MAPPING BALD EAGLE COMMUNAL NIGHT ROOST HABITAT IN NORTHWEST WASHINGTON USING SATELLITE IMAGERY

BY

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Accepted in Partial Completion

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Master of Science

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MASTER'S THESIS

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A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
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Lise P. Grace
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Abstract

Bald eagles (*Haliaeetus leucocephalus*) in the contiguous United States have experienced a gradual population decline over the last two centuries due to persecution and habitat loss. The rapid bald eagle population decline in the 1940's-1960's stemming from DDT use, which prompted listing of the species as endangered under the Endangered Species Act in 1978, appears to have ended. While the population has recovered substantially, leading to a proposed delisting, continued habitat loss associated with human population growth and land development will probably result in bald eagle population declines again in the near future.

The Pacific Northwest attracts large congregations of wintering bald eagles on its major river systems, with some of the largest gatherings occurring on the Skagit, Nooksack, Sauk, and North Fork Stillaguamish Rivers. Eagles migrate to these rivers from breeding territories in Canada and Alaska to feed on the notable accumulation of spawned-out chum salmon (*Onchorynchus keta*) carcasses on river bars and in side channels between November and February. While in the area, bald eagles use communal night roosts in forest stands that are close to key foraging areas, provide thermal cover, and are shielded from human disturbance. Daytime foraging surveys have documented up to several hundred eagles using each of these major rivers, but only 25 to 30 percent of these birds have been accounted for in the known night roosts.

I developed a set of forward step-wise logistic regression models, using Akaike's Information Criterion, to predict the spatial distribution of additional bald eagle night roost habitat for these four watersheds. I used 50 known night roost locations from Washington Department of Fish and Wildlife databases and a set of 200 random sites in the logistic regression modeling. Predictor variables included topographic attributes such as elevation, slope, and aspect. I also used distance to salmon-bearing streams, road density, and a variety of vegetation parameters as predictors. I modeled the potential night roost habitat at four spatial scales, 10, 40, 70, and 100 ha, to approximate the range of known roost sizes.

The best predictors of potential bald eagle night roost habitat included mean elevation, road density, mode of Quadratic Mean Diameter (tree size class), mean slope,

mean distance to salmon-bearing streams, and standard deviation of aspect. I assessed model classification accuracy using a jackknife procedure. The model had an overall classification accuracy of 83.2%, with roosts correctly classified at 82.0% and random sites at 83.5%. I then used the model to estimate both current potential habitat and potential habitat for 1973. Over 50% of current potential roost habitat is located on private land, and another 20% and 16% are located on Washington Department of Natural Resources (DNR) and United States Forest Service lands, respectively. I detected a net loss of roughly 2,000 ha of night roost habitat between 1973 and 2000, the bulk of which occurred on DNR and private lands.

My map of potential bald eagle habitat in the study area will be useful for directing future roost survey efforts as well as for providing managers with guidance in decision-making and conservation organizations with identification of critical areas for land acquisition efforts. Current potential habitat occupies 66,000 ha of the study area and should be more than adequate to accommodate the "missing" roosts, used by the other 70-75% of the wintering bald eagle population.

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Introduction

Bald eagle protection status and winter ecology

The bald eagle is North America's only native sea eagle. Historically widespread, its population in the contiguous United States has experienced a gradual decline over the last two centuries due to persecution and habitat loss (Stalmaster 1987). Beginning in the 1940's, and continuing for several decades thereafter, the bald eagle population declined precipitously due to the widespread use of DDT and other chlorinated hydrocarbon-based pesticides (Stinson et al. 2001). DDT bioaccumulated up the food web and led to reduced reproductive success in bald eagles as a result of eggshell thinning. In response to this pesticide-induced population decline, in 1978 the United States Fish and Wildlife Service (USFWS) listed the bald eagle (*Haliaeetus leucocephalus*) as an endangered species in the lower 48 states except Michigan, Minnesota, Wisconsin, Oregon and Washington, where it was designated as threatened (USFWS 1999). With the 1972 ban of the use of DDT in the United States along with continuous monitoring and management of bald eagle populations and breeding habitat, their numbers have increased substantially over much of their range.

The bald eagle was downlisted from endangered to threatened in 1995. In July of 1999, the USFWS issued an Advance Notice of Intent to delist the bald eagle. Protection against harassment, injury or killing bald eagles will still be afforded under several federal laws (The Lacey Act, The Migratory Bird Treaty Act, and The Bald and Golden Eagle Protection Act), but removal from the endangered and threatened species list will remove much of the current habitat protection. While its recovery may be considered a success story, loss of habitat could lead to future population decline as carrying capacity is eroded (Watts 1999). Thus while the rapid bald eagle population decline stemming from DDT use appears to have ended and the population has recovered substantially, continued habitat loss associated with human population growth and land development will probably result in the resumption of population declines for the bald eagle in the near future.

The importance of protecting bald eagle breeding habitat has been widely recognized for several decades, and nest sites have been well-characterized (Anthony et al. 1982, Anthony and Isaacs 1989, Wood et al. 1989, Livingston et al. 1990). The negative effect of human disturbance around nest sites has also been observed (Watson and Pierce 1998). However, researchers are increasingly focusing attention on the importance of bald eagle winter habitat, sparked in part by the annual winter phenomenon of large congregations of eagles observed in key areas of the United States. In winter, large numbers of the northern subspecies of bald eagle (*Haliaeetus leucocephalus alascensus*) migrate from their breeding range in Alaska and Canada and congregate in the Pacific Northwest, along the Mississippi River, in the Chesapeake Bay, and in the Great Lakes states.

The wintering population in the Pacific Northwest, and especially in northwest Washington, has been the subject of many studies. The lower Skagit River watershed of northwest Washington hosts one of the largest wintering bald eagle populations in the contiguous 48 states, much of which is concentrated in the Skagit River Bald Eagle Natural Area (SRBENA) (Watson and Pierce 2001). Notable populations have also been observed in northwest Washington during the winter on the Nooksack River (Stalmaster 1976, Hansen 1978) and on the Sauk and North Fork Stillaguamish Rivers (Green 1999).

Radio-telemetry studies have determined that the majority of the population that winters on the major river systems of northwest Washington comes from Alaska, the Yukon, the Northwest Territories, and British Columbia (Watson and Pierce 2001). Bald eagle migration to the region coincides with the chum salmon (*Oncorhynchus keta*) run, which typically begins in November and tapers off by February. Chum salmon have the widest geographic distribution of the seven Pacific salmon species and have historically represented up to half of the annual biomass of salmon in the North Pacific Ocean (Groot and Margolis 1991). The spawned-out carcasses of these semelparous fish comprise a major portion of the bald eagles' winter diet, particularly in even-numbered years when returning chum numbers are greater. Chum salmon are primarily mainstem spawners whose carcasses are routinely stranded on the rivers' banks and gravel bars, making them widely available to foraging eagles. Bald eagles will also feed on coho salmon

(*Oncorhynchus kisutch*) (Stalmaster 1976), pink salmon (*Oncorhynchus gorbuscha*), and Chinook salmon (*Oncorhynchus tshawytscha*) (Servheen 1975). These three species are less available to wintering eagles, however, due to the timing and locations of the runs. For example, pink salmon on the Skagit River only spawn in odd-numbered years and thus do not comprise a large portion of the wintering eagles' diet.

Winter imposes several key stressors on bald eagles in northwest Washington (Stellini 1987). First, food supplies may be reduced due to depressed salmon runs or made unavailable due to flooding or snow. Second, potential for human disturbance is increased as the prime foraging areas are also popular sites for sport fishing and recreation and are also under increasing pressure for development. Also, the presence of the eagles themselves draws many sightseers to these easily accessible foraging areas, especially along the Skagit and Nooksack Rivers. This disturbance may interrupt or prevent feeding as well as force eagles to expend additional energy when flushed. Furthermore, the wintering population of bald eagles in this region may be less habituated to people and as they spend the other eight months of the year in more remote regions of Canada and Alaska. Third, optimal communal night roosting habitat may be far from foraging areas, again necessitating the expenditure of critical energy reserves.

Possible functions of communal roost use

Communal roosting has been observed in many avian species, and a variety of functions and advantages for this behavior have been proposed. Communal roosts may serve as "information centers" where knowledge about food source locations is exchanged, enhancing foraging success for roost members (Ward and Zahavi 1973). In support of this theory, Rabenold (1987) suggested that in a marked population of black vultures in North Carolina, recruitment to food was the primary function of communal roosting. She observed that vultures roosted in larger groups when food sources were scarce and that successful foragers returned to experimental food sources on subsequent days and left the roosts in the morning to forage earlier than did new arrivals or "naive" birds.

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Weatherhead (1983) argued that no single theory explains observed roosting behavior for all individuals in a roost and instead purported that the two primary functions are protection from predation and social food-finding. Thus subordinate individuals benefit from following superior foragers to food sources but are relegated to peripheral positions in the roost that are more vulnerable to predation. The dominant birds gain a buffer against predation by the subordinates that outweighs the cost of food supply "information parasitism."

Another critical feature of a communal night roost is the more favorable microclimate it confers compared to surrounding area. Thompson et al. (1990) observed that wintering turkey vultures in the Mid-Atlantic region roosted communally in forest stands with trees taller and larger in diameter than random sites and theorized it was related to the thermal protection the stands provided. Bald eagle energetics modeling through the use of roost microclimate measurements revealed favorable conditions and reduced nightly energy demands within roosts compared to feeding areas in northern California and Oregon (Keister et al. 1985).

While the behavior is not fully understood, wintering bald eagles in the Pacific Northwest appear to roost communally for several reasons. First, the information center theory has been promoted as the eagles depend primarily on salmon carcasses, a patchily-distributed and ephemeral food source (Servheen 1975, Hansen et al. 1980). Evidence in support of this idea includes observations that new arrivals to the wintering grounds or young, inexperienced birds follow adult individuals to foraging areas (Knight and Knight 1983). Knight and Knight (1983) found that among bald eagles wintering on the Nooksack River, immature birds followed others departing roosts in the morning and entering roosts at night more often than did adults. They also reported that adults had a greater probability of being followed when departing roosts than were immature birds during a flood event in which salmon carcasses were washed away.

Second, bald eagle communal roosts are generally located in sites that provide thermal cover (Hansen et al. 1980, Stalmaster and Gessaman 1984, Keister et al. 1985, Stellini 1987) and are often in proximity to key foraging areas (Watson and Pierce 1998). Hansen (1978) found roosts along the Nooksack River experienced lower wind speeds

and warmer temperatures at night than day-use sites. Roost trees are typically larger in diameter and height than surrounding trees and offer clear lines-of-sight to foraging areas, and roost stands exhibit large variability in individual tree size (multilayered canopies) (Hansen et al. 1980, Anthony et al. 1982). Roost trees generally have an open structure with stout limbs (Stellini 1987, Watson and Pierce 1998). Buehler et al. (1991) found bald eagle roost stands located further from human disturbance and development than random sites on the northern Chesapeake Bay.

Finally, roosts may be used to establish social hierarchies, with older or dominant birds assuming preferred roost positions that provide either greater protection from predation or reduced energetics costs (Zahavi 1970, Adams et al. 2000). Moreover, pair bonds may be formed or renewed in roosts. Allen and Young (1982) proposed this as a possible function for late-winter and early-spring communally roosting bald eagles based on their observations of the species in western North America.

Forest stand composition of bald eagle roosts varies regionally. Eagles have been observed roosting in stands of ponderosa pine (*Pinus ponderosa*) in California, Douglas fir (*Pseudotsuga menziesii*) in Washington, black cottonwood (*Populus trichocarpa*) in Washington and Montana, western larch (*Larix occidentalis*) in Montana, and mixed conifers in Oregon and Washington (Anthony et al. 1982). Wintering bald eagles in northwestern Washington primarily select black cottonwoods or Douglas fir for roosting (Hansen et al. 1980). Despite the diversity in tree species used from region to region, bald eagles do select for stands with old-growth structural components across regions.

An additional component of roosting habitat is the use of "staging areas." These are conspicuous sites where eagles can easily see one another and are usually located on the flight path between foraging areas and roosts. Researchers have speculated that staging areas are used to advertise the departure to the roost (Hansen et al. 1980, Stalmaster 1987). Bald eagles congregate in these areas at dusk and then fly in groups to the roost, often soaring and vocalizing over it before landing. This behavior is thought to be a means of identifying the roost's location.

Loss of access to communal night roosts through habitat destruction or disturbance may adversely affect winter survival rates as eagles are forced to expend

extra energy, depleting critical reserves (Knight and Knight 1984, Stalmaster 1987, Stalmaster and Kaiser 1998). Under such conditions, there may be a decrease in individual fitness, compromising reproductive success and possibly leading to population decline. The once vast coniferous forests of the Pacific Northwest have been heavily logged and subjected to rigorous fire suppression over the last century. With most forests managed on 40- to 80-year rotations and bald eagles clearly selecting for mature stands with at least some trees exhibiting old-growth characteristics, availability of bald eagle roosting habitat is expected to decline. Another critical threat to the availability of roost habitat is rapidly increasing development in rural areas, especially along rivers and shorelines.

Habitat modeling

The use of multivariate statistical analysis in modeling wildlife-habitat relationships has been used increasingly since the 1970's as researchers have recognized its utility in identifying important, measurable micro-habitat variables and subsequent application to management (Shugart 1981). These multivariate approaches bear a fundamental connection to Hutchinson's n-dimensional hypervolume conceptualization of a species' ecological niche. The habitat component of the niche can be characterized by measuring the appropriate suite of environmental variables and using multivariate statistical analysis (Green 1971, Capen 1986). Thus potential habitat for individual species or suites of species can be mapped and population sizes estimated for rare or cryptic species.

Major advances in computing power and software capabilities in the last decade have greatly facilitated habitat modeling, particularly at broader spatial scales, thereby facilitating modeling of macro-habitats. The use of Geographical Information Systems (GIS), remotely-sensed data, and the increasing availability of spatial datasets have also contributed to the growth of habitat modeling at larger scales. Remotely sensed data reduces the need for costly, labor-intensive fieldwork to characterize and quantify habitat variables. GIS software advances allow researchers to process and analyze remotely

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sensed data and perform calculations on large digital spatial datasets. Thus researchers can ask increasingly complex ecological questions, incorporate heterogeneity when considering a species' response to its environment, and predict temporal changes associated with disturbances such as land-use change.

Moreover, the increasing availability and reduced cost of satellite imagery in the last decade has had a dramatic effect on regional- and landscape-scale ecological research and habitat modeling. A variety of studies have shown that land use effects on forest cover can be quantified with the use of remotely sensed data (Hall et al. 1991, Ripple et al. 1991, Spies et al. 1994, Cohen et al. 1995, Cohen et al. 1996, Zheng et al. 1997). This critical information often cannot be collected at the broader scales required for habitat modeling using on-the-ground techniques. Others have demonstrated that satellite data can be used to quantify potential habitat for selected species (Thompson et al. 1980, Saxon 1983, Palmeirim 1988, Jakubauskas 1992, Aspinall and Veitch 1993, Osborne 2001, Wallin et al. in review).

Logistic regression is commonly among the multivariate statistical methods used in wildlife habitat mapping. It is particularly useful for modeling presence/absence data in which a wildlife species has been determined through surveying to be present in some areas and absent in others. The dependent variable, species presence, is binary. If absence data is unavailable, models can be built using a set of random locations against which to compare the presence data (Pereira and Itami 1991, Osborne 2001). Logistic regression is frequently used when data deviate from multivariate normality as it is relatively robust to violations of the assumptions of parametric statistical approaches. Additional functionality is provided in its ability to handle simultaneously both continuous and discrete data types. This statistical approach has been used to model and map potential habitat for many wildlife species including gray wolves in the northern Great Lakes States (Mladenoff et al. 1995), Mt. Graham red squirrels in southeastern Arizona (Pereira and Itami 1991), and mountain goats on Mt. Evans, Colorado (Gross et al. 2002). A multitude of studies have used logistic regression to model potential habitat for a wide variety of avian species (Johnson and Temple 1986, Brennan et al. 1986, Capen et al. 1986, Antonova 2000, Budnik et al. 2002, Dettmers et al. 2002). The use of

multivariate statistical modeling using logistic regression with GIS and remotely sensed data has been well demonstrated as a powerful means to predict the probability of occurrence or the distribution of a species over large areas where field data collection may be logistically or financially prohibitive.

Research objectives

Bald eagle communal night roosts on the Nooksack River were identified in the 1970's and 1980's (Stalmaster 1976, Hansen et al. 1980). Many of the communal night roosts along the Skagit River were mapped and described during the 1980's (Stellini 1987, Watson and Pierce 1998). Efforts by the Mt. Baker-Snoqualmie National Forest to identify, census and map night roosts on the Sauk River, which drains into the Skagit River, began in 1987 (Green 1999). Beginning in the winter of 1996-97, The Nature Conservancy (TNC) and the Mt. Baker-Snoqualmie National Forest coordinated annual volunteer-conducted eagle day use and roost censuses on the N. Fork Stillaguamish, lower Suiattle and lower Sauk Rivers (Raven 1997). However, the roosts identified to date on the Sauk River account for only one third of the eagles that forage on the river during the day (Green 1999). The proportion of foraging eagles accounted for in night roosts is similar for the Skagit watershed (Watson and Pierce 1998). Hansen (1978) observed half the number of eagles roosting as seen during the day along the Nooksack River. Thus it remains unclear where the majority of these birds roost at night. While there appears to be long-term fidelity to roosts in protected areas within these watersheds, some sites appear to have been abandoned in response to human disturbance and land use changes (Hansen et al. 1980, Watson and Pierce 2001). Loss of access to night roosts could adversely impact winter survival even if the foraging areas are protected, indicating a need to identify new roosts and potential roosting habitat.

To date, there has been no comprehensive effort to assess the availability of bald eagle night roost habitat throughout these watersheds. An exhaustive survey effort to locate additional night roost habitat is not practical due to the spatial extent and number of people needed. A modeling effort that utilizes survey data, in conjunction with

information derived from satellite data and GIS coverages, may provide a more practical approach to mapping and monitoring potential night roosts at the individual watershed or regional scale.

The purpose of this study is to identify the ecological variables that are characteristic of known bald eagle night roosts in northwestern Washington and to develop a statistical model from this information that can identify other locations exhibiting these characteristics. These other sites may encompass the "missing" roosts used by wintering bald eagles in the region. I model the potential bald eagle night roost habitat in the Skagit, Sauk, North Fork Stillaguamish, and Nooksack River watersheds through the combined use of remotely sensed data, eagle roost field data collected from the 1970's to present, ancillary GIS topographic and land use/land cover data, and logistic regression analysis. I select a variety of landscape- and stand-level predictor variables identified in the literature as important in bald eagle night roost habitat selection. These include slope, aspect, elevation, vegetation cover, road density, proximity to foraging areas, and timber harvest. The effect of spatial scale on the habitat models is examined using model classification accuracies to determine the scale at which bald eagles may be responding to selected environmental variables. I assess the change in available night roost habitat between 1973 and 2000 by comparing the maps produced after applying the models to current and 1973 habitat conditions (estimated from satellite imagery). This study demonstrates the utility of employing logistic regression with remotely sensed data to model bald eagle night roost habitat.

Specifically, the models will be used to:

1) Discriminate between active night roosts and randomly selected sites using landscape-level variables derived from satellite imagery and GIS coverages (vegetation cover, topographic setting, roads and proximity to feeding areas).

2) Assess the change in availability of night roosting habitat within the study area over the past 30 years.

3) Develop a more complete picture of the distribution of potential night roost habitat throughout the study area from which to make management recommendations.

4) Provide a tool to guide future potential bald eagle night roost survey efforts.

Methods

Study area

The study area is located in northwest Washington state and includes most of the Nooksack, Skagit, Sauk, and North Fork Stillaguamish River watersheds, just under 800,000 ha (Figure 1). The study area was selected based on known bald eagle communal night roost locations in Washington and was further constrained to a region bounded by the Landsat7 ETM+ satellite imagery used in the habitat modeling. It is bounded to the north by the Canadian border, to the east by the crest of the Cascade Mountains, and to the south by the lower edge of the Landsat7 scene (path 46, row 26). The western edge of the Western Cascades of Washington region of the Interagency Vegetation Mapping Project (IVMP) (Browning 2002a) defines the study area's western border.

The majority of the study area is in the western hemlock (*Tsuga heterophylla*) vegetation zone and is dominated by Douglas fir (*Pseudotsuga menzeisii*), western hemlock, western red cedar (*Thuja plicata*), and red alder (*Alnus rubra*) (Franklin and Dyrness 1988). Other common tree species include northern black cottonwood (*Populus trichocarpa*), Pacific silver fir (*Abies amabilis*), grand fir (*Abies grandis*), paper birch (*Betula papyrifera*), and big leaf maple (*Acer macrophyllum*). Mild, wet winters and relatively dry summers characterize the maritime climate of the western hemlock zone. The heavy precipitation (130-300 cm) occurs primarily between October and March; summers receive 6 to 9 percent of the annual precipitation (Franklin and Dyrness 1988).

Data

The Washington Department of Fish and Wildlife (WDFW) provided the bald eagle communal night roost data for Whatcom, Skagit, and Snohomish counties in two GIS layers. A layer representing night roost locations as points came from WDFW's Heritage database, with all but two of 118 roost locations confirmed to within 0.4 kilometers by a reliable source. These two roosts "unconfirmed" roosts were located to
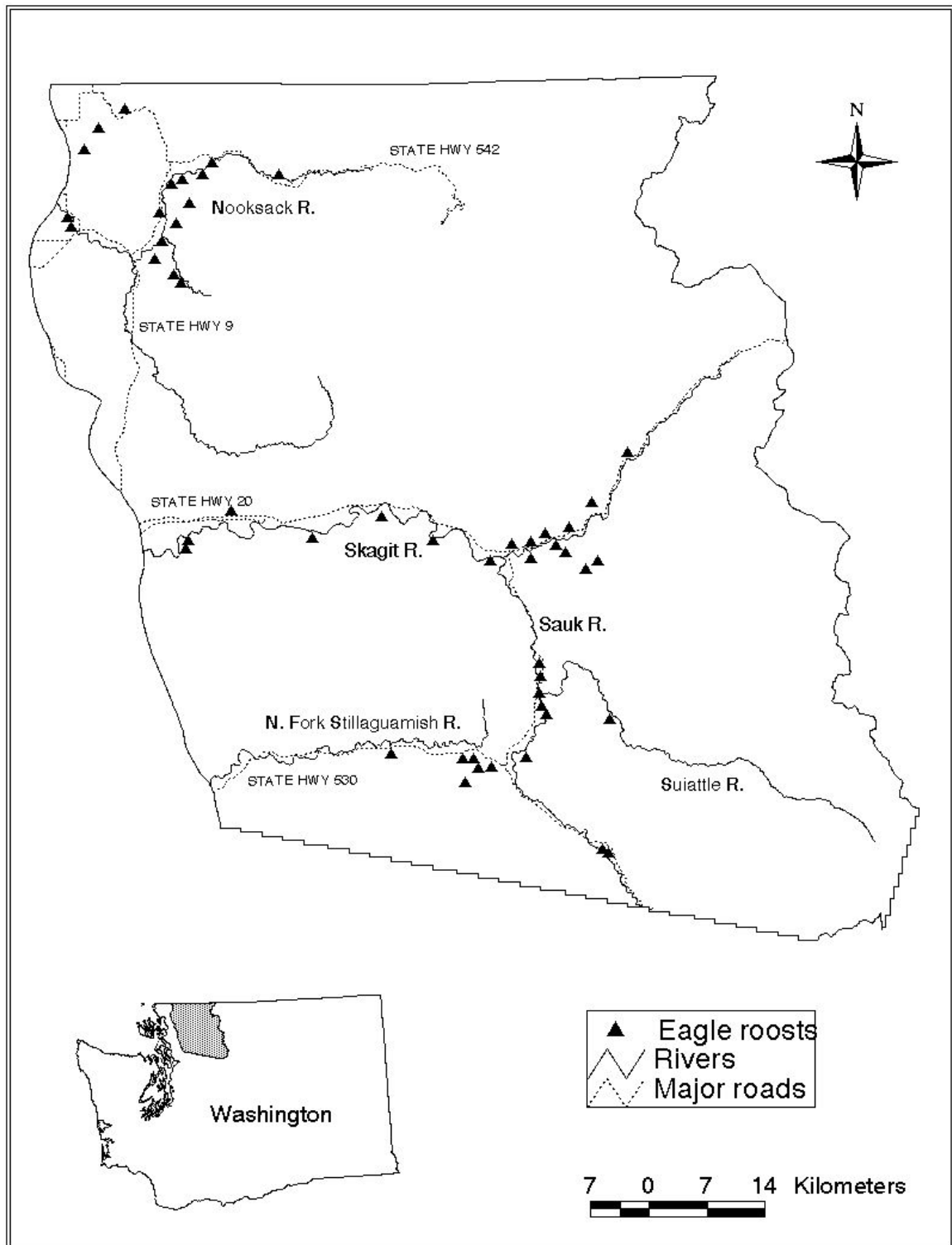
Figure 1. Study area and known bald eagle communal night roost locations in northwest Washington.

within 0.4 kilometers but had not yet been verified by a professional biologist. A second layer representing night roost locations as polygons at the 1:24,000 scale came from WDFW's Priority Habitats and Species database, and all 60 roost locations were confirmed to within 0.4 kilometers by a reliable source. Roost polygons ranged in size from less than one ha to roughly 80 ha and averaged 54 ha. WDFW defines a bald eagle communal night roost as an area used by two or more birds for two or more nights (Stoffel, pers. comm.). While some roosts may be used by up to several hundred bald eagles, most observed in the study area average one to a few dozen bald eagles (Watson and Pierce 1998, Green 1999, and Stinson et al. 2001). The roosts identified were the result of over 25 years of surveys, with some dating back to 1976. I reconciled the two datasets by eliminating any roost polygons already represented in the points layer, deriving centroids for polygons not present in the points layer, and merging the points and centroids layers. This resulted in 57 roosts within the study area. For both the WDFW datasets, the year of the most recent known roost usage was recorded, and this attribute was retained in the merged dataset. The independence of roost datapoints was difficult to ascertain; my criteria for roost independence was to eliminate any that overlapped when buffered with a circle 500 meters in diameter. I chose a buffer size slightly larger than the largest roost area reported in the literature or observed in the WDFW database, and this resulted in 50 bald eagle night roosts to use in the habitat modeling.

During the 2000-2001 bald eagle winter roost survey conducted by TNC, I recorded the locations of two additional roost areas using a Trimble Pathfinder Pro XR Global Positioning System (GPS). Eagles have been observed using these two roosts for the last four years of TNC surveys but the roosts have not yet been submitted to the WDFW for inclusion in the database. I included these two areas in my analysis, resulting in fifty roosts within the study area.

Vegetation cover information was acquired from the Interagency Vegetation Mapping Project (Browning et al. 2002a). This dataset was created from 1992 Landsat TM data and was provided in a continuous format at a 25 meter gridcell resolution. It included four GIS layers: percent broadleaf cover, percent conifer cover, percent

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vegetation cover, and quadratic mean diameter (QMD). QMD was defined as the diameter at breast height (dbh) of a tree of average basal area for the stand and was based on only dominant and co-dominant trees. QMD had values ranging from 0 to 75 inches. Further, all layers had other classes (coded with values >100) representing non-vegetation such as urban areas, agriculture, permanent snow and ice, and rocky or barren areas. For each of the percent vegetation, conifer and broadleaf cover layers, these non-vegetation classes were reclassified as 0 percent vegetation, 0 percent conifer and 0 percent broadleaf cover, respectively. The QMD layer had two additional classes (coded with values >100) with no QMD values: less than 70 percent vegetation cover and less than 30 percent conifer cover. As these areas were assumed to have some trees present, I reclassified them to the QMD value of 0 inches. As explained below, the QMD data were ultimately grouped into broad classes and the areas with QMD values of 0 were thus included in a QMD class of 0-20 inches. The remaining non-vegetation QMD classes retained their coded values >100 and were ignored in all subsequent calculations and analyses except as noted. The IVMP team recommended collapsing these four continuous vegetation grids into a maximum of four classes for percent broadleaf, conifer, and vegetation cover and a maximum of three classes for QMD for improved accuracy (Browning et al. 2002a, 2002b). I collapsed these layers into classes as detailed below.

Roosts in the WDFW datasets were discovered and mapped at different points in time over the last several decades. Many have not been resurveyed recently to verify current use, while others are known to be currently active. For roost habitat modeling, it was necessary to modify the 1992 IVMP vegetation data layers to reflect conditions at each roost when it was last deemed active. These past and present vegetation cover conditions were derived using the IVMP layers and two forest cover change-detection layers, one that mapped change between 1995 and 2000 and one that mapped change for five time periods between 1973 and 1995. I developed the 1995-2000 change-detection layer (Appendix A) using a 1995 Landsat5 TM satellite image and a 2000 Landsat7 ETM+ satellite image to map forest cover change between 1995 and 2000 (Figure 2). I
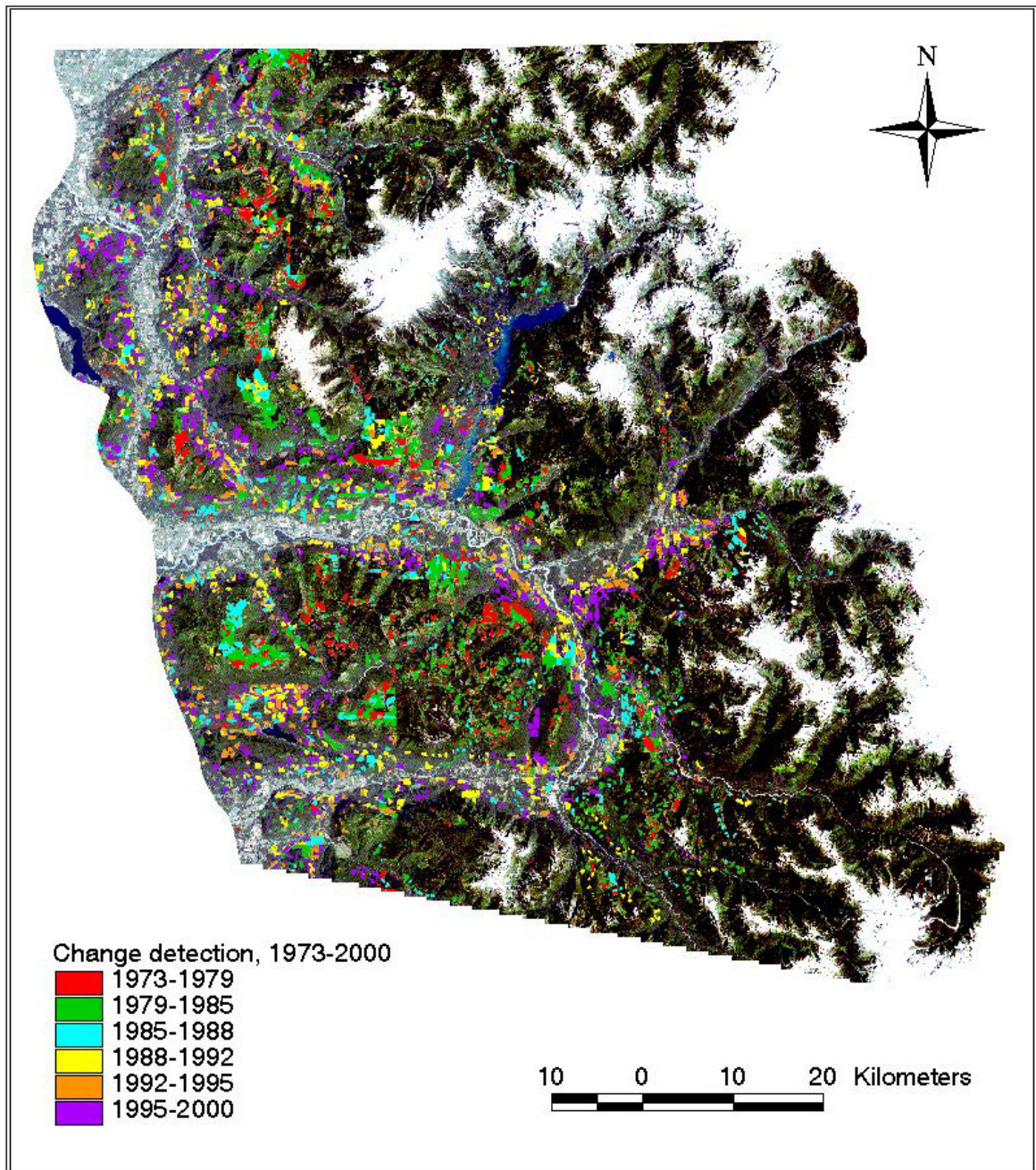
Figure 2. 1973-2000 forest cover change-detection layer for northwest Washington used
to update and backdate 1992 IVMP vegetation layers.*

*Boyce (1999) developed the 1973-1995 time-steps.

used the general methodology of Boyce (1999) such that the 1995-2000 change-detection would provide a sixth time-step to the existing 1973-1995 layer (Boyce 1999). The objective of this change analysis was to map timber harvest and wildfire. The vast majority of the change in the 1973-1995 layer was due to timber harvest rather than wildfire (Boyce 1999), and similar results were expected for the 1995-2000 layer.

Boyce (1999) used an elevation threshold mask to eliminate areas 100 meters below and 1700 meters above sea level in his 1973-1995 change-detection analysis. Areas of apparent change below 100 meters are usually associated with urban growth and agricultural land use changes. Areas of apparent change above 1700 meters are usually associated with interannual differences in snowpack. The results from the 1995-2000 change-detection analysis revealed that in many high elevation areas, changes in late-season senescent vegetation had spectral characteristics that were confused with those for areas where forest cover had been removed. To remedy this, I modified the upper threshold of the elevation mask used by Boyce (1999) from 1700 meters to 1400 meters for the 1995-2000 change-detection analysis to eliminate these areas as forest harvest does not typically occur above this elevation. This procedure did not eliminate all problematic areas in higher elevations, most of which occurred within the North Cascades National Park and wilderness area boundaries. I therefore decided to mask out any change polygons within these boundaries, using a USGS Land Use/Land Cover layer, under the assumption that forest harvest had not occurred there. The 1992 IVMP layers were "updated" to 1995 using the Boyce (1999) change-detection layer, and the resulting 1995 vegetation layers were then used in conjunction with the 1995-2000 change-detection to create 2000 vegetation layers. These procedures are detailed below.

The 1992 IVMP data layers were backdated using the Boyce (1999) change-detection. This data layer mapped areas harvested during five time periods between 1973 and 1995 using Landsat TM satellite images from 1995, 1992, 1988, and 1985 and Landsat MSS satellite images from 1979 and 1973. To make the two change-detection layers consistent, I again masked out change polygons within the North Cascades National Park and wilderness area boundaries due to the aforementioned problems arising from the 1995-2000 change-detection. I applied this change-detection to the 1992

IVMP layers creating "backdated" vegetation grids for each of five time steps between 1973 and 1992, also detailed below.

To benefit from the IVMP reported improved accuracy of collapsing the vegetation layers into categories, I selected the maximum number of classes recommended, four for percent broadleaf, conifer, and vegetation cover and three for QMD. In doing so, I hoped to minimize information loss from the original continuous data. I wanted roughly equally sized categories of which the smallest would best approximate recently harvested vegetation to be used in the updating, or "clearing," procedure and of which the middle or largest would best approximate vegetation conditions at the time of harvest to be used in the backdating, or "restoring," procedure.

Information about percent vegetation, conifer and broadleaf cover prior to harvest was not readily known. I estimated this by examining the 1992 IVMP vegetation layers in conjunction with the 1992-1995 and 1995-2000 harvest polygons. I calculated the mean, mode and median for percent vegetation, conifer, and broadleaf cover within polygons harvested since 1992 to determine the characteristics of stands that were selected for timber harvesting. I also used these statistics to identify the classes into which to collapse these layers such that I would have equally sized classes and that the midpoints of two of them would be appropriate for "clearing" and "restoring" vegetation (Table 1). The four classes selected for percent vegetation, conifer and broadleaf cover were: 0-25 percent, 25-50 percent, 50-75 percent, and 75-100 percent. Each of these three vegetation grids was then reclassified to the class midpoints (Table 2).

I determined that the mode and mean values of vegetation conditions within disturbance areas were closely approximated by the following reclassified (midpoint) vegetation values: 87 percent for conifer and vegetation cover and 12 percent for broadleaf cover. I used these values to "restore" vegetation within pre-1992 harvest polygons (Table 2). This enabled me to create vegetation layers for 1973, 1979, 1985 and 1988. To estimate vegetation conditions for 1995 and 2000, I "cleared" vegetation in each of these three IVMP layers by reclassifying them, within the 1992-1995 and 1995-2000 harvest polygons, to their smallest class size (which included 0 percent cover).

Table 1. 1992 IVMP vegetation cover values within 1992-1995 and 1995-2000 harvest polygons in northwest Washington.

IVMP layer	Mean		Mode		Median	
	1992-1995	1995-2000	1992-1995	1995-2000	1992-1995	1995-2000
Vegetation (% cover)	91	91	100	100	94	95
Conifer (% cover)	71	69	100	100	77	75
Broadleaf (% cover)	21	23	0	0	15	18

Table 2. Classes selected for continuous 1992 IVMP vegetation layers and reclassification values for restoring vegetation cover back in time between 1992 and 1973 and for clearing vegetation cover forward in time between 1992 and 2000.

IVMP layer	Class 1	Midpoint	Class 2	Midpoint	Class 3	Midpoint	Class 4	Midpoint	vegetation restoring value	vegetation clearing value
Broadleaf cover (%)	0-25	12	26-50	37	51-75	62	76-100	87	12	12
Conifer cover (%)	0-25	12	26-50	37	51-75	62	76-100	87	87	12
Vegetation cover (%)	0-25	12	26-50	37	51-75	62	76-100	87	87	12
QMD (in.)	0-20	10	21-40	30	41-75	50	---	---	30	10

Thus percent broadleaf, conifer and vegetation cover disturbance areas were reclassified to 12 percent, and I was able to create vegetation layers for 1995 and 2000 (Table 2).

The QMD layer was reclassified using anecdotal information about forest harvest patterns in Washington state because such patterns have changed notably over recent decades. I wanted to best approximate the average size of trees harvested with respect to both land ownership and the decline in availability of larger trees over this time period. Trees harvested since the 1980's on state lands are typically 60-80 years old and average 30 inches dbh while those harvested on private lands are younger, usually 35-40 years old and average 15 inches dbh (Douglas Couvelier, pers. comm.). However, trees harvested earlier than the 1980's were generally larger. Moreover, harvest is occurring at greater rates on state and private lands and decreasing dramatically on federal lands (Boyce 1999). Based on these considerations, I selected the following classes for the QMD layer: 0-20 inches, 20-40 inches, and 40-75 inches (Table 2). I assumed that trees greater than 50 inches dbh were relatively rare across the landscape and thus selected this value for the QMD 40-75 inch class. To "restore" QMD values back in time, I selected 30 inches (the midpoint of the 20-40 inch class). The QMD layer was "cleared" for the 1995 and 2000 layers using the value of 10 inches (the mid-point of the 0-20 inch class).

Ancillary data included 10-meter resolution Digital Elevation Models (DEMs) acquired from the United States Geologic Survey (USGS) which I mosaiced and resampled to 25 meter resolution. I derived slope and aspect from the DEM using the ArcInfo GRID module. The Washington State Department of Natural Resources (DNR) provided a roads GIS layer at the 1:24,000 scale. This vector layer was rasterized to a 25 meter grid. A 1:100,000 scale streams layer came from the WDFW StreamNet database from which information about anadromous fish presence, including spawning and rearing areas, was derived. I rasterized this layer and created a 25-meter grid representing distance to salmon-bearing streams.

Analysis

I generated 200 random sites within the study area bounds to be used in conjunction with the known bald eagle night roost sites in the habitat modeling. I did not want the random sites to be in areas known to lack potential as bald eagle night roost habitat because inclusion of those areas would produce a less finely-tuned model. As the average distance of roosts to salmon-bearing streams in the study area was 448 meters, and the maximum distance was 2213 meters, I constrained random site selection to an area such that none would be located more than 2500 meters from salmon-bearing streams. Furthermore, random sites were limited to areas below the 1400 meters elevation threshold used in the 2000 change-detection since none of the eagle roosts in the WDFW dataset were above that elevation.

For each of the 50 night roosts and 200 random sites, a variety of vegetation, land use and topographic attributes were extracted from these data layers using a custom C program. These attributes were calculated for each of four square sampling window sizes (10, 40, 70 and 100 ha) centered over each roost and random site. The window sizes were selected to encompass the range of roost sizes reported in the literature and determined from the WDFW bald eagle roost polygon coverage. For each of elevation, slope, percent vegetation cover, percent broadleaf cover, and percent conifer cover, the program calculated a mean and standard deviation for the sampling window. A modified version of the program calculated a circular mean (Zar 1996) and standard deviation for aspect. For percent vegetation cover, proportion of the sampling window occupied by the largest and smallest classes was also calculated. For QMD, the program calculated the mean and standard deviation and the proportion of the window occupied by the smallest and largest size classes, ignoring the cells with values >100 which represented non-vegetation classes. The program also calculated the size class mode which included the three QMD size classes as well as an additional class containing all non-vegetation classes (values >100) lumped together. From the extracted attributes, I manually calculated the proportion of the window occupied by non-forested areas. Finally, the program calculated road density (km/km^2) and mean distance (m) to salmon-bearing streams.

When extracting attributes from the elevation, slope, aspect, road density, and distance to salmon-bearing stream layers, I used all 50 eagle roosts and 200 random points. I assumed these conditions had not changed significantly over the 26 years during which eagle roost data were collected. To extract attributes from the derived vegetation layers, the 50 eagle roosts were lumped into groups corresponding to the six time steps based on the year in which each roost was identified or last surveyed (when available). I randomly selected a proportional number of random points from the 200 random points, relative to the number of roosts, for each time step. The six groups of eagle roosts and subdivided random points were then used in extracting attributes from the vegetation layers of the corresponding time steps.

These extracted attributes were used as predictor variables in a forward step-wise logistic regression model to discriminate between the roosts and random sites. First, all variables were screened for multicollinearity using a correlation matrix in SPSS (2001). I also performed univariate logistic regression analyses of all variables using R software (R Core Team 2001) using an α of 0.2 to select those to be used in the multivariate logistic regression. I wanted to reduce the number of candidate variables yet not remove from analysis any that, while not statistically significant at the traditional α level of 0.05, might still be important in a multivariate context as well as being ecologically relevant (Hosmer and Lemeshow 2000). For any pair of remaining variables that were significantly correlated (Spearman's Rho value ≥ 0.7), I selected the one with the lowest Akaike's Information Criterion (AIC) value and eliminated the other from further analysis.

I then performed multivariate logistic regression using the remaining candidate variables for each of the four window sizes. Variables were selected for entry in the step-wise model building based on their AIC_C value (Young and Hutto 2002). The AIC_C is an AIC value corrected for small sample size (case-to-variable ratios <40) that imposes a penalty for increasing numbers of parameters to minimize over-fitting the model (Burnham and Anderson 2002). An over-fit model is characterized by unrealistically large estimated coefficients and their standard errors and reduced stability (Hosmer and Lemeshow 2000).

Model fit and performance was assessed using classification accuracy. Due to the small sample size, I was not able to divide the roost locations in half for model building and model testing (cross-validation). Instead, I used the Leave-One-Out technique (a form of jackknifing) to derive an unbiased estimate of the models' classification accuracy (Dunham et al. 2002). This is an iterative procedure in which each case is recursively withheld for calculation of model parameters and is then classified by the model derived from the remaining cases. I plotted model sensitivity and specificity for all possible probability thresholds to determine the classification cut-point that maximized both model sensitivity (true positives) and specificity (true negatives) (Hosmer and Lemeshow 2000). This would provide the highest classification success rates for both roost and random sites. I also examined the Receiver Operating Characteristics (ROC) curves as an additional assessment of the models' abilities to discriminate between roost and random sites (Pearce and Ferrier 2000).

Habitat mapping

The model with the highest classification accuracy was used to produce a map of potential bald eagle roost habitat in the study area using a custom "moving window" C program. The program applied the model to the original habitat variable grids by calculating a new grid in which each cell was classified, using the model coefficients and selected cut-point value, as either habitat or non-habitat. For any vegetation variables included in the model, the corresponding derived 2000 vegetation grids were used in the program to estimate current vegetation conditions. The resulting map identified current potential communal night roost habitat in the study area. I also applied the model to the habitat variable grids, using the derived 1973 vegetation grids for any vegetation variables included in the model, to assess how the availability of night roost habitat has changed with respect to land use change over the last several decades. Finally, I used the model to produce a habitat probability map in which each cell had a value between 0 and 1, indicating the probability of the cell being bald eagle night roost habitat.

I evaluated the temporal and spatial distribution of potential bald eagle roost habitat by land ownership using the DNR Major Public Lands GIS layer which identified

private, state, and federal lands. I also used a TNC GIS ownership layer to assess the distribution of current potential roost habitat within TNC preserves.

Results

Data screening and logistic regression analysis

After screening the original 22 variables for multicollinearity and the univariate analyses, I retained 11 variables for the 10 ha analysis window, 12 variables for the 40 ha analysis window, and 10 variables for the 70 and 100 ha analysis windows, respectively, as candidates for entry into the multivariate, forward step-wise logistic regression analysis (Table 3).

I selected the variable with the lowest AIC_C from the univariate analyses as the first variable entered in the forward step-wise logistic regression analysis. After the addition of each variable, I compared the resulting model AIC_C value to the previous model. If the variable addition produced a model AIC_C value lower than that of the previous model, that model was retained and another variable was added and evaluated. If the variable addition did not produce a model AIC_C value lower than that of the previous model, the analysis was terminated at the previous step. For all analysis window sizes, mean elevation was selected as the first variable, and road density was selected as the second (Table 4). Other variables selected, but not for all analysis window sizes, included mean distance to streams, standard deviation of aspect, standard deviation of QMD, mean and standard deviation of slope, standard deviation of percent vegetation cover, mean percent broadleaf cover, proportion of analysis window occupied by non-forest, and QMD mode (Table 4). For each of the 40, 70, and 100 ha analysis windows, I selected five variables in the logistic regression modeling. For the 10 ha window, I selected seven variables. One of the seven variables selected in this model was QMD mode which, because of its three dummy variables, meant nine degrees of freedom were used in the model (Table 4).

For both the 40 ha and 70 ha window sizes, when I added the fifth variable, the AIC_C dropped by <0.2 AIC_C units, a <0.2 percent decline. I deemed this reduction as nominal and chose to retain the two models with only four variables in an effort to avoid over-fitting the model. The addition of the seventh variable for the 10 ha window size

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Table 3. Variables selected from univariate screening for entry into forward stepwise logistic regression model of bald eagle night roost habitat in northwest Washington.

10 ha window	40 ha window	70 ha window	100 ha window
streammean[a]	streammean	streammean	streammean
slopemean[b]	----	----	----
slopesd[c]	slopesd	slopesd	slopesd
elevmean[d]	elevmean	elevmean	elevmean
----	elevsd[e]	----	----
----	aspectmean (sin+cos)[f]	----	----
aspectsd[g]	aspectsd	aspectsd	aspectsd
roaddens[h]	roaddens	roaddens	roaddens
vegsd[i]	vegsd	vegsd	vegsd
qmdsd[j]	qmdsd	qmdsd	qmdsd
conifsd[k]	conifsd	conifsd	conifsd
bdlfmean[l]	bdlfmean	bdlfmean	bdlfmean
qmdmode (qmd1 + qmd2 + qmd3)[m]	----	----	----
----	pctnonforest[n]	pctnonforest	pctnonforest

[a] streammean = mean distance to salmon-bearing stream (m)

[b] slopemean = mean slope (deg.)

[c] slopesd = standard deviation of slope (deg.)

[d] elevmean = mean elevation (m)

[e] elevsd = standard devation of elevation (m)

[f] aspectmean (sin+cos) = mean aspect (deg.)

[g] aspectsd = standard devation of aspect (deg.)

[h] roaddens = road density (km/km^2)

[i] vegsd = standard deviation of vegetation cover (%)

[j] qmdsd = standard deviation of QMD (in.)

[k] conifsd = standard deviation of conifer cover (%)

[l] bdlfmean = mean broadleaf cover (%)

[m] qmdmode (qmd1+qmd2+qmd3) = QMD mode (in.)

[n] pctnonforest = non-forest cover (%)

Table 4. Candidate logistic regression models of bald eagle night roost habitat in northwest Washington for the four analysis window sizes.

10 ha, 6 variables (8 df used due to QMD dummy variables)[b]

	β	SE	Residual Deviance[a]	df	AIC$_C$
Model			141.54	241	163.05
Intercept	-8.557	14.336			
elevmean	-0.009	0.002			
roaddens	-0.452	0.117			
qmd1	9.468	14.324			
qmd2	10.198	14.341			
qmd3	11.291	14.371			
slopemean	0.075	0.026			
streammean	-0.001	0.001			
aspectsd	0.018	0.009			

10 ha, 7 variables (9 df used due to QMD dummy variables)

	β	SE	Residual Deviance	df	AIC$_C$
Model			137.92	240	162.69
Intercept	-8.907	13.857			
elevmean	-0.010	0.002			
roaddens	-0.427	0.116			
qmd1	9.971	13.845			
qmd2	10.665	13.862			
qmd3	12.145	13.898			
slopemean	0.122	0.038			
streammean	-0.001	0.001			
aspectsd	0.022	0.010			
slopesd	-0.147	0.082			

40 ha, 4 variables[b]

	β	SE	Residual Deviance	df	AIC$_C$
Model			159.2	245	170.09
Intercept	1.5038	0.7189			
elevmean	-0.0081	0.0014			
roaddens	-0.5851	0.1406			
pctnonforest	-0.0251	0.0126			
qmdsd	0.1065	0.0549			

40 ha, 5 variables

	β	SE	Residual Deviance	df	AIC$_C$
Model			156.55	244	169.91
Intercept	0.7526	0.8554			
elevmean	-0.0073	0.0014			
roaddens	-0.6087	0.1444			
pctnonforest	-0.0353	0.0168			
qmdsd	0.1112	0.0564			
vegsd	0.0394	0.0252			

70 ha, 4 variables[b]

	β	SE	Residual Deviance	df	AIC$_C$
Model			162.2	245	173.09
Intercept	-0.9943	0.9651			
elevmean	-0.0065	0.0012			
roaddens	-0.5253	0.1421			
qmdsd	0.1726	0.0572			
bdlfmean	0.0428	0.0208			

70 ha, 5 variables

	β	SE	Residual Deviance	df	AIC$_C$
Model			159.61	244	172.97
Intercept	-0.8126	0.9858			
elevmean	-0.0054	0.0014			
roaddens	-0.5028	0.1436			
qmdsd	0.1691	0.0572			
bdlfmean	0.0427	0.0213			
streammean	-0.0008	0.0005			

100 ha, 5 variables[b]

	β	SE	Residual Deviance	df	AIC$_C$
Model			160.99	244	174.35
Intercept	-0.8029	1.0292			
elevmean	-0.0053	0.0014			
roaddens	-0.5021	0.1551			
qmdsd	0.1767	0.0580			
bdlfmean	0.0449	0.0228			
streammean	-0.0010	0.0005			

[a] Null deviance for all models was 250.2

[b] Final candidate model selected for each analysis window size

reduced the AIC_C by <0.4 AIC_C units, a <0.3 percent decline. Again, I regarded this as inconsequential and selected the model with six variables to reduce model over-fitting (Table 4). Moreover, the classification accuracies of the eliminated models were exactly the same for the 10 ha analysis window and only marginally improved (~1%) for the 40 and 70 ha analysis windows (not presented).

For the "best model" selected for each of the analysis window sizes, bald eagle roost habitat had a negative relationship with increasing elevation and road density, as indicated by the negative sign of the variable coefficients (Table 4). Similarly, roost habitat had a negative relationship with increasing distance to salmon-bearing streams for all analysis window sizes. For the 40 ha analysis window, roost habitat also had a negative relationship with increasing percent of the window occupied by non-forest. Conversely, roost habitat had a positive relationship with increasing standard deviation of QMD for all analysis window sizes. The association between roost habitat and mean percent broadleaf cover was positive for the 70 and 100 ha windows as it was with mean slope for the 10 ha window. QMD mode was represented by 3 dummy variables, QMD1, QMD2, and QMD3, which corresponded to increasing QMD size classes. Roost habitat had a positive relationship with all QMD mode dummy variables, indicating that it is associated with areas that have trees present.

Among the four models selected as the "best models" (one model for each of the four analysis window sizes), overall results of model performance and classification accuracy were similar. Each of the four models had ROC Area-Under-the-Curve (AUC) values ranging from 0.888 to 0.918, all of which differed significantly (p<0.001) from the null hypothesis that the AUC = 0.5 (Table 5). The results of the cross-validation procedure for each of the four models indicated similar classification accuracies (Table 5). The percent of roosts correctly classified as habitat ranged from 80.0 to 84.0, while the percent of random sites correctly classified as non-habitat ranged from 79.5 to 83.5. Overall classification accuracies ranged from 80.0 to 83.2 percent. The classification cut-points used to obtain these results were selected to maximize model sensitivity and specificity and ranged from 0.25 to 0.29. For example, the model derived from the 10 ha analysis window maximized sensitivity and specificity with a classification cut-point of

Table 5. Logistic regression model assessment: ROC AUC values and cutpoints selected for classification of roosts and random sites, and classification accuracies using the Leave-One-Out procedure.

Window size	ROC AUC	Cut-point	Roost % correct	Random % correct	Overall % correct
10 ha	0.918*	0.29	82.0	83.5	83.2
40 ha	0.895*	0.26	80.0	80.0	80.0
70 ha	0.888*	0.27	80.0	81.5	81.2
100 ha	0.888*	0.25	84.0	79.5	80.4

* P<0.001

Table 6. Change in availability of potential bald eagle night roost habitat in northwest Washington between 1973 and 2000.

	1973	2000
Total habitat in study area (ha)	68158	66098
Habitat as percentage of study area	8.6	8.3
Habitat loss since 1973 (ha)	---	2235
Habitat gain since 1973 (ha)	---	176
Net habitat loss since 1973 (ha)	---	2060
Net habitat loss since 1973 (%)	---	0.3

0.29 (Figure 3). At the classification cut-point of 0.29, the commission error rate, or misclassification of random sites as roosts, and the omission error rate, or roosts misclassified as non-habitat, was less than twenty percent (Figure 3). The model derived from the 10 ha analysis window had the highest overall classification accuracy and ROC AUC value (Table 5, Figure 4).

Habitat mapping

I selected the model derived from the 10 ha analysis window for its highest overall classification accuracy and its largest ROC AUC value and used it to paint the maps of potential bald eagle night roost habitat for 1973 and 2000. The map of current potential habitat (produced using the QMD layer updated to 2000) comprised approximately 8 percent, or roughly 66,000 ha, of the entire study area (Table 6). The habitat was largely concentrated along the lower elevation reaches of the Nooksack, Skagit, Sauk, Samish and North Fork Stillaguamish Rivers while the remainder of the study area was classified as non-habitat (Figure 5). The overlay of known roost locations on the potential habitat showed strong agreement between actual roost sites and predicted roost habitat (Figure 5). The map produced using the QMD layer backdated to 1973 identified about 9 percent of the study area as potential habitat, just over 68,000 ha (Table 6). This represented less than a 1 percent decrease in potential habitat since 1973 in the study area. The spatial distribution of the 1973 potential habitat was similar to that of the 2000 potential habitat (not presented). Approximately 176 ha of potential habitat was gained in the study area between 1973 and 2000, while 2235 ha of potential habitat was lost, resulting in a net loss of roughly 2000 ha of potential habitat (Table 6).

For the bald eagle night roost habitat probability map, I grouped potential habitat probabilities into the following categories: 0-0.2, 0.21-0.4, 0.41-0.6, 0.61-0.8, and 0.81-1 (Figure 6). The habitat with the highest probability values was largely concentrated along the major river corridors in a pattern similar to that of the binary habitat maps for 1973 (not presented) and 2000 (Figure 5). Darker areas, representing higher probability values, are most abundant along the Skagit, Nooksack, Sauk, and North Fork
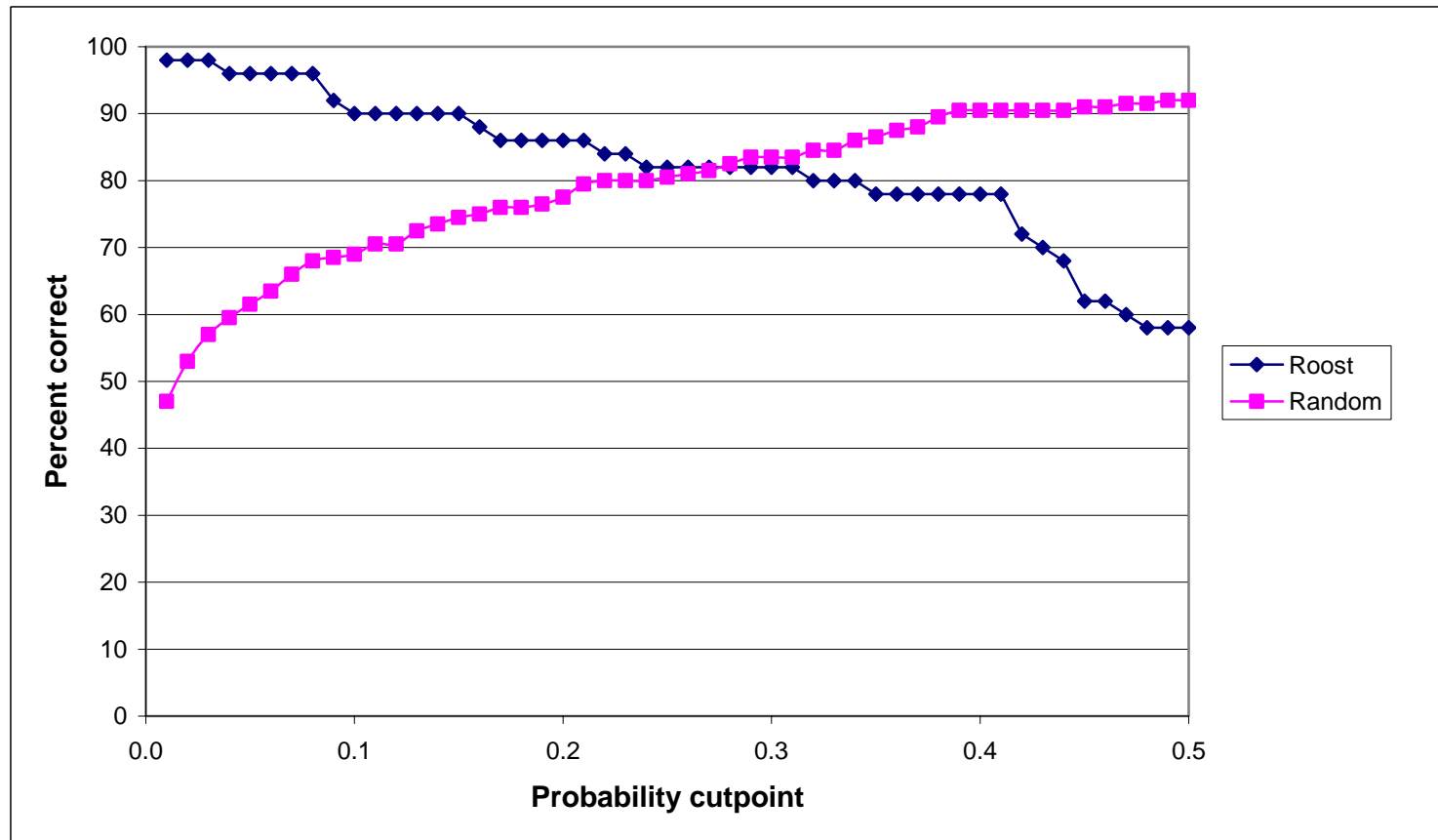
Figure 3. Sensitivity and specificity for the 10 ha model (6 variables) of bald eagle night roost habitat over the range of potential classification cut-points.
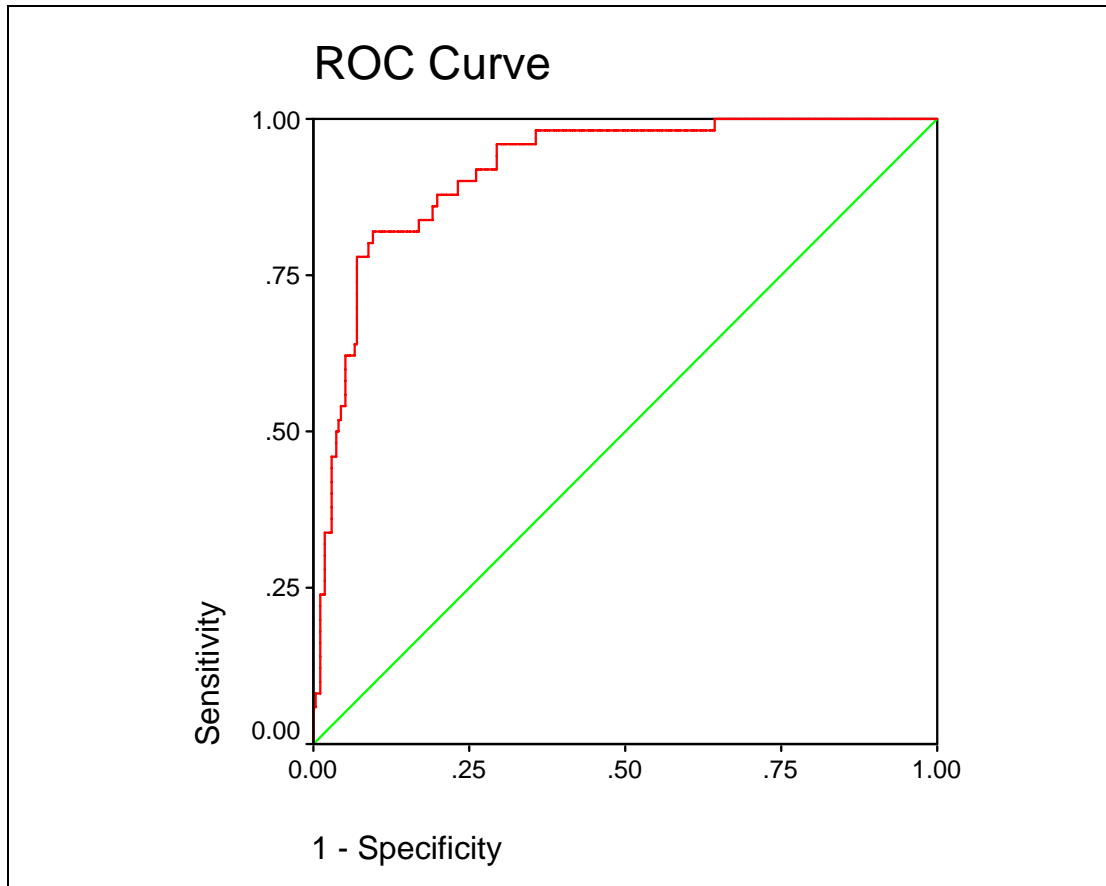
Figure 4. ROC curve for final bald eagle night roost habitat model based on 10 ha analysis window.
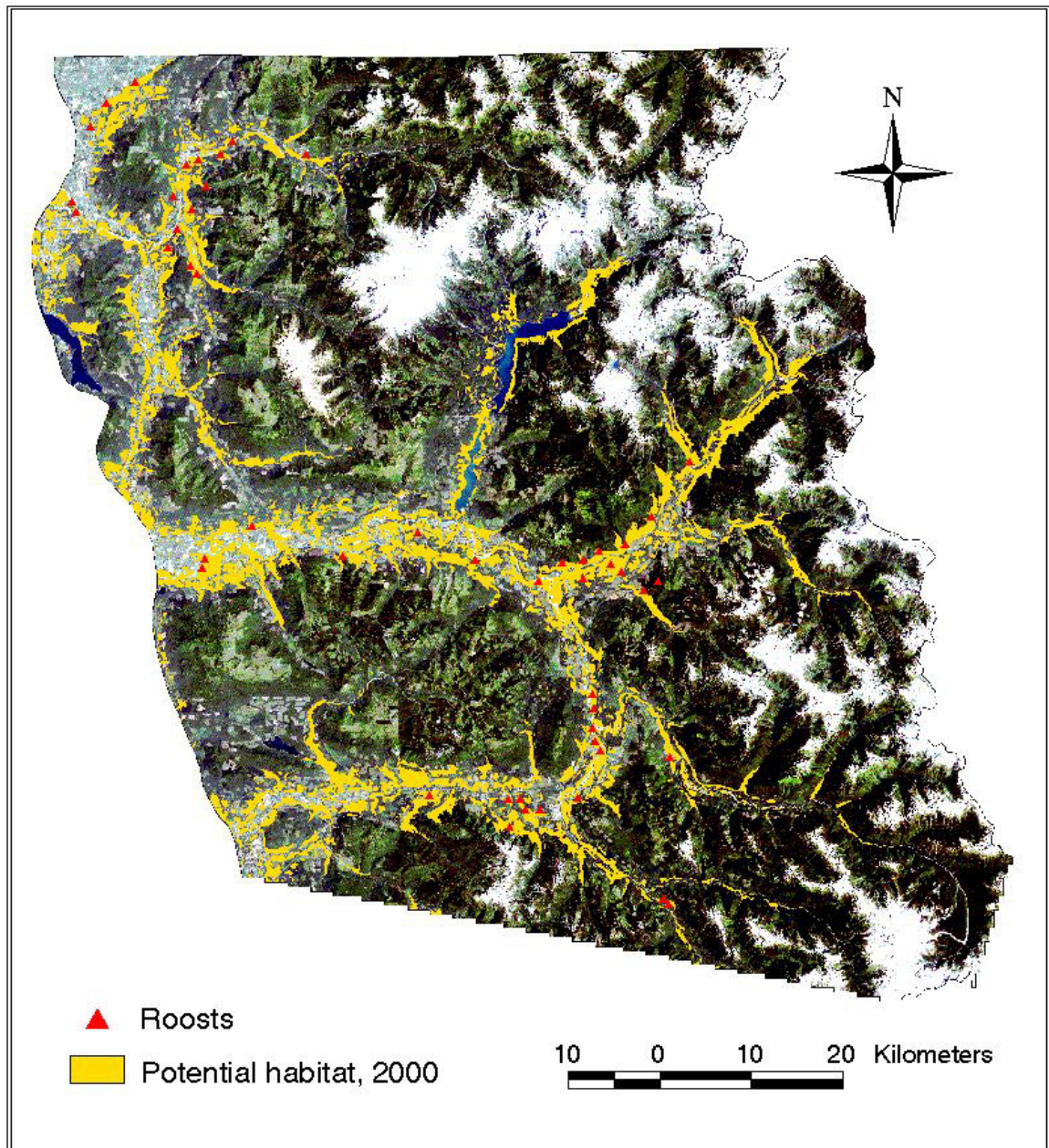
Figure 5. Potential bald eagle night roost habitat in 2000 and known bald eagle communal night roost sites in northwest Washington.

Figure 6. Bald eagle night roost habitat probability and known bald eagle night roost locations in northwest Washington in 2000.

Stillaguamish Rivers and are generally restricted to the lower elevation regions of the study area. In the overlay of the known bald eagle communal night roosts on the habitat probability map, known roost sites were generally distributed, with just a few exceptions, in the higher probability areas. Almost half of the known bald eagle night roosts were located in the 0.61-0.8 probability areas, roughly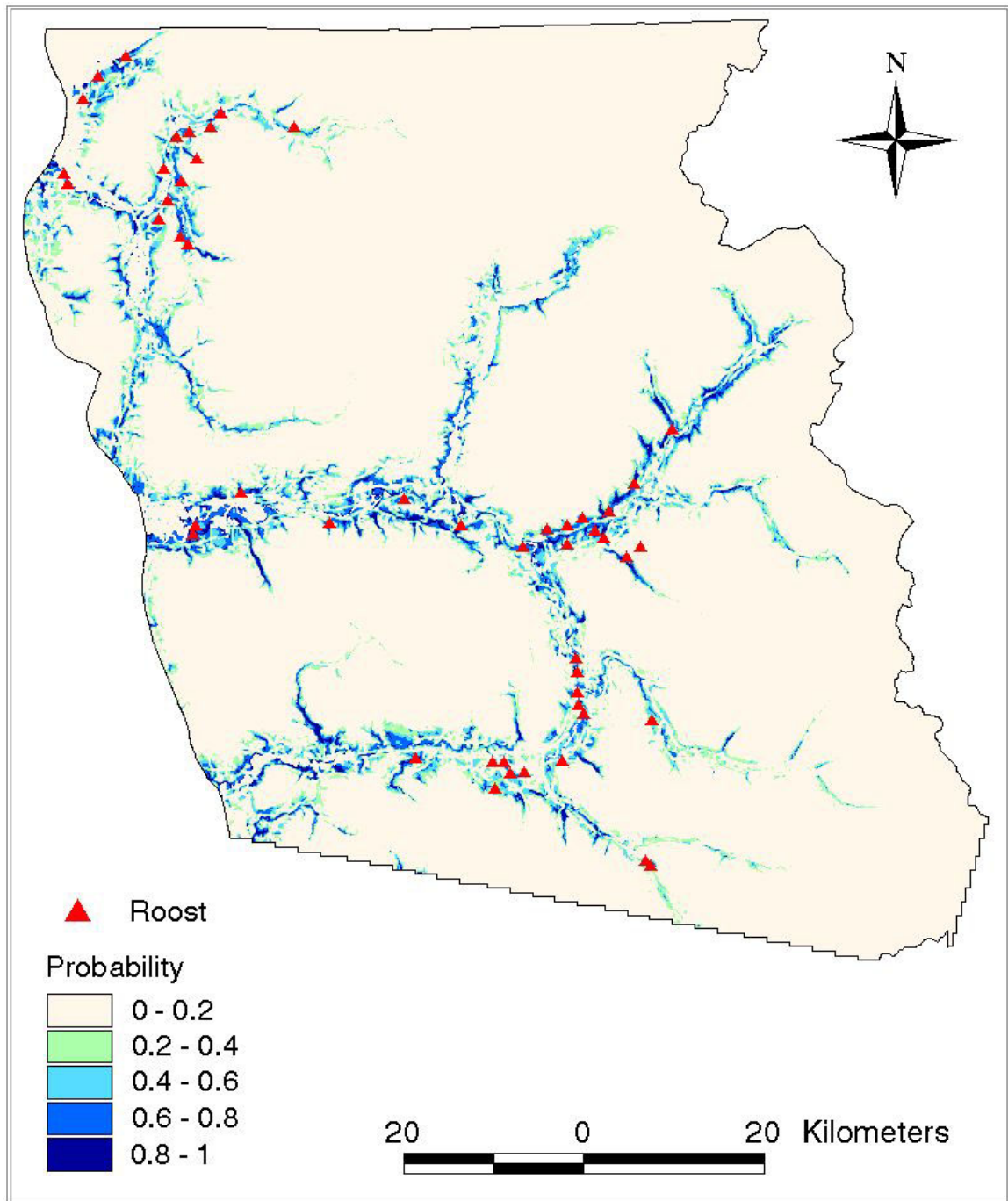 25 percent of the roosts were within the 0.41-0.6 probability areas, and the remaining roosts were distributed among the 0-0.2, 0.21-0.4, and 0.81-1 probability areas (Figure 7). In contrast, nearly 80 percent of the area within 2500 meters of streams (the area used to constrain the random points in the modeling procedure) was located in the 0-0.2 probability areas and the remaining 20 percent was distributed in decreasing amounts among the 0.21-0.4, 0.41-0.6, 0.61-0.8, and 0.81-1 probability areas (Figure 7).

Potential habitat by land ownership

The vast majority, over 55 percent, of potential bald eagle night roost habitat was located on privately held lands, and another 40 percent was distributed, in decreasing amounts, among the DNR, the United States Forest Service (USFS), and the North Cascades National Park (NPS) (Figure 8). No potential habitat was located on county park lands, and only a nominal amount was found on lands managed by the Washington state park system, the Bureau of Land Management (BLM), and the U.S. Department of Defense (DOD). A similarly small amount of potential habitat existed in USFS wilderness areas. Only a slight change in the distribution of potential habitat by land ownership occurred between 1973 and 2000, with most of the change manifested as a decrease in proportion of potential habitat on DNR and private lands and an increase in proportion of potential habitat on TNC lands (Figure 8). Proportion of potential habitat increased by a very small amount on NPS and wilderness lands.
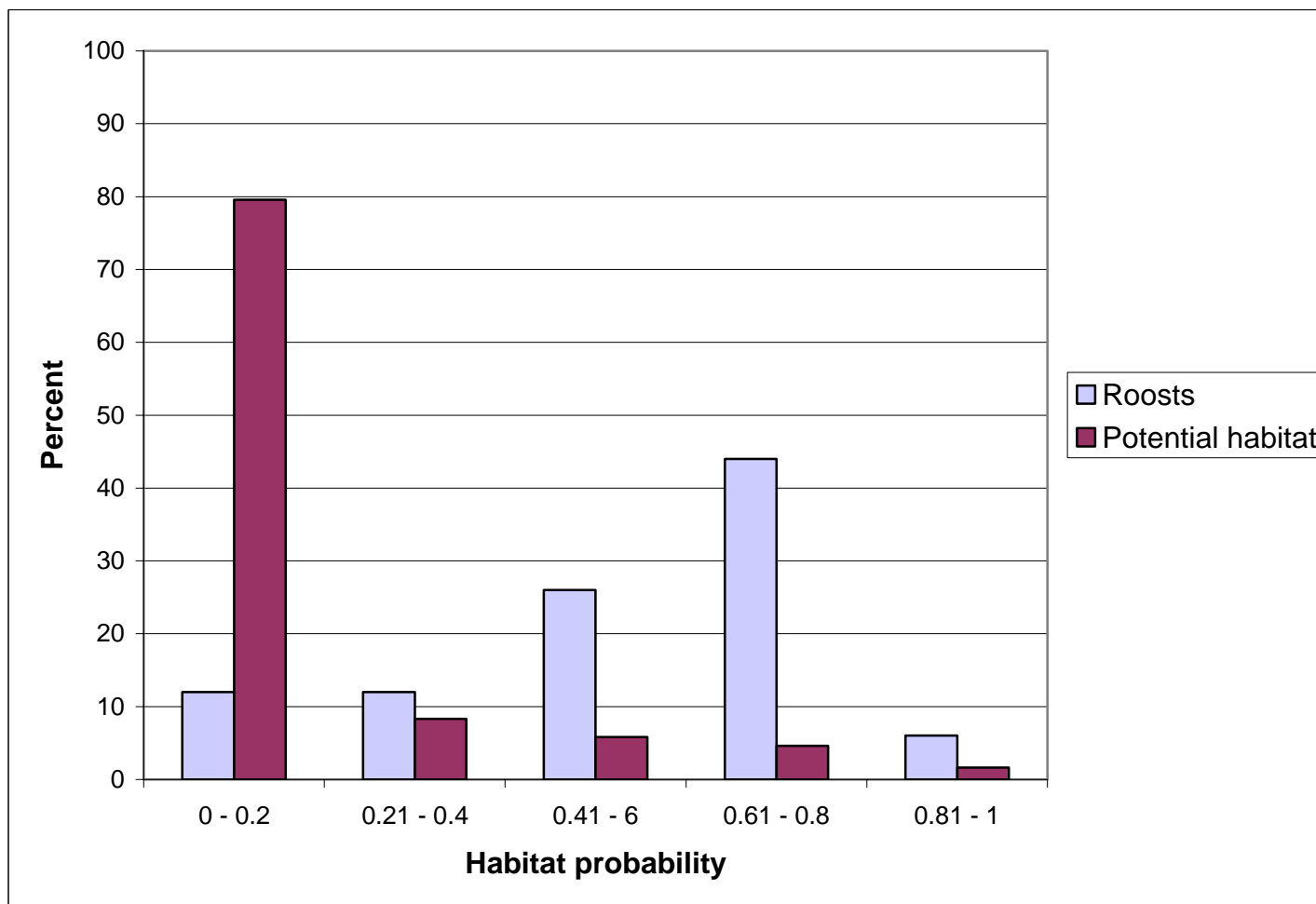
Figure 7. Percent of known bald eagle night roost sites and percent of potential habitat area* by five probability categories for northwest Washington in 2000.

*Area of potential habitat within probability categories was calculated only for the area within the 2500 meter buffer used to constrain

the random points while modeling.
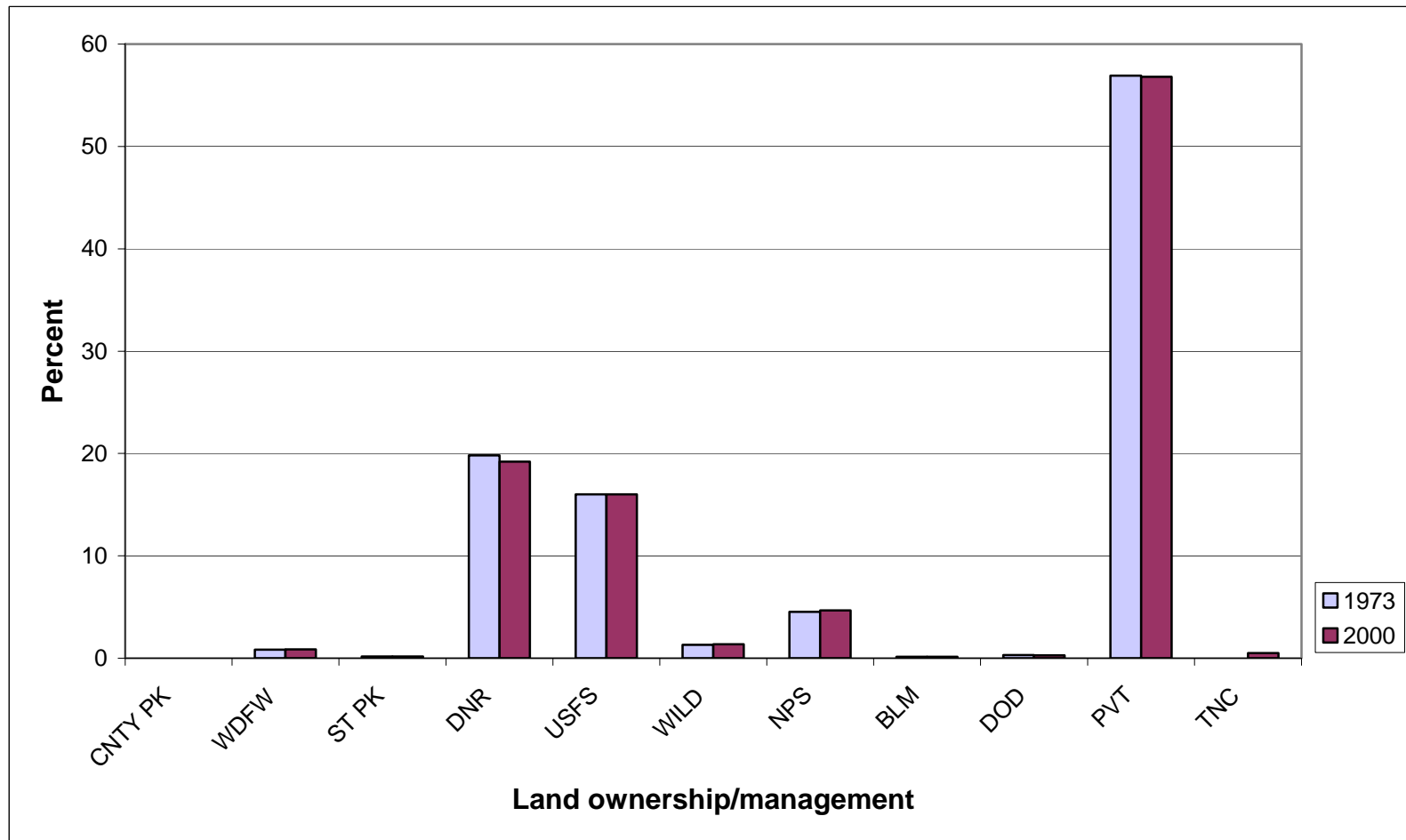
Figure 8. Distribution of potential bald eagle night roost habitat in northwest Washington by land ownership and management as percentage of total potential habitat in 1973 and 2000.

CNTY PK = county park, WDFW = Washington Department of Fish and Wildlife, ST PK = state park, DNR = Washington Department of Natural Resources, USFS = United States Forest Service, WILD = USFS wilderness, NPS = National Park Service, BLM = Bureau of Land Management, DOD = US Department of Defense, PVT = private.

Variable selection and ecological relevance of model

The results of the bald eagle night roost habitat modeling are congruent with our understanding of bald eagle natural history and, specifically, winter roost habitat preferences. Wintering bald eagles select roost sites that are close to food and foraging areas, provide thermal cover, have larger trees with suitable perches, and are away from human development and disturbance (Anthony et al. 1982, Stellini 1987, Buehler 1991). The variables included in the various candidate models are all related to these broad factors in night roost habitat characteristics (Table 4). Distance to food and foraging areas is directly quantified by distance to salmon-bearing streams. Mean elevation, aspect standard deviation, and mean slope are measures of, albeit indirect, thermal cover. Some of the other vegetation variables such as mean percent broadleaf cover, standard deviation of percent vegetation cover, and percent non-forest may also relate to thermal cover. QMD mode and standard deviation, as statistics of the diameter of trees of average basal area in a stand, can indicate the presence of large trees. Finally, road density is one method of quantifying human development and disturbance. Wintering bald eagles in the Skagit, Nooksack, Sauk, and North Fork Stillaguamish Rivers watersheds clearly choose sites for roosting that are close to salmon-bearing streams, are low in elevation, and have fewer roads than the surrounding areas (Table 4). All candidate models included the mean elevation and road density variables, and these were always the first two variables selected for entry in the forward step-wise logistic regression. This attests to the importance and strength of these factors in predicting night roost habitat.

The inclusion of mean elevation as a strong predictor variable for bald eagle night roost habitat is likely an effect of several factors. The negative relationship between increasing elevation and roost habitat probably relates to bald eagle preference for sites that provide thermal protection. Mean ambient temperatures generally decrease with increasing elevation. Also, the preferred foraging areas are generally located below a few

hundred meters in elevation; the chum salmon that comprise the bulk of wintering eagles'
diet generally spawn in the mainstems and sloughs of major rivers and are thus at lower
elevations.

Numerous studies have documented sensitivity of wintering bald eagles to human
disturbance resulting from home construction, timber harvest, fishing, and recreation
(Stalmaster 1976, Knight and Knight 1984, Stalmaster and Kaiser 1998). Buehler et al.
(1991) characterized Chesapeake Bay bald eagle winter roosts as being away from paved
roads and not in areas with human development. They found building density within 500
meters of roosts to be much less than that of random sites. Watson and Pierce (1998)
documented that roads were located between 86 percent of the roosts and the nearest
water and that homes were located between 50 percent of the roosts and the nearest
water. The distance to nearest water, however, did not necessarily indicate primary
foraging areas. Moreover, no statistical comparisons of roosts to other areas were
reported regarding the presence or number of roads or homes. While the findings of
Watson and Pierce (1998) seem inconclusive, most studies that examined the effect of
human disturbance and development on availability of roost habitat determined that
eagles preferred roost sites away from such areas (Hansen et al. 1980, Buehler et al.
1991).

My results differ; road density was an important predictor variable that had a
negative relationship with roost habitat. Most roosts have been identified by observing
bald eagles at key foraging areas in the late afternoon and watching where they
congregate (staging areas) just before dusk. The birds then typically fly in short
succession or in groups to the roost stand. Because the viewing access to the foraging
locations is almost always provided by roads, a potential exists for bias in assessing the
relationship between roosts and the presence of roads. This exemplifies a common
problem with the collection of wildlife survey data. Antonova (2000) expected that
distance to roads was an important factor in ferruginous hawk nest site selection as the
species is sensitive to human disturbance, but she could not include it as a potential
variable in habitat modeling because the majority of known ferruginous hawk nests were
found during surveys conducted along roads. Hence, she anticipated a positive bias

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between nests and distance to roads which would not reflect the true influence of roads on ferruginous hawk nest site selection. In spite of the potential for a spurious positive relationship between bald eagle night roosts and road density in my models, this predictor variable emerged as a strong measure of the negative impact human disturbance has on bald eagle roost site selection.

The mean distance to salmon-bearing streams was another important variable included in half the candidate models and in the final model. Across their wintering range, bald eagles frequently select communal night roost sites that are close to foraging areas (Hansen 1978, Keister and Anthony 1983, Stellini 1987, Watson and Pierce 1998). In northwest Washington, foraging areas include lakes, shorelines, and most notably, rivers with high numbers of spawning salmon. The inclusion of the mean distance to salmon-bearing streams in the model relates directly to bald eagles' preference for sites close to foraging areas. This in turn relates to reduced energetics costs in not having to fly great distances between prime feeding areas and roost sites.

Mean slope was selected in the final model and had a positive association with bald eagle night roost habitat. Wintering bald eagles in this region have been shown to choose sites that are steeper than surrounding areas (Hansen 1978). Researchers speculate that this may be due to the clear lines-of-sight to foraging areas and flight corridors provided by sites on steeper terrain. This variable was only selected for the two candidate models derived from the 10 ha analysis window which suggests that it is more of a stand-level characteristic and is probably not important at a landscape scale.

Studies conducted across the range of wintering bald eagles have clearly demonstrated that roost trees are the tallest and largest diameter trees available in the stand (DellaSala 1998, Watson and Pierce 1998). Roost stands typically have some remnant old-growth characteristics (Anthony et al. 1982, Keister and Anthony 1983, Stalmaster and Kaiser 1997). The selection of QMD mode in the model may corroborate this, based on its positive association with roost habitat indicates. However, interpretation of dummy variable coefficients in logistic regression modeling is somewhat problematic. Here, I can conclude that roost habitat has a greater probability of occurring on sites where trees are present when compared to random locations. I cannot, however,

make generalizations about the influence of QMD size class, based on the relative size of the QMD mode dummy variable coefficients, on the probability of roost habitat. In the logistic regression analysis, the dummy variables for QMD mode were compared to the reference category of areas with no trees present. A different dummy variable coding scheme for QMD mode would be required to make comparisons between the various QMD size classes. From a statistical hypothesis-testing standpoint, an obvious caveat regarding QMD mode would be that the coefficients' standard errors are larger than the coefficients themselves and thus could include a coefficient value of zero, suggesting that QMD mode may not be contributing substantially to the model. QMD mode was selected, though, using the AIC_C criteria, and reduced the AIC_C value by almost 10 units, over 5 percent (not presented). Its inclusion in the model makes sense ecologically and reflects the importance of the presence of trees to wintering bald eagles. This is not a surprising result, but future analyses should aim to include variables that more directly relate to bald eagle preference for larger trees. Different vegetation information, perhaps at a finer, stand-level scale, may be required to elucidate this relationship.

Previous studies have demonstrated that wintering bald eagles prefer leeward slopes when selecting communal night roosts (Hansen 1978, Buehler et al. 1991, Watson and Pierce 1998). This substantiates the theory that eagles seek forest stands with more favorable microclimates. Stellini (1987) and Hansen (1978) measured microclimate variables in bald eagle winter roost stands in the Skagit and Nooksack Rivers, respectively, and found wind speeds to be lower and temperatures to be higher than surrounding areas. I expected mean aspect to be an important predictor variable, but suspect that for a study area of this size, it failed to be included in the model due to differences in local ground air movements and prevailing wind direction between the major watersheds. Had I modeled habitat within just one watershed, or modeled each watershed separately, a pattern regarding aspect may have emerged. The standard deviation of aspect was selected in the modeling process, however, and this suggests the importance of stand-level heterogeneity. Meso-scale heterogeneity may provide more options for thermal protection regardless of wind direction. Eagles may relocate within a stand according to changing weather and wind conditions. If this is the case, I would

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surmise that the failure of aspect standard deviation to be included in the candidate models derived from the 40, 70, and 100 ha analysis windows is a function of spatial scale.

In general, I expected that the vegetation variables would be important predictors of bald eagle roosting habitat, but for all candidate models, only one or, at most, two vegetation variables were selected (Table 4). It may be that the vegetation characteristics eagles respond to in habitat selection are not well captured at the spatial scales of this analysis. The IVMP vegetation layers are relatively coarse, particularly in terms of characterizing forest structure and identifying stand-level characteristics. QMD only approximates stand age, which in turn would reflect the canopy structure that bald eagles may respond to in roost site selection. Within these IVMP vegetation layers, forest composition is identified only as conifer or broadleaf. Further, both the percent broadleaf cover and percent vegetation cover layers included shrubs and herbaceous vegetation types which are not likely relevant to bald eagle winter habitat preference but may obscure the importance of, in particular, the percent broadleaf cover. Wintering bald eagles in northwest Washington roost in black cottonwood, big leaf maple, and red alder, especially early in the season when they tend to select on-river sites (Green 1999). Later in the winter they tend to shift roost use to off-river sites dominated by conifers, probably for the increased thermal protection provided by evergreen tree species.

Another consideration is that the accuracy reported for the IVMP data is not especially high. Using the IVMP team's recommendation of not more than 4 classes for collapsing the percent vegetation, broadleaf and conifer cover layers, the overall accuracy for these layers is approximately 86, 56, and 70 percent, respectively (Browning et al. 2002b). Further, the accuracies for federally managed lands within the percent broadleaf and conifer cover layers are >20 percent higher than those for non-federal lands in these layers. This is attributed to the availability of far more ground-truthed data from federal lands than from non-federal lands for the IVMP accuracy assessment. Only for the percent vegetation cover layer are these two accuracies similar. Using the IVMP team's recommendation of not more than 3 classes for collapsing the QMD data layer, the overall accuracy is about 77 percent, with the accuracy for federally managed lands being

20 percent greater than for non-federally managed lands (Browning 2002b). With nearly 50 percent of the known night roosts located on private land, and almost 40 percent of the entire study area in private ownership, the reduced accuracy for non-federally managed lands relative to federally managed lands could impact the effect of the vegetation variables in the habitat modeling.

An additional factor in evaluating the vegetation variables is the accuracy of the vegetation layers resulting from application of the change-detection layers as well as that of the change-detection layers themselves. The 1973-1995 change-detection layer had accuracies of 95 and 100 percent for change and no-change areas, respectively (Boyce 1999). The change-detection 1995-2000 layer had similar accuracies of 94 and 100 percent for change and no-change areas, respectively, once the problematic areas in high elevation wilderness and NPS lands were masked out. As the 1992 IVMP vegetation layers were updated and backdated using the 1995-2000 and 1973-1995 change-detection layers, respectively, errors likely compounded with each time-step forward from 1992 and backward from 1992. It is difficult to ascertain how large these errors might be or the magnitude of their effect on the vegetation variables and subsequent modeling.

Model assessment and final model selection

Logistic regression modeling has been widely used in modeling wildlife-habitat relationships, and there are a variety of approaches that can be used to select variables for inclusion in these models (Brennan et al. 1986, Mladenoff 1995, Pearce and Ferrier 2000, Osborne 2001). Among these, the use of information theory, and especially Akaike's Information Criterion, has gained increasing support in the literature (Watson and Pierce 1998, Budnik et al. 2002, Dettmers et al. 2002, Dunham et al. 2002, Gross 2002). One of the features of model selection based on AIC, or in this case AIC_C, is that it may not identify a single best model but instead results in a set of competing best models from which robust "multimodel inferences" may still be made (Burnham and Anderson 2002). AIC is based not on statistical hypothesis testing but on an information-theoretic approach in which the Kullback-Leibler (K-L) information is minimized. K-L

information is the "information" lost when a model is used to approximate "full reality." Since full reality can never be known, this K-L information, or "distance" between full reality and the approximating model, is estimated based on the empirical log-likelihood function. Thus a model is selected from candidate models based not on an arbitrary α level but on its ability to minimize the loss of information contained within a dataset.

Having chosen this approach for my bald eagle roost habitat modeling, I had to make some decisions about several issues that arose. First, my goal was not only to produce a powerful model of bald eagle winter roost habitat but also to paint a map of potential habitat across the study area. Therefore, I needed to select one model from the many models generated to paint the potential habitat map. Second, while AIC_C imposes a penalty for increasing numbers of parameters to reduce model over-fitting, I still had concerns about the case-to-variable ratios of my models. Third, a constraint of the AIC_C-based model selection approach is that it cannot be used to compare models of different datasets, which was the case in selecting a model from among the four analysis window sizes. I identified a set of criteria to reduce the number of candidate models and to choose the final model for potential habitat mapping. These involved balancing the examination of model classification accuracy and ROC AUC values against minimizing the AIC_C values. The AUC statistic tests whether the curve resulting from plotting sensitivity (proportion of true positives) versus 1-specificity (proportion of false positives) has an area >0.5 (Fielding 2002). If the null hypothesis is rejected, then the model will discriminate between roosts and random sites with better than a fifty-fifty chance. This set of model selection criteria notwithstanding, arriving at the best model for potential habitat mapping was not an obvious choice.

First, I reduced the six candidate models (Table 4) to a set of four models, one for each analysis window size (Table 5). These selections were primarily based on the nominal reductions in AIC_C. The resulting four models all had high classification accuracies (Table 5), acceptable by researcher and manager standards alike (Dettmers et al. 2002). They also all had high AUC values, ranging from 0.888 to 0.918. While I had concerns about over-parameterizing the model, I decided on the one resulting from the 10 ha window logistic regression analysis. The model from the 100 ha analysis window had

the highest classification accuracy for roosts, but the model from the 10 ha window had the highest overall classification accuracy as well as the largest AUC value (Table 5). Its AUC value of 0.918 indicates that for a random selection from the set of observed roosts, 91.8 percent of the time the model will assign a higher probability to the roost than to a random selection from the set of random sites. Based on these findings, I suspect that the 10 ha analysis window may be the best of the four spatial scales for roost habitat modeling given the suite of available potential predictor variables.

To maximize model sensitivity and specificity and improve classification accuracies for both roost and random sites, I examined all possible classification cut-points and determined that values between 0.25 and 0.29 were best (Table 5). This might be expected given the ratio of roost to random sites. Had they been more balanced, a cut-point closer to 0.5 might have achieved similar results.

While a test of model performance using an independent dataset is preferable, I was not able to do this due to small sample size. However, cross-validation procedures are frequently used in which a portion of the observations is used as training data and the remaining portion is used for model testing (see Scott et al. 2003 for numerous discussions on this topic). I chose the Leave-One-Out method to obtain an unbiased estimate of classification accuracy. My model could be tested using independent data if additional bald eagle night roost data becomes available.

Change in potential habitat availability

It was surprising that the change in bald eagle night roost habitat availability between 1973 and 2000 was so slight. As with any research that has a temporal component, estimation of environmental conditions at points back in time presents obvious as well as unforeseen challenges. I was able to use the IVMP dataset and the change-detection datasets (Boyce 1999, Appendix A) to derive a set of vegetation layers representing conditions both for the present as well as for several decades ago. However, I was not able to do the same for the other variables in the model. I assumed, however, that elevation, slope, and aspect have not changed over the time period of the study.

Similarly, while some streams may have shifted within their channels or floodplains, the minor shifts are not enough to affect significantly the mean distance to salmon-bearing streams variable over the last 3 decades. Furthermore, the salmon presence information derived from the StreamNet layer was based on 1997 data. While some anadromous fish stocks have experienced recent declines in numbers, wintering bald eagles' primary prey species is chum salmon, which has experienced a population increase in recent years (Figure 9) (WDFW 2003).

In contrast, road density has likely changed dramatically over this time period. While few additional public roads have been built in rural Whatcom County since the 1970's, large numbers of private roads have been constructed to accommodate the rapid growth in single family dwellings and sub-divisions. In the Cascade Mountain foothills, and especially up the three forks of the Nooksack River, roughly 40-50 new lots a year have been developed since at least the 1980's and perhaps earlier (Donahue, pers. comm.). A comparable trend could be expected within Skagit County, particularly along the lower reaches of the mainstem Skagit River, and perhaps to a lesser extent, along the Sauk and North Fork Stillaguamish Rivers in Snohomish County. The roads layer I obtained from the DNR was based on 1996 information, and while not current, certainly reflects a greater road density than existed in the previous two decades. Because no road layer reflecting conditions in the 1970's was available, I had to use this same 1996 road layer when using the habitat model to paint the map of potential night roost habitat for 1973. Thus the potential roost habitat map for 1973 based on the 1973 QMD layer (with the other variables unchanged) likely underestimated the amount of potential habitat since the road density values used in the model are higher than actually existed at that time. I expect that the loss of bald eagle night roost habitat is probably greater than the two maps suggest.

Another factor that may have contributed to the unexpected similarity in amount of potential habitat over the 1973-2000 time period is that the two change-detection layers used in updating and backdating the 1992 IVMP vegetation layers did not map any change in forest cover below 100 meters in elevation. Boyce (1999) chose that elevation threshold in his 1973-1995 change-detection analysis under the assumption that any land
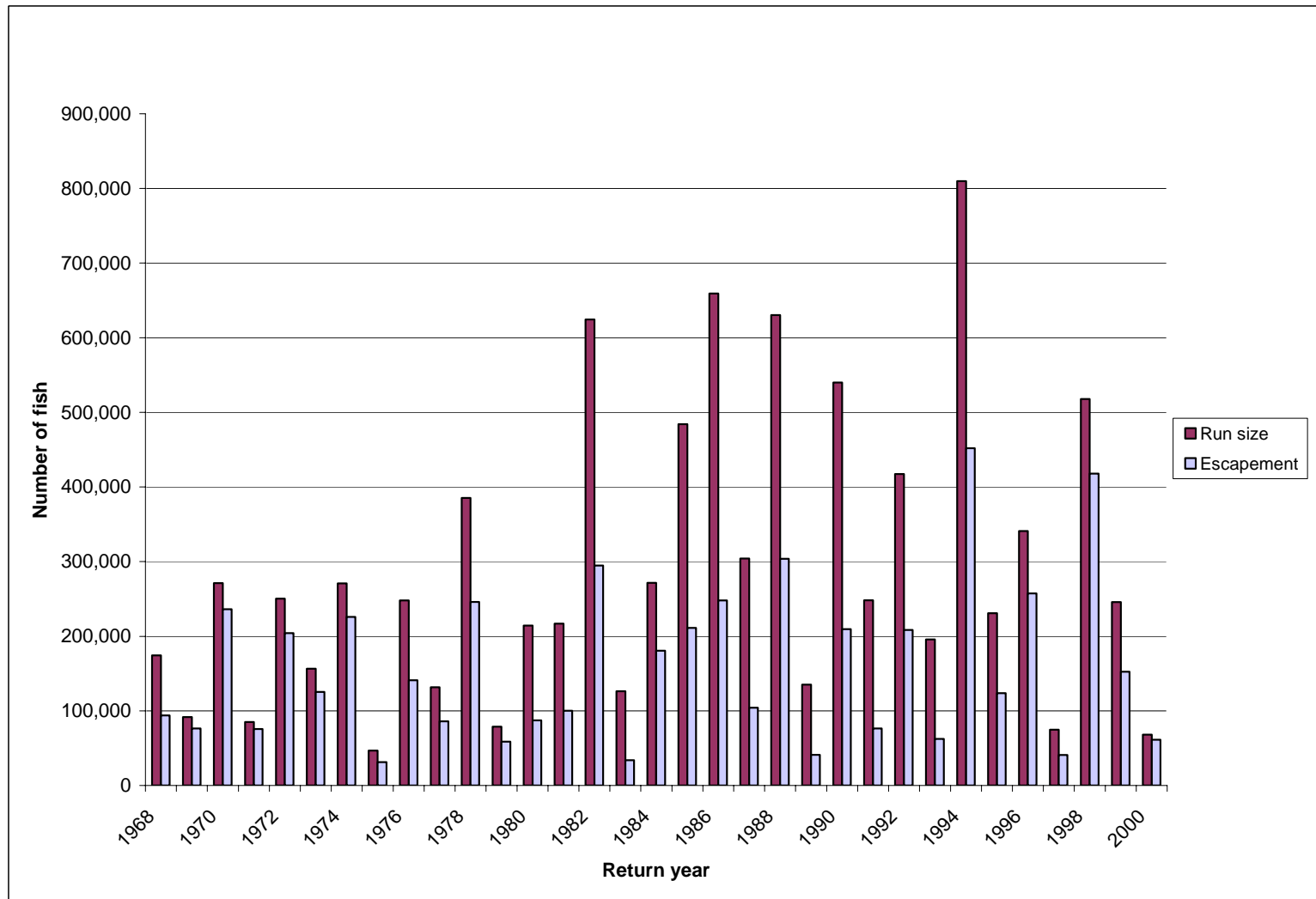
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Figure 9. North Puget Sound fall wild chum salmon run size and escapement, 1968-2000 (Washington Department of Fish and Wildlife 2003).

cover change detected in those areas would be largely attributed to changes in urban and agricultural environments. I used the same threshold in the 1995-2000 change-detection analysis for consistency. However, 13 of the 50 known bald eagle communal roosts used in this modeling project were at elevations below 100 meters. Areas below 100 meters in elevation represented 6 percent of the entire study area and 11 percent of the area within the 2500 meter stream buffer from which the random points were drawn. Any changes in forest cover near low elevation roost sites, over the time period of interest, would not have been quantified in the updated and backdated IVMP vegetation layers. Consequently, for the roosts known to be active at points in time earlier than 1992, percent vegetation, broadleaf, and conifer cover as well as QMD may have been underestimated.

Land ownership

Over 55 percent of the available potential habitat was located on private land, which is not surprising considering that wintering bald eagles in the region feed primarily on spawned-out salmon carcasses in the major rivers of the study area and select roosting sites close to these foraging areas. The spatial distribution of this key prey source and of the preferred stands for roosting is generally restricted to low elevation areas which are predominantly in private ownership. The DNR and USFS lands also had large proportions of total potential habitat. Other land ownership categories such as county and state parks, WDFW, United States Department of Defense (DOD), and BLM comprise only a tiny fraction of the study area and simply cannot represent a significant contribution to the amount of potential night roost habitat.

The largest changes in distribution of habitat by land ownership between 1973 and 2000, albeit slight, were observed on DNR, TNC, NPS and private lands (Figure 5). These are probably attributed first and foremost to the proportion of the study area these ownership categories represent. Nevertheless, DNR and private lands have likely experienced far greater changes in land use over this time period than all other land ownership categories. The corresponding decrease in vegetation cover (reflected in

QMD mode) was captured in the habitat model and caused the decrease in habitat availability. In contrast, the proportion of potential habitat increased slightly on NPS land, which was a result of the loss of habitat on DNR and private lands. The increase in the proportion of potential habitat on TNC lands may be due in part to the loss of habitat on DNR and private land but is predominantly due to TNC acquiring prime bald eagle habitat in the Skagit River watershed beginning in 1975. By 1977, TNC had preserved over 3,000 ha in the SRBENA (Krause 1980). Of the 3,000 ha preserved, the vast majority is managed by WDFW. Of the 450 ha in the SRBENA owned and managed by TNC (identified from the TNC GIS ownership coverage), 332 ha were classified by my model as potential habitat in 2000.

Of the 66,000 ha of current potential bald eagle night roost habitat identified by my model (Table 6), only seven percent is on protected lands such as in North Cascades National Park, wilderness areas, and TNC preserves. Bald eagle winter roost habitat on these lands is not in danger of destruction since these lands are managed for conservation and recreation rather than resource extraction and development. The remaining 93 percent of current potential habitat is on private land or lands managed by the DNR, WDFW, DOD, BLM and USFS. While bald eagle communal night roost habitat is technically protected under state and federal law, substantial habitat alteration may still be permitted, rendering roost habitat at risk on unprotected lands. As directed by the Washington State Bald Eagle Protection Rules (WAC-232-12-292), WDFW works with private landowners as well as with state and local agencies to develop site management plans for any proposed land action that potentially impacts a known bald eagle night roost (Stinson et al. 2001). However, these plans often permit activities that may be detrimental to roost habitat as they must balance the needs and goals of the landowners which are frequently in conflict with habitat conservation.

Management implications

Watson and Pierce (2001) captured and telemetered 26 wintering bald eagles on the Skagit River between 1996 and 1999 and found that these birds exhibit strong

philopatry, with 65 percent of the eagles returning to the Skagit River each winter. Many also returned each year to the same perches and foraging sandbars, indicating site fidelity. Results of their study also showed that 91 percent of the wintering Skagit River eagles were from source populations that breed north of 49 degrees latitude, predominantly in Alaska, central British Columbia, and the Northwest Territories. As these wintering bald eagles spend the majority of the year in more remote regions of northern Canada and Alaska, they may be less habituated to humans and human disturbance, making the protection of their winter habitat more critical. These source population breeding territories exist with a variety of state, provincial and international jurisdictions and therefore management should be driven by cooperative, international efforts (Watson and Pierce 2001).

Researchers have suggested that maintaining healthy chum salmon runs in northwest Washington rivers may be the single most important factor in conserving the region's wintering bald eagle population (Stalmaster 1987, Watson and Pierce 2001). As numbers of bald eagles wintering on the Skagit River are correlated with chum salmon escapement (Dunwiddie and Kuntz 2002), measures to enhance chum spawning would likely have a positive effect on conserving the wintering bald eagle population in the region. Watson and Pierce (1998) point out that flow stabilization from dam releases and siltation from the Chocolate glacier on the Sauk River have resulted in increased sedimentation of the lower Skagit River and may relate to a substantial drop in salmonid recruitment in recent years. This may explain the observed increase in chum salmon escapement on the upper Skagit River and the corresponding wintering bald eagle population shift from the lower to upper Skagit River documented in recent years (Dunwiddie and Kuntz 2002).

As wintering bald eagle distribution shifts in response to changes in the size, location, and timing of chum salmon runs, new roosts will be established if suitable habitat is available (Watson and Pierce 1998). While attention must be given to protecting chum salmon spawning habitat, protecting bald eagle roosting habitat is also critical to maintaining a healthy wintering bald eagle population. Currently, bald eagles in the Nooksack, Skagit, Sauk and North Fork Stillaguamish Rivers watersheds do not

have to fly great distances to find roost habitat. As habitat is lost, however, they will have to fly longer distances and thus experience greater energetic demands. Given what we know about bald eagle roost site selection, forest stands of potential habitat should be managed to enhance the preferred characteristics. Bald eagles clearly prefer larger trees with an open branching structure (DellaSala et al. 1998, Watson and Pierce 1998). These trees have stronger and more easily accessed perches for roosting. Potential roost habitat should be protected against clearcutting to promote availability of more mature stands with larger trees. Thinning, however, could be used to promote tree growth as well as to improve lines-of-sight and access to flight corridors. Managers could also select for conservation sites that have leeward slopes, are close to foraging areas, and are further from potential human disturbance. Guidelines for the management of existing bald eagle night roosts are delineated in the Washington State Status Report for the Bald Eagle and based on general recommendations from current research or specific information about individual eagles and their habitat use for the area in question as well as landowner objectives (Stinson 2001). These address many of the aforementioned concerns and include specification of buffer widths around core roost areas, providing vegetation screens to minimize human disturbance, and timing land use activities for periods when wintering bald eagles are not using the area in question (Stinson et al. 2001).

My model of potential bald eagle communal night roost habitat can be modified in a number of ways to achieve variety of management and conservation goals. I selected a classification cut-point that maximized model sensitivity and specificity to demonstrate what could be achieved in overall model performance. However, for managers who were interested in a more broad-brush approach to identifying potential habitat, the classification cut-point could be decreased. This would increase model sensitivity, or true positives, and would include more area as potential habitat such that managers could be assured of protecting as much potential habitat as possible. However, increased sensitivity reduces 1-specificity, or errors of commission (Figure 3). Areas with lower probability of being potential habitat, or marginal areas, would be included, and more areas that are not actual bald eagle roost sites would be classified as potential roost sites (Figures 6 and 7).

Conversely, adjusting the classification cut-point to a higher value would discriminate more strongly in favor of areas with the highest probability of being potential habitat. Organizations such as TNC that may be interested in purchasing land to conserve bald eagle night roost habitat could use a map produced by this less sensitive classification criterion to ensure the most judicious use of limited funds. While less potential habitat would be identified and errors of omission would increase, this would increase the chances that the best available habitat is protected (Figures 6 and 7).

Conclusions and future research recommendations

I have identified some critical ecological factors in night roost habitat selection by wintering bald eagle in northwest Washington and have developed a statistical model that discriminates with high accuracy between actual roost sites and random sites. Bald eagles select roost sites that are low in elevation, close to foraging areas, and farther from roads. Furthermore, I have demonstrated the utility of using remotely sensed data and GIS to produce a bald eagle habitat model. The model I developed, however, is not applicable to other regions as other variables may be important to bald eagle habitat selection, but my approach could be used.

The vast majority of wintering bald eagles in northwest Washington congregate on the major salmon-bearing river systems, but the population is clearly mobile. Numbers of eagles in various 'hotspots' shift in response to changes in prey availability and weather (Watson and Pierce 2001, Dunwiddie and Kuntz 2002). While many studies have been conducted on Washington's major river systems, little is known about wintering bald eagle habitat use in the coastal areas of northwest Washington. These areas are under great development pressure, and the potential for human disturbance of wintering eagles is likely higher than further inland. Magan (1999) conducted one of the first studies of wintering eagles in the lower Skagit River drainage and Samish Flats of Skagit County. He verified eagle use of two possible communal night roosts and observed key habitats used by eagles included areas along rivers, streams, sloughs and bays as well as forested areas adjacent to pastures. Food sources were more varied than

those of bald eagles in the upper reaches of the Nooksack, Skagit and Sauk Rivers. Bald eagles wintering on the Samish and Skagit flats consumed voles, ducks, snow geese, crows and gulls. More information is needed about these differences in habitat use and prey selection in various regions to assure the health of the entire population wintering in northwest Washington. I did not model roosting habitat for these coastal areas due to problems with mosaicing the Puget Lowlands IVMP vegetation dataset with the Western Cascades IVMP vegetation dataset. The IVMP team modeled the vegetation for the various provinces of Oregon and Washington individually and did not recommend mosaicing them together (Browning, pers. comm.).

Moreover, the clear association between bald eagle night roost habitat and sites that are further from human disturbance and development indicates that modeling other measures of these factors in addition to road density would be helpful. A GIS layer of homes and buildings for the entire study area was not available, but I would have anticipated these to be important predictors of potential habitat as well. Indeed, the presence of homes and buildings might be a better measure of human disturbance and thus predictor, as there is a stronger correlation between homes and potential for human disturbance. The presence of roads may not reflect rates of human disturbance as much as homes would since some roads are used only seasonally, and many others, especially old logging roads, may be abandoned.

This study has provided a more complete picture of the distribution and abundance of bald eagle communal night roosts throughout the study area. The current map of potential night roost habitat could contribute to more effective management of wintering bald eagles in northwest Washington through guiding land use decision-making. Agencies and organizations interested in conserving bald eagle winter habitat may use the map to identify critical areas to protect through easements or acquisition. Furthermore, only 25-30 percent of the estimated wintering bald eagle population has been accounted for in known roosts in the Skagit, Sauk, Nooksack, and North Fork Stillaguamish Rivers watersheds. The lingering question as to where the other 70-75 percent of the population roosts may soon be answered. While on-the-ground efforts to locate the "missing" bald eagle night roosts is logistically untenable, my map of potential

habitat could be used to direct future survey efforts to locate these unknown roosts before this habitat is adversely affected. Watson and Pierce (1998) reported an average core roost size of 9 ha for 26 northwest Washington bald eagle roosts. The average size of bald eagle roosts from the WDFW Priority Habitats and Species database used in my model was 54 ha and likely includes other components of roost habitat such as flight corridors and staging areas. Given these two figures, and using the habitat probability classification cut-point of 0.29, the 66,000 ha of current potential habitat could include between roughly 1200 and 7000 additional roosts (Figure 5). However, depending on the habitat probability classification cut-point selected, substantially less potential habitat may be identified.

On a final note, as more roosts are located, they could be used to validate and further refine the model. The identification of more roosts, by increasing sample size, would also facilitate the specification of the model for individual watersheds as needed. This could allow more site-specific management plans or habitat conservation directives.

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Appendix A

Image-processing and classification for the 1995-2000 forest cover change-detection.

      To create the 1995-2000 forest cover change-detection, I followed the general methodology used by Boyce (1999) in which he developed a forest cover change-detection for 5 time steps from 1973 to 1995. The 1995-2000 change-detection would add a sixth time step to the 1973-1995 layer and utilized the same 1995 TM scene used by Boyce.

      A Landsat 7 ETM+ satellite scene was acquired from Earth Observing System Data Gateway. The scene was path 46 and row 26 and was imaged by the satellite on September 25, 2000. This L1G product (radiometrically and geometrically corrected) was resampled by the cubic convolution method, and the reflective bands (1-5, 7) were resampled from 30-meter to 25-meter resolution.

      All image processing and classification was performed using PCI v6.2 (PCI Geomatics 1997). I used the CDLAND7 task in XPACE to import the raw data for bands 1-5 and 7 into a PIX file. I georeferenced the 2000 scene to the previously georectified 1995 Landsat TM scene (Boyce 1999) using GCPWorks. I selected 38 Ground Control Points (GCPs) based on permanent features, such as road intersections and buildings, that were easily visible in both scenes. The GCPs were used in a first order polynomial transformation which had a Root Mean Square (RMS) error of less than one pixel. A visual assessment using an overlay of a roads GIS vector layer confirmed the accuracy of the 2000 scene georeferencing to be generally within a pixel.

      I used a Tasseled Cap (TC) equivalent transformation (Crist 1985) to calculate scene brightness and greenness, rather than the TC transformation (Crist and Cicone 1984) used by Boyce (1999). The TC coefficients for TM imagery developed by Crist and Cicone (1984) could not be used for ETM+ imagery because they are sensor-dependent. I converted the 2000 scenes digital numbers first to radiance values and then to at-satellite reflectance before applying the TC equivalent transformation (Huang et al. 2002) (Appendix A Table 1).

Table 1. Coefficients for the TM equivalent transformation (Crist 1985).

	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6
Brightness	0.2043	0.4158	0.5524	0.5741	0.3124	0.2303
Greenness	-0.1603	-0.2819	-0.4934	0.794	-0.0002	-0.1446
Wetness	0.0315	0.2021	0.3102	0.1594	-0.6806	-0.6109

I obtained 2000-1995 brightness and greenness differenced images by subtracting the 1995 brightness and greenness channels from the 2000 brightness and greenness channels, respectively. The results were written into two signed 16-bit channels and were clipped to the study area defined by the 1973-1995 change-detection.

The 2000-1995 brightness and greenness image-difference channels were entered into an ISODATA (ISOCLUS task in XPACE) clustering algorithm. An initial ISODATA run revealed widespread confusion of forest cover change with some areas of smoke or fog in the northeast region of the 2000 scene as well as with some areas known not to have forest cover. To eliminate these areas of confusion during the clustering, I developed a mask from a USGS Land Use/Land Cover layer, the National Land Cover Data layer, and a British Columbia Land Use/Land Cover layer. I selected the following cover types to be masked out: tundra, perennial snowfields and glaciers, water, mining and barren areas, urban and recreational areas (parks, golf courses, and lawns). The mask was created in the ArcINFO GRID module and imported into PCI as an asciigrid file.

I reran the ISODATA routine on areas not under the mask, initially producing 59 clusters. I ultimately wanted only two clusters: forest cover change and no-change, so I used a "cluster-busting" approach whereby input channel pixels are iteratively clustered and then aggregated into classes (Jensen et al. 1987). After running the ISODATA routine, clusters were assigned to one of three classes: change, no-change, or confused. I assigned clusters to classes by visual assessment of the 2000 scene visible bands as well as the brightness and greenness image-difference channels in which loss of forest cover was readily identifiable on-screen. Confused clusters were then reentered into the ISODATA clustering algorithm and reaggregated until all clusters had been assigned to the change or no-change classes.

Clean-up of the final change results involved several procedures performed using PCI. To smooth the change polygons and eliminate any change errors of commission due resulting from misregistration of the 2000 scene to the 1995 scene, I applied a 5 x 5 mode filter. Because the majority of forest harvest units are larger than 2 ha, I wanted to remove change polygons <2 ha in size. I accomplished this using a sieving procedure. This final change channel was exported from PCI as an ERDAS image and then converted to a polygon GIS layer in ArcINFO. Some of the areas of confusion associated with the smoke or fog in the northeast part of the 2000 scene remained and were easily identified onscreen and manually deleted from the polygon GIS layer.

Boyce (1999) masked non-forest areas from his 1973-1995 disturbance map to eliminate any areas of change not related to forest cover change, such as changes in snow cover, water levels, and agricultural land cover. The mask was derived from a DEM, Land Use/Land Cover layers, and a mask he created previously to deal with clouds in the 1995 scene. Boyce (1999) determined that areas below 100 meters and above 1700 meters were generally non-forested and thus incorporated the DEM into his mask for non-forest. Owing to much change confusion in high elevation areas of the 2000 scene (see Methods), I lowered the upper elevation threshold of the DEM to 1400 meters before incorporating it into Boyce's mask.

I then performed an IDENTITY procedure in ArcINFO using a vector version of the non-forest mask and the polygon GIS layer to identify polygons completely under the mask, polygons completely outside of the mask and polygons split by the mask. I used a custom C program to identify those polygons that had >50 percent of their area outside the mask to be kept for further analysis along with the polygons completely outside of the mask. The remaining polygons, which had >50 percent of their area under the mask, were discarded.

Finally, I performed a visual, pixel level accuracy assessment of the 1995-2000 change-detection layer. I randomly selected 100 pixels from within change polygons and 100 pixels outside of change polygons and examined them onscreen with the 2000 scene visual, TC, and image-difference channels. The no-change pixels had an accuracy of 100 percent, while the change pixels had an accuracy of 84 percent. The primary source of

error for the change pixels was due to loss of forest cover being confused with two non-forest cover related changes in higher elevation areas. One was caused by changes in snowpack between the two dates, which was especially pronounced for this time step as the 2000 scene was acquired the summer following record breaking snowfalls in the Washington Cascade Mountains. The second is suspected to stem from the confounding spectral response of late-season senescent vegetation in avalanche chutes and other open areas that may not have been eliminated by the non-forest mask. These changes related to senescent vegetation appear to mimic forest cover loss. Secondary sources of error relate to forest cover changes being confused with river course changes on the mainstem of the Nooksack and Skagit Rivers and changes in agricultural land use.

The shape and pattern of the change polygons in the USFS wilderness and NPS regions of the study area clearly reflected the error related to the aforementioned high elevation factors. I assumed that no forest harvest had occurred in these areas. Furthermore, over 90 percent of forest cover change mapped by Boyce (1999) was identified as timber harvest rather than wildfire. As I expected similar results for the 1995-2000 change-detection polygons in the USFS wilderness and NPS ownership categories, I discarded them from the change-detection. With these problematic areas removed, the accuracy for the change polygons increased to 94 percent.

The amount of forest cover lost between 1995 and 2000, as a percent of the total forested area, ranged from roughly 0.2 to 2 percent, with the smallest loss on USFS lands and the greatest loss on private lands (Appendix A Table 2). The rate of forest harvest

Table 2. Percent of forest harvested and rates of harvest by land ownership, 1995-2000			
	USFS	DNR	PVT
Forest harvest (% of forest area)	0.19	1.05	2.12
Rate (% per year)	0.04	0.21	0.42

was lowest, at 0.04 percent per year, for USFS lands and greatest, at 0.42 percent per year, on private lands.

In the 1995-2000 time period, overall rate of forest harvest for USFS, DNR, and private lands was lower than all previous time periods (Appendix A Figure 1). For DNR lands, the rate of forest harvest was lowest for all time periods, while on USFS lands, the

rate was unchanged from the overall low of the 1992-1995 time period. Only the rate of forest harvest on private lands had not returned to its lowest rate which occurred in the 1973-1979 time period.
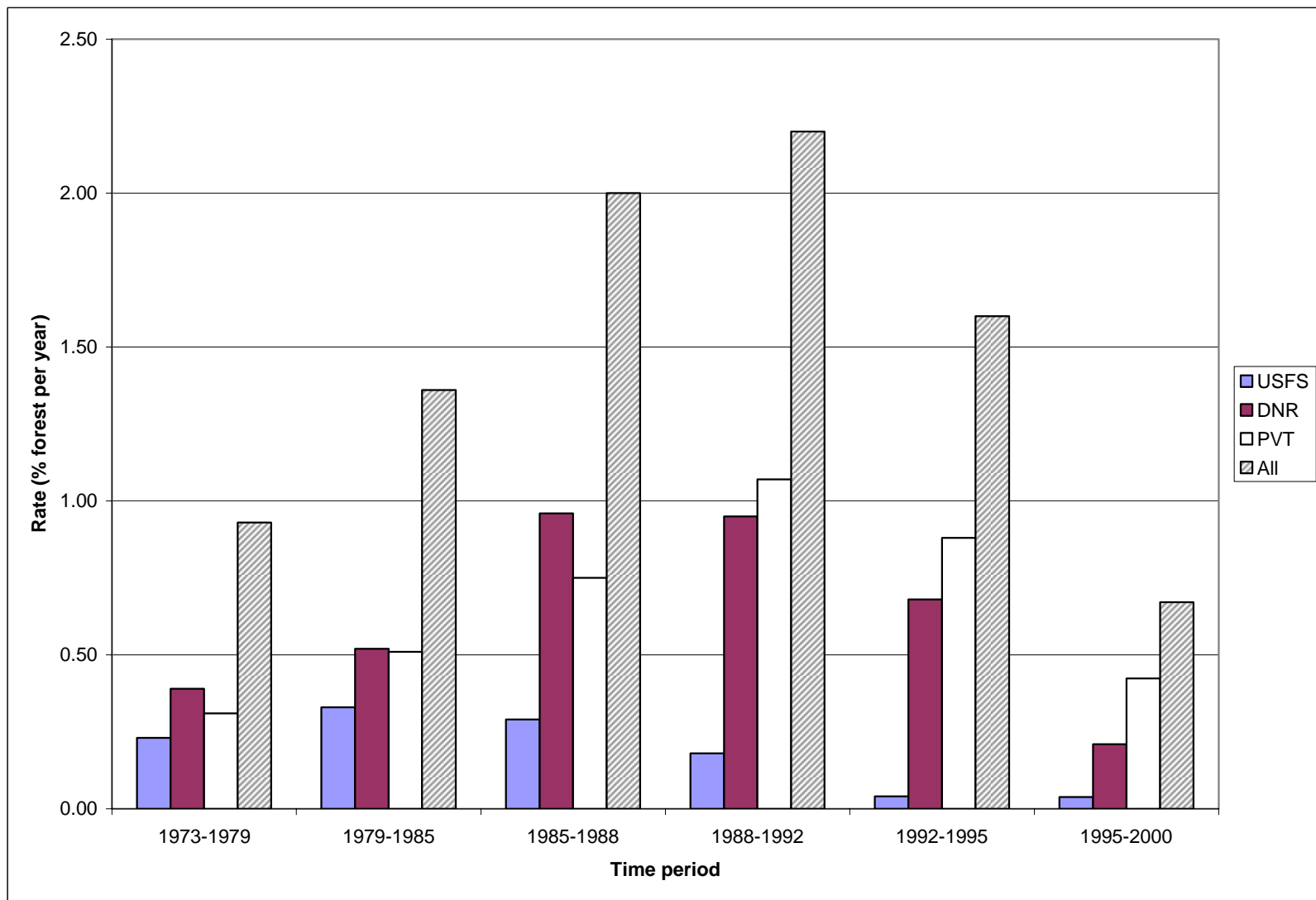
Appendix A, Figure 1. Rates of forest harvest in study area by land ownership, 1973-2000.