Global Positioning System (GPS) Bias Correction and Habitat Analysis of Mountain Goats Oreamnos americanus in the Cascades of Washington State, USA

by

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MASTER'S THESIS

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A Thesis
Presented to
The Faculty of
Western Washington University

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Abstract

Seasonal variation in habitat selection by the mountain goat *Oreamnos americanus* is not well understood due to the difficulties of monitoring animal movement in all months of the year. The use of global positioning system (GPS) wildlife telemetry collars offers an opportunity to overcome this obstacle, however satellite acquisition problems associated with GPS wildlife telemetry collars create an observational bias of animal locations towards areas of favorable signal reception. To correct for this bias in data from GPS collared mountain goats in the Cascades of Washington State, I used an intensive field sampling exercise to model the amount of variation in position acquisition rates (PAR) based on remotely sensed vegetation and topographic landscape characteristics in a geographic information system (GIS) framework. I then derived GIS habitat maps of predicted potential mountain goat habitat in the Western Cascades of Washington.

I used non-linear mixed modeling with Akaike's Information Criteria (AIC) and a generalized estimating equation (GEE), autoregressive correlation structure (m =1), to account for the random effects of the binary clustered GPS bias correction experimental design. I used vegetation data from satellite imagery provided by the Interagency Vegetation Management Project (IVMP) and a 10 m digital elevation model (DEM) to derive a set of predictor variables. I sampled GPS PAR at 543 sites across two study areas, the Western and Eastern Cascades, which covers roughly 5 million hectares. I analyzed the data at two spatial resolutions, 25 m x 25 m and 75 m x 75 m. For both study areas, the 25 m x 25 m resolution yielded the best models with areas under the receiver-operating curve (ROC) of 0.70 and 0.69, for the Western and Eastern Cascades, respectively. Both models fit with expected ecological patterns. These two models were used to produce a continuous GIS raster map of predicted GPS PAR for the entire mountain range in Washington. This data, used with an inverse weighting scheme, reduced the signal reception bias found in a habitat study of GPS collared mountain goats. The correction factor helped to account for habitats likely used by coastal ecotype mountain goats but unfavorable to GPS satellite acquisition.

Past research into Washington State's mountain goats has not documented well winter habitat selection. These widely overlooked habitats, lower elevation forests with dense canopy cover, may provide critical over-wintering sites for mountain goats. I analyzed data collected over a two-year period from 39 GPS collared mountain goats in the Washington

Cascades. The data set included over 86,000 individual locations from 39 animals. Each location was weighted with the inverse of the predicted GPS PAR to account for the GPS bias. I used a weighted logistic regression procedure with Akaike's Information Criteria (AIC) to choose the most parsimonious model out of an *a priori* selected set of models. Predictor variables were derived from vegetation layers developed by the Interagency Vegetation Mapping Project (IVMP) and a 10 m digital elevation model (DEM). Candidate models were developed on the basis of ecological relevance and available GIS data. I partitioned the data into eight datasets, based upon elevation quartiles of mountain goat locations and a northern and southern division of available sites.   The individual habitat maps were mosaiced into one map and compared with a map generated with the same models not taking into account the weighting factor. The weighted models classified more terrain as habitat and had slightly higher classification accuracies. I also combined predicted potential habitat maps with proportional use of each elevation band during summer (July-September) and winter (December-April) to examine seasonal differences in habitat use. The final product will assist with management activities, conservation planning and ecological studies of Washington's endemic mountain goat populations.

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Table of Contents

List of Figures

List of Tables

Chapter One:

WILDLIFE TELEMETRY GLOBAL POSITIONING SYSTEM (GPS) BIAS CORRECTION IN THE CASCADE MOUNTAINS OF WASHINGTON STATE, USA

Introduction

The addition of Global Positioning System (GPS) receivers to wildlife radio telemetry collars has enabled automated recording of animal position information that has largely overcome seasonal, daily and weather related observational biases associated in traditional wildlife telemetry studies. Automated data collection reduced the stress and biases associated with repeated disturbance of study animals and decreased positional errors of animal locations. Refinements in hardware, software and the deactivation of selective availability have reduce positional error to 10 m or less under optimal conditions (Johnson & Barton 2004). This level of accuracy generally exceeds the spatial resolution of satellite imagery and Geographic Information Systems (GIS) data layers used to model habitat. (Rempel & Rodgers 1997; Rodges 2001; Di Orio *et al.* 2003).

Despite these advantages, GPS receivers often fail to obtain a position under dense forest canopy or when topography blocks signals from orbiting satellites (Gerlach & Jasumbach 1989). Ignoring this issue, when evaluating data from GPS-collared animals, provides a biased view of habitat use towards areas of favorable GPS reception (Rempel *et al.* 1995; Deckert & Bolstad 1996; Edenius 1997; Dussault *et al.* 1999; Gamo & Rumble 2000; Licoppe 2001; Rodgers 2001; D'Eon *et al.* 2002; Taylor 2002; Di Orio *et al.* 2003; Frair *et al.* 2004; Cain *et al.* 2005; Sager 2005). In light of these findings, I examined the GPS Position Acquisition Rate (PAR) across the Cascade Mountain range of Washington State for incorporation into a habitat analysis of GPS collared mountain goats *Oreamnos americanus*.

The Cascade Mountains of Washington State represent a sizeable portion of the historic range of the mountain goat (Johnson 1983). Mountain goats have inhabited the Pacific Northwest of the United States and coastal British Columbia Canada for at least the past 12,000 years (Nagorsen & Keddie 2000). This highly recognized, uniquely adapted ungulate has also plays a prominent role in the cultural histories of the indigenous people of the region. Over the last 40-50 years, this charismatic species experienced a substantial population decrease in many parts of its native range (Table 1). In particular, this decline has been readily apparent in the traditional tribal territories of the Sauk-Suiattle Nation, located in the vicinity of Darrington, WA. Some mountain goat populations in this area have decreased by 70-90% over the last 40 years (Ryals, pers. com.)

This overall decline in population numbers has largely restricted the permitted hunting of mountain goats in Washington State for the second time in state history. Sanctioned mountain goat hunting started in 1897, was closed entirely in 1925 and resumed in 1948 after populations reached carrying capacity (Johnson 1983). By the mid 1960's, the state was annually issuing over 1,000 permits. By 1997 that number had dropped to 52 and in 2005, the Washington Department of Fish and Wildlife (WDFW) issued 19 mountain goat permits.

Between 2003 and 2005, WDFW captured and collared 50 mountain goats in the Washington Cascades to establish a baseline of mountain goat ecology. WDFW wanted to assess the magnitude, extent and causes for declines in Washington's endemic mountain goat populations. As part of this study, I have evaluated the relative influence of topography and vegetation on GPS PAR with a field-sampling regime. I hypothesized that the rates at which GPS collars successfully recorded data were predictable based on remotely sensed vegetation and GIS derived topographic characteristics. In Chapter One, I developed a predictive model encompassing the whole of the Washington Cascade mountain range to weight location data acquired from GPS collared animals during a habitat analysis. The final products were designed to assist in future wildlife management efforts, conservation activities and habitat connectivity analysis taking into account the observational bias generated by GPS wildlife telemetry collars towards areas of favorable satellite signal reception.

Literature Review of Previously Published GPS Bias-Correction Studies

The GPS collar bias issue has stimulated interest in the development of new methodologies to minimize these observational biases. The typical methodology involves placing collars in the field, programmed to record GPS fix attempts at a consistent interval for a minimum of 24 hours. The orbital geometry of the constellation of GPS satellites repeats once per sidereal day, about 23 hours and 56 minutes (Hoffmann-Wellenhof *et al*. 1997), so a 24-hour sampling period covers the full range of satellite geometries at a given site. At each sample location, data from the collars yields GPS PAR, or the percentage of successful fix attempts. Site characteristics either observed on the ground or derived from GIS layers provide predictor variables. A statistical model based upon these data can then be developed to predict GPS PAR across the entire landscape.

Since 1995, several published studies used this basic approach (Table 2). These studies evaluated GPS performance across areas of a few tens of thousands of hectares. Many took place in Canada including studies in coastal and interior British Columbia (Taylor 2002; D'Eon *et al.* 2002), Alberta (Frair *et al.* 2004), Ontario (Rempel *et al.* 1995) and Québec (Dussault *et al.* 1999). Studies in the United States occurred in California (Di'Orio *et al.* 2003) the Black Hills of North Dakota (Gamo & Rumble 2000) and in the temperate forests of the Olympic Mountains of Washington State (Sager 2005). The progression of these studies reflect an increased understanding and shift of focus from initially demonstrating the existence of the GPS PAR observational bias issues, to quantifying the effects of the bias and finally correcting for it. For a more complete list of published studies see Cain *et al.* (2005) who also found that GPS PAR success was correlated with the interval of GPS fix acquisition attempts.

Methods

Study Area

The study area spanned the indigenous range of the mountain goat in the Cascades of Washington State (Johnson 1983) divided along the Cascade crest into two regions; east (2,585,240 hectares) and west (2,744,521 hectares) (Fig. 1). The major ecological zones occupied by mountain goats include the subalpine and alpine communities and to a lesser, fairly unknown extent, the montane zone (Johnson 1983). The Cascades house five stratovolcanoes, four of them over 3200 m, and numerous peaks surpassing 2000 m. The combination of dense forests and narrow valleys at lower elevations and treeless ridgelines higher up provided a range of conditions for testing GPS receivers. The spatial extent of the Inter-Agency Vegetation Mapping Project's (IVMP) Western and Eastern Cascades of Washington (O'Neil *et al*. 2002; Browning *et al.* 2003) defines the study area boundaries and provided the available remotely sensed vegetation data for my analysis.

The montane zone generally occurs between 450 m and 1050 m extending from the dense, lower elevation forests up to the beginnings of the subalpine zones. In the western and northern Cascades, the Pacific Silver fir/Western hemlock *Abies amabilis/Tsuga heterophylla* forests represent the most common forest community (Franklin & Dryness 1988). Common associated overstory species include: Douglas-fir *Psuedotsuga menziesii* (Mirb. Franco), Red alder *Alnus rubra* (Bong.) and Western red cedar *Thuja plicata* (Donn ex D. Donn). The eastern slope of the Cascades has more drought tolerant and fire resistant tree species. Ponderosa pine *Pinus ponderosa* (Dougl. ex Laws) dominates the landscape at lower elevations. Common associates include Douglas-fir, Engelman spruce *Picea engelmannii* (Parry ex Engelm.), Subalpine fir *Abies lasiocarpa* (Hook. Nutt.) Western larch *Laryix occidentallis* (Nutt.) and Lodgepole pine *Pinus contorta* (Dougl. Ex Loud.).

In mesic montane sites, these trees often occur with Skunk-cabbage *Lysichitum ameicanum*, Ladyfern *Athytium fillix-femina*, Devils club *Oplopanex horridum* and Swordfern *Polystichum munitum*. At slightly drier sites, common associates include Huckleberry *Vaccimuim alaskaense*, Dogwood bunchberry *Cornus canadensis*, Salal *Gaultheria shallon*, Vanilla leaf *Achlys triphylla* and Oregon grape *Berberis nervosa* (Topik 1986). At some very dry sites, especially further south in the range, Madrone *Arbutus menziesii* and Ocean spray *Holodiscus discolor* occur (Topik 1986). At higher elevations *Xerophyllum tenax*, Cascade azalea *Rhododendron albiflorum* and Fool's huckleberry *Menziesia ferrugie*a commonly grow (Brockway 1983).

The subalpine zone ranges between 1050 m and 1500 m and consists of a mixture of forests and meadows extending up to tree line. The lower regions of the subalpine zone transition from Western hemlock to Mountain hemlock *Tsuga mertensiana* (Bong. Carr.) with tree stature often reaching full development. Pacific silver fir grows across both the upper montane and into the subalpine zones. At some of the higher elevations, Subalpine fir and Alaska-cedar *Chamaecyparis nootkatensis* (D. Don, Spach) exist. Krummholz and dwarf shrub communities commonly develop at the higher elevations due to the effects of wind, snow and temperature (Taylor 1986).

The most pronounced subalpine meadows develop beneath the upper portions of the tree line in avalanche paths (Taylor 1986) and after forest fires (Johnson 1983). Vegetation community types found within the subalpine include: snowbed (Saxifrage-Woodrush *Saxifraga tomliei-Luzula piperi* and Sedge *Carex nigricans*) mesic herb (Lupine *Lupinus latifolis*, Fescue *Festuca viridula*, Huckleberry *Vaccinium deliciosum*, sedge *Carex spectabilis*, Buckwheat *Polygonum bistortoides*, Valerian *Valeriana sitchensis* and Daisy fleabane *Erigeron pereginus* var. *scaposus*) Dwarf shrub (Heather *Cassiope mertensiana*, Mountain-Heath *Phyllodoce empetriformis* and *P. glanuliflora*, Crowberry *Empetrum nigrum*, Bearberry *Arctostaphylos uva-ursi*, Partridgefoot *Luteka pectinata*, Huckleberry

Vaccinium deliciosum, Everlasting; Pusstoes *Antennaria lanata*, Willow *Salix nivalis* and *S. cacadensis* and Mountain-avens *Dryas octopetala*) and dry gaminoid (Oatgrass *Danthonia intermedia* and Sedge *Carex spectabilis* and *C.* var. *pseudoscicrpoidea)* (Douglas & Bliss 1977).

The alpine zone, dominated by rock and ice and free of overstory vegetation, extends up from subalpine zone around 1500 m to the mountain summits. The high alpine tundra provides areas for evaluating GPS-collar performance under the optimal conditions of no canopy and views of the sky that are unobstructed by topography (Rempel *et al.* 1995). The alpine and subalpine zones also typify common impressions and interpretations of mountain goat habitat.

Herbfields, fellfields, and boulder fields characterize the alpine zone (Taylor 1986). Vegetation community types found within these features include: dwarf shrub (Mountain-heath *Phyllodoce grandiflora* & *P. empetriformis* and Heather *Cassiope mertensiana*), mesic herb (Lupine *Lupinus latifolis* and Fescue grass *Festuca viridula*), dry gaminoid (Oatgrass *Danthonia intermedia*, Reedgrass *Calamgrostis purpurascens*, Sedge *Carex spectabilis*, *C. phaeocephala*, *C. scirpoidea* var. *pseudoscicrpoidea* and *C. nardina*, and Kobresia *Kobresia myosuroides*) and snowbed communities (Sedge *Carex breweri C. capitata* and *C. scirpoide*, Cinquefoil *Potentilla diversifolia* var. *diversifolia*, Goldenrod *Solildago multiradiata*, Willow *Salix cascadensis* and Fescue *Festuca ovina*) (Douglas & Bliss 1977).

Field Work

I tested collars throughout the study area during the summer of 2004, winter 2004-2005 and summer 2005. Prior to collection of field data, I benchmarked the Vectronic-Aerospace GPS Plus collars (v6, Vectronic Aerospace, Berlin Germany) at a known location with an unobstructed view of the sky to ensure proper functioning (Moen *et al.* 1997). For logistical reasons, I sampled sites near existing trail networks. Random selection of field sites for collecting PAR data was not practical due to the rugged inaccessible terrain. I generally sampled above a minimum elevation of 1000 m, and placed collars at least 200 m apart. Field placement of GPS units mimicked the height and orientation of a GPS unit on a collared mountain goat, approximately 1.0 m above ground. GPS units were secured with bamboo tripods or natural materials found on site, including saplings, tree branches, downed logs, stumps and rocks. Field measurement taken at each site for ground-truthing GIS data layers included: aspect, slope, elevation and canopy cover. Site selection focused on areas with relatively uniform vegetation characteristics within 30-50 m of the GPS units. Ignoring this issue, and using sites near the edge of a forest or alpine meadow, for example, could have resulted in differences between actual site conditions and the GIS data due to mis-registration of the raster files.

GPS units were programmed to attempt a 3-minute fix every 30 minutes for no less than 24 hours (Frair *et al.* 2004). Positional dilution of precision (PDOP) of the Vectronic-Aerospace collars reached 48.6 when a fix attempt failed. The collars ignored satellites within 5° of the horizon in order to minimize multi-path errors (Schulte, personal communication). I calculated average positional location for all successful fixes for data extraction and calculated PAR as the percentage of successful fix attempts (including both 2D and 3D fixes) during the full duration of GPS unit deployment (D'Eon *et al.* 2002).

I also deployed a Trimble GeoExplorer3 handheld GPS unit (v1.20, Trimble Navigation Ltd., Sunnyvale, California USA) within 3 m of the collar at some of the sites to test relative GPS PAR between brands and to determine if GPS PAR model development was possible with alternative manufacturers once collars were unavailable. Configuring the Trimble units with custom external battery packs enabled 24-hour continuous operation. I programmed a 15-minute (900 s) interval of fix attempts to match the 30-minute interval of the Vectronic collars. The Trimble units had a maximum time interval of 999 s. I set the Trimble horizontal dilution of precision (HDOP) mask to 60 initially, the signal to noise ratio mask to 1 and an elevation mask of 5°. I reset the HDOP to 48.6 after preliminary data collection to match the Vectronic units. After analyzing the performance of Vectronic versus Trimble data from the summer of 2004, I also analyzed the relative performance of pairs of Vectronic units. During the winter of 2004-2005, I tested the Vectronic collars against each other to look at simultaneous performance of the collars under equivalent site conditions. At a limited number of sites I placed two collars within 1 m of each other programmed to record fixes on the same 30-minute interval.

GIS Data

Vegetation Predictor Variables:

Variables derived for statistical modeling of GPS PAR came from existing, 25 m resolution, raster files created by the Interagency Vegetation Mapping Project (IVMP), utilizing Landsat imagery from the mid-1990's (O'Neil *et al.* 2002; Browning *et al.* 2003). The IVMP data consists of four vegetation layers: percent total vegetation cover (TVC), percent conifer cover (CC), percent broadleaf cover (BC) and quadratic mean diameter of overstory trees (QMD). The IVMP provides each of these four layers as continuous variables, but recommends subdividing each layer into three or four user-defined categories based on tradeoffs between accuracy and category size. To remain consistent with the release documentation of the IVMP data sets and accuracy assessment, I classified each vegetation layer into discrete categories based on the frequency distribution of the number of sites in each class (Table 3). I attempted to maintain an even balance of the number of sites in each class. Documentation provided by IVMP indicates this categorization of data layers should yield classification accuracies of approximately 78% (TVC), 73% (CC), 46% (BC) and 62% (QMD) for the westside and 68% (TVC), 55% (CC), 61% (BC) and 57% (QMD) for the eastside.

Topographic Predictor Variables:

I derived topographic predictor variables from a 10 m digital elevation model (DEM). I masked the necessary DEM to the spatial extent of the IVMP data and resampled the pixel size to 25 m. In addition to elevation, I created slope, aspect and sky visibility data layers (Deckert & Bolstad 1996; Gamo & Rumble 2000; D'Eon *et al.* 2002). The sky visibility layer considered the uneven distribution of GPS satellite orbits in the sky. The existing constellation of GPS satellites, distributed in 6 orbital planes inclined at 55° relative to the equator (Hoffmann-Wellenhof *et al*. 1997), dictates that no GPS satellites pass over a substantial portion of the sky (Fig. 2). In generating the sky visibility layer (Appendix A), I excluded portions of the sky within this "hole" from the calculations and I expected sample sites located on northerly aspects to achieve lower PAR then those on southerly ones.

Stratification

The logistical challenges associated with sampling the full range of conditions across a 5 million hectare study area warranted substantial consideration. Examination of the IVMP and DEM files insured field-sampling efforts focused on the major combinations of GIS derivable topographic and vegetation site characteristics in the region. I stratified both study areas using a merged set of predictor variables (Table 4); forest type (based on the first three IVMP layers), QMD classes, slope combined with aspect (flat, steep and north facing, or steep and south facing) and sky visibility. I used identical stratification rules for both areas with the exception of QMD classification. Cross-tabulation resulted in 81 different combinations of these four variables in the western half of the study area and 54 in the eastern half. Due to logistical constraints, the majority of field sampling on the western slope concentrated in the northern portion (Mount Baker-Snoqualmie National Forest) of the study area and on the eastern slope in the southern portion (Wenatchee National Forest) (Fig. 1).

Data Analysis

Extraction:

For each sample site, I extracted predictor variables from the IVMP and DEM layers. I developed two sets of predictor variables for each half of the Cascades (Table 5). The first set of variables was extracted for the single 25 m by 25 m grid cell that contained the sample site. The second set of predictor variables was extracted for a three by three or 9 75 m x 75 m square extraction window that was centered on the pixel containing each sample site. These two data sets enabled examination of the relationship between GPS performance and site conditions at two spatial resolutions.

Modeling:

I initially examined the breadth of coverage that field sampling efforts yielded based upon the stratification classifications rules for both study areas. I looked at relative performance of GPS units between brands and among collars and screened for outliers based on cluster size and improbable GPS PAR values. GPS PAR rates of less than 10% were excluded from the analysis due to suspected collar malfunctions or disturbances to the sample site.

I used non-linear mixed modeling logistic regression, information theory and generalized estimating equations (GEE) to model GPS PAR as clustered binary responses (Pendergast *et al.* 1996; Heagerty 1999; Horton & Lipsitz 1999; Hosmer & Lemeshow 2000; Teachman & Crowder 2002). Fix attempts at each trial site, coded as successful or not, had the same predictor variables over the course of the entire sampling period. The lack of independence due to repeated observations at each sample site required modeling of the internal correlation structure by means of a GEE. The GEE modeling changed the values of the standard errors bounding the parameter coefficient estimates from those obtained by ordinary logistic regression. Use of the auto-regressive (m=1) GEE was based on the observation that the correlation structure of the waypoints clustered by site had some diagonal relationships. The fact that the constellation of the GPS satellites repeats just short of a full 24 hour day meant that the correlation structure within sites shifted as a function of position within the cluster. The moment that the satellites were in the same configuration as the previous day shifts four minutes back each time the satellites repeat their orbital geometry. This shifts the correlation structure within the sample sites across the data set.

I *a priori* selected a set of models for testing GPS PAR for each of the two spatial resolutions (Burnham & Anderson 2002). I tested a global model utilizing all of the applicable predictor variables and selected model subsets (Appendix B). For each spatial resolution, I selected the most parsimonious models based on non-linear mixed modeling procedure (Appendix C) and the AICc. I calculated the area under the receiver-operating curve (ROC) for both spatial resolutions' most parsimonious model using the ROC package in R (Gentleman *et al*. 2004; Development Core Team *2005*). The parameter estimates, confidence intervals and robust standard error estimates were generated with SAS (8.0, SAS Institute Inc. Cary, NC) using an auto-regressive GEE. In selecting a model to use for mapping GPS PAR in each province, I used the most parsimonious model for the resolution with the highest area under the ROC (Pearce 2000) and calculated variance inflation factors ($\hat{c}$).

I analyzed site level GPS PAR data based on the most parsimonious models for the optimal spatial resolution to quantify predictive power. I randomly split the data in half for model building and testing subsets. I regenerated parameter estimates with the selected models using the building subset and calculated GPS PAR for the remaining data in the model testing subset. I applied the model testing data created from all acquisition attempts to the site level data of each GPS PAR test site and plotted observed GPS success against the predicted GPS PAR of each trial site. I calculated the coefficient of determination to quantify the amount of variation explained by the models (Menard 2000)

I painted predictive maps of GPS PAR for each province and merged them into one data layer. I used ArcMap 9.0’s Spatial Analyst Raster calculator to calculate the pixel-by-pixel values of predicted GPS PAR across both study areas. I mosaiced the study areas together to form one layer for the entire Cascade Range of Washington State. I designed the final data layer for incorporation into a habitat analysis based upon an inverse weighting scheme of predicted GPS PAR for a fix acquired from collared animals. These final data layers calculated the predicted GPS PAR for each 25 X 25 m pixel based on the logit formula (eqn 1) and the predicted probability (eqn 2).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_3 + \ldots + \beta_p X_p + e \qquad \text{eqn 1}$$

$$\text{GPS PAR} = \exp Y / (1 + \exp Y) \qquad \text{eqn 2}$$

Results

Ground Truthing

A correlation analysis showed a high degree of correlation between field measurements of topographic features and GIS predictor variables. Elevation measured in feet in the field and the data from the 10 m DEM had a simple correlation coefficient of R = 0.92. Aspect and slope, both derived from the 10 m DEM, had values of R = 0.56 and R = 0.60, respectively. Vegetation data recorded in the field with a spherical densiometer and total vegetation cover derived from the IVMP as a continuous variable had a lower value of R = 0.37 (Zar, 1996). Spherical densiometer measurements are often quite subjective especially when multiple observers are used (Vales & Bunnell 1988).

Stratification

I sampled GPS PAR at a total of 543 sites (Fig. 1) in the Washington Cascade Mountain Range. In the Western Cascades Province, I sampled GPS PAR at 209 sites during the summer of 2004, 64 sites during the winter of 2004-05 and 51 sites during the summer of 2005. In the Eastern Cascades Province, I sampled GPS PAR at 219 sites during the summer of 2005.

Of the 81 possible combinations of variables (Table 4) in the west side stratification model, 42 conditions each individually covered more than 0.5% of the study area for a total of 94.33% of the Western Cascade Province. I sampled 39 of these 42 combinations. The three combinations omitted, defined as Mixed/Broadleaf forests with varying topography, covered 2.59% of the study area. All together, west side sampling efforts covered 91.74% of the defined stratification classes by area.

Of the possible 54 combinations of variables on the east side, 34 each individually covered more than 1% of the study area, for a total of 88.9% of Eastern Cascade Province. I sampled 33 of these 54 total combinations for a grand total of 94.2% of total area. One dominating cover type (flat open sites with high sky visibility) accounted for 21.6% of the total area, and 16.4% of the samples.

By elevation, the distribution of our sample sites was similar to that of over 30,000 mountain goat locations (from over 40 mountain goats). I over-sampled slightly at lower elevation (<1,000 m) and under-sampled slightly at higher elevations (>1,600 m) (Fig. 3).

Collar comparison

Trimble vs. Vectronic:

Of the 138 sites with both a Trimble GeoExplorer3 data logger and a GPS collar the correlation coefficient (Zar 1996) of GPS PAR between these units was $R = 0.67$ (Fig. 4). Most of the results of GPS PAR fell within the 90-100% range. Neither brand consistently outperformed the other.

Vectronic vs. Vectronic:

At the 16 sites during the winter of 2004-2005, I placed two Vectronic collars under "identical" conditions to assess relative GPS PAR. The correlation coefficient (Zar 1996) of GPS PAR between these sites was $R = 0.83$ (Fig. 5).

Global positioning system position acquisition rate; GPS PAR

Vectronic Collars:

The 324 Western Cascades sample sites originally consisted of 20,740 acquisition attempts. I removed seven sample sites entirely due to poor GPS PAR suggestive of equipment problems. Although all sample sites had a minimum sampling period of 24 hours, some sites recorded data for upwards of 72 hours. These large differences in the number of fix attempts per site caused the statistical program to fail due to difficulties in modeling the correlation structure within sites. Therefore, I used a maximum of 48 attempts per sample site for the Westside data. This reduced the data set to 15,550 acquisition attempts. I retained all the 219 Eastern Cascade sample sites tallying 11,057 acquisition attempts since the data had a smaller range of sample site fix attempts. The more even sampling allowed for successful modeling of the correlation structure. The average overall GPS PAR in the Western and Eastern Cascades was 78.8% and 92.4%, respectively.

Out of the entire set of *a priori* defined models (Appendix B), the three highest ranked models in each data set had Akaike's weights >0.01 (Table 6). The most parsimonious Western Cascade model had an area under the ROC of 0.70 based on a 25 m x 25 m spatial resolution and 0.69 based on a 75 m x 75 m spatial resolution. This suggested a slightly higher predictive power of the 25 m x 25 m resolution. The Western Cascade 75 m x 75 m resolution also had small effect size ($P>|z|$ <0.001) for two variables' parameter estimates and multiple coefficient confidence intervals bounding zero. The Eastern Cascade models had nearly equivalent areas under the ROC (0.68) based on the 25 m x 25 m and the 75 m x 75 m resolution. Considering that both spatial resolutions returned the same model parameters for the most parsimonious Eastern Province models this result was not unexpected. For the Western Cascades model, I opted to use the model based on a 25 m x 25 m spatial resolution due to the area under the ROC and for consistency sake, the same spatial resolution on the east side.

The coefficients for the 25 m x 25 m models for Cascade GPS PAR (Tables 7 & 8) indicated strong evidence of significance and confidence intervals that did not bound zero. These models also have similar variable types, the cosine of aspect in radians and one entire class of categorical vegetation variables. The global models yielded variance inflation factors for the western province ($\hat{c}$ = 8.4) and eastern province ($\hat{c}$ = 19.5) indicating some structural lack of fit.

Analysis of the coefficient of determination based on randomly splitting the data and regenerating parameter estimates based upon the previously selected model returned similar values for both provinces. The Western Cascades model (R^2 = 0.175) and the eastern (R^2 = 0.184) each explained almost 20% of the variation of GPS PAR based on remotely sensed vegetation and topographic predictor variables (Fig. 6 & Fig. 7).

Mountain goats:

I examined approximately 10,000 GPS fixes over the course of two years of summer and winter data from 16 mountain goats in the Mt. Baker-Snoqualmie National Forest. I arbitrarily defined summer and winter seasons by dates; as July 1st to August 15th and November 15th to January 1st, respectively. Summer GPS PAR rates from collared goats exceed 50% for each animal with the majority of rates above 80% ($\bar{x}$ = 81%). Conversely, as expected, most winter GPS PAR rates decreased and were generally around 40% ($\bar{x}$ =44%) (Fig. 8).

Painted PAR map

To include estimated GPS PAR (Fig. 1) into a habitat analysis across the entire study area, I created a data layer based on the selected model using the 25 m x 25 m spatial resolution (Table 7 & 8). The Western Cascade model included the cosine of aspect in radians and the amount of coniferous coverage while the Eastern Cascade model included the cosine of aspect in radians and the amount of total vegetation cover. As expected, the Cascades generally showed a much higher probability GPS PAR east of the Cascades crest. Surprisingly, southerly aspects showed a lower PAR throughout the range. A closer examination of the odds-ratios of obtaining of GPS fix by aspect binned into the eight cardinal direction revealed this pattern in both data sets. The final model also yielded GPS PAR ranging from 64% to 99%.

Discussion

The predictive ability of my bias correction model for the Cascades of Washington performed as expected based on the range of values previously reported in the literature. This study however, encompassed a much larger area and therefore intensive sampling scheme and stratification. I over sampled lower elevations where expected bias in the mountain goat data prevailed. I omitted a few areas of low topographic relief and vegetative obstructions from the sampling. Collar comparison between brands dismissed future use of Trimble Geo3 Explorer's from inclusion in model development due to lack of consistency and low correlation between brands. Comparison among Vectronic units and predictive power suggested that micro-site features played a critical and hereto unexplained role in GPS PAR. The final chosen models for both sides of the Cascades fit with ecological expectations and had exceptable area under the ROC scores but with a measure of over dispersion entering the data. The final product, a GIS raster dataset, incorporated into habitat modeling as the inverse of expected GPS PAR reduced observational bias of GPS collared mountain goats. This bias correction factor will help account for areas used by GPS collared wildlife that have poor expected GPS satellite signal reception.

Stratification

At 5 million hectares, this analysis covered a much larger area than previously published studies of GPS PAR both in terms of the number of sample sites and the spatial extent of the study area. I felt confident that the stratified sampling scheme provided adequate coverage in order to extend the results to the entire study area and range of conditions therein. I felt justified applying the final GPS PAR model to the entire study area due to careful sampling of these stratification classes used in accordance with the IVMP release documentation (O'Neil 2002 *et al.*; Browning *et al.* 2003). On the west side, the combinations of vegetation and topography that I omitted represented mixed and broadleaf forest types that I did not expect to be used by mountain goats, nor did I expect to be of any consequence to GPS PAR due to the predominately evergreen nature of the forest communities in western Washington. On the eastside, I did not sample stratification classes that composed 5.80% of the study area. Only one of these classes (southern facing open sites with sky visibility of 61-70%) composed more than 1% of the study area individually. Without empirical evidence, I expected a high GPS PAR at such sites.

The elevation distribution of sample sites resembled the elevation distribution of locations obtained from GPS collared mountain goats (Fig. 3). I slightly over-sampled lower elevations since these elevations typically had lower PAR due to dense forest cover and greater topographic obstructions. I anticipated that these sites presented greater challenges for adequately characterizing habitat use due to lower PAR. The elevation distribution of bias correction sample sites accounted for this expected range of data loss.

GPS data loss, and subsequent observational bias, from collared goats occurred more often in the winter when mountain goats descend to lower elevations (Fig. 8). Data acquired over two years of collection from collared animals thus exhibited the anticipated GPS bias that PAR-modeling efforts reduced.

Collar Comparison

In the side-by-side comparison of GPS units between brands neither the Trimble Geo3Explorer (R = 0.67) nor the Vectronic-Aerospace unit consistently outperformed the other. The low correlation between brands (Fig. 4) and the slightly higher correlation among Vectronic-Aerospace collars (R = 0.83) (Fig. 5) contradicted my expectations. I expected one of the brands to consistently and predictably outperform the other. These poor correlations may have resulted from variation in performance among individual GPS units of one or both brands. My experimental design was not ideal for addressing this issue. I did not expect nor test for this hypothesis and excluded any GeoExplorer3 data in the bias correction model.

The slightly higher correlation among the Vectronic units may have been due to the use of identical units. Another interpretation suggested that the generally low correlation was due to differences in canopy architecture at the microsite level. In the Trimble vs. Vectronic comparison, the units were placed up to 3 m apart and in the Vectronic vs. Vectronic comparison, the units were placed closer together; no more than 1 m apart. Even for GPS units located 1 to 3 m apart; there are minor differences in the relative position of tree boles and small canopy openings. These differences have been enough to provide a different view of the sky and differences in access to satellites resulting in different GPS PAR between units placed only a few meters apart. The slightly higher correlation of the Vectronic vs. Vectronic comparison may have resulted from more comparable microsite condition for units located 1 m apart rather than for units place 3 m apart. When using a handheld GPS unit in a forest it is not uncommon to lose or gain satellite contact after moving only a few meters. If this variation in canopy architecture at the microsite level was in fact a major factor in controlling GPS PAR, then the correlation coefficient (R = 0.67) of the Trimble vs. Vectronic pairing may provide a rough estimate of the upper limit of how much variability in PAR can be explained on the basis of macro-scale site conditions derived from GIS data.

These findings of predicted GPS PAR and low correlation among GPS units placed at the same site suggested an unmeasured component of the forest canopy heavily impacting GPS PAR. This, again, remained consistent with prior studies on this subject that explained only a portion of GPS PAR bias (Table 1). This GPS PAR bias correction study ultimately only reduced, but did not eliminate, bias due to satellite signal blockage. The scale that satellite signal interference occurred most likely surpasses the scale at which the predictive model operated. A broad characterization of the landscape, such as the 25 m resolution level, characterized those types of habitats where micro-site heterogeneity was likely to increase (i.e. increased canopy cover, larger trees and more conifers) but did not account for all site specific factors determining GPS PAR. Nevertheless, this model explained nearly one fifth of the variation in GPS PAR.

The remaining variation in PAR possibly controlled by micro-site conditions might be described on the basis of detailed stem maps and hemispherical photographs of the canopy. In principle, these measurements could be obtained for a limited number of sample points but impractical to utilize over any study area of reasonable size. Another alternative might incorporate Light Image Detection and Ranging (LIDAR) data (Lefsky *et al.* 2002). LIDAR has made it possible to quantify aspects of forest canopy structure including canopy height and vertical biomass distribution quickly and continuously over large areas. As LIDAR becomes more available, incorporation of these data into GPS PAR analyses might facilitate characterization of micro-site features at a finer scale, both in terms of vegetation and topography.

An alternative approach considered for correcting GPS bias involved an iterative process to estimate missed animal locations based on predicted GPS PAR, known animal locations, and theoretical movements across the landscape (Frair *et al.* 2004). This approach however, warranted far more intensive data management, calculations and corrections for individually missed animal locations and did not perform as well as GPS PAR modeling.

Global positioning system position acquisition rate; GPS PAR

Once final models were selected for both spatial resolutions and for both study areas, I needed to select one or the other for final development. I opted to use the area under the ROC curve to distinguish if the 25 m x 25 m or the 75 m x 75 m spatial resolution performed better. On the west side, the small difference between 0.69 (75 m) and 0.70 (25 m) warranted use of the finer resolution. The east side model's area under the ROC curves were virtually identical, so in order to remain consistent with the west side model I opted to use the 25 m x 25 m spatial resolution. Area under the ROC values > 0.70 indicated “a reasonable discrimination ability appropriate for many uses,” (Pearce & Ferrier 2000). The final model thus utilized 25 m x 25 m spatial resolution for the entire study area.

After selecting the models developed at the 25 m x 25 m resolution, I tested the global models of both data sets for over dispersion and goodness of fit. Variance inflation values much greater then 4 indicated structure lack of fit and over dispersion of the data for both models (Burnham & Anderson 2002). The predictive model did not perform well at low predicted probabilities (<0.60) when compared with observed PAR rates, displaying poor model refinement (Figs. 6 & 7). The final data layer, however, had values ranging from 0.64 to 0.99.

Mapping

The final model developed for the Washington Cascades predicted GPS PAR across mountain goat habitat and reduced observational bias generated by vegetative and topographic features of the landscape. Final predictor variables included: the total vegetation cover, coniferous coverage and aspect. The predictive model of GPS PAR developed from stationary collars sampled across the mountain range performed within the range of expectation based on previous research in this field (Rempel *et al.* 1995; Deckert & Bolstad 1996; Edenius 1997; Dussault *et al.* 1999; Gamo & Rumble 2000; Licoppe 2001; Rodgers 2001; D'Eon *et al.* 2002; Taylor 2002; Di Orio *et al.* 2003; Frair *et al.* 2004; Cain *et al.* 2005; Sager 2005). This supported the application of a bias correction factor to analysis of GPS data from collared mountain goats.

The final data layers predicted GPS PAR for collared mountain goats across the Western and Eastern provinces of the Washington Cascades. These combined into one final data layer predicting GPS PAR across both IVMP Washington Cascade regions. Much of these regions lie below 800 m in elevation beneath the minimum sampling elevation. The overriding nature of vegetation variables impacting GPS PAR more so than topography allowed reasonable extrapolation of the model to these lower elevations. The analysis indicated that elevation alone was not a strong predictor of PAR. This suggested that the model may perform adequately even at low elevations if the canopy cover of the forest did not change much from the lowest sampled GPS PAR. Examination of the eastern reaches of the data layer where the mountains begin to merge with the central Washington highlands and deserts predicted a high PAR, as expected. Closer examination of detail on the map and parameter estimates provided one counter intuitive finding. In the Washington Cascades, southern facing slopes predicted a lower GPS PAR, not what was expected based on the satellite sky plot of GPS satellite orbital geometry (Fig. 2). I expected that the gap in satellite coverage over the north pole to result in lower GPS PAR on slope facing this direction.

Applying such a model outside the study area and with different hardware was not recommended by any of the previous authors published in this field of research. I certainly agreed with the notion of not applying this model to areas outside the Cascades of Washington (although areas of the Oregon Cascades might have applied), however, I considered the merits of applying this data layer to other GPS collared wildlife with in the region. The fundamental decision to do so lies within any future projects' objectives, resources available, known improvements or difference in hardware, margins of error and costs of a Type I or Type II error.

Tables

Table 1: Population estimates of mountain goats across portions of their native range since the 1960's depicting a long-term decline in the population.

British Columbia

- 1961-est. 100,000
- 1977-est. 63,000 (Macgregor 1977)
- 2000-est. 36,000-63,000 (Côté and Festa-Bianchet 2003)

Washington

- 1961-est. 10,655
- 1983-est. 7350 (Johnson 1983)
- 2005-est. 3500-4000 (Rice pers. comm. 2005)

Entire Range-introduced and native

- 2000-est. 75,000-110,000 (Côté and Festa-Bianchet 2003)

Table 2: Prior studies of GPS wildlife telemetry observational biases.

Author	Test	Test Statistic	Independent Variable
Rempel *et al.* 1995	[1]LR	X^2 (P < 0.001)	tree spacing
Dussault *et al*. 1999	[2]SMLR	R^2= 0.16 (fall)	tree height
		R^2=0.34 (winter)	tree height, basal area of deciduous trees
Gamo & Rumble 2000	SMLR		
		R^2= 0.39 (*P.ponderosa*)	slope, CC
		R^2= 0.40 (*P.tremuloides*)	Visible Horizon, Dbh
		R^2= 0.50 (*P.glauca*)	CC
D 'Eon *et al*. 2002	SMLR	R^2= 0.22	[4]CC, [5]SV
Taylor 2002	SMLR	R^2= 0.76	SV, [6]age, clearings
Di'Orio *et al*. 2003	SMLR	R^2= 0.57	basal area
Frair *et al*. 2004	LR [3]AIC	ROC= 0.68	vegetation type, slope
Sager 2005	LR	$\hat{c}$=1.0282	CC, SV, [7]elev., CC*SV

[1]LR= Logistic Regression, [2]SMLR= Stepwise Multiple Linear Regression,
[3]AIC= Akaike information criterion, [4] CC=Canopy Cover, [5]SV=Sky Visibility, [6]age=Forest age & [7]elev.= elevation

Table 3: Discrete categorization of vegetative predictor variables for the Western (wcw) and Eastern (ecw) Cascades of Washington GPS PAR data. Bold face type of the region indicates selected variables in final model.

1. Percent Total Vegetation Cover (TVC);
   - wcw & **ecw**: 0-60% , 60-90% & 90-100%
2. Percent Conifer Cover (CC);
   - **wcw** & ecw: 0-40%, 40-80% & 80-100%
3. Percent Broadleaf Cover (BC);
   - wcw & ecw: 0%, 0-10%, 10-20% & 20-100%,
4. Quadratic Mean Diameter of overstory trees (QMD);
   - wcw: 0, 0-25.4 cm, 25.4-50.8 cm & >50.8 cm
   - ecw: 0-12.4 cm & >12.4 cm

Table 4: Stratification variable organization and definition used in field sampling efforts of GPS PAR across the entire Cascades of Washington based on the IVMP data sets.

1. Forest type
   - Open: TVC <30%
   - Semi-open: 30% ≥ TVC < 70%
   - Conifer: TVC ≥ 70%; CC >= 70%
   - Mixed: TVC ≥ 70%; CC and BC < 70%
2. QMD

   Western Cascades
   - 0-30 cm
   - 31-60 cm
   - 61-190cm

   Eastern Cascades
   - 0-25cm
   - 25-190cm
3. Slope and aspect
   - slope < 20 degrees
   - north-facing slopes > 20 degrees
   - south-facing slopes > 20 degrees
4. Sky visibility
   - 0-60%
   - 60-70%
   - 70- 80%
   - 80-100%

Table 5: Definition of predictor variables and nomenclature thereof for a 25 m x 25 m and a 75 m x 75 m spatial resolution used to build predictive models of GPS PAR.

Type	Sampling Window	Variable	Nomenclature
Topographic	1&9	Cosine of radial aspect	ASP
	1&9	Slope (degrees); mean	SLP
	9	Slope; standard deviation	SLPSD
	1&9	Elevation (m); mean	ELEV
	9	Elevation; standard deviation	ELEVSD
	1&9	Sky visibility; mean	SV
	9	Sky visibility; standard deviation	SVSD
Vegetative	1&9	Mode of QMD[1]	QMD
	9	Number of QMD classes	
	1&9	Mode of BC[2]	BC
	9	Number of BC classes	
	1&9	Mode of CC[3]	CC
	9	Number of CC classes	
	1&9	Mode of TVC[4]	TVC
	9	Number of TVC classes	

QMD[1]=Quadratic mean diameter, BC[2]= Broadleaf cover, CC[3]= Conifer cover & TVC[4]=Total vegetation cove

Table 6: Results from model testing of Cascade GPS PAR based on a 25 m and 75 m spatial resolution for the Western and Eastern Cascades of Washington State, USA shown with negative log likelihood (-LL), number of parameters (K), Akaike's Information Criteria (AICc), criterion difference (Δ_i) and weights (w_i).

Region	**Resolution**	**Rank**	**Model**	**-LL**	**K**	**AICc**	Δ_i	w_i
West	25 m	1	ASP & CC	5184.2	4	10378.5	0	0.81
		2	CC	5186.9	3	10381.8	3.3	0.16
		3	ASP, SLP, ELEV & TVC	5185.7	6	10385.3	6.8	0.03
West	75 m	1	ASP, SLP, ELEV, SV & TVC	6980.5	7	13972.5	0	0.40
		2	TVC	6983.2	4	13973.1	0.6	0.30
		3	ASP & TVC	6980.5	5	13973.1	0.6	0.30
East	25 m	1	ASP & TVC	2396.6	4	4803.2	0	0.63
		2	ASP, SLP, ELEV & TVC	2395.2	6	4804.4	1.2	0.35
		3	ASP, CC & QMD	2400.2	4	4810.4	7.2	0.02
East	75 m	1	ASP & TVC	2396.5	4	4803.0	0	0.46
		2	ASP, SLP, SLPSD & ELEVSD	2394.2	6	4803.3	0.3	0.40
		3	ASP, TVC, QMD & CC	2396.6	4	4805.3	2.3	0.14

Table 7: The most parsimonious selected model for the Western Cascades of Washington GPS position acquisition rate's parameters, coefficients *(β)* robust error estimates and confidence intervals (*n* =15,550; *N* =317) based on a 25 m x 25 m resolution with an auto-regressive GEE (*m*=1) modeling correlation structure.

Variable	*β*	Std. Err.	*z*	*P*>|*z*|	[*95%*]	
ASP	0.2568	0.1235	2.08	0.0376	0.0147	0.4989
CCdv2	-1.0156	0.3013	-3.37	0.0007	-1.6061	-0.4251
CCdv3	-1.7966	0.2799	-6.42	<0.0001	-2.3451	-1.2480
Intercept	2.6484	0.2584	10.25	<0.0001	2.1420	3.1549

Table 8: The most parsimonious model for the Eastern Cascades of Washington GPS position acquisition rate's parameters, coefficients (*β*) robust error and confidence intervals (*n* = 11,057; *N* = 219) based on a 25 m x 25 m spatial resolution with an auto-regressive GEE (*m*=1) modeling correlation structure.

Variable	*β*	Std. Err.	*z*	*P*>|*z*|	[*95%*]	
ASP	0.4291	0.1685	2.55	0.0109	0.0989	0.7594
TVCdv2	-0.9634	0.3119	-3.09	0.0020	-1.5747	-0.3521
TVCdv3	-1.6989	0.2900	-5.86	<0.0001	-2.2673	-1.1306
Intercept	3.5887	0.2637	13.61	<0.0001	3.0719	4.1055

Figures

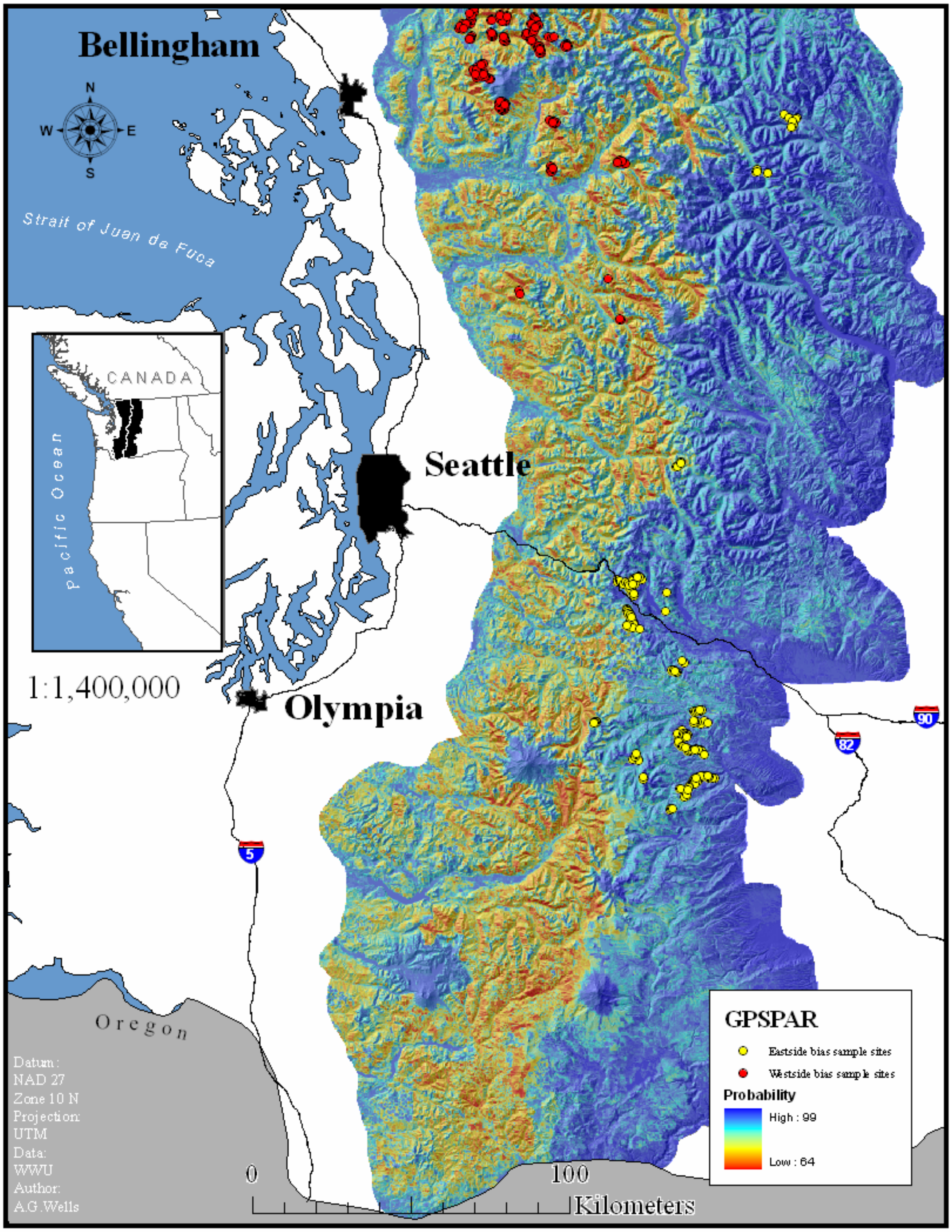


Fig. 1: Map showing predicted GPS Position Acquisition Rate (PAR) for the Cascades of Washington State used to offset bias generated during habitat analysis of GPS data from collared mountain goats. This combines the two study areas, east and west of the Cascade crest, into a single unified data layer and shows the location of sample sites.

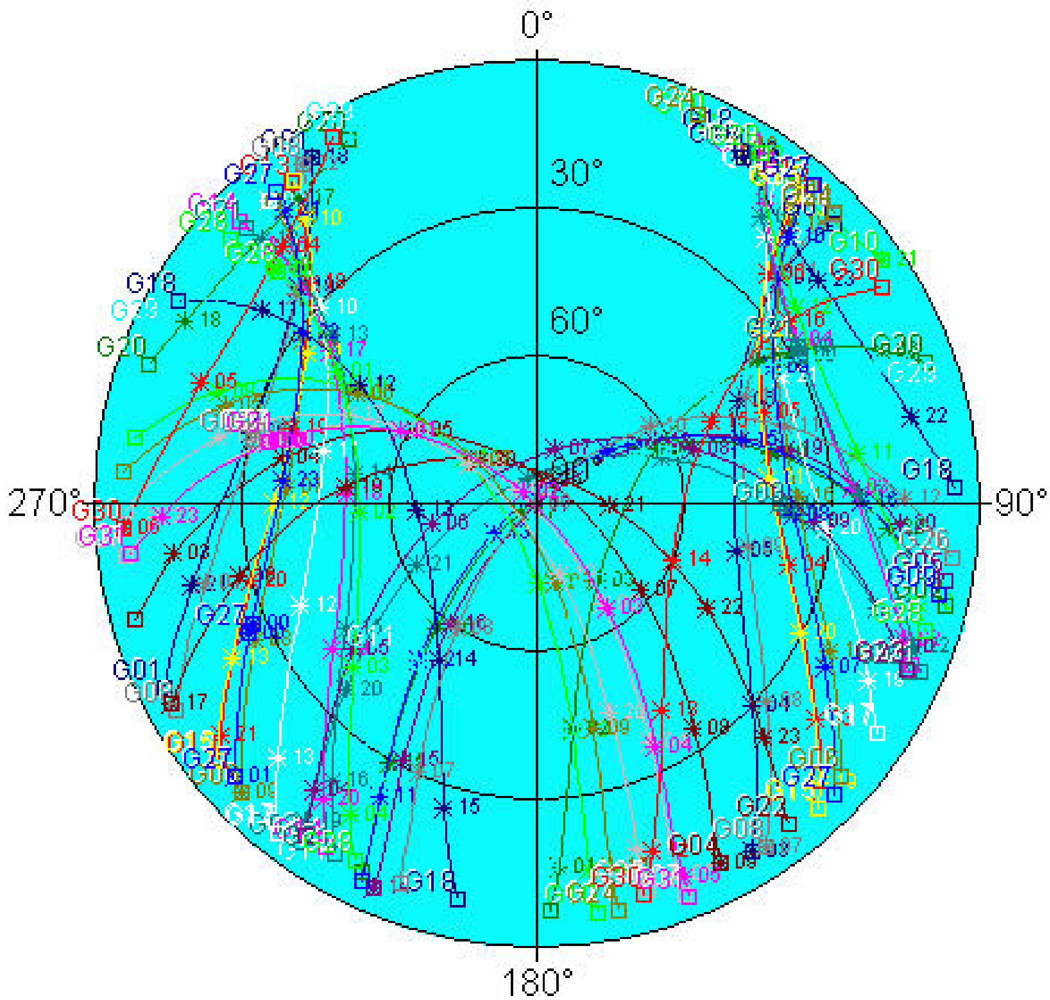


Fig. 2: Skyplot showing orbital geometry of GPS satellites in the sky as viewed from Seattle, WA showing a gap in coverage over the north pole. Image generated with Trimble's Planning Version 2.7 © available free online.

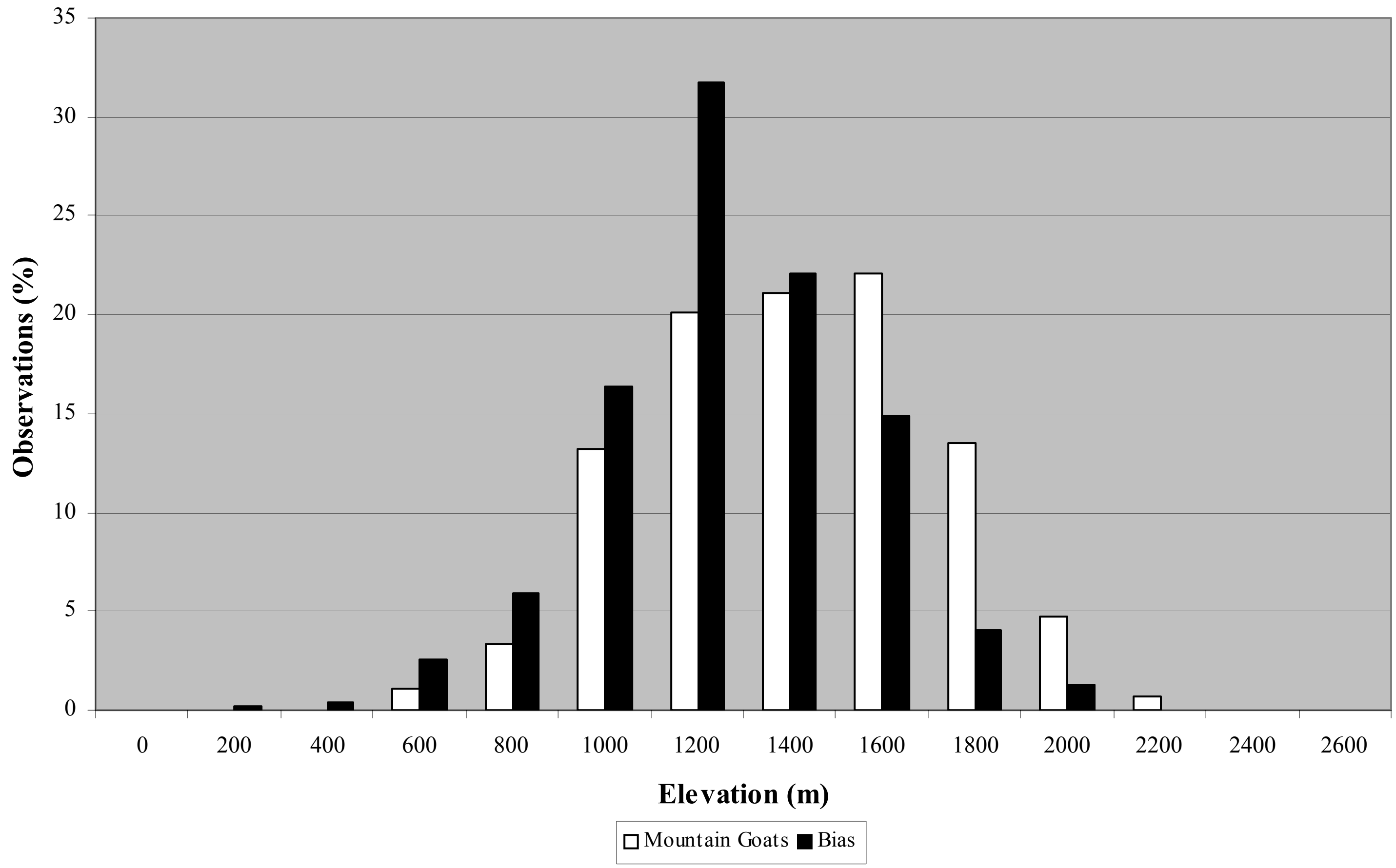


Fig. 3: Distribution of elevations sampled during GPS bias correction work and elevations sampled from over 30,000 mountain goat GPS fixes showing a slight under sampling of GPS PAR at higher elevations and over sampling at lower elevation where GPS PAR from mountain goats was expected to be higher and lower, respectively.

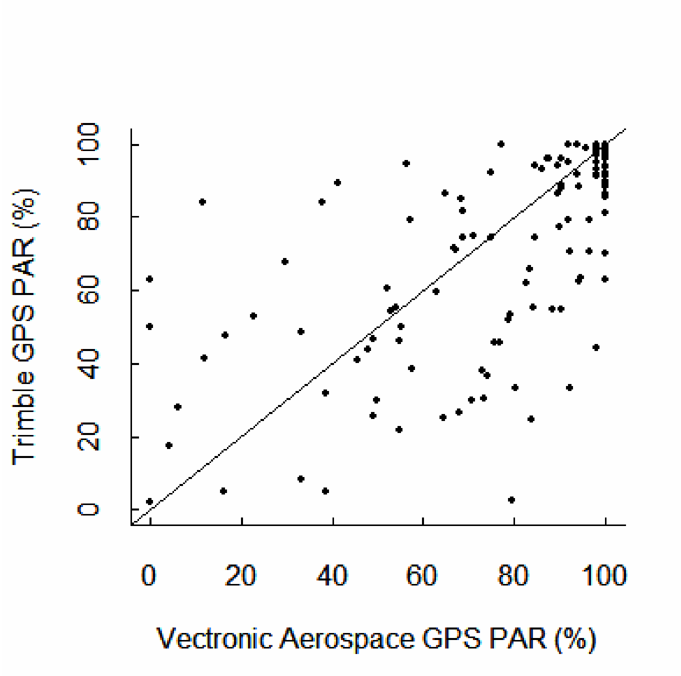


Fig. 4: Relative GPS PAR between a Trimble GeoExplorer3 and Vectronic-Aerospace wildlife telemetry collar at 138 sites across the Washington Cascades shown with a one to one fit line.

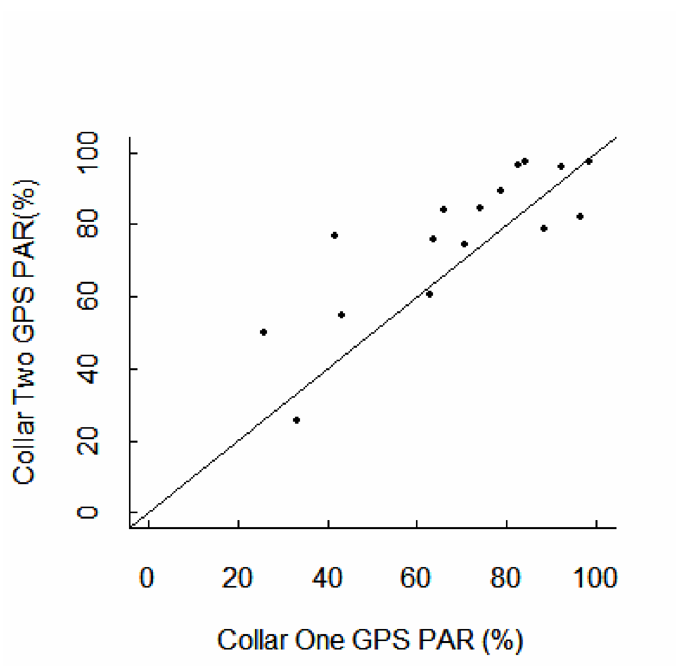


Fig. 5: Correlation of GPS PAR between two Vectronic-Aerospace GPS wildlife collars place within 1 m of each other at 16 different sites in the North Cascades shown with a one to one fit line.

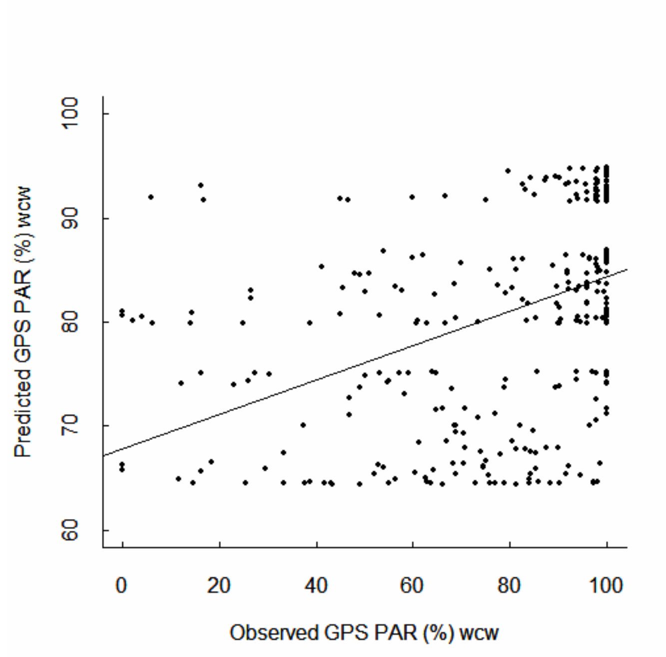


Fig. 6: A comparison of observed GPS PAR and predicted GPS PAR for the Western Cascades of Washington (wcw) based on a 25 m x 25 m spatial resolution using all fixes shown with a line of best fit.

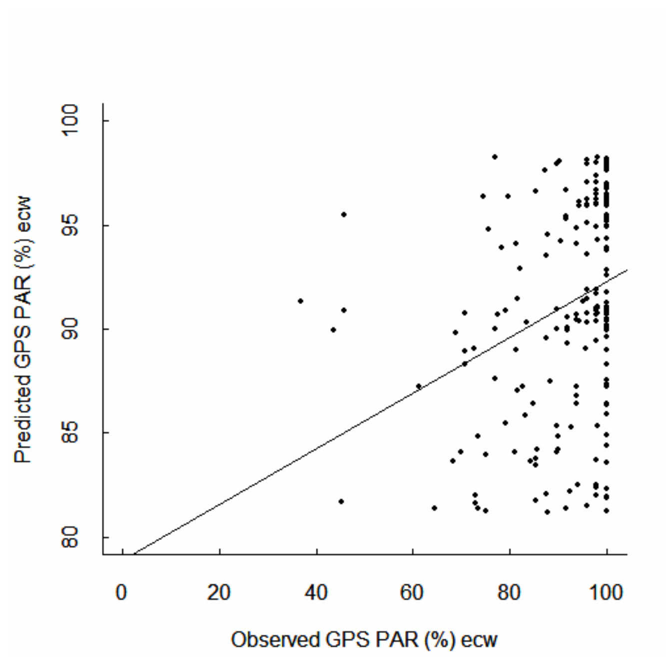


Fig. 7: A comparison of observed GPS PAR and predicted GPS PAR for the Eastern Cascades of Washington (ecw) based on a 25 m x 25 m using all fixes shown with a line of best fit.

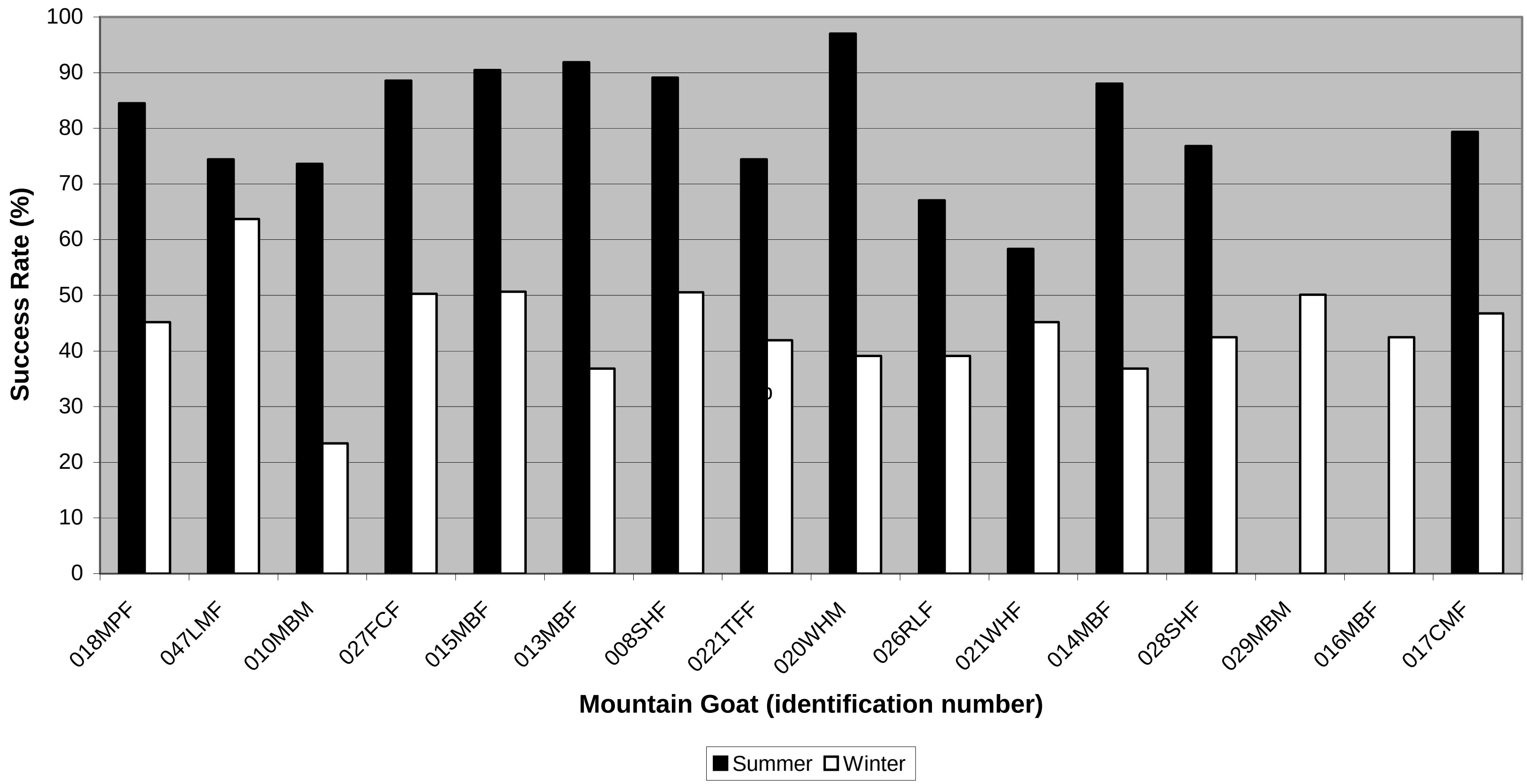
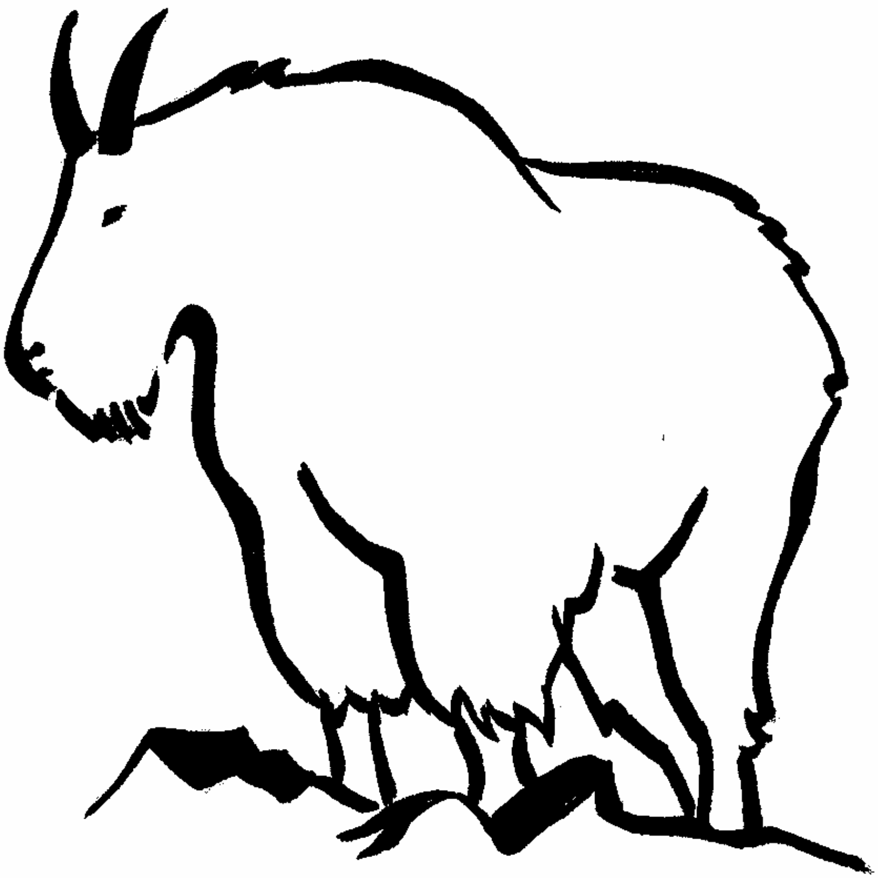


Fig. 8: Seasonal comparison of GPS PAR from collared goats in the northern region of the Western Cascades based on 10,000 locations obtained between July 15 to August 31 of 2004 and 2005 (black) and December 15 to January 31 during the winters of 2003-04 and 2004-05 (white).

Chapter Two:

HABITAT SELECTION BY MOUNTAIN GOATS <u>OREAMNOS AMERICANUS</u> IN THE WASHINGTON CASCADE



Introduction

Mountain goats inhabit some the most rugged terrestrial environments of the North American west (Côté and Festa-Bianchet 2003). The harsh environment that they inhabit results in low fecundity, low survivorship and poorly understood population dynamics (Adams and Bailey 1982). Their selection of cliffs evolutionarily decreased their predation pressure, but use of these sites carries with it an increased risk of death or injury due to falls and rock slides (Johnson 1983). Characteristically rugged, this species has shown in the past the ability to colonize new territory (Hayden 1984) and quickly disappear in others (Kuch 1977).

Native mountain goat populations of the Washington Cascades have decreased over the last several decades (Côté & Festa-Bianchet 2003). Some rough estimates suggest declines of as much as 70% over the last forty years (Rice pers. comm.). In some locales that once had dozens of goats, for instance the wintering grounds at Penders Canyon just west of the Glacier Peak Wilderness area, recent surveys have found few small bands or no goats at all. These declines have resulted in a major reduction of the permitted hunt. Concern over the population decline also prompted studies investigating the reasons behind this trend. Possible explanations for the population decline include: over hunting, increased recreational disturbances, increased cougar *Felis concolor* populations, disease, population fragmentation, loss of genetic viability, habitat loss, land use changes particularly in wintering and dispersal habitat, climate change and the combination of multiple stressors.

Most previous work on mountain goat habitat has focused on summer months. Severe weather and logistical issues have made it problematic to address seasonal variation in habitat use in any systematic fashion. Understanding total year round available habitat can assist land-use managers and applied conservation strategies designed to assist in mountain goat recovery. To augment the existing, largely summer, anecdotal accounts of mountain goat habitat (Gross *et al.* 2002), I have developed a year round GIS habitat model based on an elevation profile of GPS collared mountain goats. The objective of this was to improve the accuracy and precision of previous modeling efforts (Johnson & Cassidy 1997), incorporate a GPS bias correction model and to designate the largely unknown (Côté and Festa-Bianchet 2003) lower elevation habitats;

areas of critical importance to over wintering success and dispersal. It is these lower reaches of habitat that often fall within areas that were most susceptible to direct disturbance from anthropogenic sources. Individual accounts of past human activities suggested that such disturbances have lead to extirpation of local populations through degradation of over wintering sites. Even minor disturbances during the winter may increase the already high mortality rates mountain goats experience at this time of year. My research will contribute to the establishment of an ecological base line by which future investigations of mountain goat ecology, population trends and habitat changes may be measured.

In this chapter, I developed a series of statistical models to identify potential mountain goat habitat on the western side of the Cascade Mountain Range in Washington State. These habitat models are based on location data collected over a two-year period from 39 GPS collared animals. These habitat models incorporate the GPS bias correction evaluation described in Chapter One. The resulting maps provide insights on the status of potential mountain goat habitat and will contribute to more effective management and possible recovery of the species in Washington State.

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Methods

Capture and Collars

The Washington Department of Fish and Wildlife captured and administered care and supervision of study animals in accordance with American Society of Mammalogists' guidelines. Mountain goats were captured via aerial and ground-based darting with 0.4-0.5 cc Carfentanil or 50-70 mg xylazine hydrochloride mixed with 0.15-0.25 mg of opiate A3080 and reversed with 3.0 cc Naltrexone or 4.0 cc Tolazine, respectively. The 39 captured individuals were outfitted with GPS telemetry collars (GPS plus collar v6, Vectronic-Aerospace GmbH, Berlin, Germany) scheduled to record a fix every 3 hours for a period of 2 years. Initially, nine of the captured animals' collars recorded fixes on a 5-hour interval accounting for 10% of the data used in this analysis. Most of these five-hour intervals were reprogrammed within 6 months. Three animals were recaptured and re-collared after hardware failure. Seven collars failed and animals were not re-collard prior to two full years worth of data collection. Six study animal mortalities occurred during the 2-year period, mostly from unknown causes. Use of data from multiple years was intended to reduce the impact of inter-annual variability in habitat selection due to weather or unusual behavior. The winter of 2004-05 had very low snow pack throughout most of the Cascades and the winter of 2005-06 had snow packs that were slightly higher than the long-term average (USDA 2006)

Data Analysis

I created eight-habitat selection models based on elevation ranges employing the use-availability design; type II sampling protocol SP-A (Manly *et al.* 2002, Keating & Cherry 2004). I used weighted logistic regression with Akaike's Information Criteria (AIC) to select the most parsimonious model based on a subset of models (Appendix D) that were defined using variables thought to be ecologically relevant based on previously published studies. I modeled the probability of a mountain goat location (π) as:

$$\pi = \frac{\exp(ß_0 + ß_1 X_1 + ß_2 X_3 + \ldots + ß_p X_p)}{1 + \exp(ß_0 + ß_1 X_1 + ß_2 X_3 + \ldots + ß_p X_p)} \qquad \text{eqn. 3}$$

The weighting factor accounted for GPS data loss due to topographic and vegetation obstructions of satellite signals using the inverse of the GPS PAR developed from Chapter One. I also generated parameter estimates for the selected models without the weighting factor to gauge the influence of the bias correction factor. I calculated cut points based on the predicted probability at the convergence of the cumulative number of goats points versus the cumulative number of available points and developed classification accuracies from these. I then multiplied the proportion of observations in each elevation band during the combined time period of June, July, August and September as well as December, January, February, March and April to look at the differences in usage of available habitat between these two times of year.

Assumptions:

The use-availability design protocols also makes a number of assumptions regarding the study design that used measurable attributes of resource use. The stated assumption, "animals have free and equal access to all available locations" (Manly *et al.* 2002) required consideration and ultimately violating, as is the case in most other habitat selection studies utilizing this design. Mountain goats inhabiting relatively small ranges with few, if any, long range dispersals could not have equal access to all locations in the entire Cascades mountain range. To model such a situation, I had to generate available locations based upon some reasonable limitation of each individual animals theoretical movements. This however, precluded modeling the entire study area as a whole range for the species. I therefore compromised, and split the available sites into northern and southern regions divided along the Interstate 90 corridor. I-90 also most likely provided a substantial obstacle for mountain goats trying to move north or south across the highway. This split the data set into 8 subsets, based on the four elevation bands, discussed below, in the north and south, which I modeled individually. Delineation of elevation quartiles was made prior to the division of habitat into two regions. I clustered an equal number of random points to mountain goat points based on this north south division. Splitting the analysis into northern and southern subsets reduced the violation of the free and equal access assumption and kept the computational loads within reasonable limits

The repeated measure of individual animals also violated the assumption of independence of observations. I attempted to model the correlation structure of the intra-cluster structure of GPS fixes of collared animals to account for this. I wanted to use a non-linear mixed model (Appendix C) during model selection to account for this clustering of observations by modeling the individual animal as a random effect. Each cluster of individual animal locations was paired with an equal number of available sites. After selecting the most parsimonious model, I wanted to use the PROC GEN MOD command in SAS to model the correlation structure of the goat fixes with a generalized estimating equation (GEE) to generate robust standard errors and modified parameter estimates. The amount of random effects variability in the datasets however, failed to achieve quadrate accuracy during model selection and failed to estimate variance with a GEE using either auto-regressive or exchangeable correlation structure. I therefore retained the initial parameter estimates generated with ordinary logistic regression for habitat modeling while recognizing the inherent flaws with the standard error estimates.

GIS habitat predictor variables

I developed a series of predictor variables to describe the vegetation and topographic characteristics of the study area. For each goat location, I extracted GIS data at one spatial scale for inclusion in the habitat analysis, 5,625 m^2 (75 m x 75 m square extraction window). I opted to use a 5,625 m^2 square extraction window recognizing that over the three hour GPS sampling interval, mountain goats likely selected habitats at a scale much larger than the finest resolution of available satellite imagery, 625 m^2 (25 m x 25 m). This scale also encompassed more of the GPS inaccuracies.

As described in Chapter One, I used the Western Cascades IVMP (O'neil *et al*. 2002) data layers to create independent vegetation variables. I created six classes of total vegetative cover: 0-20%, 20-40%, 40-60%, 60-80%, 80-100% total cover and areas classified as rock and ice. I broke the QMD data layers into four classes: No cover, 0-30cm, 31-60cm and 61-190cm. The CC layer I classified into three discrete categories: 0-30%, 30-70% and 71-100%. I did not select even intervals for the CC due to prior definitions of areas with no cover in the QMD layer as specified by the IVMP. The IVMP considers areas with less than 30% CC as areas with a QMD of 0. This way the lowest definition of CC remained consistent with the QMD layer. I did not include any variables representing broadleaf coverage in the analysis. The final vegetation variables used for model creation included the mode and variety of pixels classified by TVC, QMD and CC for each square extraction window at the 75 m x 75 m resolution. I treated the vegetation variables as categorical represented by implied dummy variables.

I derived topographic predictor variables from a 10 m DEM masked to the same spatial extent and resampled to the same pixel size as the Western Cascades of Washington IVMP data set (25 m). I created slope and aspect layers with Spatial Analyst (ESRI 2004) using the surface tool set. In the analysis, I used slope as a continuous variable directly exported from the GIS. Considering the circular nature of aspect and the possible importance of this as a factor in mountain goat habitat selection, I opted to transform aspect into two distinct continuous covariates (Gross *et. al.* 2002). I used the cosine and sine of aspect, in radians, to test for mountain goats habitat selection for slopes along either a north to south or east to west axis. The ecological rationale for this differentiation had to do with expected differences in thermal cover, forest type and snow loading issues.

The distance to escape terrain data layer involved a few additional calculations. I defined escape terrain as areas with slopes greater than 35° based on an average of previously reported values (Fox and Taber 1981; Johnson 1983; Varley 1994; Fox 1989; Welch *1990*; Gross *et al*. 2002). I used a slope layer created at the 10 m resolution and reclassified areas with slopes greater than 35° as escape terrain. I made this distinction prior to reclassifying the pixels to the 25 m cell size in order to retain the finest possible resolution for defining distance to escape terrain. The 10 m pixel size is simply too computationally intensive to used for the entire model despite having a greater precision. I then used the Euclidean distance tool to calculate the distance from the center of each 25 m pixel in the raster file to the edge of the nearest pixel of escape terrain. The final topographic predictor variables available for model building came from a 75 m x 75 m resolution (3 x 3 pixel extraction window) and included mean degree slope, standard deviation of slope, elevation (m), sine and cosine of aspect and distance to escape terrain (m).

Results

Initially, I wanted to define seasonal habitats used by mountain goats in the sense of a calendar driven definition of seasons. In other words, goats inhabited a particular region during the summer and another region during the winter. Describing habitat in this framework however, failed for a number of reasons. Some animals changed elevation frequently, others much less. Some animals went high on the slopes of volcanoes while others did, or could not, given the geomorphic setting that they occupied. Comparing animals revealed that many may have moved lower at the same time in the fall, but using any sort of average date, showed an earlier change for those that started higher (Fig. 9). Apparently, some individuals had access to low elevation habitats and others simply did not.

In a biological sense, the whole phenomenon of seasonal differences in habitat selection likely hinged on weather patterns, and only made sense in a broad sense because of the relationship between season and weather. The variability of weather within a season and between years created part of the problem. Natural history of the mountain goat suggests that animals respond to weather in their use of different seasonal habitats (Johnson 1983). So, if an animal moved to high ground in March because of "good weather" and back down in April during "bad weather", how does fit into the notion of calendar driven seasons? Did the goat use summer habitat in March and winter habitat in April? Or does the "winter" habitat include the March locations? If the animal went to "summer" habitat during the mild spell, then returned to "winter" habitat with the return of poor weather then partitioning seasons by date defied efficient data management, analysis and ecological relevant partitioning of habitat ranges.

Instead, I looked at the habitat usage by elevation. In this way, the habitat modeling predicted that when a mountain goat was at any give elevation, its selection of habitats may have been based on these different characteristics. When a goat responded to a weather driven phenomenon and moved to a different elevation band, the modeling scheme accounted for these intra-seasonal (in a calendar defined) changes in habitat use. The final modeling scheme then predicted habitat use across four bands of elevation. From a land use managers perspective however, some subjective definitions of seasons was required for certain activities like road closures and snow park operation. I therefore used the proportion of mountain goat fixes in each elevation band during "summer" (June, July, August, and September) and winter (December, January, February, March and April) to look at the differences in habitat availability across a yearly temporal scale.

I acquired 86,826 GPS locations from the 39 collared mountain goats roughly distributed in five regions across the Western Cascades (Fig. 13). The elevation distribution of these points based on GIS elevations, rather then the recorded GPS elevations, followed a Gaussian curve (Fig. 10). The eight data subsets had a range of total number of GPS locations from 3,843 in the lowest elevation band in the southern Cascades to 17,751 locations in the northern Cascades lowest elevation quartile. The 4 northern Cascades elevation bands constituted 51,881 GPS locations while the 4 southern subsets tallied 34,945 locations. In the northern region, each quartile contained locations from 21 animals, while the southern region had 11 animals in the 1st quartile, 15 in the 2nd and 16 in both the 3rd and 4th quartile.

From these GIS extracted elevations I determined the 1^{st} quartile at 1187 m, the median at 1455 m and the 3^{rd} quartile at 1670 m. The upper elevation of the 4^{th} quartile was bounded at 3100 m above which no mountain goat locations were recorded. The distribution of goat locations by month within these quartiles follows expected trends of seasonal goat movement (Fig. 11). The use-availability experimental design in habitat selection modeling called for a set of random or available points. I used Hawth's analysis tools (Beyer 2004) to generate random points in accordance with the elevation quartiles of GIS mountain goats locations. I bound the lower limit of the first quartile of random points with a conservative estimate of 300 m based on the lowest extracted GIS elevation of a successful GPS fix from a mountain goat (322 m). I defined the upper limit of the 4^{th} quartile random points at 3100 m based on a conservative buffer around the highest observed mountain goat elevation and maintained a 1:1 ratio of individual goat locations to random points in each quartile.

The proportion of use of each elevation band during June, July, August and September across the entire study area were as follows: 1^{st} quartile (300-1187 m) = 0.07, 2^{nd} quartile (1187-1455 m) = 0.21, 3^{rd} quartile (1455-1670 m) = 0.38 and the 4^{th} quartile (1670-3100 m) = 0.46. The proportion of use during December, January, February, March and April were: 1^{st} quartile = 0.59, 2^{nd} quartile = 0.41, 3^{rd} quartile = 0.24 and 4^{th} quartile = 0.21.

The most parsimonious models for the eight datasets based on weighted goat locations followed similar patterns of variable inclusion. The global model along with two similar models, one excluding the first class of QMD and the other the variety of QMD classes in the extraction window, constituted the highest ranked subset of models according to the AIC scores (Table 9.0) for all the datasets. The selected models were not the same for the 1^{st} and 4^{th} elevation quartiles across the two regions. The 3^{rd} and 2^{nd} quartiles had the same model parameters in both regions. All of the models included the topographic variables distance to escape terrain, both measures of aspect, elevation, slope and standard deviation of slope. The vegetation variables included in the models varied slightly but all included each category of variable; QMD, conifer cover and total vegetation cover (Table 9.1-9.8). Empirical cumulative frequency distributions of topographic predictor variables showed selection by goats for areas closer to distance to escape terrain and areas with steeper slope (Fig. 12).

The cut points between the number of available sites and mountain goat sites were lower for the un-weighted habitat map (Table 10). Based on these cut points, the classification accuracies for the weighted maps were slightly better in four of the eight datasets and virtually equal in the remaining four. Area under the receiver operating curve (ROC) for each of the eight weighted models exceeded 0.70 (Table 10) based upon independent data. In each elevation band, I reserved 25% of the GPS locations for model testing.

The final habitat map displayed the continuous probability of potential mountain goat habitat taking into account the GPS bias correction-weighting factor across the Western Cascades Province (Fig. 13). Taking the average cut point for all quartiles from the weighted ($\bar{x}$ = 0.60) and un-weighted map ($\bar{x}$ = 0.58) and reclassifying all probabilities as habitat or not indicated a total of 253,638 ha and 249,715 ha of total available mountain goat terrain respectively. This amounted to 9.2% and 9.0% of the total area in the Western Cascades of Washington. Multiplying the predicted potential habitat in each elevation band with the proportion of use during "summer" (June, July, August and September) as well as "winter" (December, January, February, March and April) altered the interpretation of the probability values in the resulting models and provided a different impression of available habitat across the year (Fig. 14).

Discussion

The final habitat map showed in one data layer, the predicted probability of the landscape being mountain goat habitat taking into account a the GPS bias correction weighting scheme developed in Chapter One. The differentiation of available sites from north to south across the mountain range as well as the four elevation quartiles used to model habitat created eight distinct models and habitat mapping regions. These eight were mosaiced into one final map interpreted as probability of mountain goat habitat. Using the optimal cut points yieled the best overall classification accuracy of mountain goat habitat, but adjusting these points based on management objectives will alter the maps towards either a more or less conservative estimate of mountain goat habitat.

The final map was consistent with known population distribution patterns of mountain goats throughout large portions of the western Cascades. The regions circumnavigating Mt. Baker (Fig. 15) showed high potential habitat in areas known to contain 300-400 mountain goats. The Three Fingers-Whitehorse mountain chain also clearly included a substantial amount of habitat (Fig. 16). The mountain goat habitat in this region appeared to lack connectivity to other nearby habitat although there did appear to be some connectivity to the southeast. Even in this direction there is a major drainage system that separates the Three Fingers-Whitehorse habitat complex from the Glacier Peak habitat complex to the east. Mount Rainier (Fig. 17) also displayed habitat along its slopes with a distinctly more sinuous structure. The habitat patches appeared longer and more narrow than those around Mt. Baker and not as well connected. This most likely stemmed from the fact Mt. Rainer stands much taller then Mt. Baker and consequently has habitat patches spread out across greater distances and much further away from one another. In 2005, surveys conducted there estimated a population of at least 120 mountain goats.

The data layer also displayed some high probabilities of potential mountain goat habitat in areas with few or no populations. In particular, the areas east of Mt. Baker towards the North Cascades National Park and the Pickett Range have some of the densest and most obvious patches of habitat (Fig. 18). This region however, does not historically support a large population of mountain goats. Looking at the differences in seasonal habitat maps (Fig. 14) suggested that a lot of this habitat might be available during the summer with fewer habitat patches and poorer connectivity in the winter. The central Cascades also have quite a bit of habitat but currently do not support strong populations of mountain goats possibly due to large harvest in the past (Fig. 19). The southern Cascades, from Goat Rocks Wilderness Area to Mt. Adams and Mt. St. Helens (Fig. 20), showed more disjointed and not nearly as much high quality habitat as the Northern Cascades although they do support mountain goat populations. There was one instance of a long distance dispersal of a juvenile male mountain goat from the Goat Rocks Wilderness area to Mt. Adams across large areas of low lying and low predicted probability habitat.

The trends in elevation use follow expected ecological patterns. There was high use of the fourth elevation quartile during June, July and August after a quick transition up from the peak usage in lower quartiles. Downward movements progressed more slowly at the end of the summer and fall months. The lowest quartile had the highest usage during the first three and last two months of the year. This fit with expected patterns of elevation changes across seasons and supported partitioning the data and modeling habitat by elevation quartiles to capture seasonal trends. This was also how I defined what months to include in the proportion of use factor for creating winter and summer models.

Weighting each of the goat location on the basis of GPS PAR did not appear to have much effect on the habitat models. The slightly lower cut points developed with models not using the weighting factor to offset GPS PAR resulted in slightly lower classification accuracies across four of the eight datasets. The difference in cut points and accuracies however, was negligible in these four models. The total area of potential habitat delineated by each set of models was similar. The greater total area of habitat based on the weighted model's mean cut points suggested the bias correction factor accounted for some habitat's where detection of study animals may have been low.

The small difference between the weighted and un-weighted models may have resulted from at least two different factors. First, the predictive power of the GPS bias correction model from Chapter One was comparable to that reported in other studies (Rempel *et al.* 1995; Deckert & Bolstad 1996; Edenius 1997; Dussault *et al.* 1999; Gamo & Rumble 2000; Licoppe 2001; Rodgers 2001; D'Eon *et al.* 2002; Taylor 2002; Di Orio *et al.* 2003; Frair *et al.* 2004; Cain *et al.* 2005; Sager 2005) but it was still relatively low.

Secondly, the effect of bias in GPS PAR may have been minimized because I developed separate habitat models for each elevation band. Had I developed a single model using location data from all elevation bands, the effect of bias in GPS PAR may have resulted in a larger difference between weighted and un-weighted habitat models. By modeling each elevation band separately and considering the effects of vegetation on satellite signal reception (Tables 7 & 8), there likely existed a correlation between the amount of canopy cover, GPS PAR and elevation quartile. The lowest quartile likely had a consistent range of predicted GPS PAR, as would the highest. If this range of GPS

PAR values, and consequently weights in the habitat model, were small enough within each quartile, the factor by which the habitat models were adjusted would essentially be constant. If the habitat models were developed as a whole with all the GPS fixes from mountain goats in one data set, the range of GPS PAR values across all elevations would increase and consequently add greater emphasis to areas with low predicted GPS PAR in the habitat modeling process.

In both the north and south, the classification accuracy and area under the ROC improved in lower elevation quartiles. This was a counterintuitive result. I expected the higher elevation habitats to be clearly delineated while the lower elevation habitats would be more difficult to define. This might have been a consequence of the lower elevation quartiles classifying more terrain as habitat or there being a more distinct difference between habitat and non-habitat in these areas. The higher elevation habitats may have lower classification accuracies due to the availability of much more moderate habitat not necessarily used when goats at high elevations may be selecting the most precipitous terrain. There also may have been more contaminated controls (Keating & Cherry 2004) at the higher elevations than at the lower elevation bands.

The habitat models showed similar patterns of variable inclusion across all eight datasets. In each model, all the topographic predictor variables were retained as well as some measure of all the three types of vegetation predictor variables. The most parsimonious models were the global model or the global model with the exclusion of one variable. These models excluded the first QMD class or the variety of QMD classes found in the 75 m x 75 m square extraction window.

Examining the results from north to south, the variable representing areas of rock and ice (Table 9.1-9.8 *tvc6*) shows a strong difference between these regions. In the southern models, all the parameter estimates have negative values while the northern regions all show positive estimates. Distance to escape terrain also had negative parameter estimates in all but one data set, the first quartile of the southern region (Table 9.5). This suggested that animals at the lowest observed elevations in this region may have shown some selection for habitats away from slopes greater then 35°. This might reflect some long distance dispersal movements recorded in that region, varying topographic features, or simply a failure of the model to capture the random effects error structure with properly robust confidence intervals. It is also possible that most of the points in this data set were close to escape terrain with few actual points in escape terrain.

The violation of certain assumptions regarding the habitat modeling process and choices therein has created some unavoidable error in modeling methodology. The lack of enough variation, or small random effects size, resulted in the choice of ordinary logistic regression that failed to account for the lack of independence among data points acquired from a single study animal. The use of the PROC GLIMMIX command in SAS may provide the ability to correctly account for these random effects and lack of independence in future modeling efforts. The largest discrepancy between a model accounting for random effects and ordinary logistic regression was in the standard error and resulting confidence intervals. The final habitat models (Table 9.1-9.8) have narrow confidence intervals because of the failure to model such small random effects. Parameter estimates may have varied slightly as well as some Chi-squared test statistics if the auto-correlation structure of the repeated measurements on individual goats was accounted for in the statistical modeling.

The final habitat maps generated in this analysis lay the groundwork for a more detailed assessment of available mountain goat habitat in the Western Cascades. Future work should look at the spatial orientation and connectivity of habitat patches. Identifying the largest patches of contiguous habitat would help in evaluating the probable success of a relocation effort and establishment of viable populations with suitable access to terrain and other animals.

To get a full picture of the habitat available to the entire Cascade population of mountain goats the Eastern Cascades of Washington also need a similar habitat model. Based on the relatively small influence of the weighting factor on the Western Cascades where I expected much lower GPS PAR, I would seriously question the merits of incorporating the weighting factor in the eastern habitat models. I expect much higher rates of GPS PAR on the east side and consequently less data loss from collared wildlife. A more prudent option to account for GPS bias might be to develop some heuristic algorithms to estimate individual missed fixes based on movement parameters. East side habitat mapping should also carefully consider the lack of independence between successive fixes. As mentioned before, the GLIMMIX procedure may handle a mixed model structure more easily. There is no need to run an initial logistic regression and then a non-linear mixed model as in the macro I used for GPS PAR (Appendix B). The GLIMMIX command should handle everything in one step. Alternatively, considering a different statistical design may account for the lack of independence by modeling each animal individually and extrapolating results to the entire range based on random available sites with spatial variables derived from polygons matching the animal's home range.

In my opinion, the results, the amount of fieldwork, the required methodological development and data analysis for developing the bias correction model incorporated into the mountain goat habitat map show the reasonable limitation expected from this type of research. The results suggested microsite features heavily influenced GPS PAR. The weighted and un-weighted habitat maps appeared almost identical, although a more thorough analysis might provide greater insight to the degree of similarity. The consequences of partitioning the habitat modeling by elevation bands likely decreased the relative influence of the correction factor. In addition, the applied nature of the habitat map with adjustable cut points based on management objectives may render the weighting factor a moot point with even a slight shift in cut points. Animal behavior may also have contributed to unexplainable GPS PAR from collared mountain goats. Nonetheless, the results have shown the advantages and improvements offered by GPS wildlife telemetry over traditional VHF-tracking and the ability to develop fine scale habitat maps based in a GIS.

Tables

Table 9.0: The models, number of parameters (K), AIC scores, delta AIC scores and AIC weights of the highest ranked models for the eight datasets used to construct the predicted potential mountain goat habitat maps for each elevation quartile (Q1,Q2,Q3 &Q4).

North		**Q1**			**Q2**			**Q3**			**Q4**		
model	*K*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	weights	*AIC*	*delta*	*weights*
global	20	13944	0	1.00	18353	2	0.27	19156	1	0.37	13017	2	0.27
global w/o qmd1	19	13985	41	.00	18351	0	0.73	19163	8	0.01	13029	14	0.00
global w/o qmd variety	19	14004	58	.00	18372	21	0.00	19155	0	0.62	13015	0	0.73

South		**Q1**			**Q2**			**Q3**			**Q4**		
model	*K*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*	*AIC*	*delta*	*weights*
global	20	1538	1	0.37	5276	1	0.38	8677	1	0.37	21595	0	1.00
global w/o qmd1	19	1537	0	0.62	5275	0	0.62	8685	9	0.01	21620	25	0.00
global w/o qmd variety	19	1546	9	0.01	5315	40	0.00	8676	0	0.62	21610	15	0.00

Table 9.1-9.8: The most parsimonious habitat models based on the lowest AIC scores in Table 9.0 for the eight datasets used to model predicted potential mountain goat habitat across the western Cascades of WA, divided by elevation quartiles and a northern (Table 9.1-9.4) and southern region (Table 9.5-9.8) along I-90.

NORTH:

Table 9.1: First Quartile (Lowest Elevation, 300 m - 1187 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-8.8672	0.2129	-9.2846	-8.4499	1734.24	<.0001
aspcos	1	-0.9412	0.0362	-1.0121	-0.8702	675.96	<.0001
aspsin	1	-0.4560	0.0331	-0.5208	-0.3912	190.18	<.0001
elev	1	0.0033	0.0001	0.0031	0.0035	805.80	<.0001
slope	1	0.1131	0.0033	0.1067	0.1196	1179.17	<.0001
slope_stdv	1	0.1562	0.0079	0.1408	0.1717	391.41	<.0001
d2et	1	-0.0095	0.0010	-0.0114	-0.0075	90.11	<.0001
tvc2	1	0.1816	0.1207	-0.0550	0.4182	2.26	0.1326
tvc3	1	0.1071	0.1085	-0.1055	0.3198	0.97	0.3235
tvc4	1	-0.5672	0.1092	-0.7812	-0.3533	27.00	<.0001
tvc5	1	-1.3474	0.1185	-1.5796	-1.1152	129.35	<.0001
tvc6 (rock&ice)	1	1.3612	0.3047	0.7639	1.9585	19.95	<.0001
tvc_variety	1	0.7106	0.0307	0.6504	0.7708	535.28	<.0001
qmd1	1	-0.6072	0.0938	-0.7910	-0.4234	41.93	<.0001
qmd2	1	-0.2758	0.0951	-0.4623	-0.0893	8.40	0.0037
qmd3	1	-0.5749	0.0867	-0.7448	-0.4049	43.95	<.0001
qmd_variety	1	0.2630	0.0304	0.2034	0.3226	74.77	<.0001
cc2	1	0.5515	0.0783	0.3981	0.7049	49.66	<.0001
cc3	1	0.5146	0.0938	0.3307	0.6985	30.08	<.0001
cc_variety	1	-0.1001	0.0398	-0.1780	-0.0222	6.34	0.0118

NORTH:

Table 9.2: Second Quartile (1187 m - 1145 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-0.8658	0.3472	-1.5462	-0.1853	6.22	0.0126
aspcos	1	-0.8536	0.0298	-0.9120	-0.7953	821.43	<.0001
aspsin	1	-0.3669	0.0283	-0.4224	-0.3114	167.81	<.0001
elev	1	-0.0014	0.0002	-0.0019	-0.0010	38.54	<.0001
slope	1	0.0508	0.0029	0.0451	0.0565	304.95	<.0001
slope_stdv	1	0.0764	0.0062	0.0643	0.0885	153.00	<.0001
d2et	1	-0.0170	0.0011	-0.0192	-0.0149	233.16	<.0001
tvc2	1	1.1969	0.0851	1.0302	1.3637	197.90	<.0001
tvc3	1	0.2065	0.0774	0.0548	0.3582	7.12	0.0076
tvc4	1	-0.1514	0.0794	-0.3071	0.0042	3.64	0.0566
tvc5	1	-0.9400	0.0842	-1.1051	-0.7749	124.56	<.0001
tvc6 (rock&ice)	1	2.3258	0.1123	2.1057	2.5460	428.69	<.0001
tvc_variety	1	0.4480	0.0238	0.4014	0.4946	355.24	<.0001
qmd2	1	-0.4754	0.0618	-0.5966	-0.3543	59.14	<.0001
qmd3	1	-1.0003	0.0546	-1.1074	-0.8932	335.32	<.0001
qmd_variety	1	0.1449	0.0275	0.0910	0.1989	27.71	<.0001
cc2	1	0.2410	0.0596	0.1241	0.3579	16.33	<.0001
cc3	1	0.4502	0.0725	0.3082	0.5923	38.60	<.0001
cc_variety	1	-0.1994	0.0336	- 0.2653	-0.1335	35.21	<.0001

NORTH:

Table 9.3: Third Quartile (1145 m - 1670 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	0.2077	0.4687	-0.7110	1.1264	0.20	0.6577
aspcos	1	-0.6919	0.0302	-0.7511	-0.6327	524.32	<.0001
aspsin	1	-0.3439	0.0269	-0.3966	-0.2912	163.62	<.0001
elev	1	-0.0018	0.0003	-0.0023	-0.0012	38.54	<.0001
slope	1	0.0557	0.0026	0.0506	0.0607	463.72	<.0001
slope_stdv	1	0.0788	0.0059	0.0673	0.0902	181.26	<.0001
d2et	1	-0.0033	0.0008	-0.0048	-0.0018	19.40	<.0001
tvc2	1	0.7059	0.0631	0.5822	0.8296	125.08	<.0001
tvc3	1	0.3897	0.0620	0.2682	0.5113	39.49	<.0001
tvc4	1	-0.0473	0.0695	-0.1835	0.0888	0.46	0.4956
tvc5	1	-0.5504	0.0824	-0.7119	-0.3889	44.60	<.0001
tvc6 (rock&ice)	1	0.9908	0.0721	0.8494	1.1322	188.71	<.0001
tvc_variety	1	0.1255	0.0217	0.0829	0.1680	33.44	<.0001
qmd1	1	-0.1845	0.0778	-0.3370	-0.0320	5.62	0.0178
qmd2	1	-1.1555	0.1006	-1.3526	-0.9584	132.03	<.0001
qmd3	1	-1.1734	0.0833	-1.3366	-1.0103	198.65	<.0001
cc2	1	-0.1561	0.0536	-0.2611	-0.0511	8.49	0.0036
cc3	1	-0.0794	0.0710	-0.2185	0.0596	1.25	0.2629
cc_variety	1	-0.0452	0.0325	-0.1089	0.0184	1.94	0.1638

NORTH:

Table 9.4: Fourth Quartile (Highest Elevation, 1670 m - 3100 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	7.2777	0.3223	6.6460	7.9095	509.83	<.0001
aspcos	1	-0.9675	0.0398	-1.0454	-0.8895	592.00	<.0001
aspsin	1	-0.2833	0.0326	-0.3471	-0.2195	75.72	<.0001
elev	1	-0.0045	0.0002	-0.0048	-0.0042	840.12	<.0001
slope	1	0.0053	0.0030	-0.0005	0.0111	3.16	0.0756
slope_stdv	1	0.0456	0.0068	0.0322	0.0590	44.44	<.0001
d2et	1	-0.0086	0.0009	-0.0103	-0.0068	89.05	<.0001
tvc2	1	0.7568	0.0675	0.6246	0.8890	125.86	<.0001
tvc3	1	0.6767	0.0729	0.5339	0.8195	86.23	<.0001
tvc4	1	0.0058	0.0958	-0.1818	0.1935	0.00	0.9513
tvc5	1	-0.8941	0.1524	-1.1928	-0.5953	34.40	<.0001
tvc6 (rock&ice)	1	0.7940	0.0646	0.6673	0.9207	150.84	<.0001
tvc_variety	1	-0.0376	0.0276	-0.0917	0.0165	1.85	0.1736
qmd1	1	-0.5551	0.1480	-0.8452	-0.2650	14.06	0.0002
qmd2	1	-2.1120	0.2978	-2.6957	-1.5283	50.29	<.0001
qmd3	1	-1.8249	0.2121	-2.2406	-1.4091	74.02	<.0001
cc2	1	0.1039	0.0698	-0.0329	0.2407	2.21	0.1368
cc3	1	0.4817	0.1019	0.2820	0.6814	22.34	<.0001
cc_variety	1	0.0697	0.0424	-0.0133	0.1527	2.71	0.1000

SOUTH:

Table 9.5: First Quartile (Lowest Elevation, 300 m - 1187 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr >ChiSq
Intercept	1	-18.5027	0.7409	-19.9548	-17.0506	623.69	<.0001
aspcos	1	-0.4339	0.1154	-0.6602	-0.2076	14.13	0.0002
aspsin	1	-0.1748	0.0957	-0.3624	0.0127	3.34	0.0677
elev	1	0.0074	0.0005	0.0065	0.0083	258.35	<.0001
slope	1	0.2501	0.0099	0.2307	0.2696	637.84	<.0001
slope_stdv	1	0.0805	0.0242	0.0331	0.1280	11.05	0.0009
d2et	1	0.0009	0.0008	-0.0006	0.0024	1.41	0.2350
ric2	1	0.6018	0.4664	-0.3122	1.5159	1.67	0.1969
ric3	1	0.2663	0.3925	-0.5030	1.0356	0.46	0.4975
ric4	1	-0.2836	0.3583	-0.9859	0.4187	0.63	0.4287
ric5	1	0.1078	0.3636	-0.6048	0.8205	0.09	0.7668
ric6 (rock&ice)	1	-21.7808	34232.09	-67115.4	67071.88	0.00	0.9995
rockice_variety	1	0.3230	0.1030	0.1211	0.5250	9.83	0.0017
qmd2	1	-0.2244	0.2012	-0.6187	0.1699	1.24	0.2647
qmd3	1	-0.0861	0.2052	-0.4883	0.3162	0.18	0.6750
qmd_variety	1	0.3518	0.1011	0.1536	0.5499	12.11	0.0005
con2	1	0.0431	0.2628	-0.4720	0.5582	0.03	0.8697
con3	1	0.5695	0.3219	-0.0614	1.2004	3.13	0.0769
con_variety	1	0.4532	0.1300	0.1985	0.7079	12.16	0.0005

SOUTH:

Table 9.6: Second Quartile (1187 m - 1145 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-16.4693	0.6912	-17.8241	-15.1145	567.68	<.0001
aspcos	1	-0.1952	0.0601	-0.3131	-0.0773	10.53	0.0012
aspsin	1	-0.2791	0.0499	-0.3770	-0.1812	31.22	<.0001
elev	1	0.0053	0.0005	0.0044	0.0062	136.78	<.0001
slope	1	0.2412	0.0063	0.2288	0.2537	1449.08	<.0001
slope_stdv	1	0.1095	0.0115	0.0870	0.1319	91.20	<.0001
d2et	1	-0.0014	0.0011	-0.0036	0.0008	1.67	0.1967
tvc2	1	0.0250	0.2084	-0.3834	0.4335	0.01	0.9044
tvc3	1	-0.4009	0.1729	-0.7398	-0.0620	5.38	0.0204
tvc4	1	-0.9617	0.1824	-1.3192	-0.6042	27.80	<.0001
tvc5	1	-0.8973	0.1850	-1.2599	-0.5346	23.52	<.0001
tvc6 (rock&ice)	1	-1.4221	0.5421	-2.4846	-0.3597	6.88	0.0087
tvc_variety	1	0.1729	0.0507	0.0736	0.2722	11.63	0.0006
qmd2	1	-0.6154	0.1095	-0.8299	-0.4008	31.60	<.0001
qmd3	1	-0.4339	0.1024	-0.6346	-0.2333	17.97	<.0001
qmd_variety	1	0.3757	0.0532	0.2714	0.4800	49.88	<.0001
cc2	1	0.1840	0.1569	-0.1236	0.4915	1.37	0.2410
cc3	1	0.1727	0.1818	-0.1837	0.5290	0.90	0.3422
cc_variety	1	0.3035	0.0647	0.1767	0.4302	22.02	<.0001

SOUTH:

Table 9.7: Third Quartile (1145 m - 1670 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-7.1235	0.7644	-8.6218	-5.6252	86.83	<.0001
aspcos	1	-0.0911	0.0511	-0.1911	0.0090	3.18	0.0745
aspsin	1	-0.4833	0.0404	-0.5624	-0.4042	143.36	<.0001
elev	1	0.0019	0.0004	0.0010	0.0028	18.23	<.0001
slope	1	0.1324	0.0050	0.1226	0.1423	694.85	<.0001
slope_stdv	1	0.1364	0.0088	0.1192	0.1536	242.52	<.0001
d2et	1	-0.0108	0.0015	-0.0137	-0.0080	55.67	<.0001
tvc2	1	-0.9992	0.1358	-1.2653	-0.7330	54.13	<.0001
tvc3	1	-1.5048	0.1220	-1.7439	-1.2656	152.09	<.0001
tvc4	1	-1.5628	0.1317	-1.8209	-1.3046	140.76	<.0001
tvc5	1	-1.7165	0.1435	-1.9976	-1.4353	143.17	<.0001
tvc6 (rock&ice)	1	-4.4578	0.4904	-5.4190	-3.4966	82.63	<.0001
tvc_variety	1	0.2342	0.0395	0.1568	0.3116	35.17	<.0001
qmd1	1	-0.3687	0.1311	-0.6257	-0.1118	7.91	0.0049
qmd2	1	-0.5861	0.1288	-0.8386	-0.3335	20.69	<.0001
qmd3	1	-0.5310	0.1212	-0.7686	-0.2935	19.20	<.0001
cc2	1	-0.1024	0.1174	-0.3325	0.1277	0.76	0.3833
cc3	1	-0.0691	0.1385	-0.3405	0.2023	0.25	0.6177
cc_variety	1	0.3110	0.0512	0.2106	0.4113	36.87	<.0001

SOUTH:

Table 9.8: Fourth Quartile (Highest Elevation, 1670 m - 3100 m)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-1.3808	0.2082	-1.7890	-0.9727	43.97	<.0001
aspcos	1	-0.2119	0.0294	-0.2696	-0.1542	51.82	<.0001
aspsin	1	-0.4271	0.0248	-0.4757	-0.3786	297.45	<.0001
elev	1	-0.0004	0.0001	-0.0005	-0.0002	15.00	0.0001
slope	1	0.0683	0.0023	0.0638	0.0728	881.86	<.0001
slope_stdv	1	0.0710	0.0055	0.0603	0.0818	167.47	<.0001
d2et	1	-0.0029	0.0003	-0.0035	-0.0023	101.10	<.0001
tvc2	1	-0.8212	0.0756	-0.9694	-0.6731	118.04	<.0001
tvc3	1	-1.0508	0.0663	-1.1807	-0.9209	251.24	<.0001
tvc4	1	-1.2842	0.0792	-1.4393	-1.1290	263.22	<.0001
tvc5	1	-1.5925	0.0959	-1.7804	-1.4045	275.74	<.0001
tvc6 (rock&ice)	1	-1.2844	0.0601	-1.4022	-1.1667	457.26	<.0001
tvc_variety	1	0.1668	0.0211	0.1255	0.2081	62.71	<.0001
qmd1	1	-0.4918	0.1016	-0.6909	-0.2927	23.44	<.0001
qmd2	1	-0.4929	0.0995	-0.6880	-0.2979	24.53	<.0001
qmd3	1	-0.2592	0.0837	-0.4233	-0.0952	9.59	0.0020
qmd_variety	1	0.1410	0.0304	0.0814	0.2006	21.47	<.0001
cc2	1	-0.0489	0.0660	-0.1782	0.0805	0.55	0.4590
cc3	1	0.1502	0.0903	-0.0267	0.3271	2.77	0.0960
cc_variety	1	0.1540	0.0349	0.0857	0.2223	19.53	<.0001

Table 10: Area under the receiver operating curve (AUC), cut points and accuracy of correctly classified independent mountain goat locations for the mountain goat habitat models. Datasets were divided into four elevation bands and two geographic regions, north and south Cascades of Washington, with and without a weighting factor incorporated to account for GPS bias. The AUC values were the same for both weighted and un-weighted models.

Cascades	Elevation		Weighted		Un-weighted	
Region	Quartile	AUC	cut point	accuracy	cut point	accuracy
North	1st	0.96	0.63	0.89	0.60	0.89
	2nd	0.88	0.60	0.80	0.56	0.79
	3rd	0.82	0.56	0.75	0.55	0.74
	4th	0.77	0.54	0.69	0.53	0.69
South	1st	0.99	0.60	0.95	0.59	0.95
	2nd	0.97	0.63	0.93	0.59	0.92
	3rd	0.94	0.64	0.87	0.62	0.87
	4th	0.84	0.54	0.77	0.54	0.76

Figures

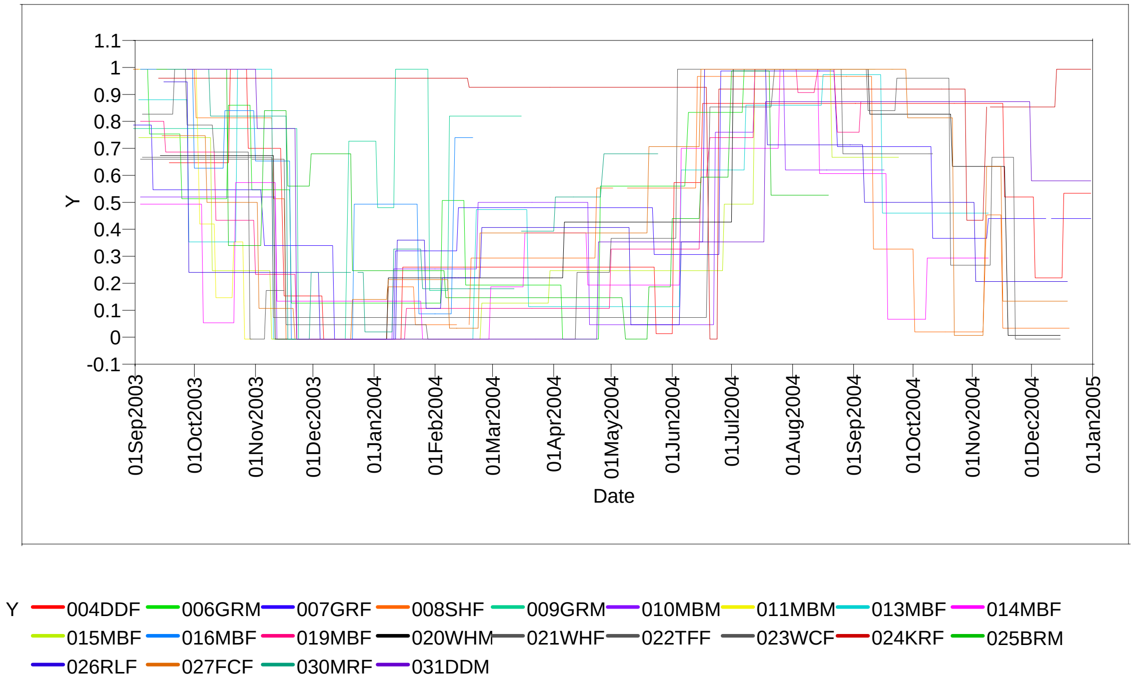

Fig. 9: Proportional elevation shifts in mountain goats from different locations showing the complexities associated with defining calendar-driven mountain goat seasons based on elevation movements. Y-axis represents changes in elevation greater than 500 m in terms of the portion of the move across the animals entire range of observed elevations.

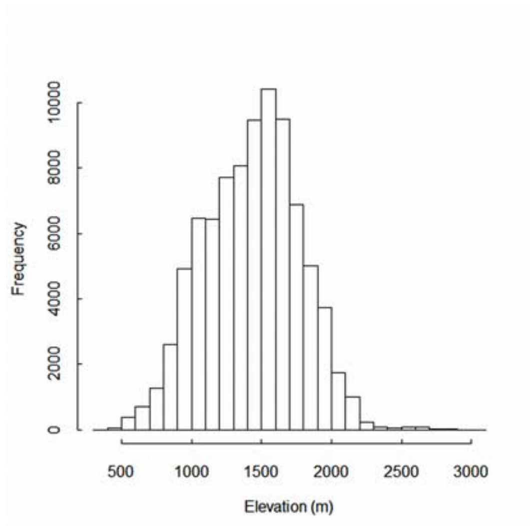

Fig. 10: Histogram of all GIS-derived mountain goat elevations from GPS points showing a Gaussian distribution and the range of observed values (Frequency = Percentage of Fixes).

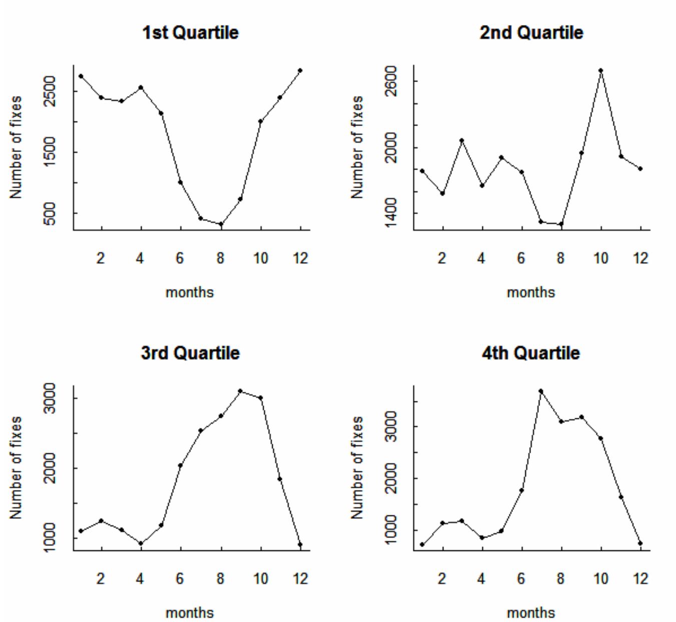

Fig. 11: Distribution of mountain goat locations acquired by month within each elevation quartile: 1st (300-1187 m), 2nd(1187-1455 m), 3rd(1455-1670 m) & 4th(1670-3000 m). The total number of fixes for the 1st through 4th quartile was, 21,598, 21,633, 21,609 and 21,988 respectively.

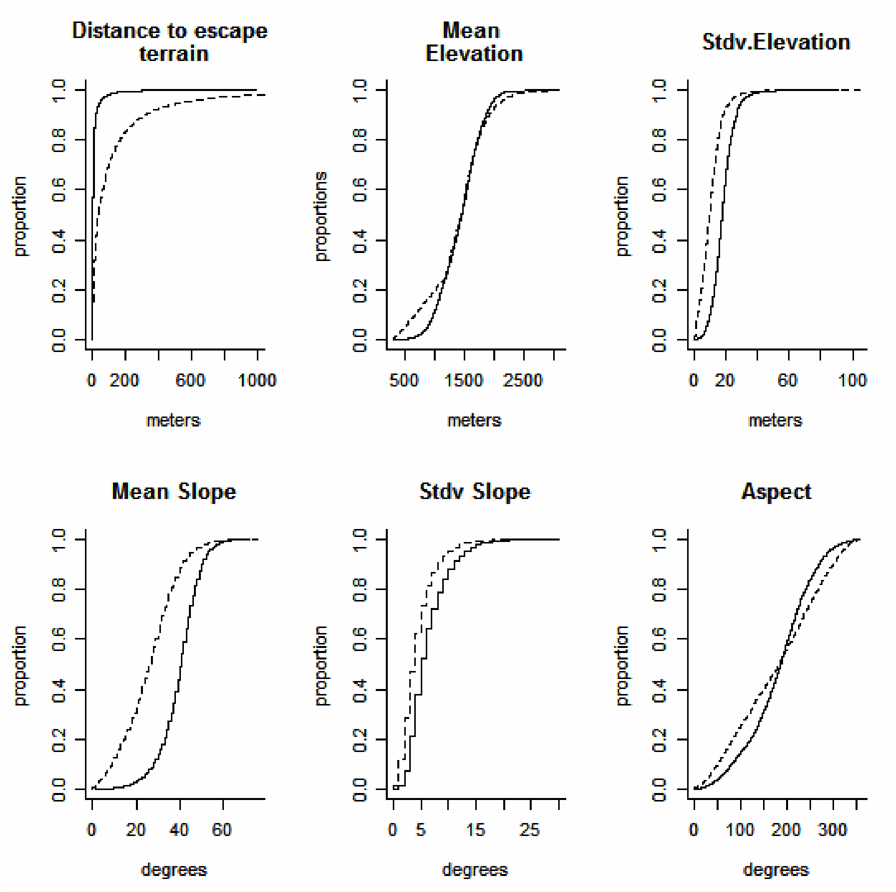

Fig. 12: Empirical cumulative frequency distributions of available (dotted) vs. goat locations (solid) for derived topographic predictor variables suggesting selection for areas closer to escape terrain and steeper slopes.

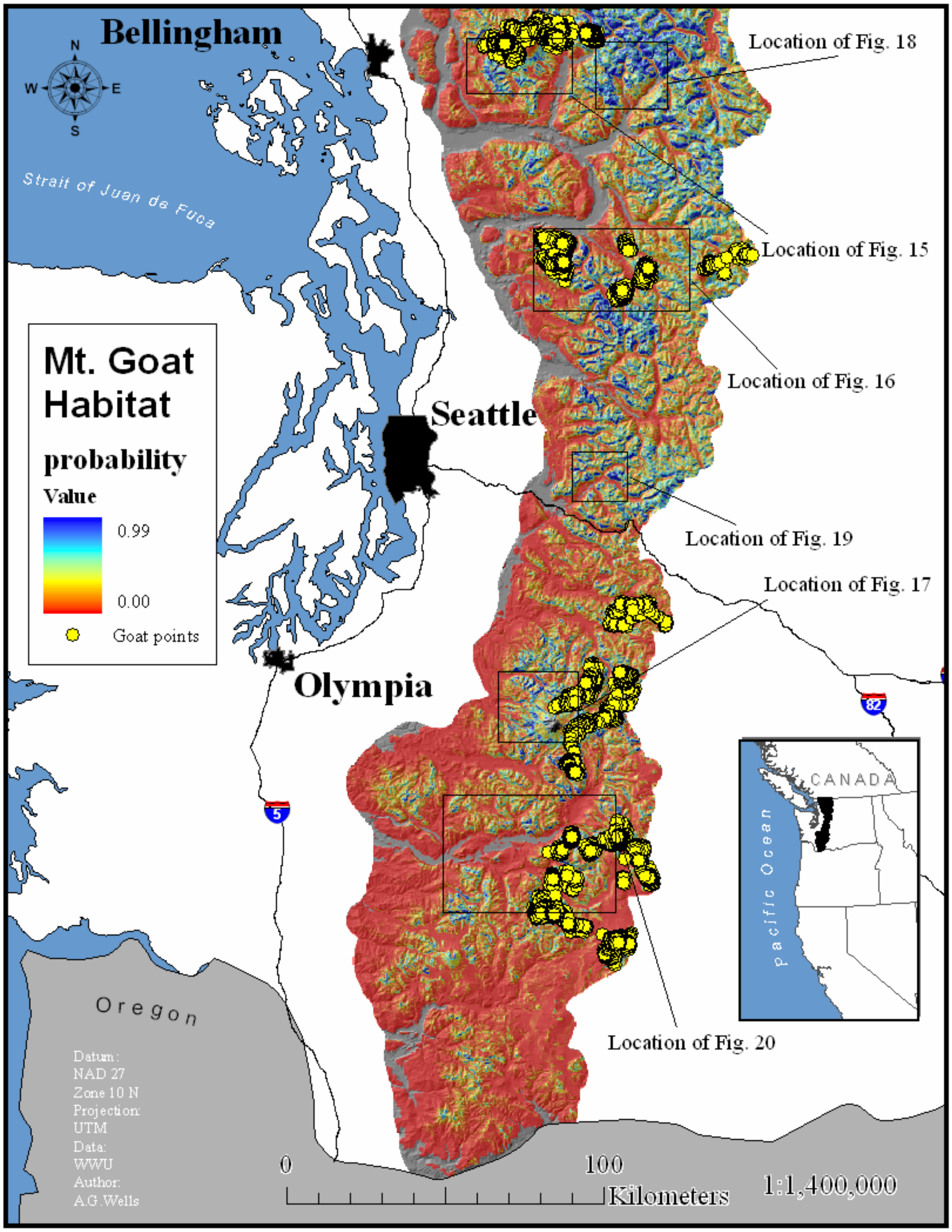

Fig. 13: Map showing continuous data layer of predicted potential mountain goat habitat for the Western Cascades of Washington based on elevation quartiles from the northern and southern halves of the Cascades, split along I-90, based on data from 39 GPS collared animals.

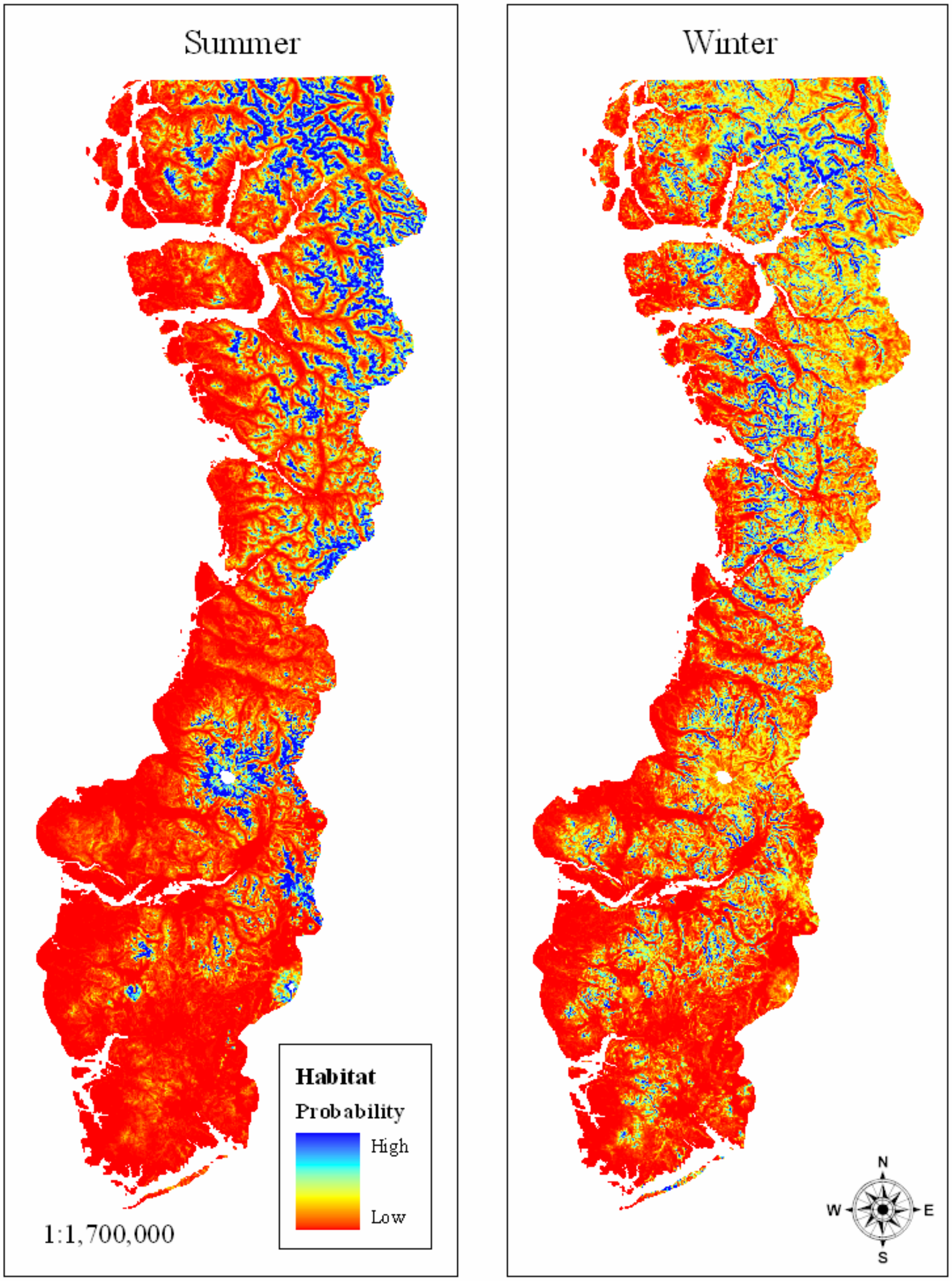

Fig. 14: Seasonal habitat maps of potential mountain goat habitat based on subjective summer (June, July, August and September) and winter (December, January, February, March and April) delineation of seasons, created by taking the predicted potential habitat in each elevation band multiplied by the proportion of use during that time frame.

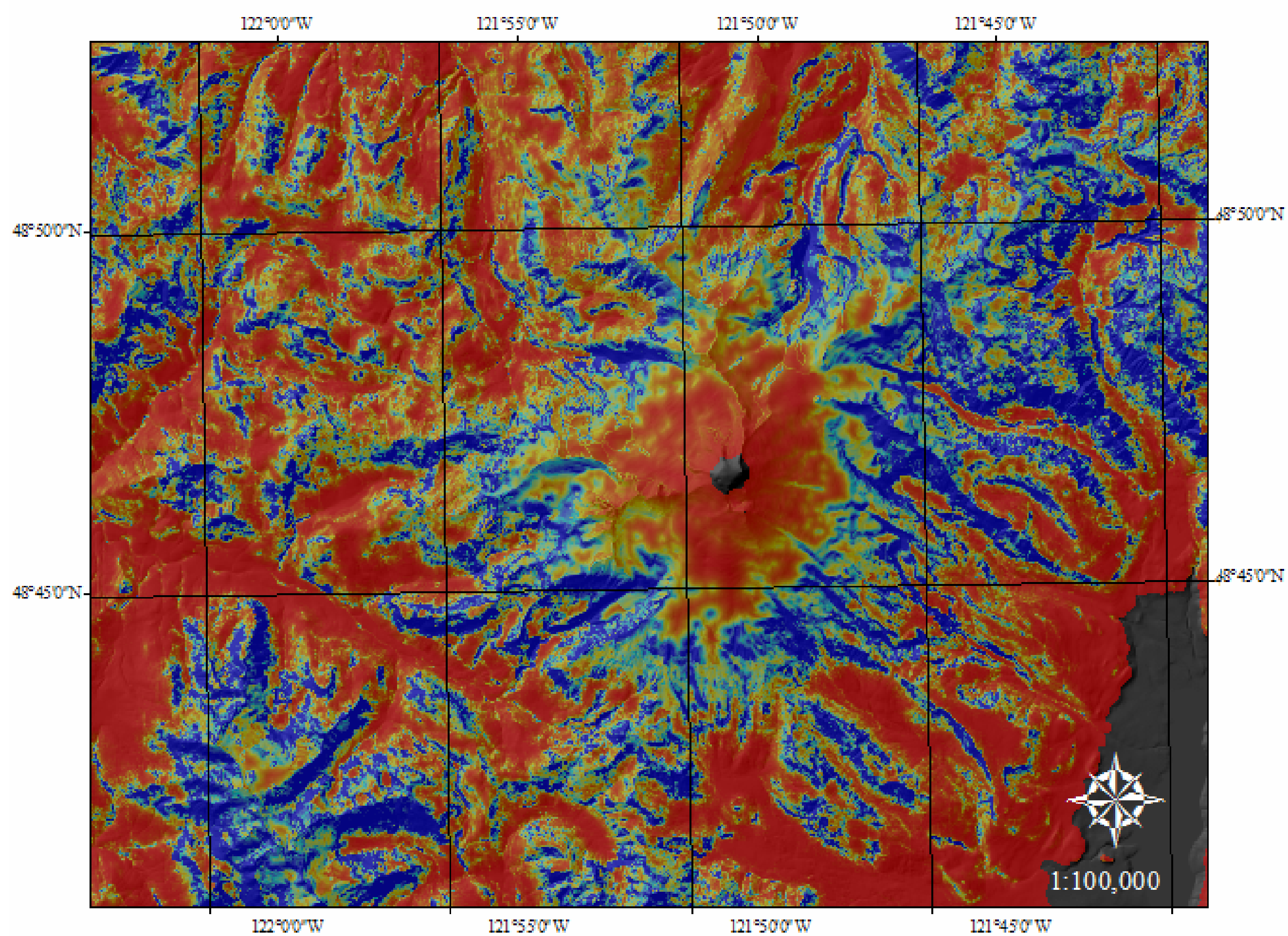

Fig. 15: Close up view of predicted potential mountain goat habitat in the vicinity of Mt. Baker, WA showing fairly contiguous habitat patches around the mountain. Blue designates high predicted probability while red denotes low predicted probability of mountain goat habitat.

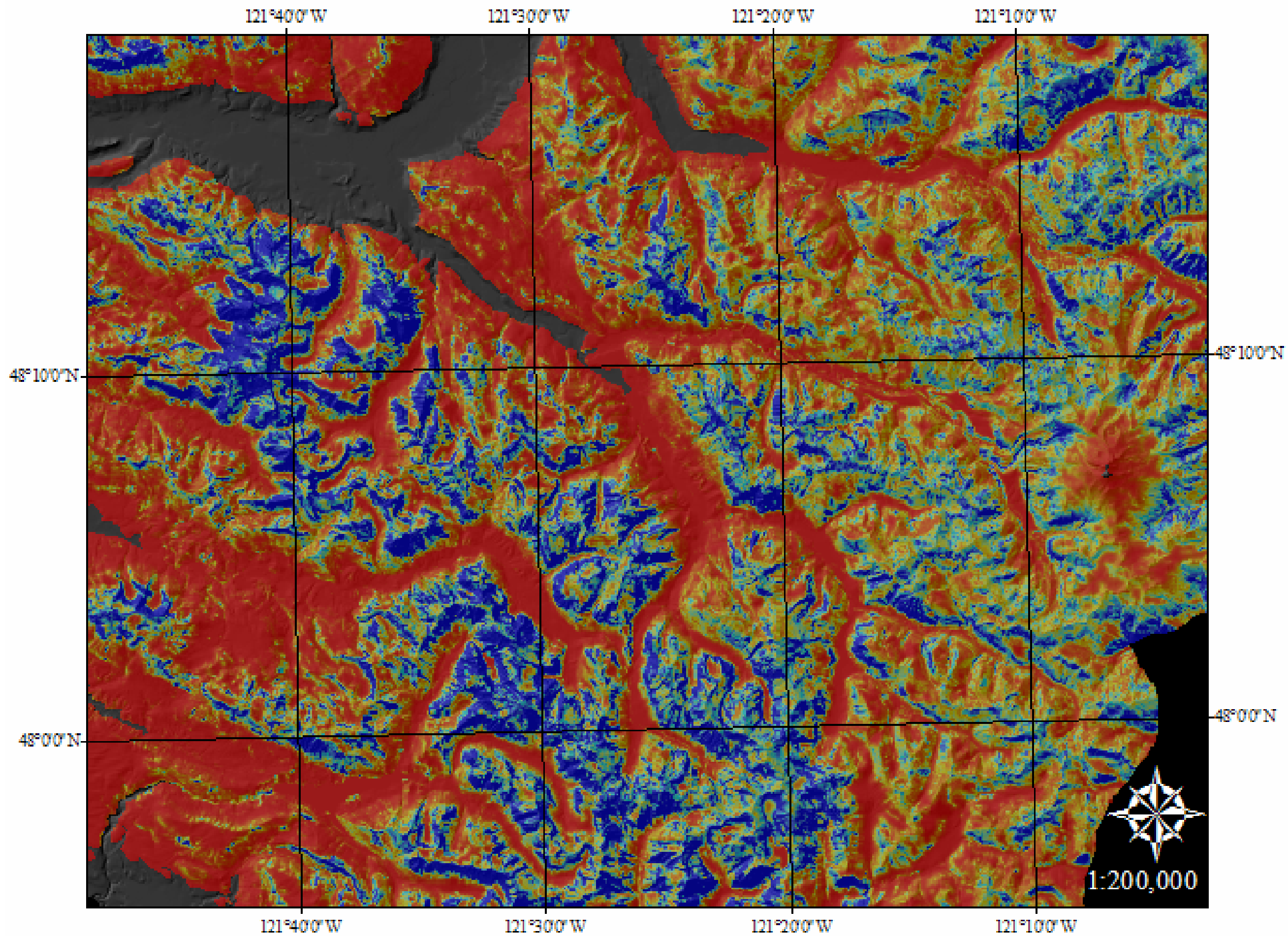

Fig. 16: Close up view of predicted potential mountain goat habitat around the Three Fingers-Whitehorse mountain complex (to the right) and of Glacier Peak, WA (to the left) showing a distinct isolation of the area from more easterly habitats. Blue designates high predicted probability while red denotes low.

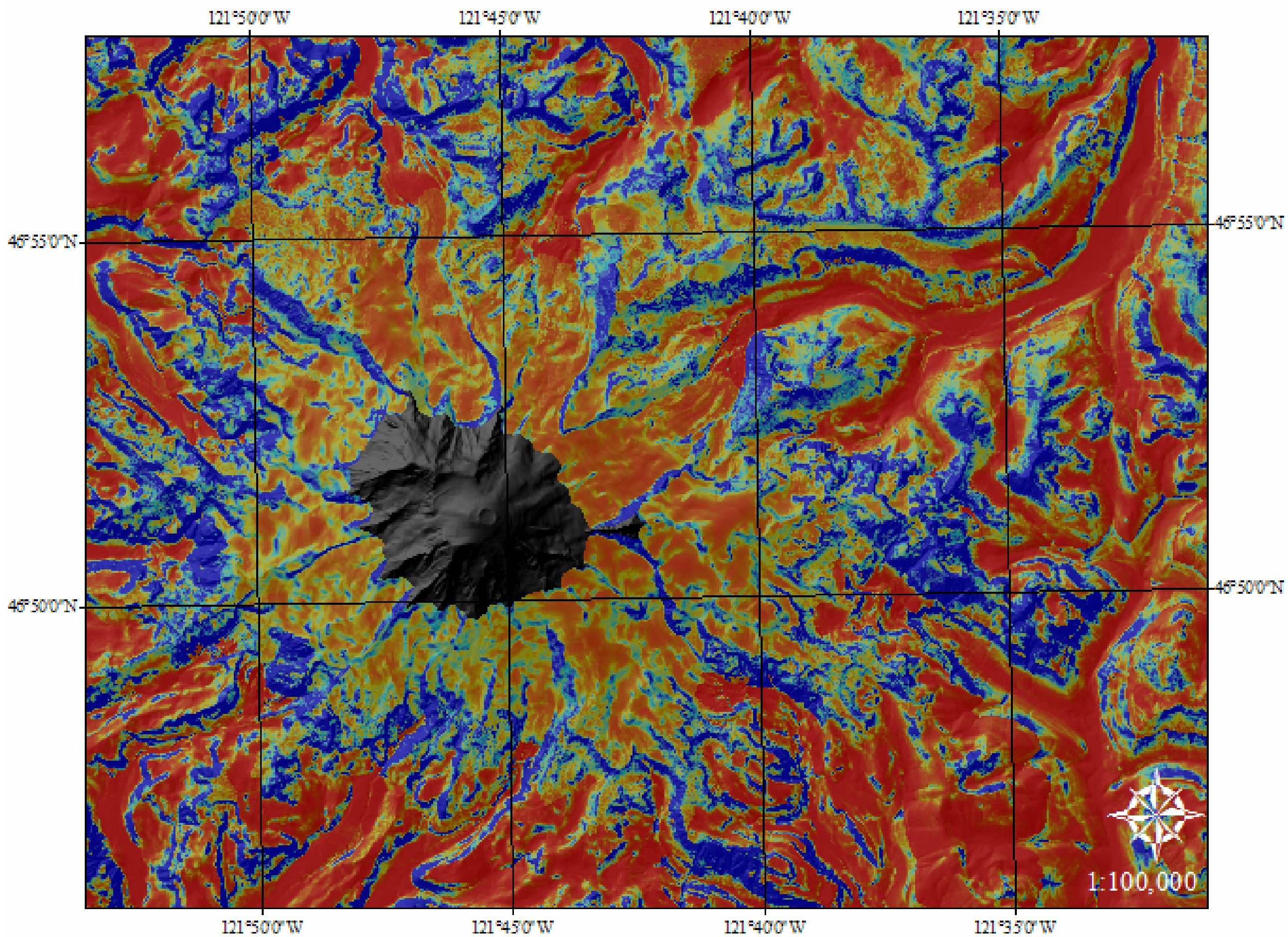

Fig. 17: Predicted potential mountain goat habitat around Mt. Rainier, WA showing a more striated pattern of habitat patches then those around Mt. Baker. Blue designates high predicted probability while red denotes low, with the grey summit falling above the highest observed mountain goat elevations and consequently outside of the analysis.

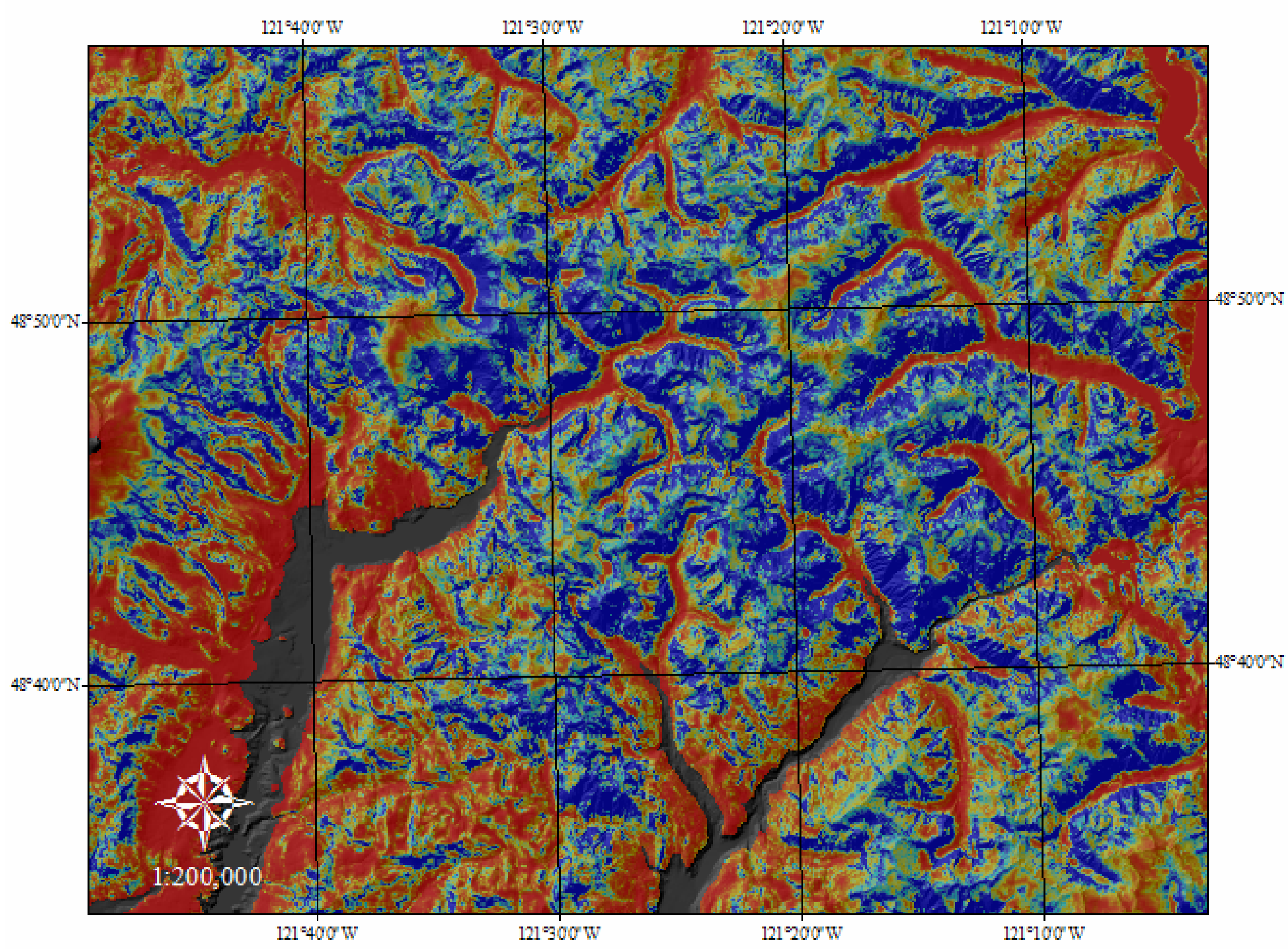

Fig. 18: Close up view of the Pickett Range, east of Mt. Baker, WA, encompassing the North Cascade National Park showing some of the highest quality, most well-connected and densest predicted habitat despite having few observed mountain goats. The Canadian border forms the northern border of the image.

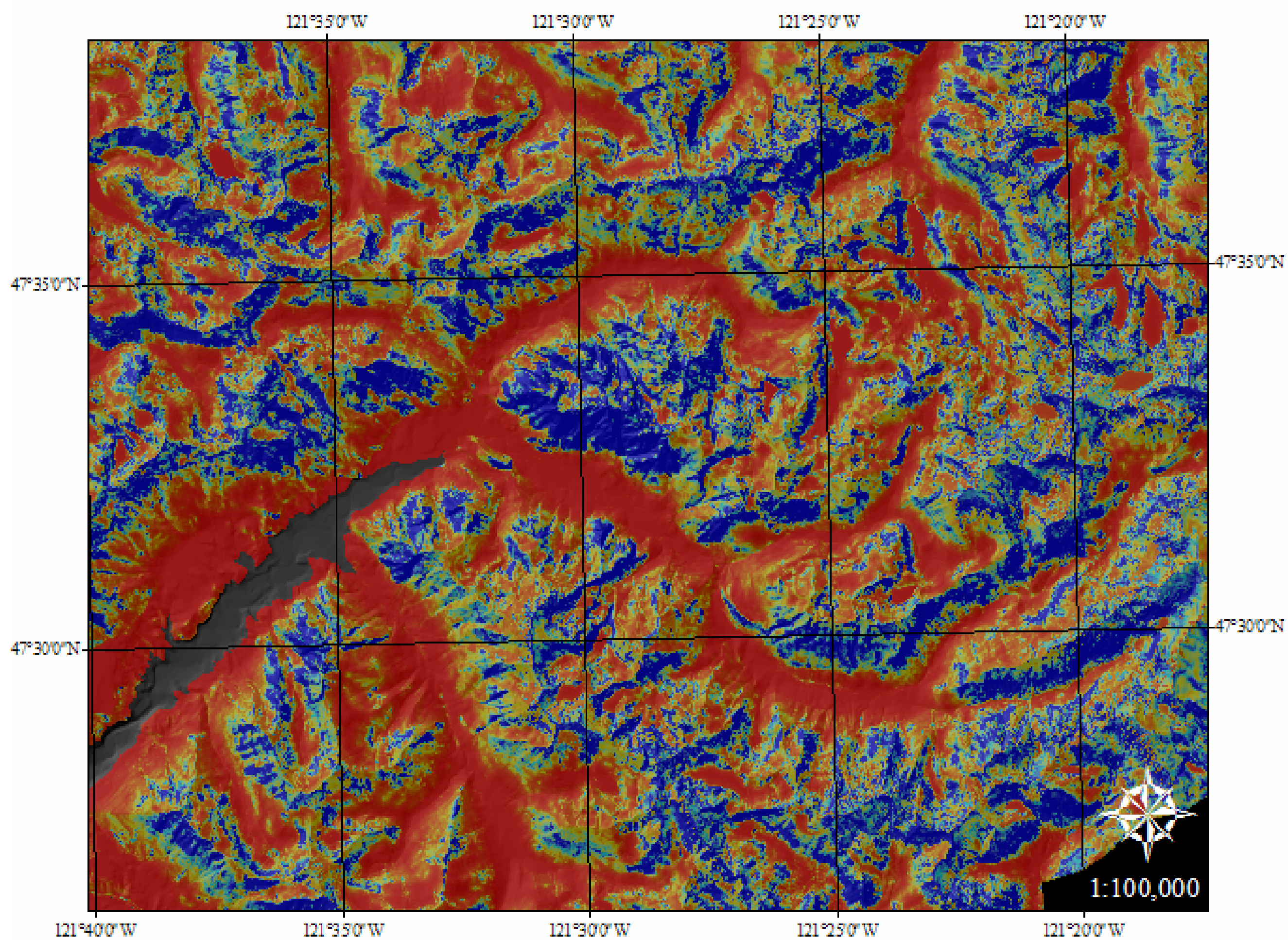

Fig. 19: Close up view of Garfield Mt. in the middle Cascades, a region with lots of predicted potential habitat but few mountain goats. Blue designates high predicted probability while red denotes low.

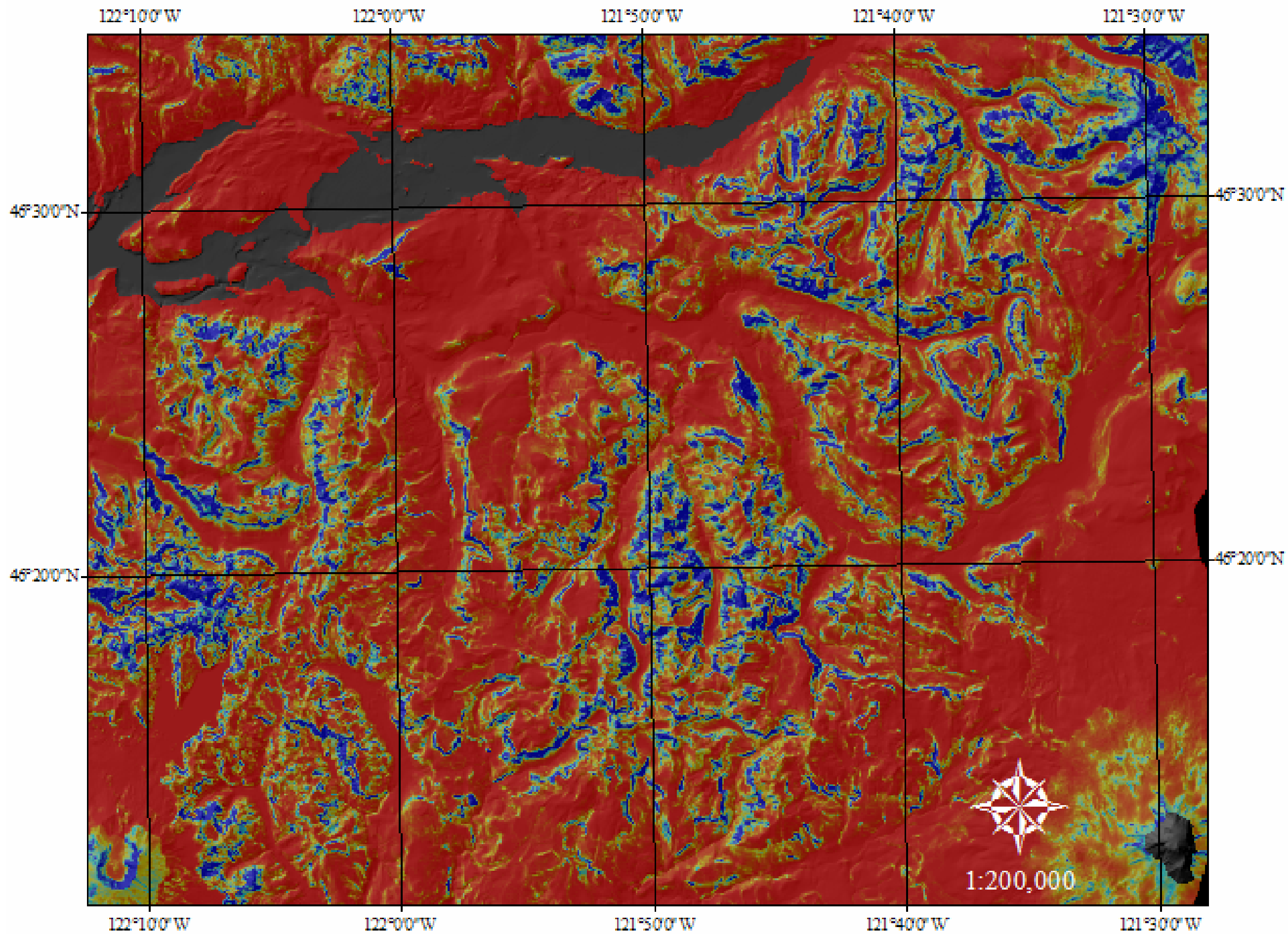

Fig. 20: Close up view of the southern Cascades depicting a more disjointed landscape of mountain goat habitat although supporting known populations of animals. Goat Rocks Wilderness area appears in the upper right, Mt. Adams (with marginal habitat at best) in the lower right and Mt. St. Helens in the lower left. Blue designates high predicted probability while red denotes low.

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Appendix

A. Sky Visibility

The sky visibility algorithm performed a discrete approximation of a hemispherical integral and worked with a large DEM (Bill Huber, pers. comm.). The algorithm generated a series of hillshade grids, each with the sun at a different elevation and azimuth angle. For a given sun elevation and azimuth, the hillshade function determined whether each grid cell fell in full sun or shadow. A final output grid consisted of a weighted tally of the number of "sun hits" each grid cell received. This weighted tally expressed the percentage of the maximum possible number of "sun hits" (the number of azimuth angles times the number of elevation angles). Each of the initial grids received weighting using the cosine of the elevation angle. This weighting corrected for the fact that low elevation angles represented a greater section of sky than high elevation angles. The net result quantified the percentage of the sky visible from each grid cell, based on surrounding topography. Unobstructed sky provided access to more satellites; topographic obstructions in one or more portions of the sky blocked access

B. GPS PAR models

This is a list of the *a prior* selected models used for testing GPS PAR based on ecological expectations based on the variable nomenclature found in Table 5.

asp elev slp sv bc2 bc3 bc4 qmd2 qmd3 cc2 cc3 tvc2 tvc3

asp slp elev qmd2 qmd3

asp slp elev bc2 bc3

asp slp elev sv cc2 cc3

asp slp elev tvc2 tvc3

asp elev slp sv qmd3 cc3 tvc3

qmd2 qmd3 cc2 cc3 tvc2 tvc3 bc2 bc3 bc4

elev slp sv asp

slp cc3 qmd3 tvc3

asp

sv

elev

slp

qmd2 qmd3

cc2 cc3

tvc2 tvc3

bc2 bc3 bc4

asp cc2 cc3

asp slp elev qmd2

asp tvc2 tvc3

asp tvc3 qmd3

asp elev slp sv bc2 bc3 bc4 qmd2 qmd3 cc2 cc3 tvc2 tvc3

asp elev slp sv tvc2 tvc3

C. Non-linear mixed macro

This is the macro written for implementation in SAS that executed the non-linear mixed modeling scheme for the GPS PAR model. The model executes an ordinary logistic regression to generate initial parameter estimates prior to using the non-linear modeling. This macro was used during model selection to account for the random effects error structure due to the repeated measure of GPS PAR at each sample site.

```
%macro Logisticmixed(data1,data2,depvar,nvars,nparm,variables,parms);
title "Initial logistic fit with covariates:&variables";
proc logistic data=&data1 descending outest=betas;
   model &depvar= &variables /aggregate=(cluster) scale=none rsquare lackfit;
         ods output FitStatistics=Fitstat LackFitChiSq=HLtest RSquare=r2;
*GoodnessOfFit=gof;
data betas; set betas;
array x{&nparm} intercept &variables;
array b{&nparm} &parms;
 do i=1 to &nparm;
   b{i}=x{i};
  end;
 keep &parms;

proc nlmixed data=&data1 technique=nrridg maxiter=500 maxfunc=500;
parms s=1 / data=&data2;
 array b{&nparm} &parms;
 array x{&nvars} &variables;
 eta=ranvar+b{1};
 do i=1 to &nvars ;
  eta=eta+b{i+1}*x{i};
  end;
  model &depvar ~ binary(1-1/exp(eta));
  random  ranvar ~ normal(0,s*s) subject=cluster;
```

```
 ods output FitStatistics=FitStatistics;

data mixedresult;
  set FitStatistics;
  length variables $ 50;
  keep AICc variables;
  if Descr= "AICC (smaller is better)" then do;
     AICc=Value;
          variables= "&variables";
          output;
        end;
  title "subset:&variables";
  data summary; set summary mixedresult Fitstat HLtest r2 ;
  run;

%mend logisticmixed:
```

D. Habitat models

This is the list of *a prior* selected models used for testing based upon ecological expectations:

d2et

slope

slope slope_stdv

elev

elev elev_stdv

aspcos

aspsin

aspsin aspcos

tvc2 tvc3 tvc4 tvc5 tvc6

tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety

cc2 cc3

cc2 cc3 cc_variety

qmd1 qmd2 qmd3

qmd1 qmd2 qmd3 qmd_variety

aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 qmd_variety cc2 cc3 cc_variety

aspcos aspsin elev slope d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 qmd_variety cc2 cc3 cc_variety

tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 qmd_variety cc2 cc3 cc_variety

qmd1 qmd2 qmd3 cc2 cc3 tvc2 tvc3 tvc4 tvc5 tvc6

tvc_variety cc_variety qmd_variety

aspcos aspsin elev elev_stdv slope slope_stdv d2et

aspcos aspsin elev slope d2et

d2et slope slope_stdv elev_stdv

d2et slope

d2et slope slope_stdv

d2et slope tvc6

slope tvc2 tvc3 tvc4 tvc5 tvc6

d2et slope cc2 cc3

d2et slope qmd1 qmd2 qmd3

d2et slope tvc6 aspsin aspcos

d2et slope tvc6 cc_variety qmd_variety

d2et slope aspcos tvc2 tvc3 tvc4 tvc5 tvc6 cc_variety cc2 cc3 qmd_variety

d2et slope aspcos aspsin elev_stdv tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety cc_variety cc2 cc3 qmd1 qmd2 qmd3 qmd_variety

d2et slope aspcos aspsin elev_stdv tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety cc_variety cc2 cc3 qmd_variety

aspsin tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety cc_variety cc2 cc3 qmd1 qmd2 qmd3 qmd_variety

aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 cc2 cc3 cc_variety

aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 qmd3 cc2 cc3

aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd3 cc2 cc3

,aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 cc2 cc3

aspcos aspsin elev elev_stdv slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 cc2 cc3 aspcos aspsin elev slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 cc2 cc3

aspcos aspsin elev slope slope_stdv d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 cc2 cc3 cc_variety

aspcos aspsin elev slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 qmd3 cc2 cc3

aspsin elev slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd3 cc2 cc3

aspcos aspsin elev slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 cc2 cc3

aspcos aspsin elev slope slope_stdv d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 qmd_variety cc2 cc3 cc_variety

aspcos aspsin elev slope slope_stdv d2et tvc4 tvc5 tvc6 tvc_variety qmd1 qmd2 qmd3 cc2 cc3

aspcos aspsin elev slope slope_stdv d2et tvc2 tvc3 tvc4 tvc5 tvc6 tvc_variety qmd2 qmd3 qmd_variety cc2 cc3 cc_variety