MAPPING FERRUGINOUS HAWK (*BUTEO REGALIS*) HABITAT USING SATELLITE DATA

BY

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<u>MASTER'S THESIS</u>

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A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
of the Requirements of the Degree
Master of Science

by
Natalya V. Antonova
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Abstract

Over the last few decades, the lands of northwestern Utah have undergone changes that greatly altered the land-use patterns in the area and affected wildlife habitat quality and abundance. One species of special concern is the ferruginous hawk (*Buteo regalis*), which experienced population declines in the last 30 years. Some of these declines have been linked to changes in the characteristics of native vegetation following invasions of exotic species and changes in wildfire regimes. I studied relationships between vegetation structure and ferruginous hawk nesting and foraging habitat selection. I mapped vegetation density for 2.1 million acres in northwestern Utah using 1993 Landsat TM satellite imagery. The goal was to create a vegetation data layer that would be used to build a ferruginous hawk habitat model and to use this model to map potential habitat distribution and abundance for this species in the study area. Knowledge of the distribution and abundance of potential habitat would improve understanding of ferruginous hawk population dynamics at a variety of spatial and temporal scales.

With unsupervised classification, I identified four vegetation classes based on variations in percent cover of vegetation communities associated with hawk habitat. The four cover classes were low vegetation density (0-20% cover), medium density (20-25%), high density (25-45%), and areas with tree cover above 10%. The overall classification accuracy was 84.95%, with producer's accuracy for four individual information classes ranging from 75.95% to 97.06%. Further subdivision of the high-density class into three categories based on heterogeneity of vegetation stature was unsuccessful due to low classification accuracy of the high-density class. Maps resulting from classification showed different patterns of density class distributions at a variety of spatial scales.

Five logistic regression models were built to distinguish nest sites from random sites in the study area using elevation and vegetation density variables derived from a DEM and the classified Landsat TM image. Four out of five models were significant with the overall success rate of 63.9% for three out of five models. Nest sites had high prediction success of 83.3-94.4% for significant models. Among the seven variables used to build the models, elevation, presence of trees, and cover type heterogeneity were important predictors of nesting habitat. Variables measuring the proportion of the area occupied by bare ground and low-density vegetation had the most predictive power for ferruginous

hawk foraging habitat. These models were used to map suitable nesting, foraging, and nesting & foraging habitat in the study area. Analysis of these maps indicated that BLM and Military reservation lands contained 60% and 26%, respectively, of available nesting & foraging habitat in the study area.

The results of the study were consistent with the published literature on ferruginous hawk and confirmed that topographic and vegetation characteristics are important to ferruginous hawk selection of nesting and foraging habitat. I also demonstrated that variables usually collected with the intensive ground-based surveys could be quantified using satellite data. This allows for mapping of potential ferruginous hawk habitat at regional scales and provides an efficient way to monitor changes in habitat quality and availability over time.

Acknowledgements

I would like to sincerely thank my advisor, Dr. David O. Wallin, for his patience, tremendous advice, and continuous support through all stages of this research. This thesis would not be possible without his remarkable knowledge of remote sensing, multivariate modeling techniques, and approaches to research. His clear vision and continuous desire for discovery have always motivated me to keep going. I also express my gratitude to my committee members Dr. Andrew Bach and Dr. John F. McLaughlin for providing helpful criticism in the revision stages of this thesis.

I thank Kirk Gardner of the Bureau of Land Management Salt Lake Field Office, for inspiring my love for ferruginous hawks and teaching me so much about the environments of northern Utah. His help was also instrumental in obtaining aerial photography and transportation for the field work part of this project. My appreciation also goes to Cheryl Johnson of the BLM for her friendship, valuable advice, and help with GIS datasets and fieldwork throughout the years.

I would like to thank all the people who participated in various stages of field surveys for this project. Volunteers and employees of the BLM have been instrumental in collecting and sharing nest data for the summers of 1998 and 1999. Alice Hreha of the Great Basin Naturalists was indispensable in initial stages of vegetation surveys and I am grateful to her for spending long hours in the field and teaching me a great deal about vegetation communities of the Great Basin. Special thanks goes to my parents and my husband: my dad for building the vegetation sampling frame, my mom for helping with the field work, and my husband for his contributions to data entry and analysis.

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Chapter 1:

ASSESSMENT OF VEGETATION DENSITY AND HETEROGENEITY IN SEMI-ARID ENVIRONMENT USING LANDSAT TM DATA

Introduction

Important problems

Land-use change and biological invasions are two of the key factors affecting wildlife diversity through changes in habitat quality and abundance (Harris, 1984; Lovejoy et al., 1984; Wilcove et al., 1986; Wilcove et al., 1998; Abramovitz, 1991; Soulé, 1991; D'Antonio and Vitousek, 1992; Noss and Cooperrider, 1993; Vitousek et al., 1996; Meffe et al., 1997; Dale et al., 2000; Mack et al., 2000). One of the major consequences of land-use change that influences the quality of wildlife habitat is alteration of natural vegetation cover. Hunter (1990) and Rodiek and Bolen (1991) recorded the importance of vegetation structure and spatial patterning in explaining animal distributions. Accurate and timely monitoring of changes in vegetation pattern is, therefore, a necessary prerequisite for our capacity to model wildlife habitat quality and distribution. Conventional ground-based methods of vegetation sampling, which can only be applied to local spatial scales due to logistic constraints, do not allow us to directly assess changes in vegetation cover on a regular basis over large areas. Analysis of satellite data, however, can provide information on temporal and spatial scales necessary for such monitoring.

Satellite imagery has been successfully used in regional scale analyses of vegetation cover in a variety of environments. Wetland delineation analysis has been conducted in both arid and temperate zones (Gilmer et al., 1980; Benger, 1997; Wang et al., 1998). Remotely sensed data have been used to determine rates of deforestation and fragmentation in the tropical and subtropical forests (Nelson et al., 1987; Sader and Joyce, 1988; Green and Sussman, 1990; Skole and Tucker, 1993; Tucker et al., 1984b; Stone and Lefebvre, 1998). Satellite imagery has also been widely used for analysis of forest age and structure and change detection studies in the temperate zone around the world (Hall et al., 1991; Ripple et al., 1991; Luque et al., 1994; Cohen et al., 1995; Turner et al., 1996; Zheng et al., 1997; Sachs et al., 1998; Boyce, 1999; Cushman and Wallin, 2000). Numerous techniques have been developed to assess vegetation extent and characteristics in these biomes. Vegetation indices, such as the normalized difference and simple ratio vegetation indices (Tucker, 1979) and linear vegetation indices (Richardson and Wiegand, 1977), have been found to be useful in mapping of vegetation cover in areas where it is abundant (Sader et al., 1989). The Tasseled Cap Transformation has also proved successful and it has been used extensively (Cohen, 1992; Cohen, 1995).

Considerably fewer successful approaches have been developed for vegetation classification in arid and semi-arid environments. These are the areas where large quantities of soil and dry litter interfere with detection and classification of vegetation cover. Sparseness of cover, high species richness, and the clumped nature of native vegetation all make satellite imagery analysis in arid environments difficult (Tueller, 1987). Huete et al. (1984) found that low-density vegetation was extremely difficult to distinguish from bare soils. Vegetation indices lose much of their utility in desert environments due to soil brightness influences (Huete and Jackson, 1987), shade differences (Tueller and Oleson, 1989) and high heterogeneity of plant structure and phenology (Satterwhite and Henley, 1987). Although normalized difference vegetation indices have been used in studies in the semi-arid zone, accuracies of such studies are usually lower than ones obtained for vegetation classifications of forested ecosystems.

Nevertheless, a variety of sensors have been used to map vegetation distribution in arid and semi-arid biomes. Extensive research on mapping arid regions during the 1980's demonstrated the usefulness of AVHRR high temporal resolution data. This particular sensor is particularly useful for regional to continental scale of seasonal and interannual vegetation changes that correlate with the movement of the rains in Africa (Tucker et al., 1984a; Tucker et al., 1985b; Tucker et al., 1985c; Tucker et al., 1986). More recently, Rogers et al. (1997) have used the same sensor to classify land cover in Nigeria using discriminant analysis techniques. Vickrey and Peters (1996) have successfully employed AVHRR data to map New Mexico grasslands and Eve and Peters (1996) were able to track changes in mesquite (*Prosopis glandulosa*) biomass to assess the effectiveness of shrub control.

For smaller study areas, Landsat MSS and TM data, have been successfully used to classify desert land cover based on vegetation composition and extent (Tueller et al., 1978; McGraw and Tueller, 1983; Price et al., 1985; Price et al., 1992; Knick et al., 1997; Abeyta and Franklin, 1998). Often, auxiliary data such as geomorphic layers or digital elevation models have to be used in conjunction with image classification in order to isolate desired vegetation parameters (Price et al., 1985).

Whereas knowledge of the extent of broad vegetation communities can be useful for general wildlife habitat identification at larger scales, as the Gap Analysis Program demonstrated, it is often not sufficient for analyzing habitat quality and abundance for individual wildlife species. The use of habitat by wildlife is more often correlated with vegetation structure rather than vegetation type, therefore an assessment of specific vegetation cover attributes that directly relate to animal foraging behavior and reproduction is needed in cases where complex habitat models are involved (Short and Williamson, 1986). In the last two decades, a number of studies have utilized satellite data to quantify and use ecologically relevant vegetation parameters in modeling potential habitat and distribution for various species and groups of species (Thompson et al., 1980; Saxon, 1983; Palmeirim, 1988; Avery and Haines-Young, 1990; Rogers and Smith, 1991; Aspinall and Veitch, 1993; Lavers et al., 1996).

While numerous successful methods have been developed in forested areas to classify vegetation attributes directly related to bird habitat (Sader et al., 1991; Hepinstall and Sader, 1997; Bosakowski, 1999; Montgomery, 1999; Wallin, in review), such methods are still being developed for arid ecosystems due to difficulties with accurate detection of vegetation cover discussed earlier. Nevertheless, several successful techniques should be emphasized. AVHRR data were used by Tucker et al. (1985a) and Hielkema et al. (1986) to analyze green vegetation blooms related to desert-locust activity. Wallin et al. (1992) used the same sensor to relate vegetation parameters to the breeding bird habitat in arid environments of Africa. In addition, Knick et al. (1997) have used Landsat TM imagery to map vegetation density in the Snake River Birds of Prey National Conservation Area in southwestern Idaho for further use in habitat model development for raptors.

Objective

Substantial losses of ferruginous hawk (*Buteo regalis*) habitat in the United States and Canada have been documented by several studies (Olendorff, 1973; Houston and Bechard, 1983; Houston and Bechard, 1984; Schmutz, 1984; USFWS, 1985; Woffinden et al., 1985; Woffinden and Murphy, 1989). Some of these losses have been associated to land-use changes that affect characteristics of native vegetation cover. Ferruginous hawks are normally found in habitats that have not been greatly disturbed by grazing or other agricultural activities (Harlow and Bloom, 1989). These anthropogenic activities result in changes in vegetation cover can be detrimental to ferruginous hawk's prey species resulting in a reduction of nesting hawks and lower productivity (Wakeley, 1978). More specifically, vegetation density, height, and heterogeneity become decisive factors in determining ferruginous hawk habitat suitability and quality (Wakeley, 1978; Jasikoff, 1982; Woffinden and Murphy, 1989). In addition to grazing and agriculture, replacement of natural communities by exotic species, namely cheatgrass (*Bromus tectorum*) advancement into sagebrush (*Artemisia spp*.) steppe, has caused major alteration and impoverishment of native vegetation cover (Billings, 1990), negatively affecting hawk's ability to capture prey. Changes in natural fire regimes, caused by the new vegetation cover conditions, have resulted in further degradation of habitat quality (Whisenant, 1990). It has also been speculated that, in recent decades, decreases in ferruginous hawk habitat abundance and lower productivity rates were related to urban expansion and increased recreational use (Olendorff 1973; Olendorff, 1975; Olendorff, 1993; Gardner, pers. comm.).

The objective for this study was to use Landsat TM data to map vegetation characteristics that are ecologically relevant to delineation of potential nesting and foraging habitat for the ferruginous hawk. This habitat layer would then be used to model ferruginous hawk habitat relationships and obtain nesting and foraging habitat suitability maps for the study area.

Methodology

Vegetation sampling plots were selected using aerial photographs and surveyed for vegetation density in the summer of 1998. Field data were subdivided into seven information classes based on percent cover and heterogeneity of vegetation. An unsupervised classification of a Landsat TM image was performed using Landsat bands 3-5 and 7, a Soil Adjusted Vegetation Index, greenness and wetness channels of Tassel Cap Transformation, and two texture channels. Spectral classes derived from classification were assigned to information classes based on field data. The resulting land cover map consisted of four information classes based on vegetation density. Heterogeneity information classes could not be successfully separated.

Study Area

The study area covers approximately 2.1 million hectares and includes most of Tooele and the extreme southern part of Box Elder counties in Utah (Figure 1). This area was chosen because of the availability of good data on ferruginous hawk nesting activities during 1992 to 1999. Land ownership includes a mixture of private, public, and military lands, with the largest proportion (42.4%) managed by the Bureau of Land Management for multiple use, including grazing and recreation.

The study area lies at the extreme east of the Great Basin section of the Great Basin and Range province of the North American deserts (Macmahon, 1979). It contains mainly northward-trending mountains, rising as high as 3300 m separated by valley floors around 1300 m in elevation (Figure 2). A number of vegetation communities exist within the area, the most extensive of which is the desert salt scrub community found at elevations below 1600 m. This community is dominated by a number of species of *Artiplex*, gray molly (*Kochia vestita*), winterfat (*Ceratoides lanata*), budsage (*Artemisia spinescens*), halogeten (*Halogeten glomeratus*), mormon tea (*Ephedra spp*.), and horsebrush (*Tetradimia canescens*). Greasewood-dominated (*Sarcobatus vermiculatus*) communities are more common on drier and saline soil types of valley bottoms. Associated species include shadscale (*Atriplex confertifolia*), seepweed (*Suaeda torreyana*), and halogeton (*Halogeton glomeratus*).

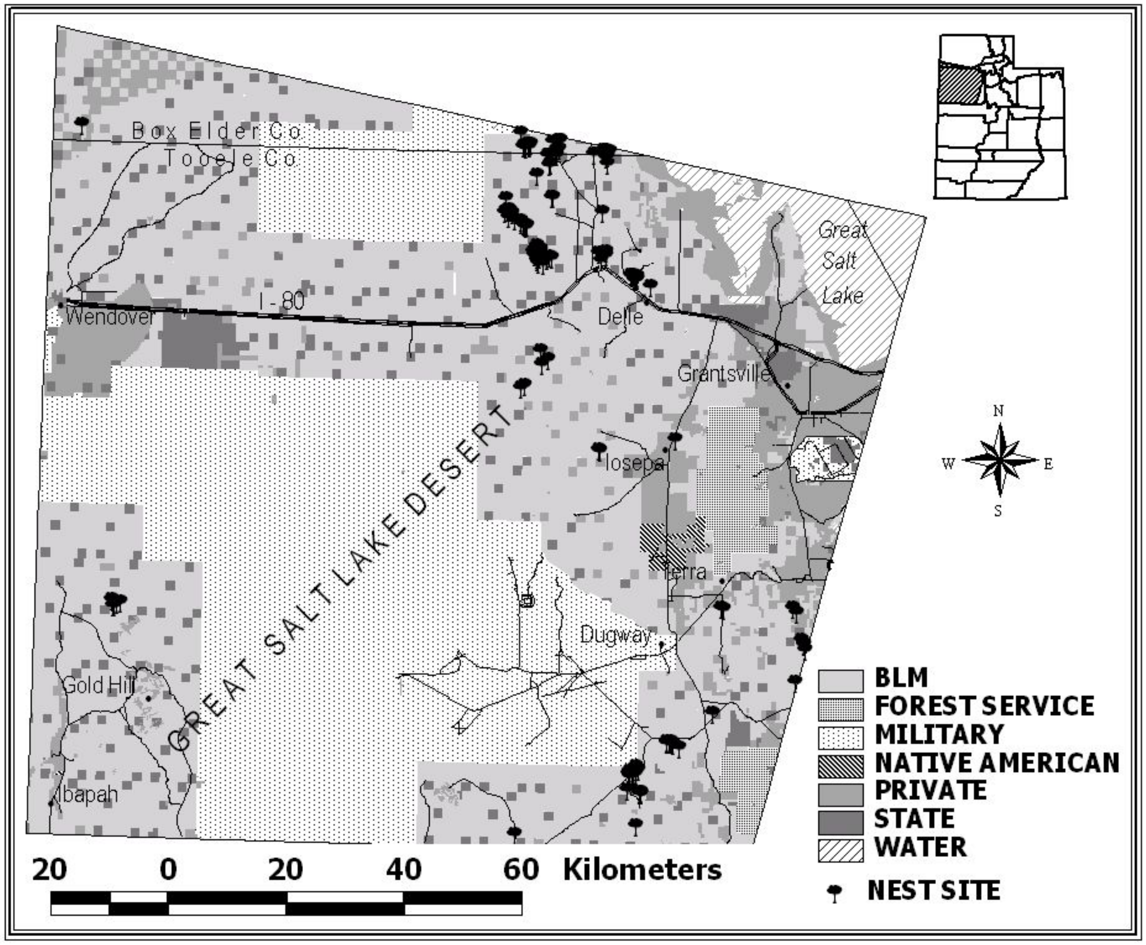

Figure 1: Land ownership and ferruginous hawk nest site locations in the study area.

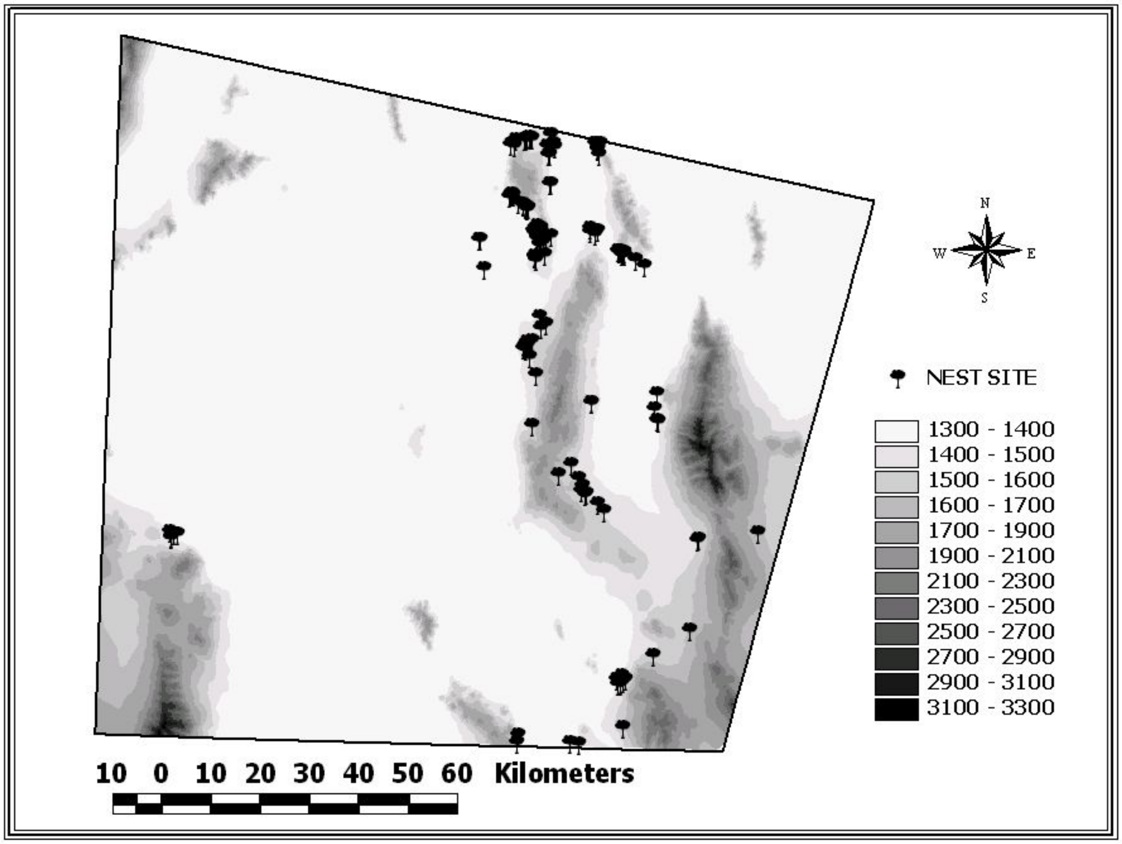

Figure 2: Elevation ranges (in meters) and ferruginous hawk nest site locations in the study area.

The sagebrush (*Artemisia spp*.) vegetation zone is found between about 1600 m to 1800 m elevations, where more moisture is available, and on deeper, alkaline and somewhat sandy or gravelly soils. Associated shrub species include rabbitbrush (*Chrysothamnus spp*.), snakeweed (*Guterrezia sarothrae*), winterfat (*Ceratoides lanata*), shadscale (*Artiplex confertifolia*), and bitterbrush (*Purshia tridentata*). Associated grass species include bluebunch wheatgrass (*Agropyron spicatum*), sandburg bluegrass (*Poa secunda*), crested wheatgrass (*Agropyron cristatum*), needlegrass (*Stipa comata*), sand dropseed (*Sporobulus cryptandrus*), Indian ricegrass (*Oryzopsis hymenoides*), and galleta (*Hilaria jamesii*). The juniper forest community is found at yet higher elevations (~ 1800 m to 1900 m). Although this community is not used by the hawks directly for hunting, individual trees in the ecotone between juniper and shrub communities are often used as nesting substrates.

Field Data Collection

In order to map vegetation density and heterogeneity in the study area, sample vegetation data were collected using aerial photography and field work. Eighty three 1:40,000 scale panchromatic aerial photographs for June of 1993 were obtained from the USDA Aerial Photography Field Office for delineation of vegetation sampling plots. These were the most recent photographs available for the study area. Twenty-two stereo-pairs of photographs were selected near locations of ferruginous hawk nesting sites, which were surveyed in the summers of 1995 through 1999. The remaining thirty nine aerial photos were chosen randomly within the vegetation zones used by the hawks to represent full range of vegetation conditions that exist in the study area. I used a general vegetation map, produced by the Utah Gap Analysis Program (Edwards et al., 1995), to determine the location of these zones (Figure 3). Salt desert scrub, sagebrush and greasewood shrublands, perennial and annual grasslands, including desert grasslands, co-dominant sagebrush and grassland community, and juniper forest community were isolated using ArcView GIS software package to create the mask. One to seven 400- by 400-m sampling areas were selected on each photograph for a total of 284 areas. All sampling areas were homogenous in vegetation cover and were selected to represent a variety of vegetation conditions on the landscape (Figure 4). A fairly large size and

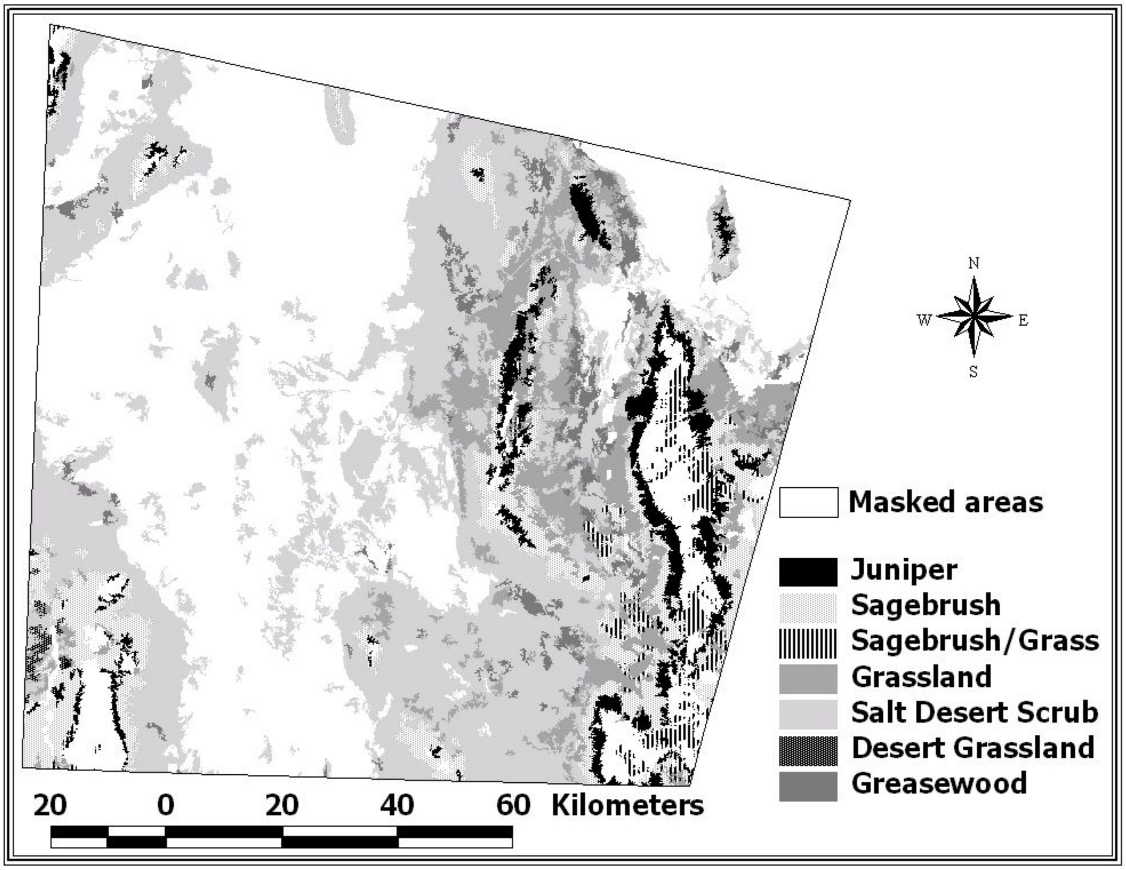

Figure 3: Vegetation mask created from the Gap Analysis Program GIS layer (Edwards et al., 1995). Vegetation classes shown are associated with ferruginous hawk nesting and foraging activities.

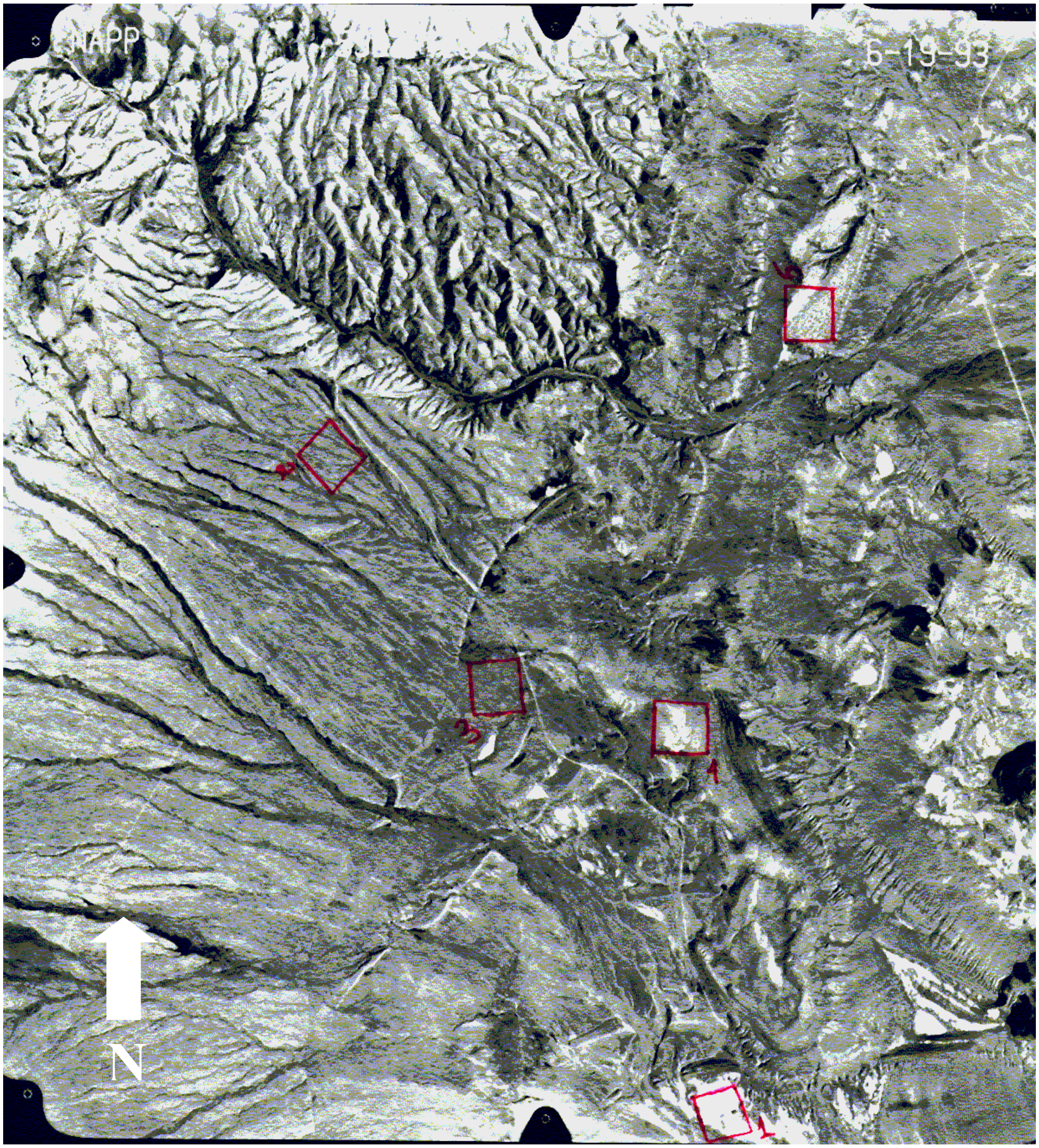

Figure 4: An example of field sampling area selection using aerial photographs. The 1:40,000 panchromatic photographs (reduced here to 1:53333) were used to delineate vegetation sampling areas approximately 400 x 400 meter in size.

homogeneity of the sampling area were necessary in order to insure geometric registration between the field plots and the satellite imagery.

Field work was conducted during June, July and September of 1998. The sampling areas outlined on the aerial photographs were located in the field using 1:24,000 USGS quadrangles. Sampling areas that appeared to have burned recently or proved to be inaccessible were either omitted or moved to a different location. One 75- by 75-m field plot was placed within each 400- by 400- m sampling area. One of the four corners of each field plot was surveyed using Trimble Pathfinder GPS equipment. The sides of field plots were then laid out from the corner at ninety-degree angles and compass directions were recorded for computer processing.

At each 75- by 75-m field plot, vegetation was characterized using thirty-two $0.5m^2$ point vegetation sampling frames (Floyd and Anderson, 1982) placed, in pairs, every 25 meters within the field plot (Figure 5). The vegetation sampling frame consisted of two layers of fifty 10- by 10-cm cells to facilitate vertical projection of each cell. For each cell, the dominant cover was recorded as either bare ground, litter, or a plant species. When a tree was encountered, the sampling frame was moved to the closest area outside the tree crown. A total of one hundred and eighty three field plots were surveyed.

Adequacy of sampling was determined using calculations of successive means (Greig-Smith, 1983). The mean number of cells occupied by vegetation was calculated for each added sampling station and plotted against the number of sampling stations. An adequate sample size is the point where the mean stabilizes. In this case, inspections of successive mean graphs for a sample of field plots indicated that the mean stabilized at about eight or nine sampling stations (Figure 6).

Field Data Processing

The GPS positions for vegetation plots were differentially corrected in the lab using Pathfinder Office software (Trimble Navigation Ltd., 1996). Compass directions and distance measures were used to construct polygons for each plot using Arc/Info COGO software.

For each 75- by 75-m field plot, the ground cover entries for each cell of the vegetation sampling frame were combined in the lab to determine the total percent cover

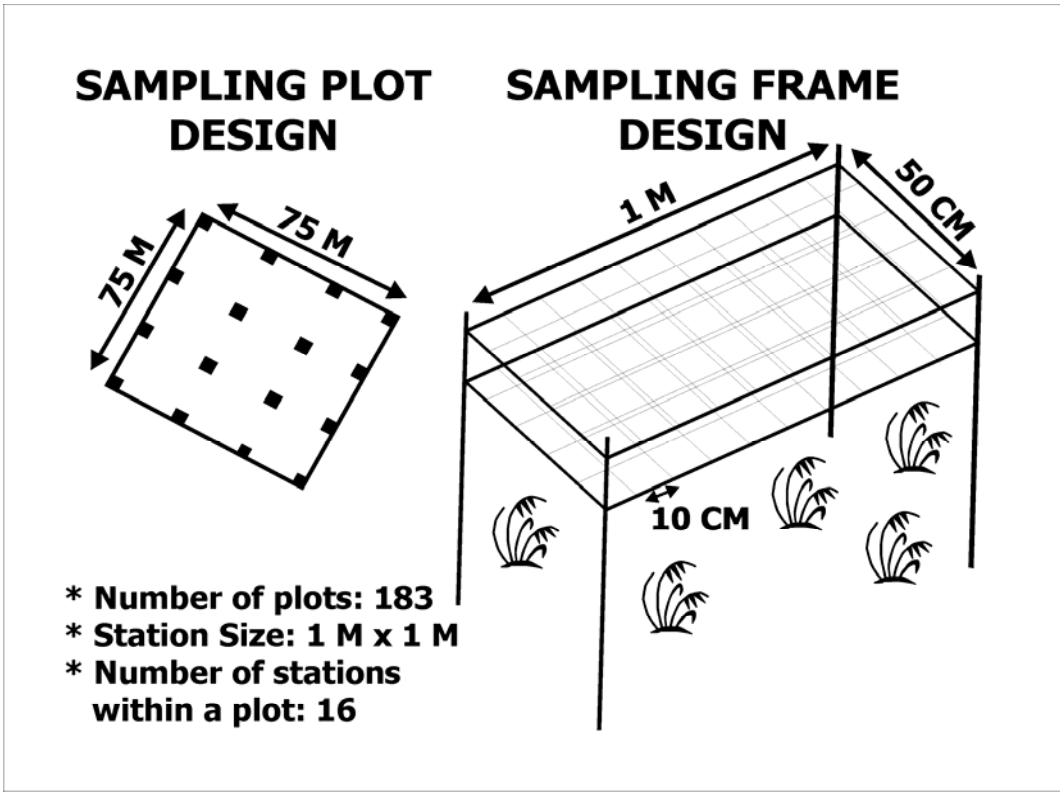

Figure 5: Layout of the field sampling plot and vegetation density sampling frame design. The height of each leg was adjusted to keep the top of the frame horizontal.

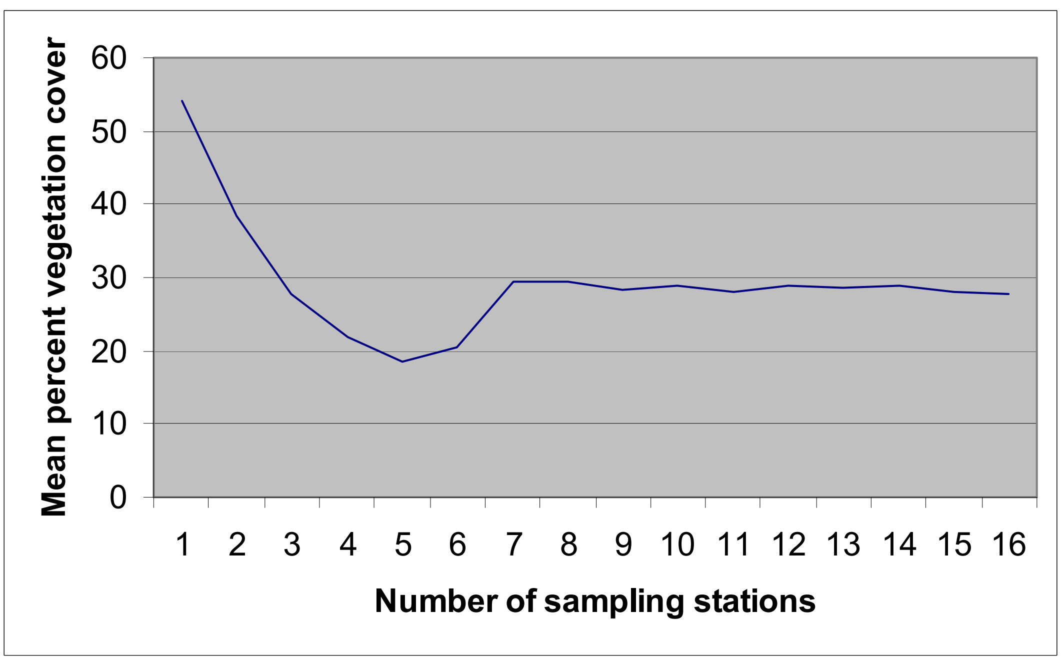

Figure 6: Successive mean estimation graph for one of the field sampling plots. For most of the field plots surveyed, the mean stabilized at eight or nine sampling stations.

for bare ground, litter, and each plant species. For the plots with tree cover, tree densities were estimated using aerial photographs that were scanned and overlaid with a point grid. Percent cover for bare ground, litter, and plant species for these plots were then recalculated. Additional twenty-seven plots in the juniper forest community were delineated using aerial photos.

Data for field plots with total vegetation density above 45% were discarded from the analysis to avoid potential classification errors due to fire occurrence since 1993. These field plots were mainly composed of cheatgrass (*Bromus tectorum*) that invaded the area after a wildfire. Since native vegetation characteristics in the study area do not change rapidly, one could be fairly certain that the same cover existed in the plots with native vegetation in 1993 and 1998. On the other hand, cheatgrass can invade an area within a year, especially after fire. Since there was a five-year lag between the date when the photographs were taken and the time the field data was collected, there was no way to tell when the disturbance occurred and whether the sampled vegetation corresponded to the conditions present in the area in 1993.

All field plots were overlaid on the satellite image and a number of them were discarded due to cloud cover. The remaining field data were subdivided into four information classes based on vegetation density and heterogeneity so that each category had an approximately even number of plots:

1) low vegetation density (<20% cover);

2) medium vegetation density (20-25% cover);

3) high vegetation density (25-45% cover);

  a) low heterogeneity - shrubs;

  b) low heterogeneity - grasses;

  c) high heterogeneity;

4) areas with juniper density higher than 10%.

Heterogeneity of the high-density plots was determined based on density of three life forms (shrubs, grasses, and forbs) within the plots. Plots with only one life form with density above 10% were considered homogeneous. There were only a few plots with high forb density, hence forbs were combined with shrubs. Plots with two life forms with density above 10% for each life form were considered heterogeneous.

Vegetation Mapping

Landsat TM satellite imagery of the study area was obtained for May 24, 1993. This scene was chosen to coincide with peak annual growth in the study area (McGraw and Tueller, 1983; Price et al., 1985) and due to the scene's sparse cloud cover. The image was georeferenced using GPS coordinates collected in the field and from 1:24,000 USGS quadrangles. Nearest neighbor resampling was used to produce a 25- by 25-m grid cell size. Clouds were masked out using the thermal channel (TM channel 6), cloud shadows were masked out using the near-infrared channel (TM channel 4). The vegetation mask created from the Gap Analysis Program vegetation layer (Edwards et al., 1995) was used to reduce spectral variability of the image by isolating grass and shrub vegetation communities associated with ferruginous hawk nesting activities.

In order to identify four information classes based on variations in percent cover of vegetation types associated with ferruginous hawk habitat, an unsupervised classification was performed using TM bands 3-5 and 7 (Price et al., 1992), brightness, greenness and wetness of Tassel Cap Transformation (Crist and Cicone, 1984), a Soil Adjusted Vegetation Index (Huete, 1988), and two texture indices. Texture data layers were derived from an absolute difference algorithm filter (Rubin, 1990) applied to brightness and greenness channels of the Tassel Cap Transformation (Cohen and Spies, 1992). A moving 3x3 pixel window was used. ISOCLUS algorithm was used for the unsupervised classification (PCI, 1998).

Information classes were linked to spectral classes using field data. Spectral classes that were confused between two or more information classes were reclassified using the same ISOCLUS algorithm. This procedure was repeated until no more spectral classes could be assigned to a unique information class. The pixels within these classes (2.69% of the classified area) were then assigned to the information classes based on an area-weighted method. For each spectral class, this involved calculating the number of pixels within four vegetation density classes and then normalizing the number of pixels by the number of field plots within that vegetation class. The spectral class was assigned to the vegetation class that contained the largest proportion of its pixels (Appendix A). Some spectral classes did not contain any field data pixels (2.15% of the classified area) and, therefore, could not be assigned to any of the information classes. These pixels were processed with a maximum likelihood classifier using signatures generated from pixels already assigned to information classes (PCI, 1998). Pixels remaining unassigned after the maximum likelihood classifier was applied (0.51% of the classified area) were assigned to an information class based on proximity.

I attempted to further subdivide the high-density vegetation class into three subclasses based on heterogeneity. However, because the classification accuracy for this high-density class was low, the accuracy of heterogeneity subclasses would have been even lower. Consequently, the classification analysis was terminated at this point.

Results

Data Distribution

Vegetation densities observed in the field ranged from 0% to 60%, with about 90% of field plots having densities between 15% and 35% (Figure 7). Field plots occupied by native vegetation had densities no higher than 45%. A large number of the plots with densities above 35% were characterized by a combination of either native shrubs and *B. tectorum* or introduced annuals and *B. tectorum*. Vegetation densities higher than 45% were found only in field plots represented by the areas that have been recently burned and were either entirely occupied by *B. tectorum* or artificially planted with non-native grasses to prevent the invasion of *B. tectorum*. As was mentioned in the methods section, plots with densities above 45% were not included in the image classification since it was unknown if the disturbance occurred before or after 1993.

Accuracy Assessment

The classification resulted in three density cover classes associated with shrublands and grasslands of lower elevations and one forest cover class where the density of juniper trees exceeded 10%. The first three classes were low-density, medium-density, and high-density vegetation classes with 0-20%, 20-25%, and 25-45% cover, respectively. The overall classification accuracy was calculated at 84.95%, with producer's accuracy for individual cover classes ranging from 97.06% to 75.95% (Table 1). The high-density vegetation class had the lowest producer's accuracy, however, the user's accuracy was calculated at 95.24%. Even proportions of this category (about 8%) were confused with each of the other three density classes. Since the producer's accuracy of the high-density vegetation class was relatively low, I did not attempt to further subdivide it based on vegetation heterogeneity. Further separation would have resulted in producer's accuracies below 76% for all heterogeneity classes. Low-density vegetation class had the highest accuracy of 97.06%.

I calculated the Kappa statistic for the classification to be 0.79, indicating that the classification is about 79% better than that expected if I randomly assigned a cover class to each image pixel (Verbyla, 1995).

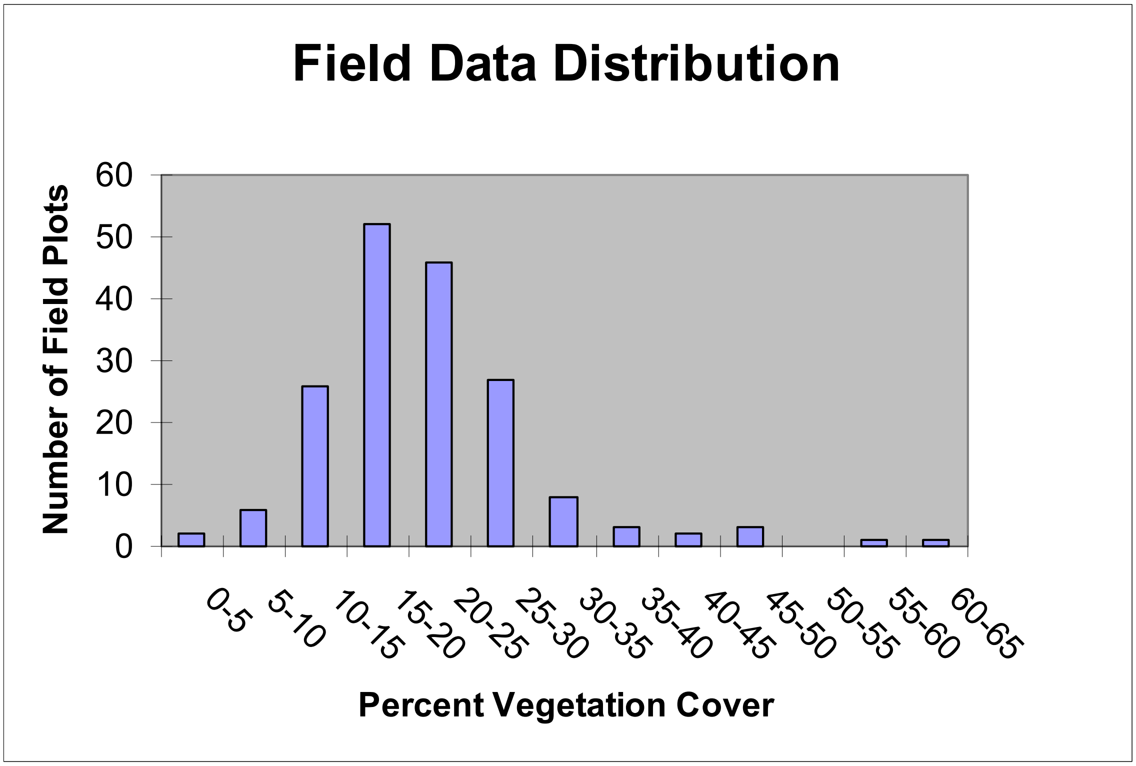

Figure 7: Frequency plot for field data vegetation density. For most of the field plots surveyed, the mean stabilized at about eight or nine sampling stattions.

Table 1: Error matrix for the land cover map. See text for description of classes.

		OBSERVED					
		Low density	Med. density	High density	Trees	Row Total	User's Accuracy (%)
PREDICTED	Low density	33	4	7		44	75
	Med. density		32	6	1	39	82.05
	High density	1		60	2	63	95.24
	Trees > 10%		1	6	33	40	82.5
	Column Total	34	37	79	36	186	
Producer's Accuracy (%)		97.06	86.49	75.95	91.67		**84.95**

Land Cover

The distribution of cover classes across the landscape generally followed an elevation gradient with low and high-density vegetation found at lower and higher elevations, respectively (Figure 8). Trees with densities above 10% were generally found above 1800 m. Within the classified area, the most abundant class was the high-density vegetation, occupying 37% of the classified image (Table 2). The low-density class was the next in abundance (26% of the classified image). Medium-density vegetation and juniper forests occupied equal areas, each comprising about 18% of the classified image.

The relative abundance of each vegetation density class varied substantially among land ownership categories (Figure 9). BLM and State ownership included a relatively even distribution of the four land cover types as a result of the uniform distribution of federal- and state-owned lands across the landscape (Figure 1). As expected, military lands contained primarily low-density vegetation cover class, since they are primarily located at lower elevations of the study area (Figures 1 and 2). Forest Service lands at higher elevations contained high percentage of forested areas and high-density shrublands adjacent to the forest. Private and Native American lands consisted primarily of high-density vegetation class reflecting a large amount of ranching activities on gentle slopes of the mountain ranges that dominate this part of the state.

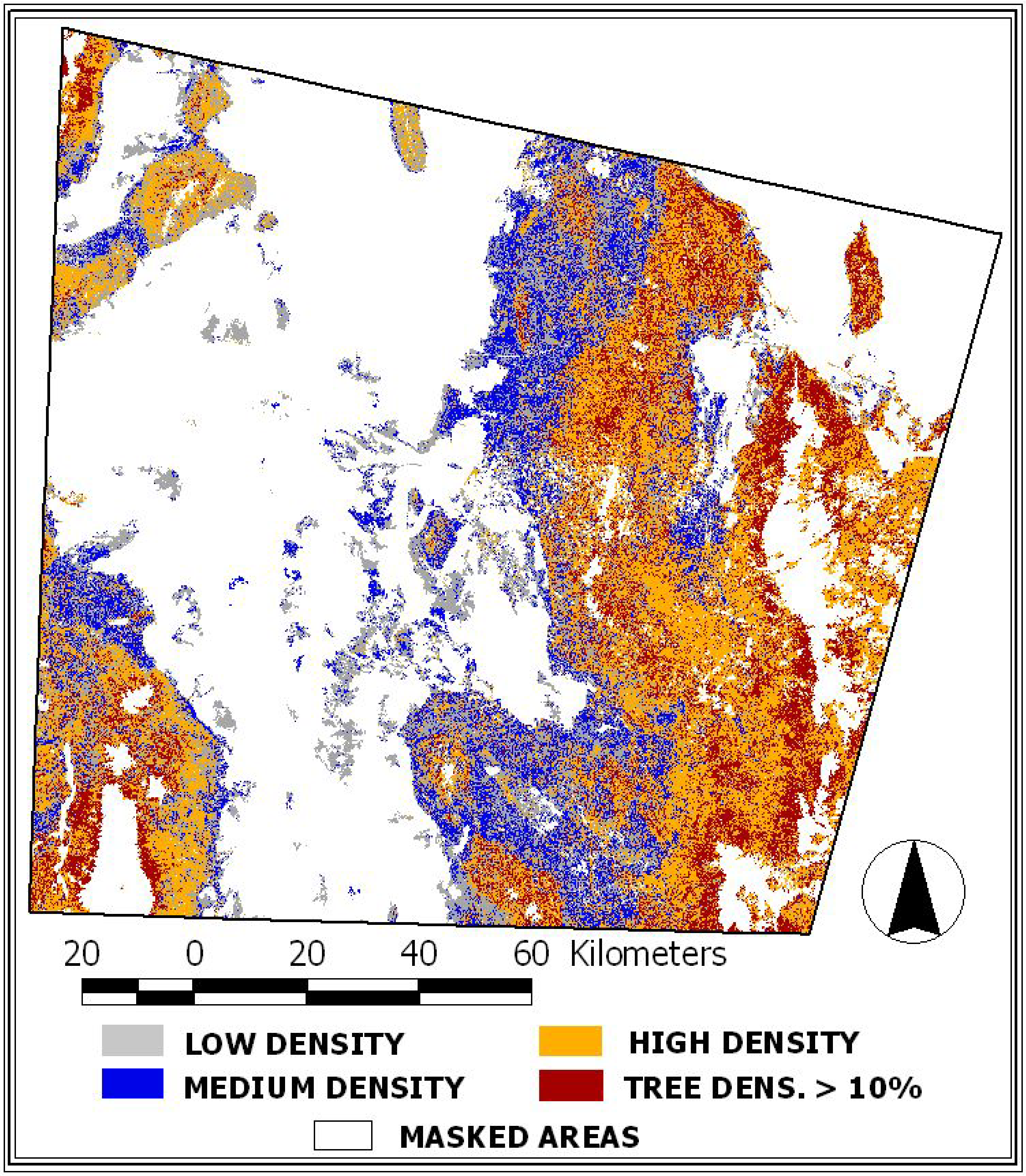

Figure 8: Results of the unsupervised classification of the Landsat TM image. See text for description of classes.

Table 2: Number of hectares and % occupied area for each cover class within the study area.

Information Class	area (ha)	% study area	% classified area
Not classified	954185	53.06	
Low density vegetation (0-20%)	218418	12.15	25.88
Med. density vegetation (20-25%)	155181	8.63	18.38
High density vegetation (25-45%)	311811	17.34	36.94
Trees with density > 10%	158690	8.82	18.80
Total	1798285		

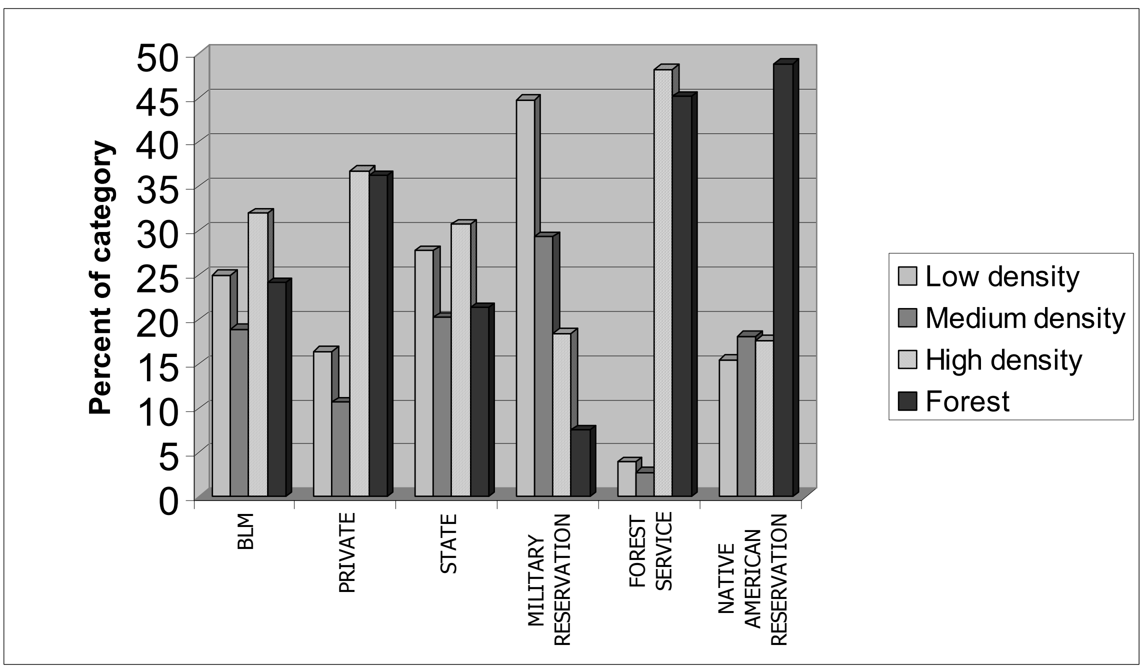

Figure 9: Distribution of land cover classes by ownership category (in percent of ownership category).

Discussion

Accuracy and class definitions

A relatively high overall classification accuracy (84.95%) was achieved for this study. This high accuracy might have been partially influenced by the fact that the months of January and February of 1993 were unusually wet in the study area (WRCC, 2000), resulting in explosive vegetation growth in the beginning of the growing season that was sustained throughout the summer. These circumstances have most likely increased the amount of vegetation cover and facilitated its detection by the satellite.

The remaining errors could be associated with several factors relating to soil characteristics in the study area. Soil texture varies considerably across the study area from heavy clays to sandy loams and sands (Gates et al., 1956). This contributes to the overall spectral variation within the image. Price et al. (1985) found that confusion among information classes in his Landsat MSS classification could be reduced by using soil texture and geomorphologic units as additional layers in classification procedures. I was not able to do so in this study due to lack of a complete soil database for the entire study area. In addition to variability in soil texture, variations in soil moisture could also be a source of some of the errors. Some parts of the study area experienced periods of rain during two days prior to the acquisition date of the satellite image (May 24, 1993). On May 22 and May 23 approximately 0.31 inches and 0.08 inches of rain fell in the study area (NOAA, 1993).

The reflectance value of an individual pixel within a satellite image is an integration of the reflectance values of all cover types found in that pixel area. In the study area, bare soil, litter, and both live and dead vegetation are the cover types that contribute to the resulting reflectance value. In addition, species composition and vegetation stature play a role in determining the ultimate numeric value of a pixel. Such complexity can easily mask or greatly modify the vegetation signal present in a pixel. In areas where vegetation density is low, the spectral signature of soil tends to dominate the reflectance value of a pixel. It is, therefore, possible that the good separation of low-density cover classes was largely based on the unique spectral characteristics of soils that dominate the ground cover in these areas, rather than accurate detection of vegetation density itself. It has been shown that, among other factors, the stature and type of vegetation in the study area are limited by soil salinity, which in turn is affected by the depth of water table (Flowers, 1934). It has been also shown that reflectance values obtained from satellite imagery can be correlated with groundwater depth of the salt flats (Johnson, 1998). Thus, the spectral classes obtained from the unsupervised classification could be largely determined by salinity and drainage properties of the soil and only indirectly relate to vegetation density.

Another aspect of this classification that should be considered is the pixel to pixel variability within a single plot of 75 by 75 meters that was used to determine vegetation density in the field. Pixel to pixel spectral variability of the low-density vegetation plots was in general relatively low, since soil is the only cover type that dominated these plots (up to 75% cover), and since vegetation cover was too sparse to significantly influence the integrated spectral signature of any single pixel within the plot. On the other hand, pixel to pixel spectral variability of the high-density vegetation plots was rather high. Native high-density vegetation cover in the study area only amounted to a maximum of 45% cover, hence high-density plots were characterized by the presence of high diversity of cover types (a variety of vegetation species of different statures, soils, and litter) Each of these cover types generated its unique and highly contrasting spectral signature, resulting in highly variable spectral reflectance values among pixels representing a single high-density plot. My methodology assigned a field plot to the information class that had the most pixels in that plot. It follows that not all pixels in the plot had to belong to the same information class, just the majority. If enough pixels composed of bare ground existed within a high-density plot, that plot was misclassified as belonging to one of the lower vegetation density classes. If this interpretation is correct, then the resulting information classes could not only be viewed as pertaining to density, but also to the heterogeneity of the ground cover. The decreasing producer's accuracies for each consecutive density class, excluding trees, could then be an indication of increasing heterogeneity of reflectance values within plots representing those particular classes.

In this study, the division of the field data into information classes was based on a continuous density gradient rather than on natural breaks in the data. Hence, it was expected that most errors would be associated with field plots with densities calculated close to boundary regions on either side of a cover class. Classification errors were examined on plot by plot basis to see if they consistently occurred in the boundary regions. Only about twenty percent of the misclassified plots could be considered to fit this category. In addition, a disproportionately large number of plots that were surveyed as "high-density" plots were misclassified as "low-density" (Table 1). I also found no consistency in vegetation type of misclassified plots. About an equal amount contained large amounts of grass, or shrubs or were heterogeneous in their composition. This provided further evidence that successful separation of the cover classes was based on soil parameters in addition to, or other than, vegetation density.

One of the goals of this study was to determine how many categories of vegetation, based on vegetation density and heterogeneity, could be separated in our study area before the accuracy started to decline and became unreliable. Cohen et al. (1995) found that increasing the number of information classes in a classification of Pacific Northwest forests caused a decline in overall accuracy. In their case, seven classes of forest of different densities and structures could be distinguished reliably. Knick et al. (1997) were able to successfully separate five categories of shrubland and grassland vegetation types, in an environment similar to this study area. They, however, were not able to distinguish vegetation categories based on percent ground cover.

This study was able to distinguish three classes of shrubland based on density and one tree class using my classification methods before the accuracy started to decline. While the studies that attempt to map vegetation categories based on composition require the sampling of only pure stands of homogeneous vegetation, mapping of vegetation density necessitates the sampling of both pure and mixed pixels. It is possible that the use of vegetation parameters other than vegetation type made the separation of more numerous classes difficult.

Choice of spectral variables

The classification approach used here involves the use of information layers conventionally employed in mapping of vegetation cover, as well as the use of texture layers. It has been found that the texture layers, derived from brightness and greenness components of the Tasseled Cap transformation (Crist and Cicone, 1984), are useful for classifying a number of stand attributes in the analysis of the Pacific Northwest forest

(Cohen and Spies, 1992). Texture attributes have also been used for mapping bird species probability of occurrence in Maine (Hepinstall and Sader, 1997). Although texture layers were not useful in this study for identification of individual plant forms because these elements are smaller than the image pixels (Woodcock and Strahler, 1987), they might have contributed to my ability to separate large vegetation stands from bare soil by highlighting the boundaries between the two ground cover types.

While the use of brightness and greenness components of the Tasseled Cap transformation is widely accepted as useful in mapping of vegetation parameters, the utility of wetness component has not been fully determined. Cohen and Spies (1992) found that wetness related not only to the amount of moisture in the Landsat TM scene, but also to forest stand structure in their study area. I included this layer in the unsupervised classification in hopes that that it would be useful in identification of heterogeneity in vegetation structure in arid environments. Although I was not able to classify my image based on vegetation structure itself, wetness might have effectively captured the heterogeneous character of the cover types present in the high-density field plots discussed earlier. Since wetness quantifies the contrast between the Landsat TM mid-infrared bands (bands 5 and 7) and the other four bands, thus bringing out the spectral contrast between soils and vegetation cover types in the study area, its presence as one of the spectral variables in the unsupervised classification might have contributed to lower producer's accuracy for high-density and forest cover classes.

Landscape Pattern and Ferruginous Hawk Habitat Characteristics

The use of landscape by wildlife occurs at different spatial and temporal scales. A landscape scale overview of the satellite image reveals a high degree of spatial heterogeneity in the distribution of cover classes. A smoothing filter was not applied to the classified image, because I felt that the spatial heterogeneity in the vegetation density map was a reflection of ecologically relevant heterogeneity in the system (Figure 10). Jasikoff (1982) and Wakeley (1978) both suggested that vegetation heterogeneity might augment ferruginous hawks' hunting success. Presence of patches of low and medium-density vegetation within high-density stands could allow for increased ability to locate and access prey.

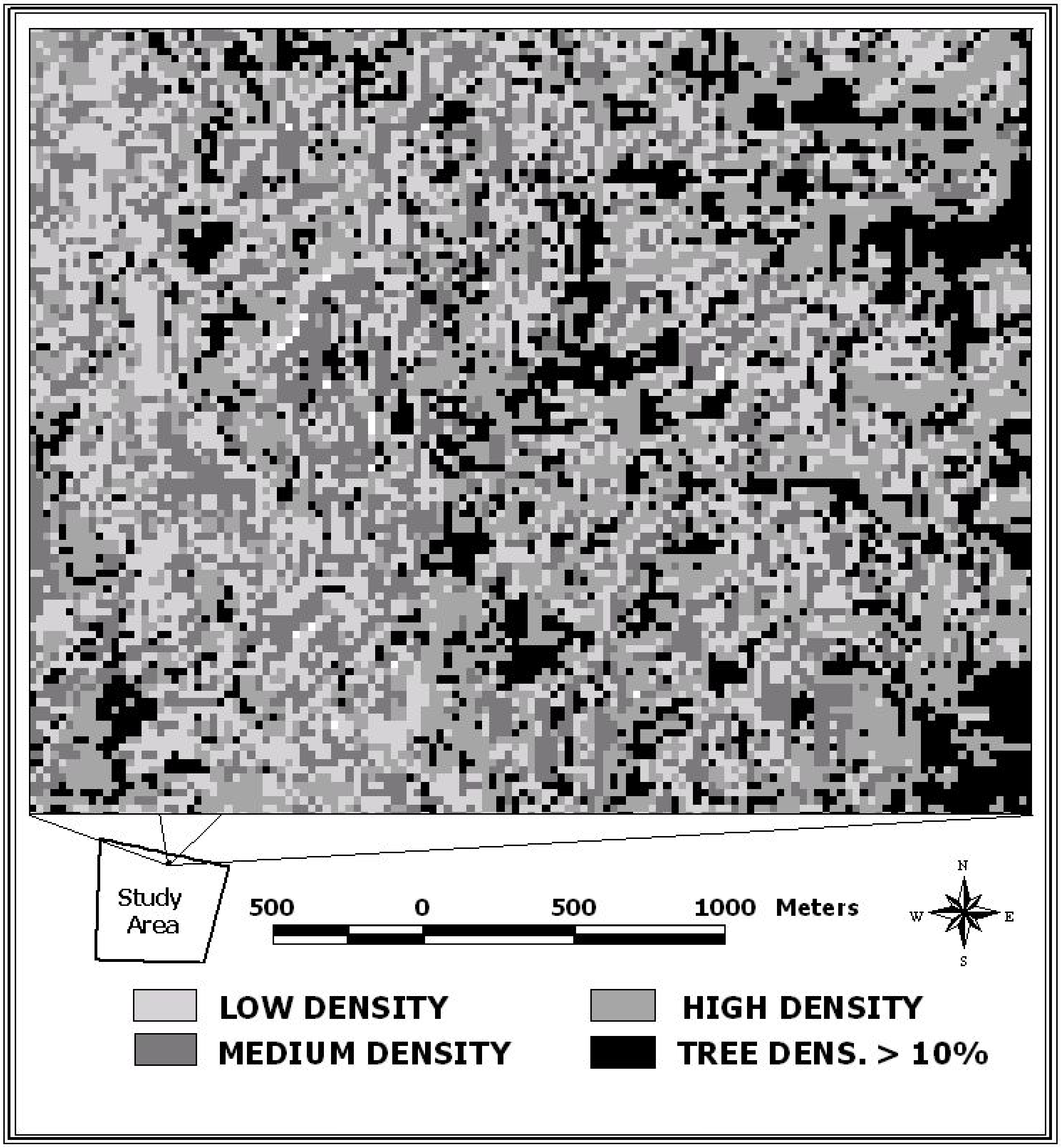

Figure 10: A sample of landscape scale heterogeneity of vegetation cover types.

On the local scale, some degree of homogeneity in vegetation density is evident (Figure 11). This aspect of vegetation cover might play an important role by providing concealment to species preyed upon by hawks. It is possible, that the combination of different densities of the vegetation cover at different scales supports an adequate prey base for a long period of time.

One of the questions I wanted to address in the study is how changes in vegetation density and heterogeneity due to replacement of native communities by exotic species influence ferruginous hawk habitat use. Changes in vegetation cover following biotic invasions affect the wildlife habitat quality in a variety of ways. Following a fire event, native patchy and relatively low-density vegetation of the study area is often completely replaced by continuous, high-density cover of *B. tectorum*, changing drastically vegetation composition and structure across the landscape. These habitat alterations, along with changes in spatial pattern of habitat elements, and changes in suitable habitat availability due to seasonal variability alter the foraging patterns of the hawks and thus influence nesting site selection and nesting success. Unfortunately, the affects of *B. tectorum* invasion on ferruginous hawk nesting patterns could not be determined due to large time-lag between the acquisition date of the satellite imagery and the date of field data collection. Since areas dominated by *B. tectorum* were not sampled in the field, they were incorporated into one of the four density classes, possibly misrepresenting the true state of vegetation cover. *B. tectorum* exhibits a very different spectral signature (reddish in the early growing season) from that of native grasslands and cannot be assumed to fall into the same information class following the unsupervised classification. It is, therefore, possible that these high-density areas were classified as low-density or forested cover types.

Monitoring of temporal changes in vegetation characteristics and landscape patterns gives wildlife scientists a more complete and detailed picture of habitat use by a species and aids in creation of spatially explicit animal models that are important in land management (Turner et al., 1995). Temporal monitoring is especially crucial in areas such as the Great Basin ecoregion, where the recent land-use changes are happening with an astounding rapidity (Knick and Rotenberry, 2000). Decrease in fire return interval from 100 years to as little as 2 years, coupled with invasion of non-native species, not

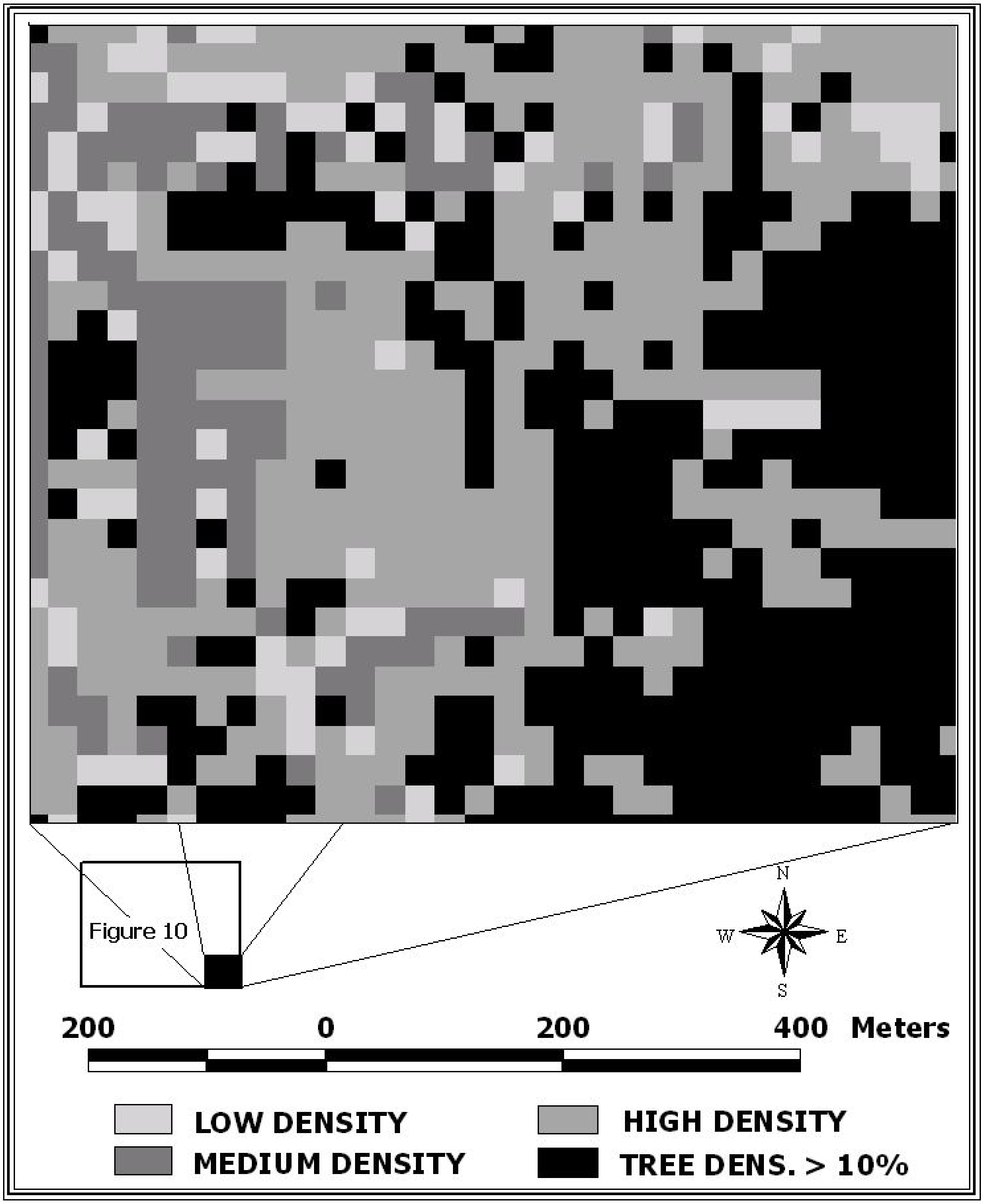

Figure 11: Aggregation of land cover types at local scale.

only dramatically changed wildlife habitat attributes but also made the use of traditional ground-based inventory of land cover virtually impossible. In order to assess the influence of vegetation cover changes on wildlife habitat, monitoring should be performed at temporal scales similar to those of disturbance regimes. Satellite imagery provides an ideal tool for such monitoring and it has been widely used in change detection studies in a variety of environments (Zheng et al., 1997; Boyce, 1999; Mas, 1999; Sohl, 1999; Cushman and Wallin, 2000). This study provided an initial step in what could become an extensive vegetation cover monitoring program in the study area. I have demonstrated that satellite imagery can be used to map vegetation parameters that are ecologically relevant to the use of habitat by wildlife. Further investigations into alternative methods of classification and mapping of different vegetation parameters are necessary to effectively use this information in wildlife habitat models.

Conclusions

Results of this study indicate that with the unsupervised classification using Landsat TM imagery, aerial photographs, and ground reference data, four vegetation density classes can be accurately mapped in the study area. A more detailed classification may have been achieved if the acquisition date of the satellite image and aerial photos more closely coincided with the time of collection of ground reference data, allowing for mapping of disturbance vegetation classes.

I found that classification accuracy decreased with the increase of fine-scale heterogeneity in land cover types within the field sampling plots. High-density vegetation class, which had the lowest producer's classification accuracy, was characterized by plots with a mixture of about equal proportions of vegetation, ground, and litter cover types. Information classes with lower vegetation density characteristics contained predominantly the bare ground cover type and had higher classification accuracies. Inclusion of variables such as texture and wetness into the classification may have contributed to the high classification accuracy by capturing the spectral variability associated with cover type. Techniques, such as mixture modeling (Smith et al., 1990) or higher spectral and spatial resolution imagery may further minimize confusion associated with this heterogeneity. Due to dominance of soil cover types in the landscape, however, it seems unlikely that the accuracy and detail of land-cover classifications in arid environments could ever approach those of forested ecosystems.

I chose the information classes in the classification based on break points that were ecologically relevant to ferruginous hawk habitat use. Examination of classification results at different spatial scales revealed patterns that could be important to ferruginous hawk foraging activities. The next step in this research is building of habitat model to reveal any important relationships between vegetation density and ferruginous hawk habitat use.

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Chapter 2:

MODELING FERRUGINOUS HAWK (*BUTEO REGALIS*) HABITAT USING VARIABLES DERIVED FROM SATELLITE IMAGERY.

Introduction

Ferruginous Hawk Ecology

The ferruginous hawk (*Buteo regalis*) is an open country species found in grasslands, sagebrush, and desert scrub habitats in the Great Plains and Great Basin regions. Several studies documented a major decline in populations of ferruginous hawks throughout its range in the United States and Canada in the 1970s and 1980s (Olendorff, 1973; Houston and Bechard, 1983; Houston and Bechard, 1984; Schmutz, 1984; USFWS, 1985; Perkins, 1989; Woffinden and Murphy, 1985; Woffinden and Murphy, 1989). These declines have been linked to changes in land-use, including increased urbanization and recreation, and replacement of native vegetation communities by exotic species. Olendorff (1973) found urbanization to be detrimental to nest establishment by the hawks. White and Thurow (1985) documented the effects of human activities on ferruginous hawk reproduction success. They found that the hawks are most sensitive when a pair is establishing a nest, when the female bird is incubating eggs, or when she is protecting newly-hatched young. Nest disturbances resulted in the adults abandoning the nest and higher nesting mortality.

Land cover of the Great Basin has been profoundly affected by the replacement of native vegetation cover by exotic species (Billings, 1990). Cheatgrass (*Bromus tectorum*) was accidentally introduced in several locations in the western U.S. through contaminated grain-seed supplies from the eastern United States and Europe. As a winter annual, cheatgrass is well adapted to the climate of the Great Basin and it spread rapidly through the overgrazed sagebrush range, occupying vacant habitat that was previously filled with native grasses. This invasion replaced the discontinuous vegetation cover of the native sagebrush (*Artemisia spp*.) steppe with continuous fuel, facilitating the spread of fires. Fire further reduced vegetation diversity allowing cheatgrass to dominate the landscape, since it matures earlier than native species (Young and Evans, 1978). Easily ignited cheatgrass cover conditions led to more frequent fires, reducing the fire return interval from an average of 85 years to less than 5 years (Whisenant, 1990). These dramatic changes in vegetation structure had a number of negative impact on the quality of ferruginous hawk foraging habitat.

Following studies of population declines and rapid reductions of ferruginous hawk habitat, Ure et al. petitioned the U.S. Fish and Wildlife Service in 1991 to list the ferruginous hawk under the Endangered Species Act. The petition was denied on the grounds that there was not sufficient information to warrant the requested action (USFWS., 1992). The 1992 U.S. Fish and Wildlife Service study actually suggested that populations had increased 1979. However, the 1979 population estimates were later revised upward and it is now thought that populations have experienced significant declines (Olendorff, 1993).

Documented ferruginous hawk population declines throughout a significant portion of its range and the need for more information for listing under the Endangered Species Act, have motivated efforts to obtain more information on ferruginous hawk foraging and nesting habitat requirements. It is known that for nesting habitat, the hawks are dependent on a variety of habitat conditions in order to successfully establish nests and reproduce. Generally they avoid elevations above 2100 m, narrow canyons, and interior regions of forests (Olendorff, 1993). This species prefers elevated nest sites, such as boulders, low cliffs, or trees (Harlow and Bloom, 1989). A pair will establish a breeding territory, often with four or five alternative nests. Each year, individual birds return to the same nesting area and often the same nest. In the Great Basin, because ferruginous hawks prefer tree substrate for their nest, but forage in shrubland, their nests are most commonly found in the ecotone between the juniper forest and the shrubland where individual trees are still present, but the landscape is open (Powers et al., 1975; Thurow et al., 1980).

It has also been found that prey species ecology can dramatically influence ferruginous hawk nesting and reproductive success. In north-western Utah, the ferruginous hawk depends on only a few prey species. Based on biomass, black-tailed jackrabbits (*Lepus californicus*) have historically been the hawk's most important prey base in this area (Howard, 1975). Because alternative food sources are limited, the hawk population is susceptible to large fluctuations in densities that directly correspond to population cycles of the primary prey species (Woffinden and Murphy, 1977; Thurow et al., 1980; Smith et al., 1981). Low prey densities can cause the birds to abandon a nest or travel further away from the nest to look for alternative sources of food. This can lead to an increase in chick mortality rates due to exposure to the elements and to predation from Golden Eagles (*Aquila chrysaetos*) (Gardner, pers. comm.).

Changes in vegetation structure can influence the abundance of ferruginous hawk prey species, which directly influences foraging habitat quality. Prey species' numbers can be reduced by conversion of native grasslands and shrublands into agricultural lands or by *B. tectorum* invasions. Jackrabbits prefer tall cover and open spaces while feeding on native grasses and/or shrub depending on the season (Taylor and Lay, 1944; Leichleitner, 1958; Fagerstone et al., 1981). Plant cover in cultivated areas and areas dominated by *B. tectorum* is usually lower and denser than that of natural vegetation (Houston and Bechard, 1984). Hence, vegetation density, height, and heterogeneity become important factors in determining the abundance of hawk prey.

In addition to prey density, several studies found prey accessibility to be an important factor influencing ferruginous hawk foraging habitat quality (Craighead and Craighead, 1956; Wakeley, 1978; Woffinden and Murphy, 1983; Woffinden and Murphy, 1989). Wakeley (1978) assessed the relationship between vegetation type, density and prey distribution and the use of hunting sites by ferruginous hawk. He found that juniper and grass-shrub cover types contained the highest amounts of prey, but also discovered that the hawk use of bare ground areas for hunting was disproportionately larger than expected. He concluded that vegetation density, which directly influences prey accessibility, plays a larger role in hawks' choice of hunting areas than prey density. Bechard (1982) came to the same conclusion while studying Swainson's hawk (*Buteo swainsoni*) in a similar environmental setting.

Following these studies, it is clear that one of the major impacts on ferruginous hawk habitat quality and abundance will come from the land-use changes that alter vegetation structure. Although much has been learned about ferruginous hawk habitat requirements as they relate to vegetation characteristics, more information is needed to determine how these requirements change in space and over time, and whether or not the habitat quality and abundance have been actually declining in recent years. Multivariate regional habitat analysis using satellite data and GIS layers could aid in estimation of ferruginous hawk habitat availability and quality and assess its changes through time.

Habitat Modeling

The roots of multivariate habitat analysis and quantification of habitat characteristics of an organism can be traced to niche theory work by Hutchinson (1957), who pioneered the concept of the niche as a multidimensional space. This theory and its similarities to n-dimensional statistical techniques, gave birth to a number of studies that quantified the organism's realized niche on the basis of a series of microhabitat variables that are most important to its individual responses to the environment (Shugart, 1981). Multivariate microhabitat analyses have made it possible to make predictions about the distribution and abundance of wildlife species in space and time. These studies have greatly increased our understanding of complex ecological interactions. Microhabitat data could only be obtained using intensive ground-based inventories and, for this reason, knowledge of microhabitat requirements prior to 1980s did not allow for regional-scale analysis. Tools and methods for the assessment of macrohabitat characteristics were needed and were eventually achieved with the growing power of computers, development of spatial pattern analysis programs, and widespread use of satellite remote sensing techniques.

Currently, techniques available for large-scale wildlife habitat modeling can be subdivided into two major categories that include general habitat association models and species-specific models (Berry, 1986). In remote sensing, these two general types of habitat models can be built by using a coarse or a fine-filter approach (Wallin, in review). General habitat association models typically assign wildlife species to broad vegetation communities based on their reproduction and feeding habitat requirements. This coarse-filter approach is often result in maps with a few general vegetation types, each associated with a particular suite of species. Such models are often too coarse to determine how individual species use the habitat or how it will be affected by subtle changes in vegetation structure and composition. Also, in developing these models, accuracy assessments are rarely performed, since knowledge of individual species and field data are limited.

The other type of wildlife habitat model, a species-specific model, mostly focusing on their relationship with various habitat attributes, such as vegetation structure and composition, topography, or human activity. These models are often applied to species whose life history attributes have been extensively studied. Development of these models requires substantial field work, but also allows for accuracy assessment using data collected in the field. Results can include the development of potential habitat maps, assessment of population levels, and ability to predict changes in population distribution and abundance with changes in habitat characteristics.

In the last two decades, a number of studies have utilized satellite data and other ancillary data to predict occurrence and map potential avian habitat in a variety of environments (Palmeirim, 1988; Sader et al., 1991; Wallin et al., 1992; Aspinall and Veitch, 1993; Lavers et al., 1996; Hepinstall and Sader, 1997; Bosakowski, 1999; Montgomery, 1999; Drolet et al., 1999; Wallin, in review). Satellite imagery has also been used for habitat modeling in environments similar to my study area. Knick et al. (1997) used Landsat TM imagery to map vegetation density in the Snake River Birds of Prey National Conservation Area in southwestern Idaho for further use in developing habitat models for raptors. And Vander Haegen et al. (2000) have used a Landsat TM vegetation structure layer to model habitat for songbirds in eastern Washington.

In addition to remote sensing, a variety of multivariate statistical techniques are now available to aid in quantifying species occurrence and predicting the distribution of potential habitat. Although such techniques simplify complex ecological processes and are often lacking complete data sets, they can provide valuable insight into environmental interactions that might not be easily detected otherwise. Discriminant function analyses and logistic regression analyses are the two techniques that have been used most frequently in wildlife habitat modeling in recent decades (Capen et al., 1986). This study uses logistic regression, because it provides more flexibility in the variable types selected for the analysis and does not the have stringent distribution requirements characteristic of parametric techniques(Tabachnick and Fidell, 1989) .

Logistic regression analysis has been used either on its own or as a validation of other multivariate techniques in a number of studies. Capen et al. (1986) used logistic regression to compare to the results of the multivariate discriminant function models that differentiated occupied and unoccupied songbird habitat in the New England Forest. Pereira and Itami (1991) used logistic regression to model habitat suitability for the Mt.

Graham red squirrel in Arizona, while Mladenoff et al. (1995) mapped potential gray wolf habitat for northern Wisconsin. More recently, Drolet et al. (1999) used logistic regression to assess relationships between songbird occurrence and forested landscape structure in eastern Canada. Vander Haegen et al. (2000) have used the same statistical techniques to develop models of species occurrence for shrubsteppe birds in eastern Washington and McBride (2000) developed a series of habitat models at different spatial scales for the Magellanic woodpecker (*Campephilus magellanicus*) in forests of Terra del Fuego.

Objectives

Multivariate wildlife habitat models have a number of advantages over conventional ground-based methods of wildlife habitat assessment. They can be used to map the distribution and abundance of potential habitat at the regional scales. This information can then be used to estimate potential population sizes and evaluate the potential impact of alternative management plans. As discussed above, the use of habitat by ferruginous hawks is more often correlated with vegetation structure rather than vegetation composition, therefore this study is aimed at assessing specific vegetation structural attributes that directly relate to foraging behavior and reproduction. More specifically, this study develops a spatial habitat layer based on vegetation density and heterogeneity that determines ferruginous hawk nest site selection. My objective was to build a series of statistical models with the use of elevation data and variables derived from a classified Landsat TM image that could be used to

1. determine which parts of a ferruginous hawk pair's home ranch are most useful for discriminating between nest sites and random sites;
2. assess the variation of suitability of ferruginous hawk potential nesting and/or foraging habitat in the study area to prioritize areas for habitat management and protection;
3. discuss management implications for the species and provide recommendations for further research.

Methods

Study Area

The study area includes most of Tooele and the extreme southern part of Box Elder counties in Utah (Figure 1). It covers approximately 2.1 million hectares. This area was chosen because of the availability of good data on ferruginous hawk nesting activities from 1992 to 1999. Land ownership includes a mixture of private, public, and military lands, with the largest proportion (42.4%) managed by the Bureau of Land Management for multiple use, including grazing and recreation.

The study area lies at the extreme east of the Great Basin section of the Great Basin and Range province of the North American deserts (Macmahon, 1979). It contains mainly northward-trending mountains, rising as high as 3300 m separated by valley floors around 1300 m in elevation (Figure 2). A number of vegetation communities exist within the area, the most extensive of which is the desert salt scrub community found below 1600 m elevations. This community is dominated by a number of species of *Artiplex*, gray molly (*Kochia vestita*), winterfat (*Ceratoides lanata*), budsage (*Artemisia spinescens*), halogeten (*Halogeten glomeratus*), mormon tea (*Ephedra spp*.), and horsebrush (*Tetradimia canescens*). Greasewood-dominated (*Sarcobatus vermiculatus*) communities are more common on drier and saline soil types of valley bottoms. Associated species include shadscale (*Atriplex confertifolia*), seepweed (*Suaeda torreyana*), and halogeton (*Halogeton glomeratus*). The sagebrush (*Artemisia spp*.) vegetation zone is found between 1600 m and 1800 m elevations, where more moisture is available, and on deeper, alkaline and somewhat sandy or gravelly soils. Associated shrub species include rabbitbrush (*Chrysothamnus spp*.), snakeweed (*Guterrezia sarothrae*), winterfat (*Ceratoides lanata*), shadscale (*Artiplex confertifolia*), and bitterbrush (*Purshia tridentata*). Associated grass species include bluebunch wheatgrass (*Agropyron spicatum*), sandburg bluegrass (*Poa secunda*), crested wheatgrass (*Agropyron cristatum*), needlegrass (*Stipa comata*), sand dropseed (*Sporobulus cryptandrus*), Indian ricegrass (*Oryzopsis hymenoides*), and galleta (*Hilaria jamesii*). The juniper forest community is found at yet higher elevations (~ 1800 m to 1900 m). Although this community is not used by the hawks directly for hunting, individual trees

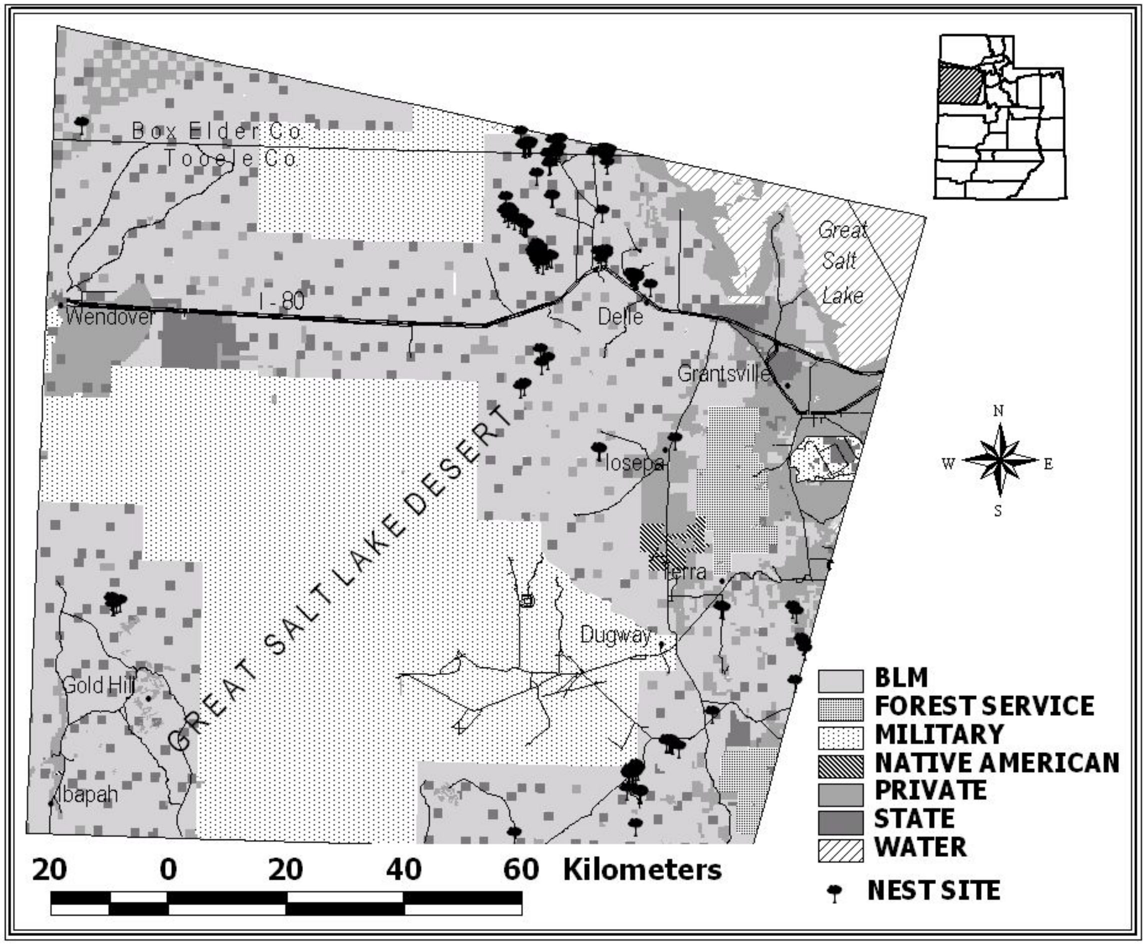


Figure 1: Land ownership and ferruginous hawk nest site locations in the study area. Nest sites were surveyed using the GPS equipment between 1995 and 1999.

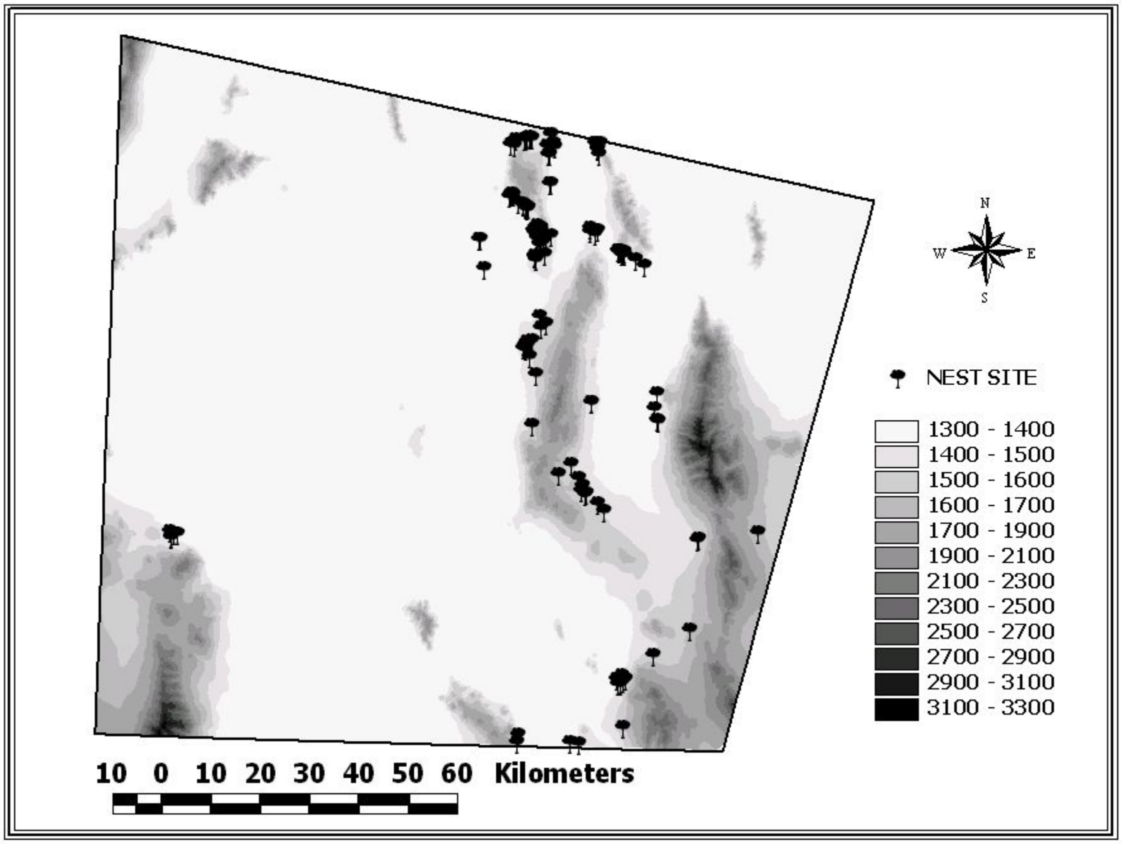


Figure 2: Elevation ranges (in meters) and ferruginous hawk nest site locations in the study area.

in the ecotone between juniper and shrub communities are often used as nesting substrates (Woffinden and Murphy, 1983).

Land-use changes in the Great Basin have also been representative of such changes in the north-western Utah, where ferruginous hawks were once abundant. In addition to a decrease of occupied ferruginous hawk nesting sites that has been documented over the past twenty years (Woffinden, 1975; Woffinden and Murphy, 1977; Woffinden and Murphy, 1989; Attix, 1996), the area has experienced rapid loss of ferruginous hawk habitat due to rapid urban expansion and increased recreational use (Gardner, pers. comm.). Human activity was also found to be a major factor in the direct ferruginous hawk mortality (Howard, 1975). A number of young and adult birds have been reportedly shot over the last five years (Gardner, pers. comm.). It is illegal to harass raptors in Utah, however these incidents continue to occur due to the lack of public awareness.

Nest Data

The location of one hundred and thirty-one ferruginous hawk nest sites in the study area were obtained from the Bureau of Land Management, Salt Lake Field Office. The locations were surveyed using Trimble Pathfinder GPS equipment during the summers of 1995 through 1999 (Figure 1). Most of the nests were in good condition and were probably constructed or rebuilt during the 1980's or 1990's. Activity surveys have been conducted by the BLM employees intermittently since 1982, so, only limited information exists on nesting activity or nesting success. Of the 131 nests, 69.5 % of the nests were located in juniper trees (dead or live), 22 % on rock ledges, 7% on rock pinnacles, and 1.5 % on artificial structures.

Within their home range, a pair builds several nests that are used in alternate years. Therefore, even though several nest sites might exist in a small area, they are used by only one pair and will result in pseudoreplication in statistical analysis if all known nests are used in habitat analysis. Published literature on ferruginous hawk habitat use was reviewed to determine the most reasonable nearest neighbor distance between active nest sites for use in statistical analysis. Ferruginous hawk's home range size averages 7.0 km^2

(Olendorff, 1993). In rare cases, two pairs may nest as close as 0.3 km from one another (Woffinden and Murphy, 1983). This close proximity of active sites might allow mutual defense of the overlapping territories from other raptor species (Thurow and White, 1983). Olendorff's (1993) review of 20 studies from several western states yielded an average nearest neighbor distance of 3.4 km, with a minimum nearest neighbor distance of 0.8 km. Howard (1975) also reported 0.8 km as the smallest nearest neighbor distance between two active nests in his study and Wakeley (1978) reported a distance of less than 1 km between two active nests in his study. In the present study area, the smallest nearest neighbor distance between active nest sites was 0.8 km.

Howard and Wolfe (1976) and McAnnis (1990) found that hunting forays usually do not extend beyond 800 m and 700 m, respectively, from the nest site. To avoid pseudoreplication but account for the clumping of the active nest sites and maximize the dataset size, 0.8 km was selected as the nearest neighbor distance. A 400-m buffer was placed around each nest and only one nest was selected if the buffers overlapped. We tried to select nests that were either known to be active sometime near 1993 or nests that were in very good condition. This process resulted in 72 ferruginous hawk nesting territories that were retained for use in the analysis.

Satellite Image Classification Data

In order to build the habitat model for the hawk, vegetation information was extracted from a classified Landsat TM image from May 24, 1993. The original 30-m resolution image was resampled to 25-m resolution for ease of calculations. The classification was performed only on "potential" ferruginous hawk habitat, i.e. only on vegetation communities that are known to be used by the hawks. Other communities, representing non-habitat were masked out using a generalized vegetation map produced for the Utah State Gap Analysis Program (Edwards et al., 1995). This allowed the development of a more detailed classification that provided additional information for plant communities that are used by the hawk. The image was classified based on native vegetation density in the study area (See Part 1). The resulting image contained the following land cover classes:

1) low vegetation density (<20% cover);

2) medium vegetation density (20-25% cover);

3) high density (25-45% cover);

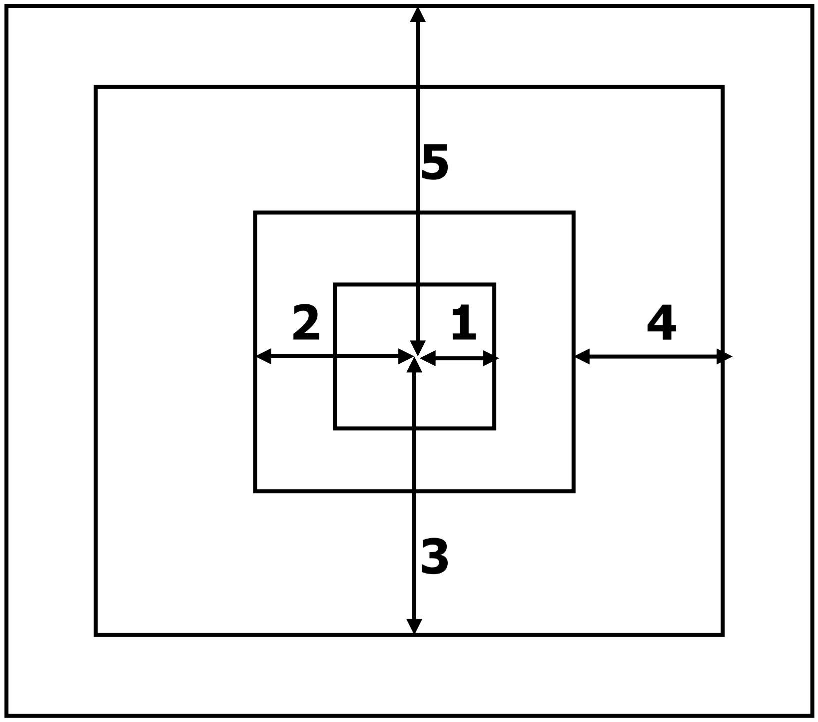
4) areas with juniper density higher than 10%.

The overall classification accuracy for the image was 85%, with producer's accuracy for individual cover classes ranging from 97% to 76% . The high density vegetation class had the lowest producer's accuracy, however, the user's accuracy was 95%. The low density vegetation class had the highest accuracy of 97%.

Variable extraction

A square sampling window was centered over the location of each of the 72 ferruginous hawk nesting sites. This sampling window was used to extract vegetation density variables from the classified image with the help of a series of programs written in C language (Table 1). These same variables were also collected for same number of randomly selected points within the study area. In addition to these vegetation variables, site elevation was used as an additional variable. I hoped that this variable would allow us to isolate the shrub steppe - juniper forest ecotone where ferruginous hawks often build their nests. To extract the elevation values, a 100-m contour elevation layer was extrapolated into a continuous elevation GRID coverage in ArcView .

Five different sampling window sizes were chosen based on ferruginous hawk habitat use (Figure 3). The Nesting habitat model was built using the smallest extraction window, which extended to 125 m from the center and represented the area immediately around the nest. A larger window was used to build the Perching habitat model. This window extended to 300 m from the center and contained the area around the nest that is generally used for perching but not necessarily hunting (McAnnis, 1990). A still larger window, extending to 700 m, was used for the Nesting & foraging model. This window approximated an area around the nest where hawks spend the majority of their time during the nesting season (McAnnis, 1990). The Foraging habitat model was built using variables extracted from a "doughnut-shaped" window containing areas that extended from 300 m to 700 m from the center. It was shown that hawk's foraging activities are concentrated within this area around the nest (McAnnis, 1990). The largest window size



Window Size	Distance (m)	Habitat Use
1	125	nesting
2	300	nesting & perching
3	700	nesting & foraging
4	300-700	foraging
5	1325	home range

Figure 3: Five sizes of sampling windows used for variable extraction from the satellite image.

was used to build the Home Range model. This window extended to 1325 m from the nest site and approximated the average home range of a ferruginous hawk (~ 7 km^2) (Olendorff, 1993).

Table 1: Variables extracted from the satellite image for use in logistic regression models:

PLOW	- proportion of the window occupied by the low density class (0-20% cover);
PMED	- proportion of the window occupied by the medium density class (20-25% cover);
PHIGH	- proportion of the window occupied by the high density class (25-45% cover);
PTREE	- proportion of the window occupied by the areas with tree density >10%;
MODE	- cover class with the highest frequency of occurrence within the window;
RICHNESS	- number of cover classes present within the window.

Habitat Model

Binary logistic regression analysis was used to build five statistical models in the SPSS software package to distinguish between ferruginous hawk nest sites and randomly selected locations within the classified image. This statistical approach was chosen due to the binary nature of the outcome variable and discrete nature of some of the independent variables (Tabachnick and Fidell, 1996). Each model was built based on variables extracted from sampling windows around the nest sites and random sites (see above for window sizes). For each analysis, nest sites and random sites with more than 10% of the window occupied by unclassified pixels were not used. This selection process resulted in 72 nest sites used for the Nesting model, 69 nest sites used in the Perching, Foraging, and Nesting & foraging models, and 63 nest sites used for the Home Range model. An equal number of nest sites and random locations was used for each model. Seventy five percent of the nests and random sites were used to build the models and obtain coefficients for classification, and the rest were used to independently validate the model.

All explanatory variables were subject to an exploratory analysis to determine if there was a significant difference between nest sites and random sites. An α-level of 0.10 was used for assessment of significance, since I was more interested in trends than rigorous significance testing. A univariate logistic regression model was built for each variable and a Kruskal-Wallis test was run for all variables except MODE, which was a nominal-scale variable. The expectation was that variables describing the random sites would have a different mean and a larger variance than the variables describing the nest sites, since random sites include both the potential hawk habitat and non-habitat. Continuous variables were examined for multicollinearity using a correlation matrix.

All variables were used in the multivariate analysis to account for any interaction that might exist among them. Forward Likelihood Ratio procedures were used (p-to-enter = 0.1, p-to-remove =0.15) with the Cut Point value ranging between 0.47 and 0.55. The Cut Point values were chosen in such a way as to maximize the classification accuracy of the nest sites, with target success rates above 80%. Lower classification accuracy was accepted for the random sites, since this category included random sites as well as potential nest sites. In addition, a lower classification accuracy of random sites was expected since the majority of non-habitat sites were eliminated before the analysis by masking out the vegetation communities not used by the hawks. Model assessments were performed using tests of individual variables, log likelihood techniques, classification accuracies of the response variable, Hosmer & Lemeshow tests, percent variance explained, and KHAT statistics.

Map of Potential Habitat

A C program, in conjunction with the coefficients derived from the logistic regression model, was used to paint maps of habitat suitability over the study area. The entire study area was analyzed by applying the logistic regression classification function to the central grid cell of the sampling window that was systematically moved across the data layers used for variable extraction. Finally, for each potential habitat image, the distribution and abundance of different categories of habitat were summarized by land ownership category using the land ownership layers obtained from the BLM Utah State office.

Results

Univariate Analysis

Analysis of descriptive statistics for interval-scaled variables for of the five models confirmed earlier expectations that variables describing random sites would have higher variability than the same variables describing the ferruginous hawk nest sites (Table 2). Coefficients of variation, shown in Table 2, were consistently smaller for the variables describing nests than the ones describing random sites, although the difference diminished as larger and larger area around the site was included in the model. Variable representing the proportion of the sampling window occupied by low density vegetation (PLOW) was the only one that consistently had larger values of CV for nest sites than random sites, although the difference was not large.

In the univariate analyses, the differences between nest sites and random sites for each variable were consistent with published habitat association data for the species (Olendorff, 1993). For most of the sampling windows, areas around nest sites had a consistently larger proportion occupied by the low-density vegetation classes (PLOW and PMED) and forested class (PTREE), indicating the importance of low-density vegetation for hunting and nest selection in close proximity to forested areas (Figures 4(a, b, d) through 8(a, b, d)). For example, I found PTREE to be a significant discriminator between nest sites and random sites in the Perching model (Kruskal-Wallis test, $p < 0.10$) (Figure 5(d)). Alternatively, in most of the models, areas around the nest sites had lower proportion occupied by the high density vegetation class (PHIGH) (Figures 4(c) through 8(c)).

The importance of vegetation density was also confirmed by frequent significance of the MODE variable, which recorded the most frequently occurring cover class within the sampling window. In the univariate logistic regression analysis, MODE was a significant discriminator ($p < 0.10$) between suitable and unsuitable habitat for the Perching model (Figure 5(g)). For both the Nesting & foraging and the Foraging models, MODE was the only variable for which there was a significant difference ($p < 0.01$ and $p < 0.001$, respectively) between nest sites and random sites (Figures 5(g) and 7(g)).

Table 2: Descriptive statistics for the interval-scaled variables in five models. CV = Coefficient of Variation = (standard deviation/mean)*100.

NESTING	**Nest Sites** (n = 72)			
Variables	Mean	Median	Variance	CV
PLOW	.206	.132	.044	101.82
PMED	.138	.084	.020	102.48
PHIGH	.443	.469	.058	54.36
PTREE	.213	.167	.037	90.31
Elevation	1460.931	1462.500	4204.713	4.44

NESTING	**Random Sites** (n = 72)			
Variables	Mean	Median	Variance	CV
PLOW	.205	.079	.059	118.49
PMED	.138	.037	.039	143.10
PHIGH	.459	.438	.086	63.89
PTREE	.199	.149	.049	111.24
Elevation	1505.181	1438.000	36884.460	12.76

PERCHING	**Nest Sites** (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.209	.171	.033	86.92
PMED	.150	.092	.018	89.44
PHIGH	.439	.431	.045	48.32
PTREE	.202	.169	.028	82.84
Elevation	1462.623	1464.000	4135.768	4.40

PERCHING	**Random Sites** (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.204	.150	.035	91.71
PMED	.184	.087	.043	112.70
PHIGH	.436	.495	.057	54.76
PTREE	.176	.137	.037	109.29
Elevation	1483.957	1411.000	25051.042	10.67

NESTING & FORAGING	**Nest Sites** (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.215	.182	.031	81.89
PMED	.153	.108	.017	85.22
PHIGH	.428	.440	.037	44.94
PTREE	.204	.190	.025	77.51
Elevation	1462.623	1464.000	4135.768	4.40

NESING & FORAGING	Random Sites (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.210	.187	.028	79.68
PMED	.182	.077	.037	105.69
PHIGH	.422	.446	.045	50.27
PTREE	.186	.117	.036	102.01
Elevation	1483.957	1411.000	25051.042	10.67

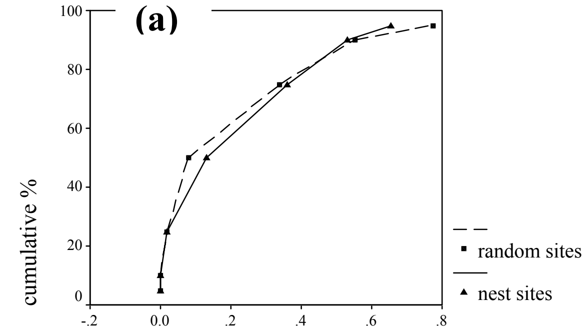
FORAGING	Nest Sites (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.217	.186	.031	81.14
PMED	.154	.095	.017	84.66
PHIGH	.425	.417	.037	45.26
PTREE	.204	.186	.025	77.51
Elevation	1462.623	1464.000	4135.768	4.40

FORAGING	Random Sites (n = 69)			
Variables	Mean	Median	Variance	CV
PLOW	.212	.198	.027	77.51
PMED	.182	.079	.036	104.25
PHIGH	.417	.423	.044	50.30
PTREE	.189	.120	.037	101.77
Elevation	1483.957	1411.000	25051.042	10.67

HOME RANGE	Nest Sites (n = 63)			
Variables	Mean	Median	Variance	CV
PLOW	.204	.136	.027	80.55
PMED	.156	.115	.016	81.08
PHIGH	.432	.429	.033	42.05
PTREE	.208	.203	.023	72.91
Elevation	1468.4	1473.000	3975.673	4.29

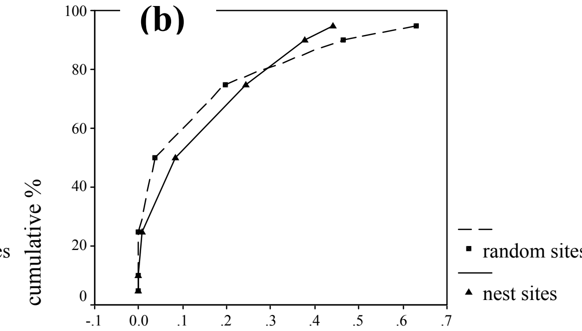
HOME RANGE	Random Sites (n = 63)			
Variables	Mean	Median	Variance	CV
PLOW	.226	.205	.031	77.91
PMED	.174	.100	.030	99.54
PHIGH	.413	.403	.040	48.43
PTREE	.187	.138	.032	95.66
Elevation	1451.88	1400.000	18141.391	9.28

Figure 4: Cumulative frequency graphs and p-values for variables considered for the Nesting model. The p-values are derived from the univariate logistic regression analyses and 2-independent-samples Kruskal-Wallis tests.



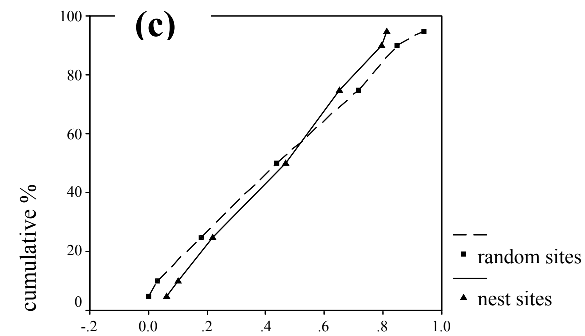
p(LR) = 0.966

p(K-W) = 0.716



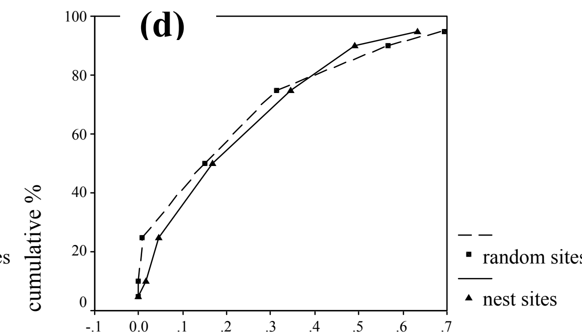
p(LR) = 0.996

p(K-W) = 0.210



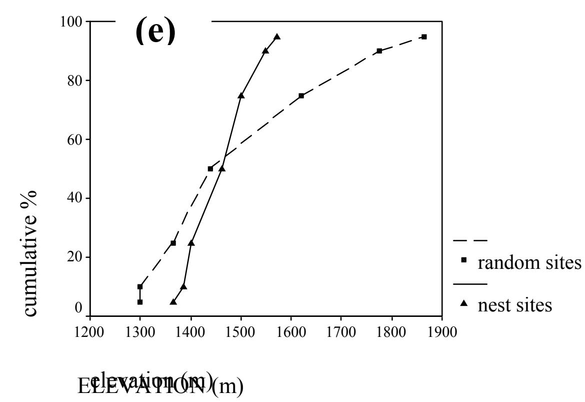
p(LR) = 0.718

p(K-W) = 0.763



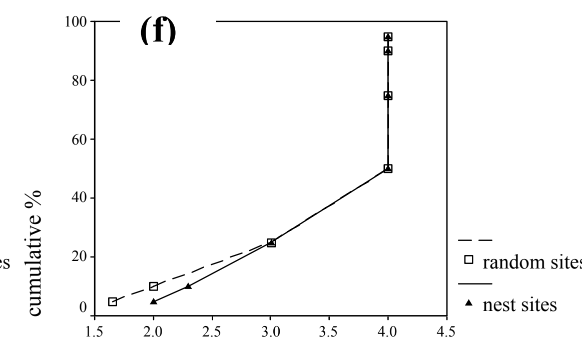
p(LR) = 0.678

p(K-W) = 0.225



p(LR) = 0.061

p(K-W) = 0.803

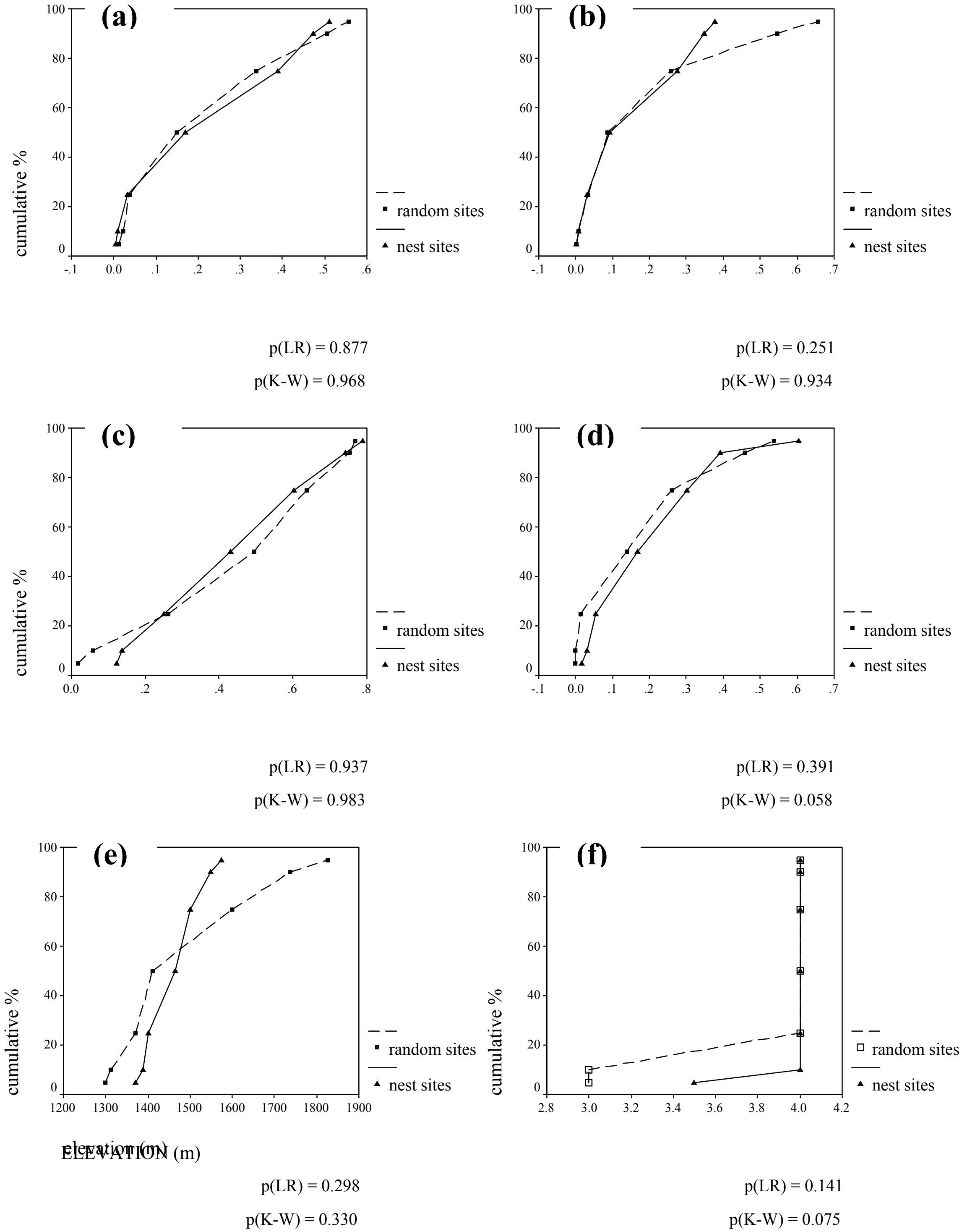


p(LR) = 0.006

p(K-W) = 0.007

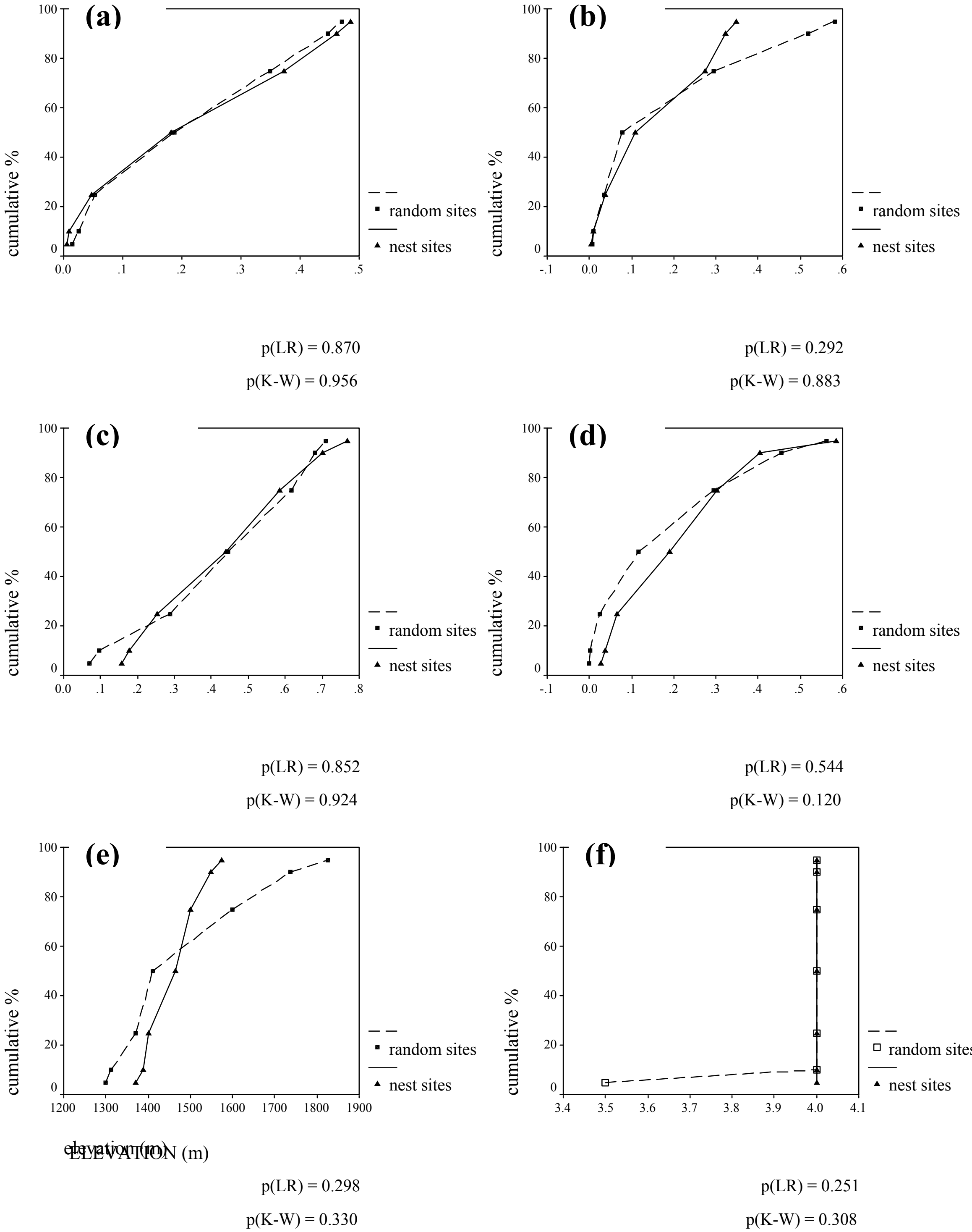
(g) For the variable MODE: P (LR) = 0.985

Figure 5: Cumulative frequency graphs and p-values for variables considered for the Perching model. The p-values are derived from the univariate logistic regression analyses and 2-independent-samples Kruskal-Wallis tests.



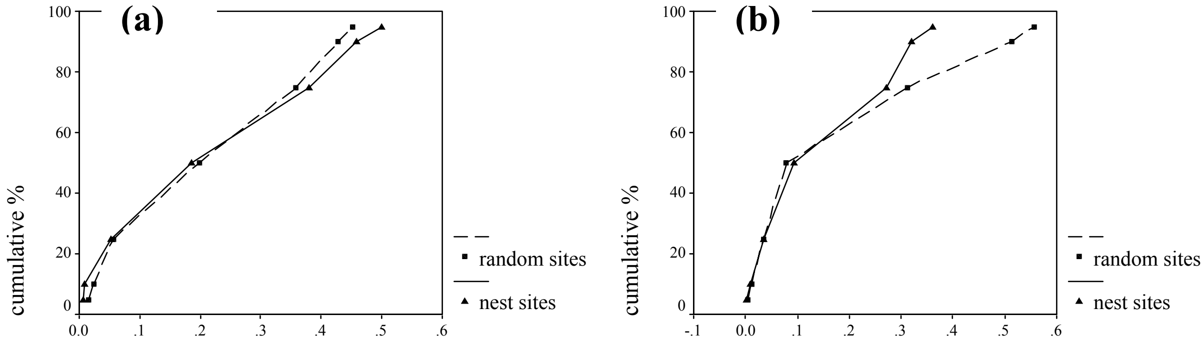
(g) For the variable MODE: P (LR) = 0.053

Figure 6: Cumulative frequency graphs and p-values for variables considered for the Nesting & foraging model. The p-values are derived from the univariate logistic regression analyses and 2-independent-samples Kruskal-Wallis tests.



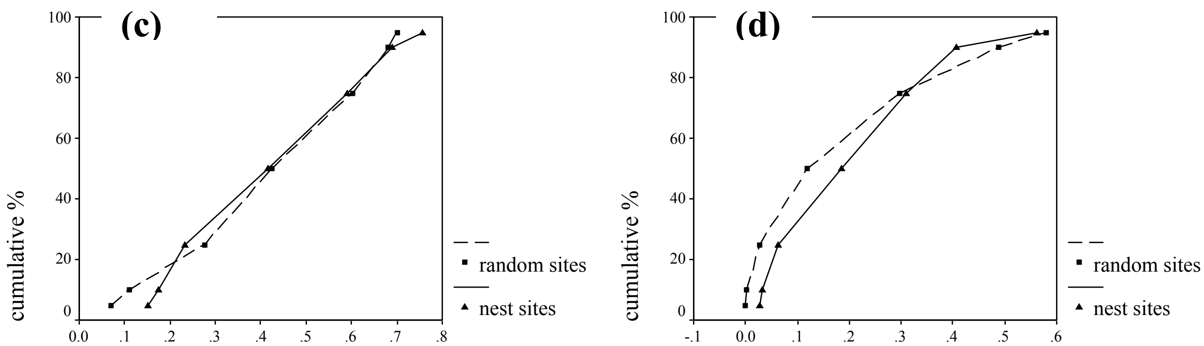
(g) For the variable MODE: P (LR) = 0.002

Figure 7: Cumulative frequency graphs and p-values for variables considered for the Foraging model. The p-values are derived from the univariate logistic regression analyses and 2-independent-samples Kruskal-Wallis tests.



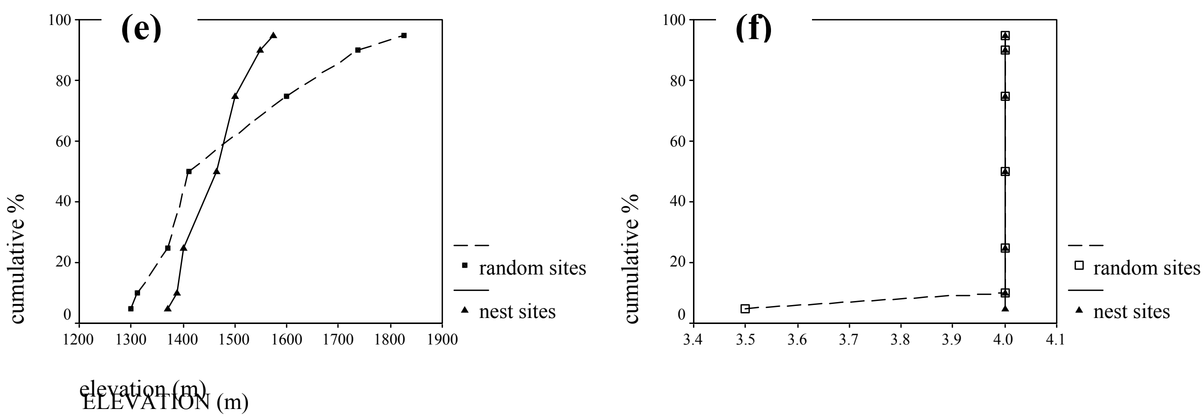
p(LR) = 0.872 p(LR) = 0.315

p(K-W) = 0.917 p(K-W) = 0.825



p(LR) = 0.822 p(LR) = 0.609

p(K-W) = 0.843 p(K-W) = 0.137

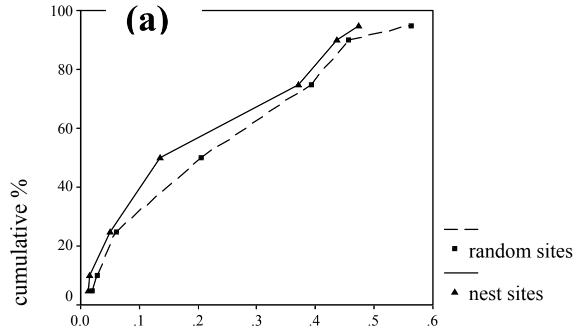


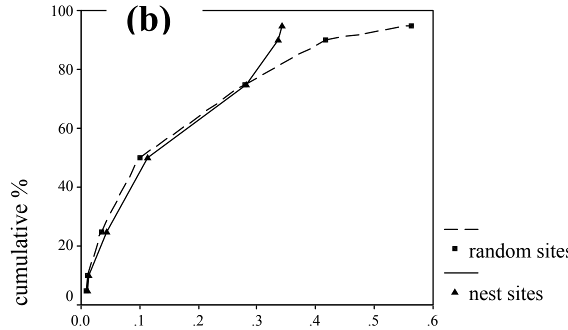
p(LR) = 0.298 p(LR) = 0.251

p(K-W) = 0.330 p(K-W) = 0.308

(g) For the variable MODE: P(LR) = 0.000

Figure 8: Cumulative frequency graphs and p-values for variables considered for the Home Range model. The p-values are derived from the univariate logistic regression analyses and 2-independent-samples Kruskal-Wallis tests.



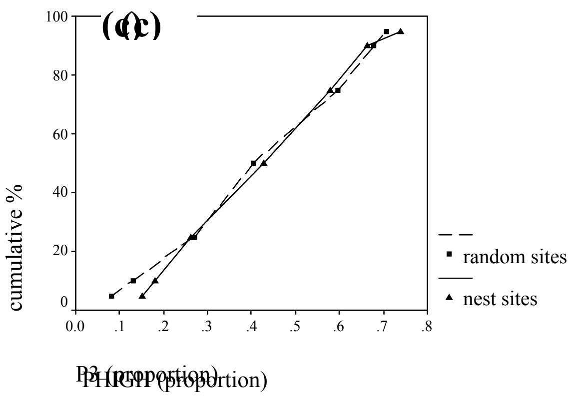


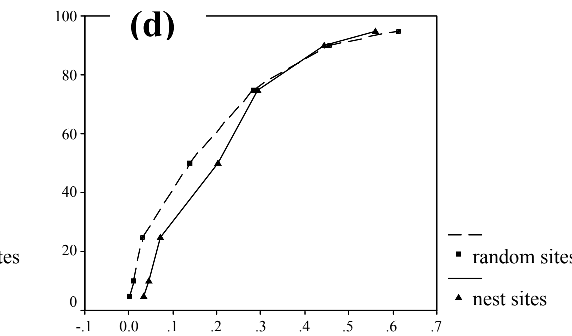
p(LR) = 0.456

p(K-W) = 0.457

p(LR) = 0.499

p(K-W) = 0.862



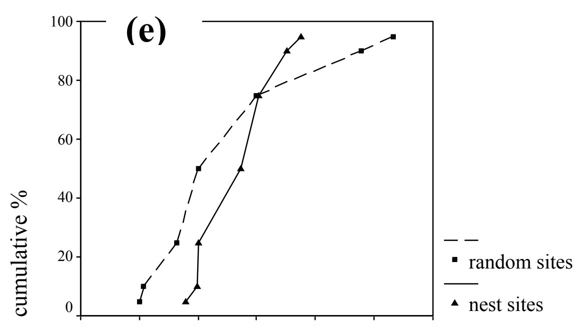


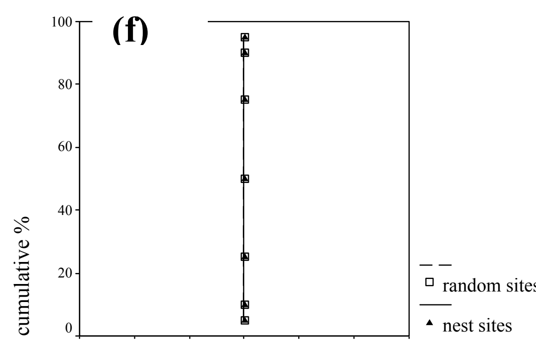
p(LR) = 0.563

p(K-W) = 0.583

p(LR) = 0.475

p(K-W) = 0.144





p(LR) = 0.373

p(K-W) = 0.012

p(K-W) = 1.00

(g) For the variable MODE: P(LR) = 0.254

Although some of the vegetation density class differences between nest sites and random sites were statistically significant, as indicated above, most of them proved not to be significant discriminators in the univariate analyses. Some variables, such as PTREE, had non-significant trends ($p < 0.15$) in the Kruskal-Wallis test in the Foraging, the Nesting & foraging, and the Home Range models (Figures 6(d), 7(d), and 8(d)).

For all models, except the Home Range model, areas around the nests had a higher diversity of vegetation density classes than areas around random sites (Figures 4(f) through 8(f)). For the Nesting model, RICHNESS was significantly different ($p < 0.01$) for nest sites and random sites in both univariate logistic regression and Kruskal-Wallis analyses (Figure 4(f)). For the Perching model, RICHNESS was also a significant discriminator between suitable and unsuitable habitat, but at lower significance level (Kruskal-Wallis test; $p < 0.10$) (Figure 5(f)).

In all of the five models, the range of elevation values was smaller for nest sites than for random sites, indicating hawk's selection the elevation zone that includes the near shrubland-forest ecotone (Figures 4(e) through 8(e)). More specifically, for the Nesting model, in the univariate logistic regression analysis nest sites and random sites showed a significant difference in ELEVATION ($p < 0.10$) (Figure 4(e)). And for Home Range model, ELEVATION was the only significant variable in the Kruskal-Wallis test ($P < 0.05$) (Figure 8(e)).

Multivariate Analysis

Five binary logistic regression models were built using one to four of the explanatory variables (Table 3). I chose three different tests to evaluate the goodness-of-fit of the models, since no one test is universally preferred, and since different tests can assess different aspects of the model (Tabachnick and Fidell, 1996; Hosmer and Lemeshow, 1989). The likelihood ratio test, or Model χ^2 in SPSS, tests the null hypothesis that there is no significant difference between a full model (model with all the predictor variables and the constant) and a constant-only model (Tabachnick and Fidell, 1996). The difference for all the models was statistically significant at 0.10 α -level, with p-values ranging from < 0.001 to 0.088 (Table 4). I used the Hosmer & Lemeshow test, which

Table 3: Logistic regression parameter estimates and classification results for the probability of a site in the study area being a potential ferruginous hawk nesting or foraging habitat. Standard errors of parameter coefficients are given in parentheses. C.P. = Cut Point is used in logistic regression to assign cases to an outcome group based on estimated probabilities. Classification accuracy is based on data not used for model building.

Model	C.P.	% correctly classified (n) nest	random	overall	Model logit =
Nesting	0.47	83.3	44.4	63.9	4.150(2.571) - 0.004(0.002)ELEVATION + 1.913(1.142)PTREE + 0.495(0.267)RICHNESS
Perching	0.48	83.3	27.8	55.6	-0.511(0.730) + 1.338(0.859)MODE1 - 0.470(0.996)MODE2 + 0.444(0.775)MODE3
Nesting & Foraging	0.49	83.3	38.9	61.1	3.419(3.607) - 0.004(0.002)ELEVATION + 4.705(2.191)PTREE + 3.421(1.386)MODE1 - 0.498(1.711)MODE2 + 1.451(1.061)MODE3
Foraging	0.5	94.4	33.3	63.9	-0.223(0.671) + 0.985(0.812)MODE1 - 1.281(1.030)MODE2 + 0.223(0.719)MODE3
Home Range	0.48	56.3	43.8	50.0	-0.462(0.337) + 2.471(1.430)PTREE

Table 4: Evaluation parameters for the five models.

Model	Hosmer & Lemeshow test		Likelihood Ratio test			Corrected R^2 (Nagelkerke, 1991)	KHAT
	χ^2	*p-value*	*Model* χ^2	*d.f.*	*p-value*		
Nesting	9.894	0.273	10.77	3	0.013	0.127	.278
Perching	0.000	1.000	6.55	3	0.088	0.083	.112
Nesting & Foraging	11.165	0.193	24.18	6	< 0.001	0.281	.278
Foraging	0.000	1.000	7.91	3	0.048	0.099	.278
Home Range	16.357	0.038	3.114	1	0.078	0.043	.000

falls into the category of deciles-of-risk statistics, to compare the actual number of cases in each decile to the number of cases predicted in the same decile by the logistic regression model. This test produces a non-significant chi-square if there is no difference between the actual and the regression-generated number of cases in deciles, which is an indication of a useful model (Tabachnick and Fidell, 1996). A non-significant chi-square was produced for all models, except the Home Range model, indicating that most of the nest sites were in the higher deciles-of-risk and most random sites in the lower ones (Table 4). In addition to the likelihood ratio and the Hosmer & Lemeshow tests, change in deviance (-2 log likelihood) was used to evaluate the goodness-of-fit (results not shown). In stepwise methods, the change in deviance tests the null hypothesis that the coefficients of the variables removed from the model are zero (SPSS, 1999). In all models the changes in deviance were significant at 0.10 α-level.

Although statistically reliable for all the models, prediction accuracy was modest, with the highest overall success rate of 63.9% for three out of five models (Table 3). The Home Range model had the lowest overall classification accuracy of 50.0%. Prediction success varied considerably between nest sites and random sites. Four out of five models correctly predicted nest sites more than 80% of the time, where as the highest prediction accuracy for the random sites did not exceed 45% in any of the models and was as low as 27.8% in the Perching model.

Percentage of variation explained by the models was low in most cases (Table 3), indicating that variables other than vegetation characteristics used in these models could be more important in ferruginous hawk habitat selection. KHAT values indicate that three out of five models were 27.8% better than a random model (Table 3). The Perching model showed only an 11.2% improvement over a random case, and the Home Range model's KHAT indicated no improvement from randomness.

Based on the order in which variables entered the models, ELEVATION, MODE, and percent of the area occupied by low density vegetation (PLOW) had the most predictive power of the seven variables used. Among the four dummy variables representing the mode, the low density vegetation class was usually the only one that made a significant contribution to discrimination among nest sites and random sites. Because of poor classification results and goodness of fit tests (Tables 3 and 4), the Perching and the

Home Range models were not used in further analysis. For the Nesting model, ELEVATION, PTREE, and RICHNESS were the best predictors of nesting habitat, indicating that hawks will likely nest at lower elevations and select areas that are in close proximity to forest and contain high diversity of vegetation density classes (Table 3). In the Foraging model, MODE was the only reliable predictor of potential habitat. Presence of areas with low and high density vegetation seemed to be important for foraging activities. ELEVATION, PLOW, PHIGH, and mode were the significant components of the Nesting & foraging model.

Maps of Potential Habitat

Maps of potential ferruginous hawk habitat were developed using the results of the Nesting, the Nesting & foraging, and the Foraging models (Table 3). The statistical models calculated the probability that each pixel represented suitable ferruginous hawk habitat. Two types of maps were created from model outputs: five-class probability maps and binary maps identifying non-habitat and potential suitable and unsuitable habitat. Non-habitat represented plant communities that were not used by the hawks for nesting or foraging (see Methods section). Suitable habitat contained areas with a probability greater than or equal to the Cut Point value determined for each model (Table 3). Five-class probability map for the Nesting model revealed a continuous gradient of probability of occupancy in the study area and a surprising scarcity of high probability habitat (Figure 9). Very few areas had a probability of occupancy higher than 0.8 and the majority of nesting sites were located in the areas of 0.4-0.8 probability(Figure 10). This indicates that there might be other variables influencing hawk nest site selection that were not included in the analysis or that quality of nesting habitat is not as important as quality of foraging habitat.

Since only a single nominal scale variable (MODE) was used to generate the Foraging model, the probability map derived from this model contained only four probability values (Figure 11). The map showed the probability values of pixels being good ferruginous hawk foraging areas and revealed an interesting mosaic pattern where many of the areas with the high probability of 0.68 were adjacent to areas of low

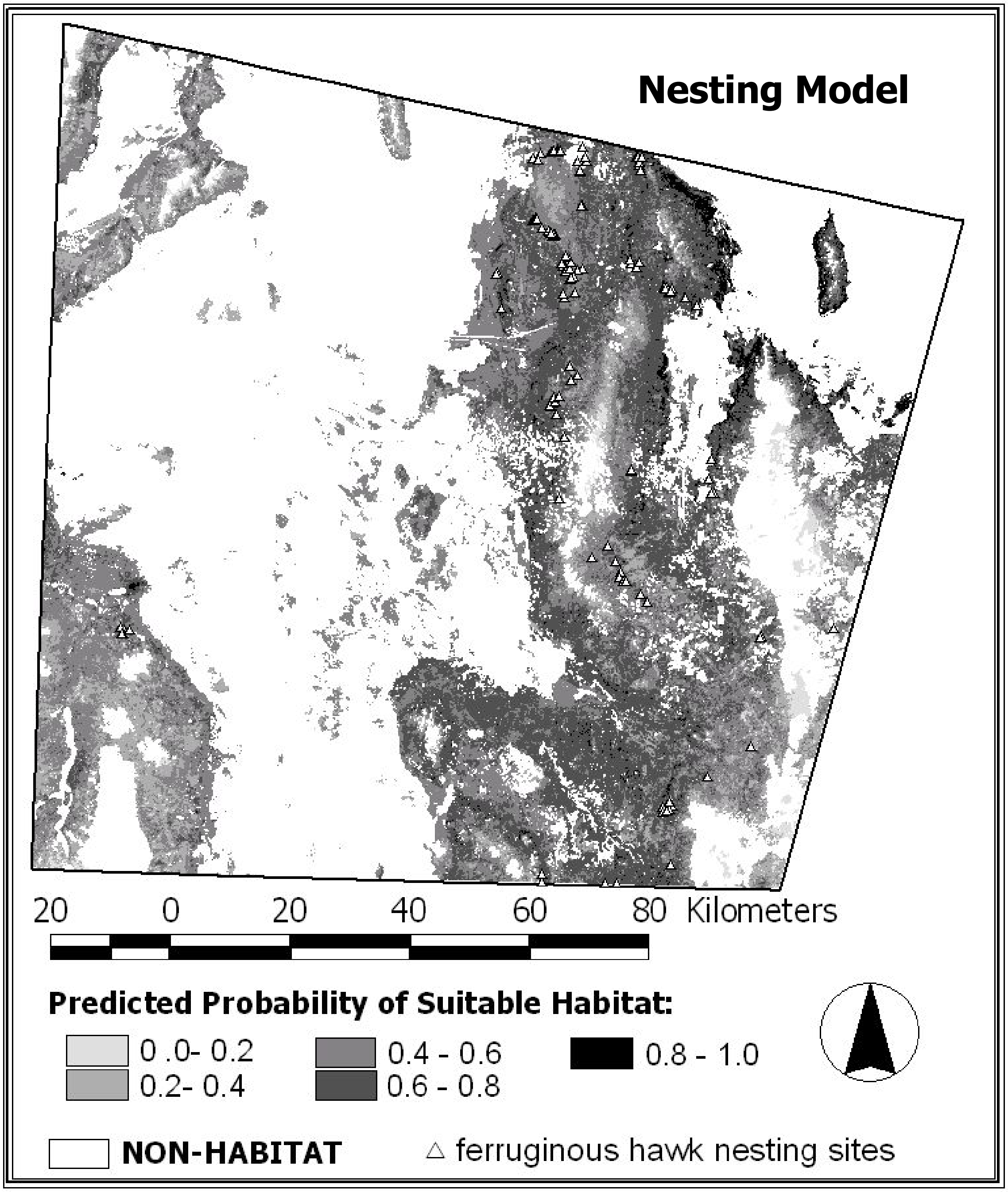


Figure 9: Five probability categories for ferruginous hawk habitat based on the Nesting model.

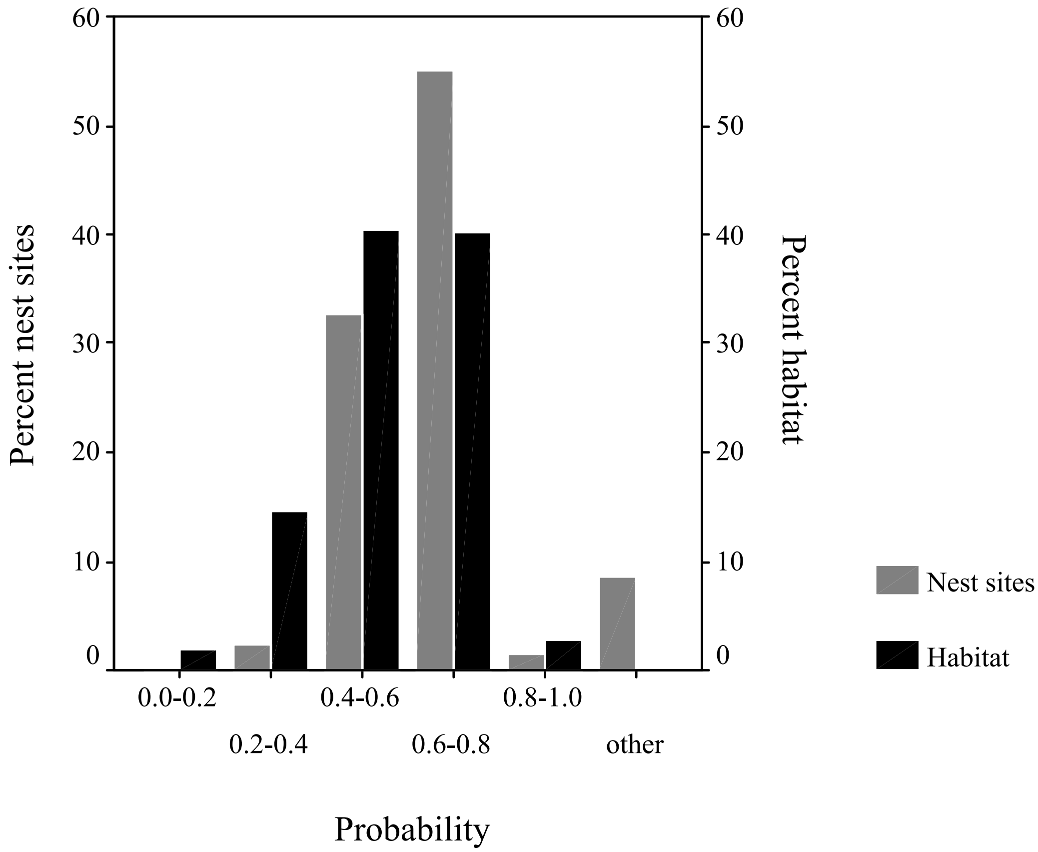


Figure 10: Percent of nest sites and percent of habitat at five probability categories for the Nesting model probability map (Figure 9). Category “other” includes areas that were masked out due to cloud cover.

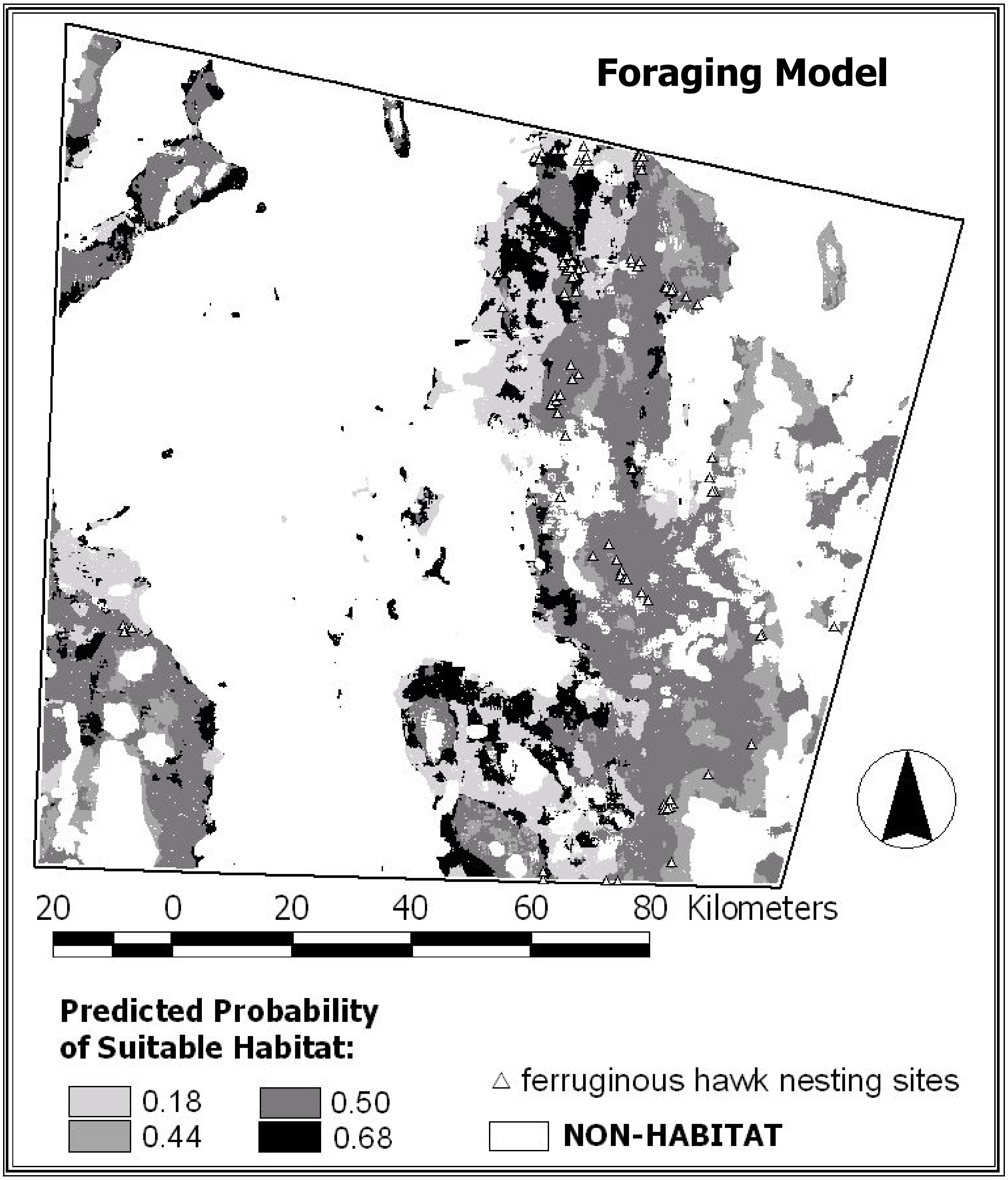


Figure 11: Four values for predicted probability of a pixel being suitable ferruginous hawk foraging habitat. Only four probability values were calculated because MODE was the only variable selected in the Foraging model.

probability of 0.18. The majority of the high quality habitat was located in the northern and south-central parts of the study area. A disproportionate number of the nests was located in pixels with the probability of 0.68 (Figure 12). Only seven percent of habitat had that probability value, as opposed to thirty two percent of nest sites. Forty four percent of the nest sites were found in pixels with the probability of 0.5.

The predicted probability map based on the Nesting & foraging model revealed a wide range of habitat suitability conditions throughout the study area (Figure 13). Most of the nest sites in the northern and southern parts of the study area were located within the 0.6-0.8 and 0.8-1.0 probability categories, while the nesting sites in the center and west were found within the 0.4-0.6 category. As with the Foraging model probability map, the majority of high quality habitat was located in the northern and south-central regions of the map. Overall, forty one percent of nest sites were located within pixels with probability between 0.8 and 1.0 (Figure 14), indicating that the combination of nesting and foraging characteristics can produce an occupancy probability superior to one created by either of the habitat types alone.

In addition to probability maps derived from the three models, binary habitat maps were created using the Nesting & Foraging model and the overlay of the Nesting and the Foraging models using their respective Cut Point values from Table 3. The Nesting & foraging binary map showed large continuous tracks of suitable nesting and foraging habitat in the western part of the study area, however the pattern appeared quite patchy in the east (Figure 15). Two binary habitat maps were created using the Nesting and the Foraging models and then overlaid on top of each other to identify background, potential nesting habitat, potential foraging habitat, and potential nesting and foraging habitat (Figure 16). This image was then compared with the Nesting & foraging image, which also modeled potential habitat based on both nesting and foraging criteria. I expected that both of these image would show similar results.

Comparison of Figures15 and 16 revealed slight differences in the amount of potential habitat available to the hawks. Overall, the combined model showed less habitat than the 1.9 km^2 model by approximately 100,000 hectares (Table 5). The largest differences between the two maps existed along the Pony Express Trail as it follows the

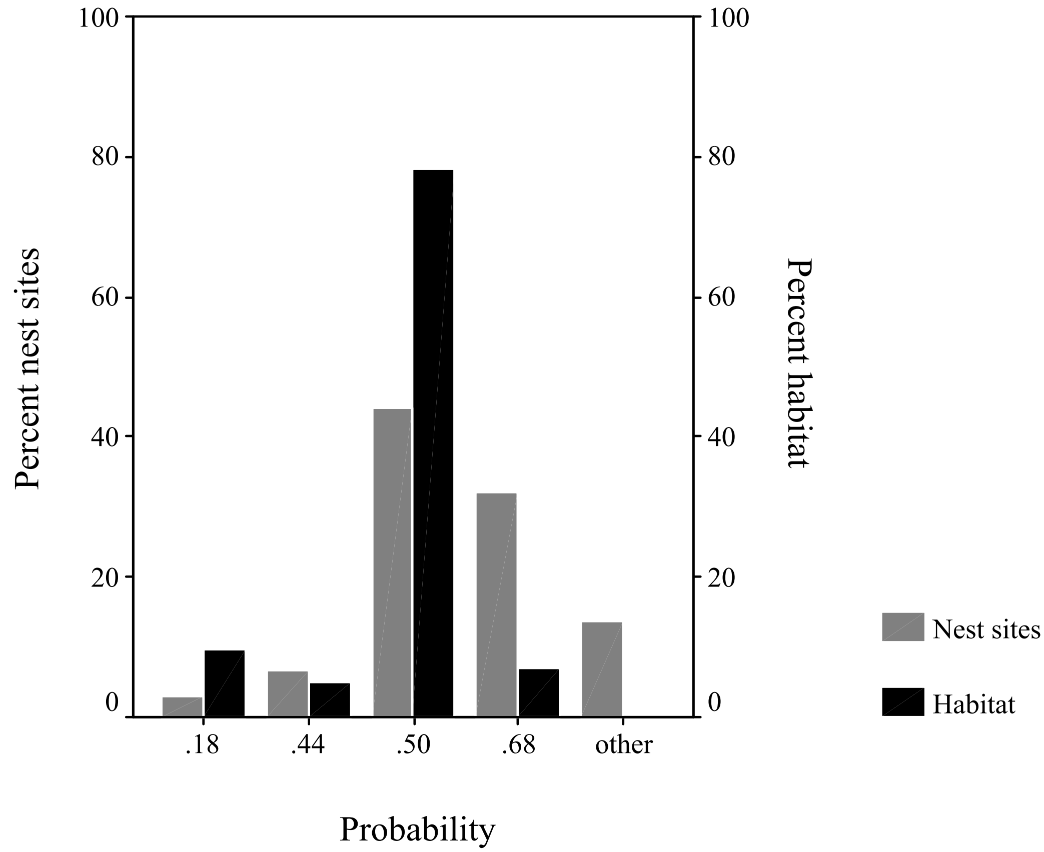


Figure 12: Percent of the nest sites and percent of habitat at four probability values for the Foraging model probability map (Figure 11). Category "other" includes areas that were masked out due to cloud cover.

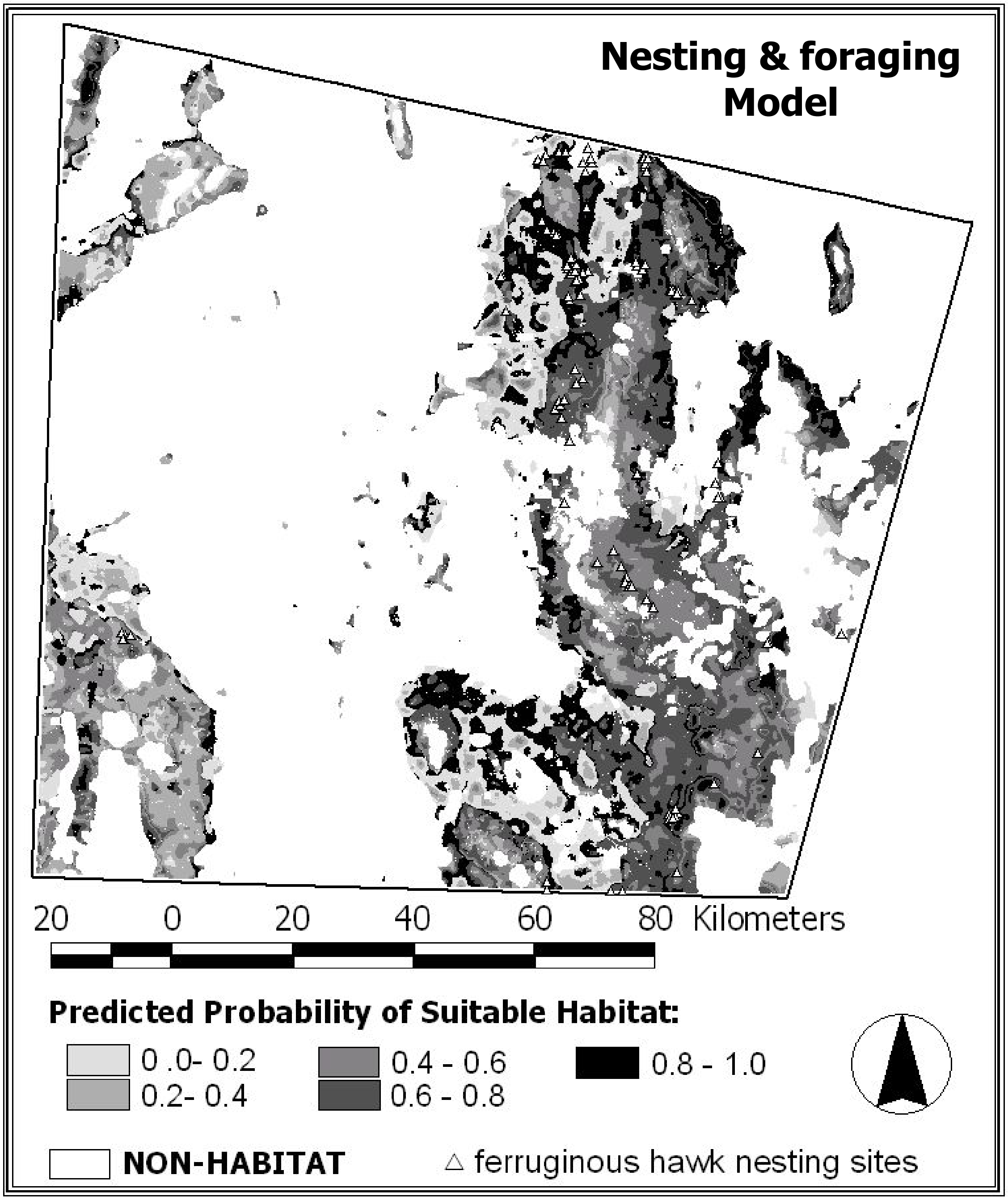


Figure 13: Five probability categories for ferruginous hawk nesting and foraging habitat based on the Nesting & foraging model.

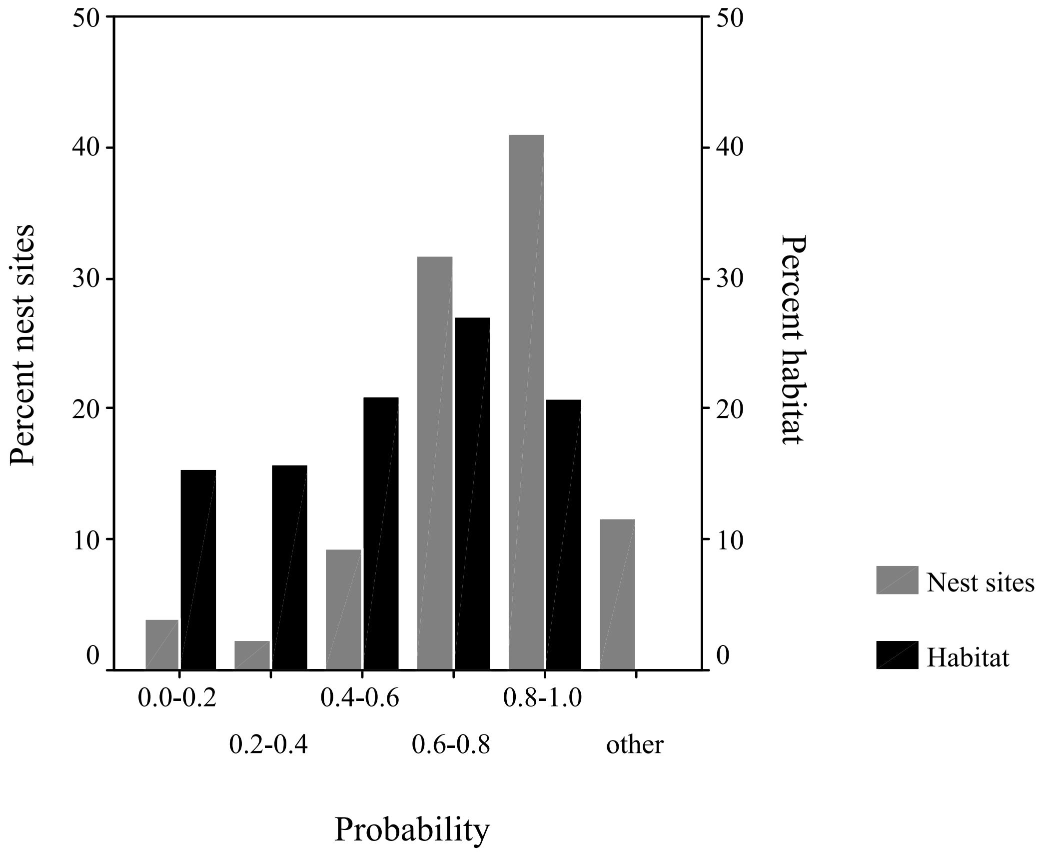


Figure 14: Percent of nest sites and percent of habitat at five probability categories for the Nesting & foraging model probability map (Figure 13). Category "other" includes areas that were masked out due to cloud cover.

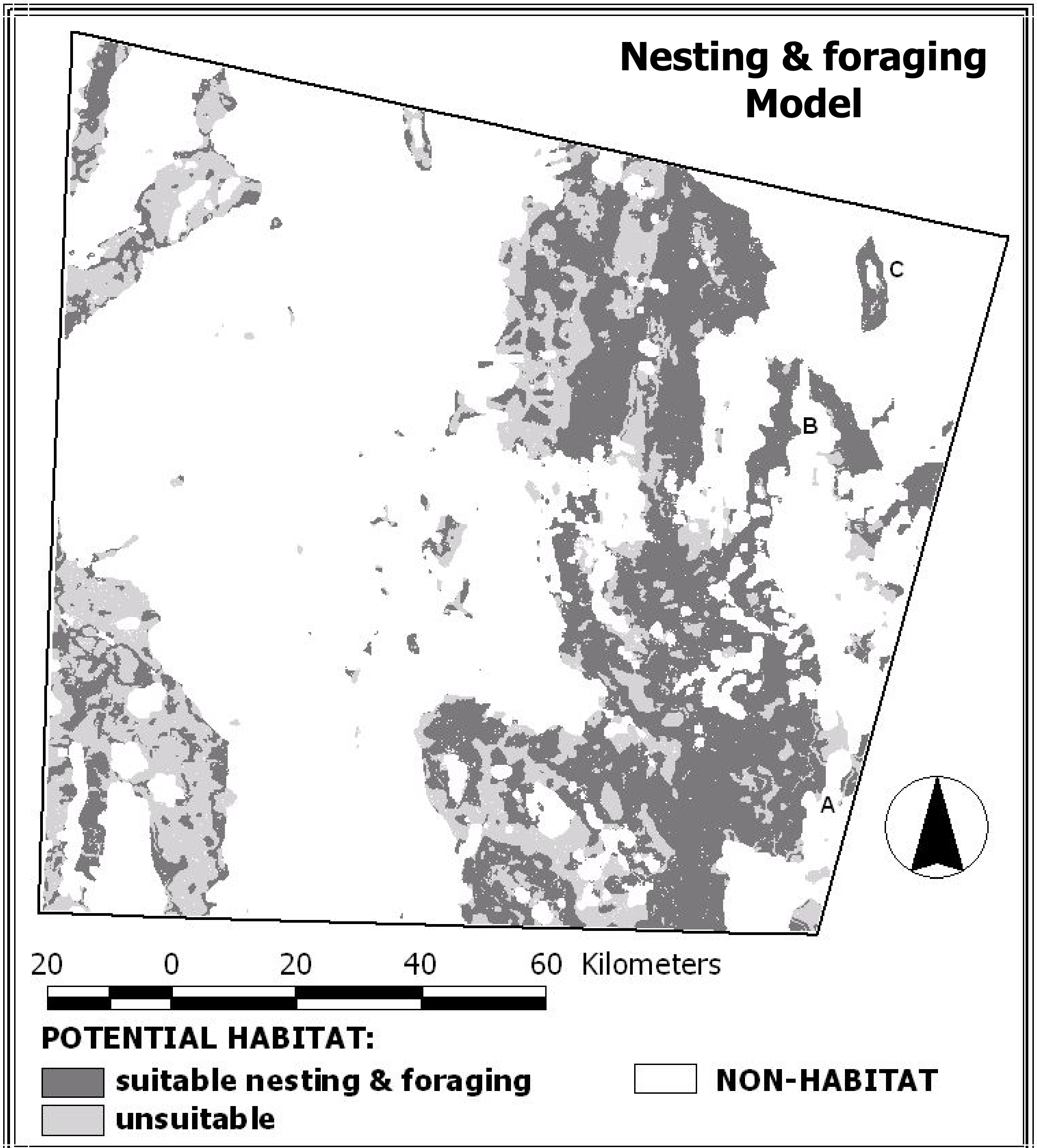


Figure 15: Binary representation of ferruginous hawk nesting and foraging habitat based on the Nesting & foraging model and using the optimum Cut Point value from Table 3.
A – areas between the Pony Express Trail and the Onaqui Mountains; B – Stansbury Mountains; C – Stansbury Island (see explanations in the text).

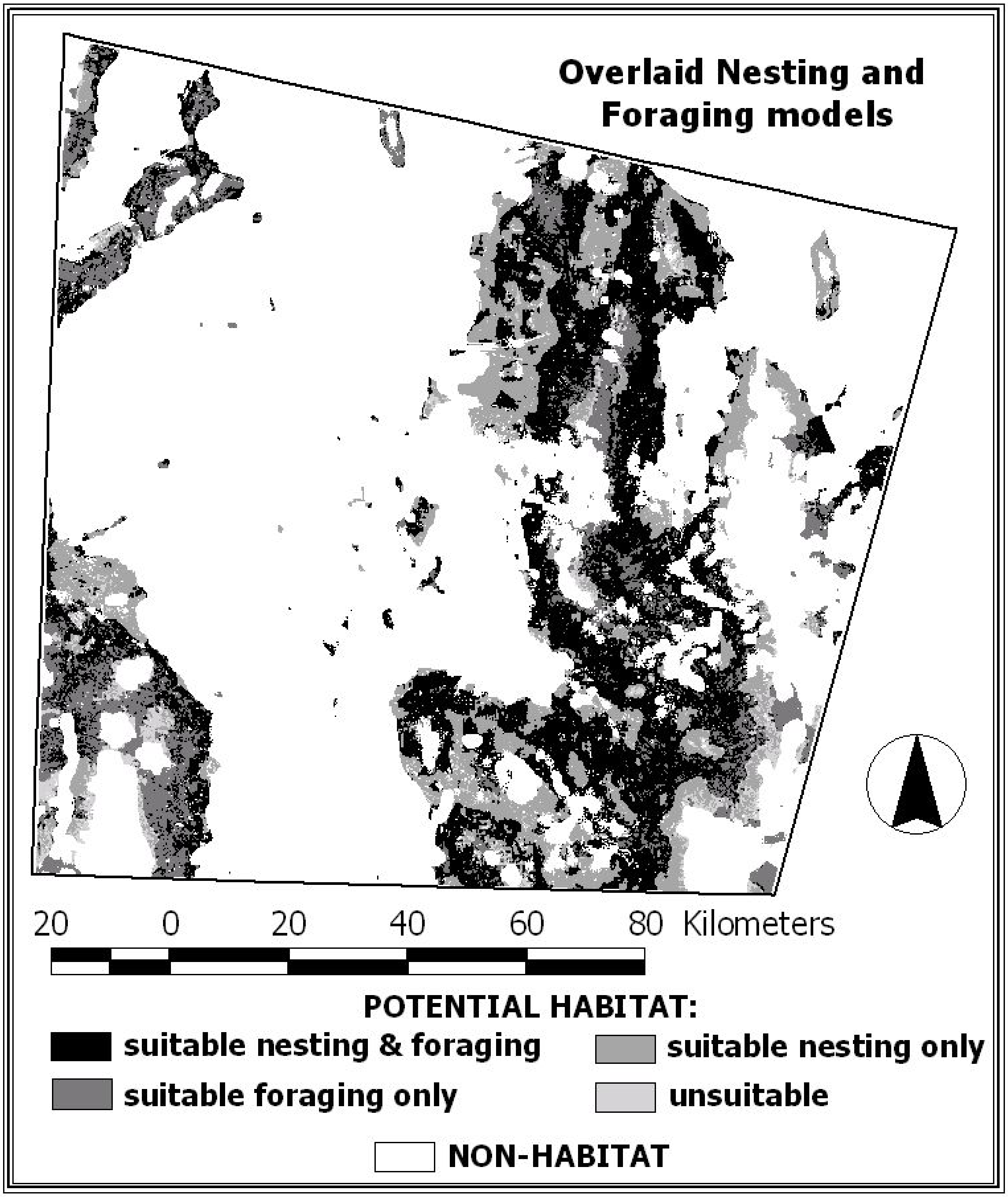


Figure 16: Binary representation of ferruginous hawk nesting and foraging habitat based on the overlay of the Nesting and the Foraging binary models and using the optimum Cut Point values from Table 3 for each of the models.

Table 5: Availability of potential ferruginous hawk habitat in the study area by land ownership category based on the Nesting & foraging binary model (Figure 15) and the overlay of the Nesting and the Foraging binary models (Figure 16).

	Area (ha)			
	Nesting & foraging Model	Overlayed Nesting and Foraging models		
Ownership Category	NESTING & FORAGING	NESTING & FORAGING	FORAGING	NESTING
BLM	230593	167644	81517	95523
PRIVATE	36087	21041	9416	11430
STATE	21952	16338	7263	9528
MILITARY	79368	72209	8102	33526
FOREST SERVICE	920	73	1605	193
NATIVE AMERICAN	2879	2170	323	241
Total	371800	279474	108226	150442

Onaqui Mountains, in the areas to the east and west of the Stansbury Mountains, and on most of Stansbury Island (A, B, and C, respectively, in Figure 15).

Analysis of the Nesting & foraging binary map based on land ownership category indicated that 62% of the potential nesting and foraging habitat exists on BLM land (Figure 17). Military reservations contain about 21% of the potential habitat, private lands about 10%, and state lands 6%. Forest Service and Native American reservation lands each contained under 1% of the habitat. On the combined map, there was a similar distribution of potential nesting and foraging habitat among the ownership categories (Figure 18). In addition, BLM lands contained 75% of all potential foraging habitat and over 60% of potential nesting habitat. Military reservations contained 7.5% and 22% of those categories, respectively.

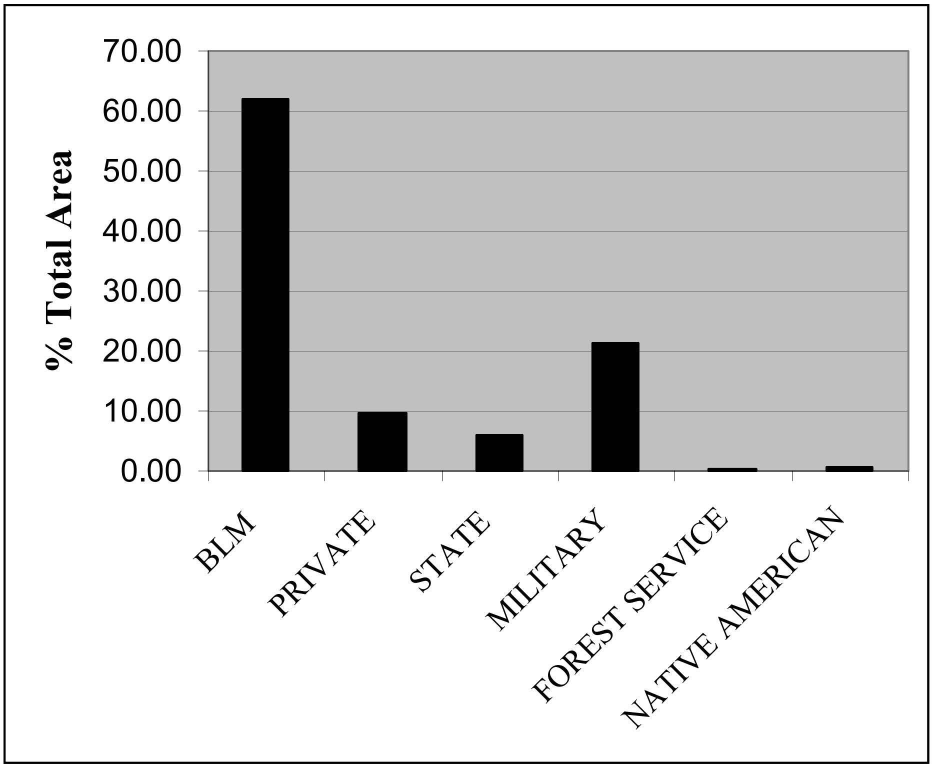


Figure 17: Distribution of potential ferruginous hawk nesting and foraging habitat by ownership category (in percentage of total potential habitat area). Results based on the Nesting & foraging model shown in Figure 15.

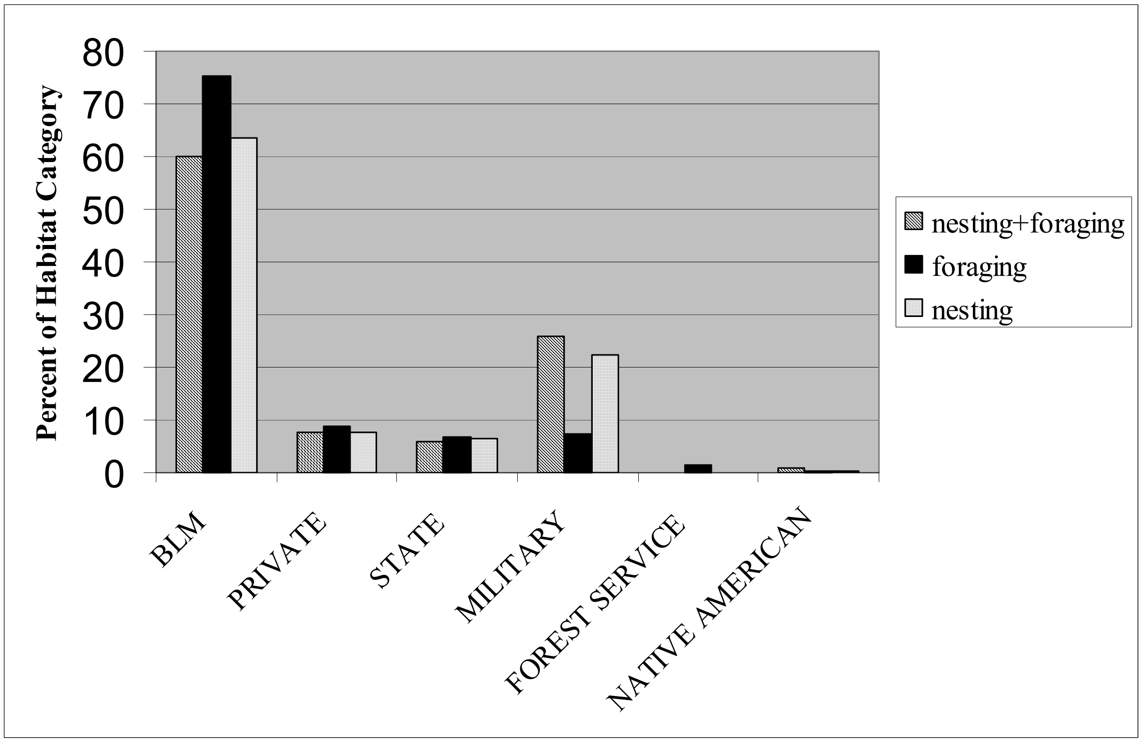


Figure 18: Distribution of potential ferruginous hawk nesting and foraging habitat by ownership category (in percentage of habitat category). Results based on the overlay of the Nesting and the Foraging binary models shown in Figure 16.

Discussion

Variable Selection

The results of this study demonstrate that various vegetation characteristics derived from satellite imagery data can be used to model potential ferruginous hawk nesting and/or foraging habitat. Delineation of nesting vs. foraging habitat was based on different suites of variables (Table 3), and these differences are consistent with what is known of the species biology. Selection of ELEVATION, RICHNESS, and PTREE variables for the Nesting model helped to delineate the ecotone between the forest and the shrubland, which is the most common location of nesting sites for the ferruginous hawk. This forest-shrubland ecotone is usually located at lower elevations of the study area where the juniper forest community is gradually replaced by the shrubland. High heterogeneity of vegetation and presence of isolated juniper trees, which are often used as nesting substrates, characterize these areas. These characteristics of nesting habitat explain the negative sign of the ELEVATION coefficient in the logistic regression model and positive coefficients for the RICHNESS and PTREE variables.

For the Foraging model, MODE was the only variable selected in the analysis. Among the dummy variables, representing the dominance of one of the four vegetation density classes, MODE3 and the intercept were not good predictors of suitable habitat, because the 68% confidence interval of the coefficients included 0 (Table 4) (Wright, 1995). Low density vegetation (MODE1) had the positive coefficients in the model and MODE2, representing the dominance of medium density vegetation received a negative coefficients. These results are consistent with published literature on ferruginous hawks themselves and their prey species (Taylor and Lay, 1944; Leichleitner, 1958; Wakeley, 1978; Fagerstone et al., 1984). The presence of open areas improves prey accessibility by the hawks. On the other hand, prey abundance is highest in areas with tall vegetation cover that are represented in the study area by native grasslands and big sagebrush- and greasewood-dominated communities. These areas most often fall into the high density vegetation category.

The Nesting & foraging model contained a combination of variables that included characteristics of both nesting and foraging ferruginous hawk habitat. Although the variables in this model contributed significantly to discrimination between nest sites and random sites (p-value < 0.001), the model is difficult to interpret. Some variables included in the model described the similar habitat characteristics and, therefore, might have introduced the problem of multicollinearity. Specifically, the model assigned a negative coefficient to PLOW and a positive coefficients to MODE1, although both of these variables are related to the abundance of low density vegetation in the sampling window. Similar inconsistencies occurred between variables PHIGH and MODE3. According to Capen et al. (1986) such contradictions of signs are a common occurrence in stepwise procedures when model includes variables that are highly correlated. Multicollinearity could not be assessed for the MODE before the analysis since it was a nominal scale variable. However, adjustments could have been made after the assessment of the resulting model. Since MODE was entered first in the regression analysis and its coefficients make more sense ecologically, PLOW and PHIGH should probably have been removed from the model as redundant variables (Hosmer and Lemeshow, 1989). Removal of these two variables would have also reduced the variable/case ratio of the model, potentially making the model more reliable (Wright, 1995).

Model Accuracy

Four out of five models had high classification accuracy for nest sites in this study, indicating high correlation between ferruginous hawk habitat selection and vegetation characteristics in the study area. The range of values for the nest site classification accuracy among the models suggested that areas of foraging habitat can be predicted with greater success than areas of nesting habitat. A prediction success of 94.4% was attained for the Foraging habitat model, however the Nesting habitat model had a lower accuracy of 83.3%. The Nesting & foraging model, representing both types of habitat, had an intermediate prediction success of 88.9%.

The overall success rate of the models was low (50-63.9%) and could be attributed to several factors associated with both the quality and detail of the available data and the nature of wildlife habitat analysis in general. The largest contribution to poor overall success rate came from the poor classification success of the random sites, which ranged from 27.8% for the Perching model to 44.4% for the Nesting model. This can be partially explained if one considers that the random site category also includes potential nesting sites that would be classified the same as the existing nest sites producing lower classification accuracy for the random site category. In addition, the variability of random sites was narrowed down significantly before the model building by elimination of areas that did not contain vegetation communities known to be used by the hawks (see Methods section). Doing so allowed a narrower focus on the analysis of vegetation characteristics such as density rather than vegetation type, but also made discrimination between nesting sites and random sites difficult. Hence, univariate analysis results show very few variables as significant discriminators of suitable and unsuitable habitat and those differences only appear as a result of interactions among the variables in the multivariate analysis.

Another factor contributing to low overall classification accuracy could be the errors associated with the satellite image analysis from which the variables for this study were derived. The overall classification accuracy of the vegetation layer used for model building was estimated at 85%. Errors present in this layer could negatively affect the ability of the model to separate habitat characteristics associated with nest sites and random sites and have a multiplicative effect on overall model accuracy. This effect could potentially be eliminated with better image classifications, however some degree of error will always remain in analyses conducted at regional scales.

I used a square window to extract vegetation variables relevant to ferruginous hawk habitat selection. Although I used an ecologically appropriate size for the window (Wakeley, 1978; McAnnis, 1990; Olendorff, 1993), the shape of the window did not correspond to findings by other studies on ferruginous hawk foraging activities. It has been shown that the hawks select foraging habitat based on topographic and vegetative patterns and may switch foraging areas throughout the nesting season depending on foraging success (Wakeley, 1978; Woffinden and Murphy, 1983). The resulting foraging areas are amoeboid, rather than square, and are temporally dynamic, rather than static. However there is not sufficient data to quantify these dynamics. The selection of a square sampling window in this study simplified the variable extraction and potential habitat mapping procedures, but also introduced noise into the models and possibly contributed to low predictive power.

The predictive power of the model could potentially be improved by including additional variables that are important to ferruginous hawk habitat selection. The low percent of variation explained by the models (R^2) indicates the existence of additional characteristics that are important for habitat selection. Jasikoff (1982) identified several variables influencing quality of nesting and foraging habitat in his ferruginous hawk habitat suitability index model. Average vegetation height, vegetation heterogeneity, and size of continuous cropland are important because they determine the availability and accessibility of prey. Although heterogeneity was not directly measured when field data were collected for the image classification, an attempt was made to use information on diversity of life forms to create additional classes within the density classification. These classes could not be accurately discriminated and the classification was limited to vegetation density. Also, since this species is very sensitive to disturbance, inclusion of variables such as distance to roads would likely improve the power of the models. Unfortunately, I was not able to use this variable in my study, because the majority of the ferruginous hawk nests were found during surveys conducted along roads. This would bias the true influence that the presence of roads has on nest site selection.

Further studies should also include variables associated with landscape pattern, as well as landscape structure. During the satellite image classification portion of this study, I noticed that different landscape patterns emerged at different scales (see Discussion section in Part I). Namely, homogeneity of vegetation density classes was observed at larger scales, where as at smaller scales patterns appeared quite heterogeneous. It is conceivable that patch size and/or patch configuration of areas with similar vegetation density influence ferruginous hawk foraging habitat selection or abundance of ferruginous hawk prey species in a given area. Equally important might be the minimum size of suitable habitat patch. Further studies should determine the minimum size of suitable habitat patch required for a pair to establish a nest and explore the relationship between patch quality and optimum patch size.

From the standpoint of ferruginous hawk ecology, the low classification accuracy of the Perching and the Home Range models could result from differences in hawk's use of its home range. The Perching model focused on an area around the nest that is usually used for nesting and perching, but not necessarily hunting. In this respect, vegetation density characteristics might not be important in this area and might not differ significantly from an area around a random site. The Home Range model had the lowest classification accuracy. Besides the areas contained in the Perching model, whose vegetation characteristics proved to be unimportant for nesting or foraging, this model also included areas on the periphery of the home range that are rarely used (Wakeley, 1978; McAnnis, 1990). Because these two areas have characteristics similar to those of random sites, it might have overwhelmed any significant variables that were present in the model.

Conclusions and Management Implications

The results of this research are consistent with the findings from the ground-based studies on ferruginous hawk. Collectively, the these studies and the current study provided important insights into habitat selection by these birds of prey. Different factors influence the selection of nesting vs. foraging habitat. The presence of nesting substrate, indirectly indicated in the models by the proximity to forested areas, heterogeneity of vegetation cover, and elevation, appeared to be the most important criterion for discriminating between nest sites and random sites. However, discriminating between foraging habitat and random sites was based solely on vegetation density. The presence of bare ground and low density vegetation appeared to be the most important components of foraging habitat, allowing easy prey access. Presence of high density vegetation was also important, indicating areas selected by prey species because of good cover and, consequently, areas of high prey density.

My results showed that not all parts of the ferruginous hawk home range are equally important for nesting and foraging activities (Tables 3 and 4). While a good prediction of nesting habitat was possible by analysis of the area immediately around the nest site (areas extending to 125 meters), use of areas that extended from 300 to 700 meters away from the nest site resulted in the best models of foraging habitat. The difference of 100,000 ha in the amount of suitable nesting and foraging habitat identified by the two binary models (Figures 15 and 16) was likely the result of the Nesting & foraging model incorporating areas other than the ones directly used by the hawks, thus introducing noise into the model.

I found that large portions of the study area were suitable ferruginous hawk habitat. This was especially true for nesting habitat in the eastern part of the study area. Seventy four percent of potential habitat areas were included in the category of suitable habitat (Figure 16). The apparent presence of such large amount of suitable nesting habitat could be explained by the fact that the variables used in this study did not directly measure presence or absence of nesting substrates. Vegetation density per se did not appear to limit nesting habitat selection by ferruginous hawks and that the variables selected for the Nesting model were more closely related to topographic and vegetation community characteristics of areas where nest substrates could be present (Table 3). Therefore, areas outlined on the binary maps as suitable nesting habitat probably represent suitable nesting habitat if natural nesting substrates are present. Absence of such substrates would make these areas unsuitable for nesting.

Suitable foraging habitat availability appeared to be more limiting than the nesting habitat. Sixty eight percent of potential habitat was classified as suitable foraging habitat (Figure 16). The maps also showed that suitable foraging and nesting habitats were not necessarily located in the same parts of the study area. Analysis of the overlaid binary maps indicated that only 49% of potential habitat could be classified as suitable for both foraging and nesting activities. This figure still represents an overestimate of available habitat in the classified portions of the study area, since human disturbance was not taken into account in the models. Several studies in South and North Dakotas and Washington suggest that ferruginous hawks avoid human disturbance (Blair, 1978; Gaines, 1985; Bechard et al., 1990). Distance of at least 0.7 km and as large as 3.3 km from human activities was found to be necessary to prevent negative impacts on ferruginous hawk nesting success. Establishing buffers of reasonable distance around roads and areas of human habitation could make a more reasonable estimate of the amount of suitable habitat in the study area.

It is important to emphasize that the classes of suitable and unsuitable habitat generated by these models represent a continuous gradient rather than a categorical or binary outcome as it appears on the maps (This does not apply to Foraging model probability map, which contains only four probability values). For each point (or pixel) on the landscape a logistic regression model generates the pixel's probability of being a suitable habitat. Therefore, large categories of potential habitat that appear on the resulting maps do not all represent high quality or low quality, but a range of habitat conditions that can be improved by the land managers if certain lacking elements are added.

Analysis of suitable habitat in relation to land ownership categories in the study area indicated that the BLM lands contained the majority of available habitat. This further justifies the agency's nesting surveys, which it has been conducting for several years, and incorporation of ferruginous hawk habitat protection in its land management guidelines. The importance of Military reservations should be emphasize, since a quarter of suitable nesting and foraging habitat is located on these lands. These areas have limited access and, as of yet, no nesting surveys have been conducted there. These areas could contain large numbers of nesting pairs that are not taken into account when population numbers are assessed. In addition, large percentages of only nesting and only foraging habitat are also available there. These areas could potentially be improved to include both types of habitat.

It is apparent that further research is needed to fully understand the relationships between ferruginous hawk nesting and foraging site selection and habitat characteristics. Because selected methodology for this study required the synchronization of aerial photography and satellite imagery acquisition dates, and because aerial photography for the study area could only be obtained for 1993, there was a five-year lag between the date of acquisition of digital data and the time when vegetation data were collected in the field for classification purposes. This resulted in two uncertainties that need to be addressed with further study. First, I was unable to incorporate areas that were invaded by cheatgrass following a fire into the analysis. Consequently, I can only speculate on what effect cheatgrass would have on ferruginous hawk habitat quality. The invasion of *B. tectorum* in the study area as a result of fire has been recognized as having possible detrimental effects on the ferruginous hawks (Hoffman, 1991). Based on the results, it can be speculated that the presence of *B. tectorum* could potentially decrease the value of habitat for ferruginous hawks due to its tendency to attain a much higher density than native vegetation. During the vegetation field surveys for the image classification part of this study I found that plots dominated by *B. tectorum* all had vegetation densities above 45%. In addition, the homogeneous nature of the cover of this species could decrease its utility as hunting grounds for the hawks. Presence of areas with low vegetation density consistently appeared as an important factor in models addressing foraging habitat. This analysis would be consistent with findings by Call (1979) who found that jackrabbits survive best in the habitats that include both shrubs and grasses and that the homogeneous grass fields were detrimental to their production.

Second, temporal ferruginous hawk habitat analysis becomes difficult when one considers the time scale of land-use changes that are occurring throughout the ferruginous hawk range. Since the imagery was acquired and, again, since vegetation surveys were conducted, dramatic change in vegetation cover have occurred in the study area due to fire and replacement of native communities by *B. tectorum* both on the Military reservations and elsewhere in the study area. Since habitat suitability maps resulting from this study correspond only to a single year, the results are not necessarily relevant to current cover conditions and might have limited usefulness for long-term management. These arguments emphasize the need for further research. This study should be considered as the first step towards creation of a complete, detailed habitat model for the ferruginous hawk that could be applied to various areas of its range. I have demonstrated that satellite imagery and GIS layers can be successfully used for identifying important ferruginous hawk habitat characteristics and mapping suitable ferruginous hawk habitat at regional scales. Now that the methodology has been developed, similar studies can be conducted much faster, allowing the analysis of short- and long-term trends in vegetation cover changes and habitat availability.

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Appendix A: Procedures for image classification, including area-weighted method and maximum likelihood classifier.

1) Run classification iteration;
2) Run 'pixcnt.eas' in PCI EASI program (see template below). Note that 'pixcnt.eas' file should be copied to User directory in the PCI directory at the hard drive. VIMAGE will collect statistics.

'pixcnt.eas'

```
! model for getting pixel counts for each statistical class
local integer i
FOR i = 1 TO a BY 1
 FILE = "pathway to .pix file (in quotes)"
 DBIC = b
 FILV = "pathway to .pix file containing vector segment (in quotes)"
 DBVS = c
 OCOLUMN = "col"+F$STRING(i)
 SAMPTYP = "HIST"+F$STRING(i)
 UNDEFVAL = 0
 RUN VIMAGE
ENDFOR
```

Where,

a = highest number of spectral class created by classification;

b = number of channel with classification results;

c = number of the vector segment containing field data polygons.

3) Run VECREP in PCI Xpace in the form of 'Table.'
4) Delete header in report in word processor.
5) Import report to spreadsheet:
    a) delete unnecessary columns;
    b) sort by information class;
    c) calculate the sum of pixels for each spectral class within each information class;
    d) for each information class, divide the sums by the total number of plots.

6) In PCI Imageworks aggregate results in a new channel by putting all spectral classes that were unique to one information class in one category (0) and the rest (including spectral classes that did not contain any pixels) into another category (1).
7) Create a bitmap using THR module in Xpace with all the pixels in category 1 turned on.
8) Run the next iteration under the bitmap created in #7. **Caution**: make sure that you save all the channels containing classification iterations! Aggregation channels can be cleared and used again once the bitmap is created.
9) Repeat #2 through #8 until no spectral classes can be assigned to a unique information class or do not contain any pixels.
10) Using the last iteration, assign confused spectral classes to information classes based on area-weighted method: i.e. at the end of step 5, compare areas occupied by a spectral class within each information class and assign the spectral class to the information class that shows the largest area.
11) Create a model similar to the example below to combine all assigned spectral classes from all the classification iterations, **including the last one**, to information classes. **Attention:** do not include spectral classes of the last iteration that do not contain any pixels (they have not been assigned to any information class yet). Run the model in PCI EASI program. Note: the file cannot be run through Xpace MODEL module due to presence of 'elseif' statements. You will get 'syntax error' message.

ag_comb.eas

```
IF (%13 = 5) or (%14 = 10) or (%15 = 2) or (%16 = 4) or (%16 = 13) or … or (%22 = 29) THEN
        %24 = 3;
elseif (%14 = 33) or (%14 =36) or (%14 =37) or (%14 = 38) or (%15 = 14) or (%15 = 22) or (%15 = 48) or
(%16 = 37) or … or (%22 = 17) THEN
        %24 = 1;
elseif (%15 = 21) or (%15 = 43) or (%16 = 46) or (%16 = 48) or … or (%20 = 167) THEN
        %24 = 2;
elseif (%14 = 2) or (%18 = 6) or … or (%22 =40) THEN
        %24 = 4;
else
        %24 = 0;
ENDIF;
```

12) Using the channel created in #11 (containing aggregated classification results), create signatures for all information classes using CSG module in Xpace. Same data layers should be used for signature generation as were used in classification iterations.
13) From the last classification iteration, aggregate, in Imageworks, all spectral classes that did not contain any pixels and create a bitmap using procedures in #7.
14) Classify pixels under the bitmap created in #13 in MLC module in Xpace using signatures generated in #12.
15) Some pixels might not be assigned to an information class in #15 if they fall outside of the parameters specified by signatures. Those pixels (NULL pixels) can be aggregated into spectral classes again (with classification procedures used in #1) and assigned to information classes based on their proximity to pixels that have already been assigned.
16) Add results from the channels created in #11, #14, and #15 into a new channel using ARI module in Xpace. This is your final classification result.