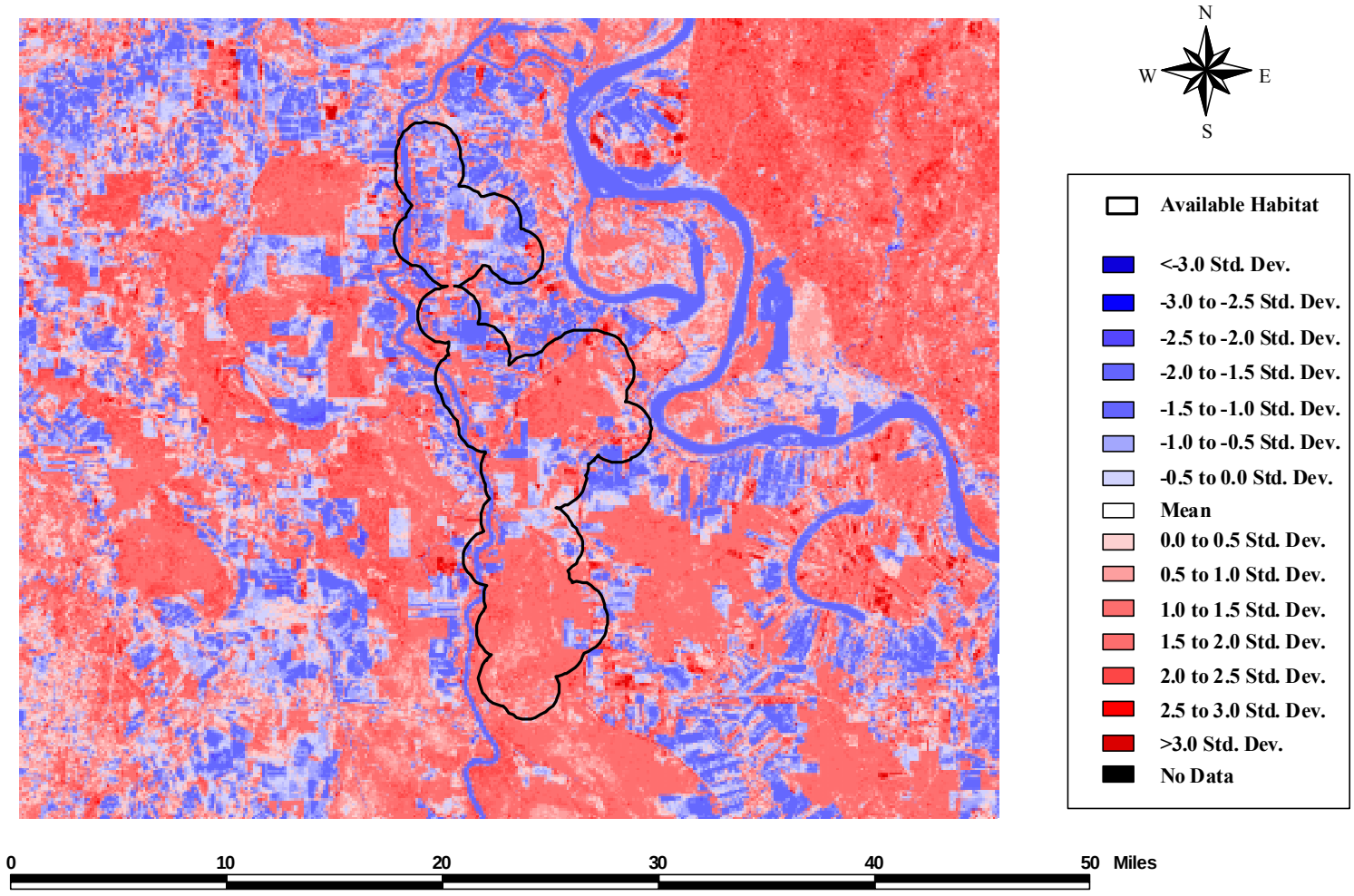
A6. At-satellite reflectance tasseled cap 3, wetness, based on data collected September 1993 in the Coastal study area.



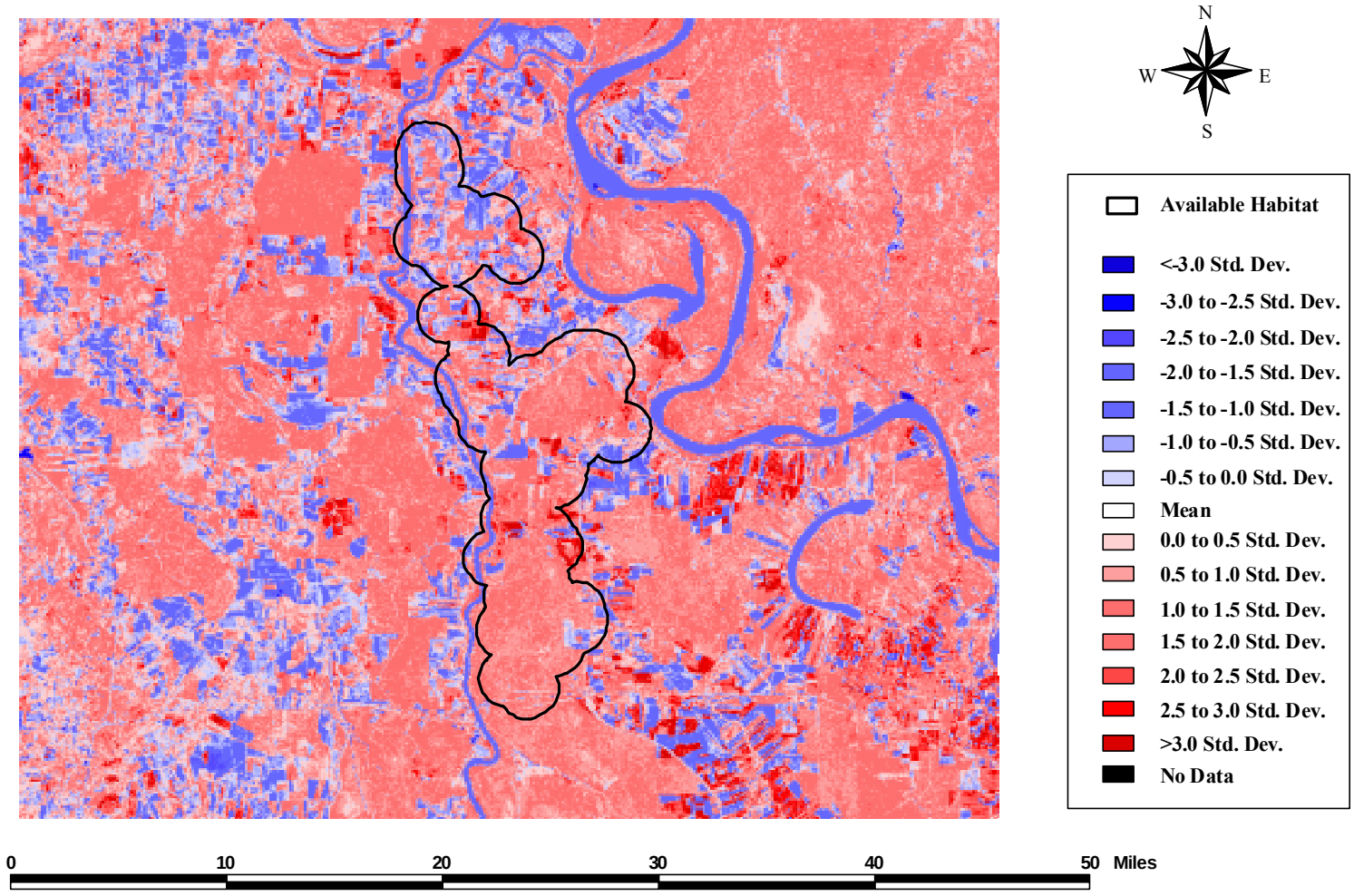
A7. At-satellite reflectance tasseled cap 1, brightness, based on data collected April 1993 in the Inland study area.



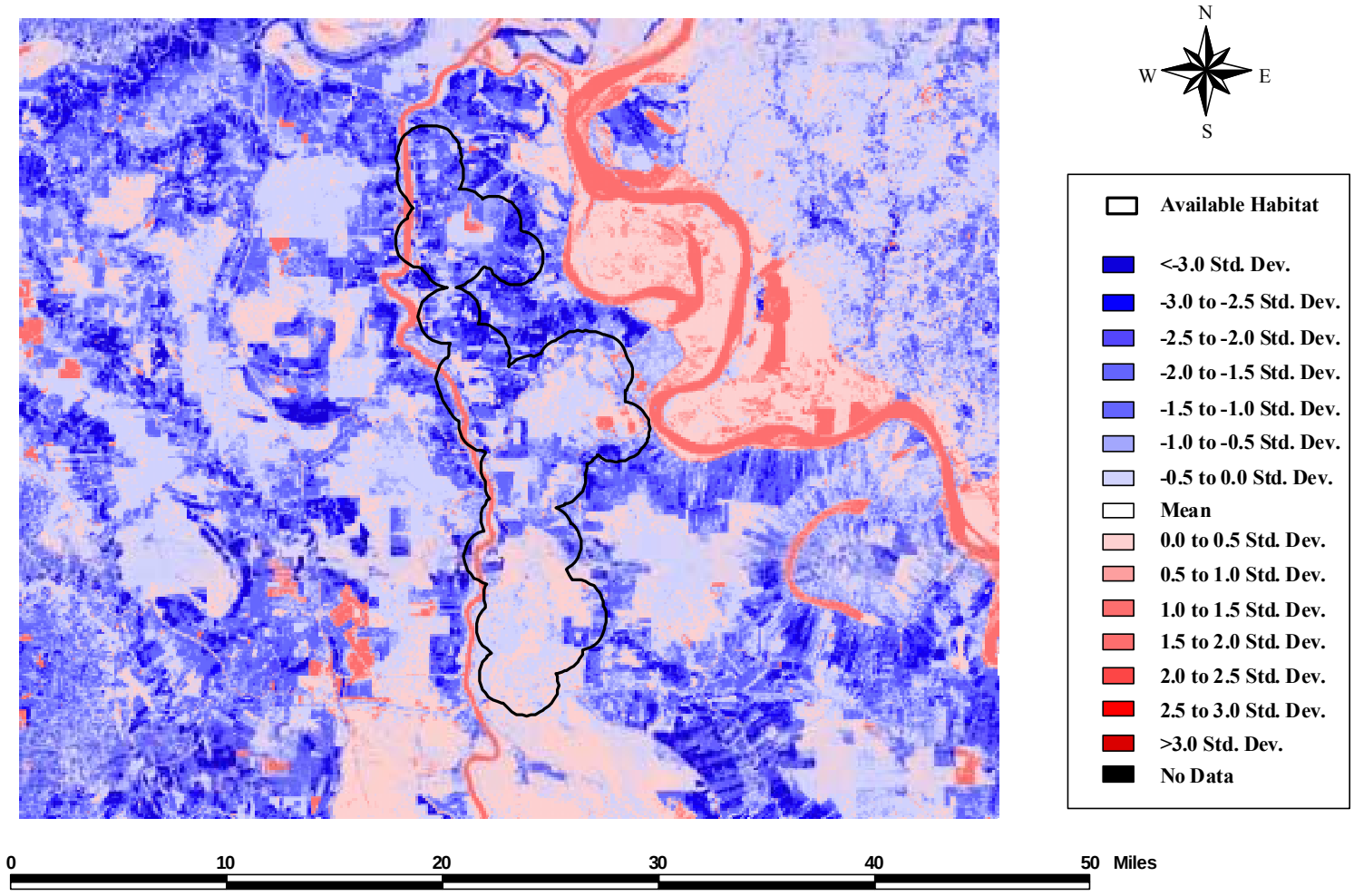
A8. At-satellite reflectance tasseled cap 1, brightness, based on data collected September 1993 in the Inland study area.



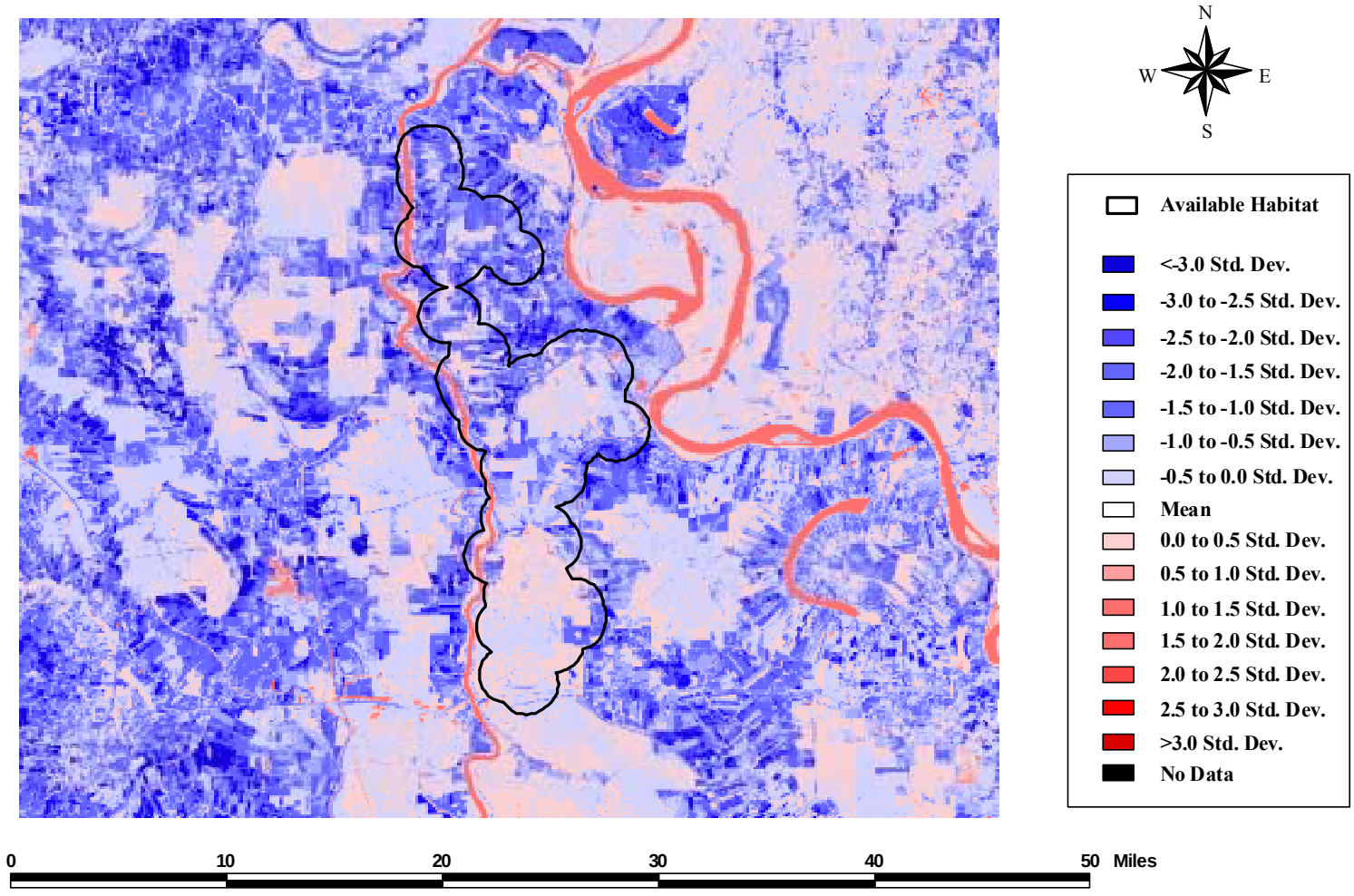
A9. At-satellite reflectance tasseled cap 2, greenness, based on data collected April 1993 in the Inland study area.



A10. At-satellite reflectance tasseled cap 2, greenness, based on data collected September 1993 in the Inland study area.



A11. At-satellite reflectance tasseled cap 3, wetness, based on data collected April 1993 in the Inland study area.



A12. At-satellite reflectance tasseled cap 3, wetness, based on data collected September 1993 in the Inland study area.

VITA

Robert Owen Wagner was born 29 May 1954, in Roswell, New Mexico. He is the son of Ms. Julia Gill Wagner and Mr. Hunter O. Wagner. He graduated from East Jefferson High School in Metairie, Louisiana, in 1972. Robert was a part-time student at the University of New Orleans (UNO) from 1975 to 1991 while raising his daughter, Nichole Wagner Dupre, and developing a general contracting and construction consulting business. He later worked for Oak Tree Capital, Inc., a real estate consulting firm, providing services to commercial banks and federal regulatory agencies, as a senior asset manager. He was responsible for the management of a portfolio of real estate assets valued in excess of $120 million, which had construction, planning, zoning, or environmental regulatory problems. He graduated from UNO in 1991 with a Bachelor of General Studies degree focused on environmental planning. Following graduation from UNO, he worked with the Louisiana Department of Environmental Quality until he enrolled in the Louisiana State University (LSU) Graduate School in 1992, to pursue a Master of Science degree in the School of Forestry, Wildlife, and Fisheries. Robert completed his thesis, "Movement patterns of black bears in south central Louisiana" and was awarded a Master of Science degree in December 1995. He immediately entered the Doctoral degree program at LSU in what is now the School of Renewable Natural Resources. Following completion of his course work in 1997, he started an ecological, natural resources and statistical services consulting business, Quantitative Ecological Services (QES). Since its formation, QES has gained 3 employees and completed over 23 projects for state and federal agencies.