

2011

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Recommended Citation

Wallin, David O.; Wells, Adam G.; Rice, Clifford G.; and Chang, Wan-Ying, "GPS Bias Correction and Habitat Selection by Mountain Goats" (2011). *Environmental Sciences Faculty Publications*. 14.

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Article

GPS Bias Correction and Habitat Selection by Mountain Goats

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Received: 23 December 2010; in revised form: 24 February 2011 / Accepted: 24 February 2011 / Published: 28 February 2011

Abstract: In Washington State, USA, mountain goats (*Oreamnos americanus*) have experienced a long-term population decline. To assist management, we created annual and seasonal (summer and winter) habitat models based on 2 years of data collected from 38 GPS-collared (GPS plus collar v6, Vectronic-Aerospace GmbH, Berlin, Germany) mountain goats in the western Cascades. To address GPS bias of position acquisition, we evaluated habitat and physiographic effects on GPS collar performance at 543 sites in the Cascades. In the western Cascades, total vegetation cover and the quadratic mean diameter of trees were shown to effect GPS performance. In the eastern Cascades, aspect and total vegetation cover were found to influence GPS performance. To evaluate the influence of bias correction on the analysis of habitat selection, we created resource selection functions with and without bias correction for mountain goats in the western Cascades. We examined how well the resultant habitat models performed with reserved data (25% of fixes from 38 study animals) and with data from 9 other GPS-collared mountain goats that were both temporally and spatially independent. The statistical properties of our GPS bias correction model were similar to those previously reported explaining between 20 and 30% of the variation, however, application of bias correction improved the accuracy of the mountain goat habitat model by only 1–2% on average and did not alter parameter estimates in a meaningful, or consistent manner. Despite statistical limitations, our habitat models, most

notably during the winter, provided the widest extent and most detailed models of the distribution of mountain goat habitat in the Cascades yet developed.

Keywords: Cascades; habitat; GPS bias; mountain goat; resource selection function

1. Introduction

Across their range, native mountain goat (*Oreamnos americanus*) populations have decreased over the last several decades [1,2]. In the Washington Cascades, some population estimates suggest declines of as much as 70% over the last 40 years (Washington Department of Fish and Wildlife unpublished data). Population declines and a re-evaluation of harvest potential for this species [3,4] have resulted in a reduction of harvest across Washington and has prompted research into the status of this unique ungulate [5]. Conservation and recovery of mountain goat populations depends upon an understanding of habitat use [6]. Therefore, we developed habitat models based on data from mountain goats fitted with Global Positioning System (GPS) collars in the Washington Cascades.

Application of GPS telemetry collars allowed for an unheralded opportunity to track mountain goats throughout the lengthy winter, a critical time period for survival, at a time when traditional telemetry and observational studies have substantial limitations. Although GPS telemetry has increased the number of locations collected on an individual animal by orders of magnitude over traditional radio tracking, GPS receivers may fail to acquire a position under forest canopies or when topography blocks satellite signals [7]. Consequently, data from GPS-collared wildlife is biased toward areas of favorable GPS reception [8-12]. We expected the GPS bias problem to coincide with habitats typical of those used by mountain goats during the winter. In the Cascades, mountain goats move to lower elevations during the winter [13] where forest canopies tend to increase in both height and structure. Thus, the GPS bias problem was most likely apparent in the time period of greatest interest for developing an understanding of habitat use and the distribution of mountain goat habitat.

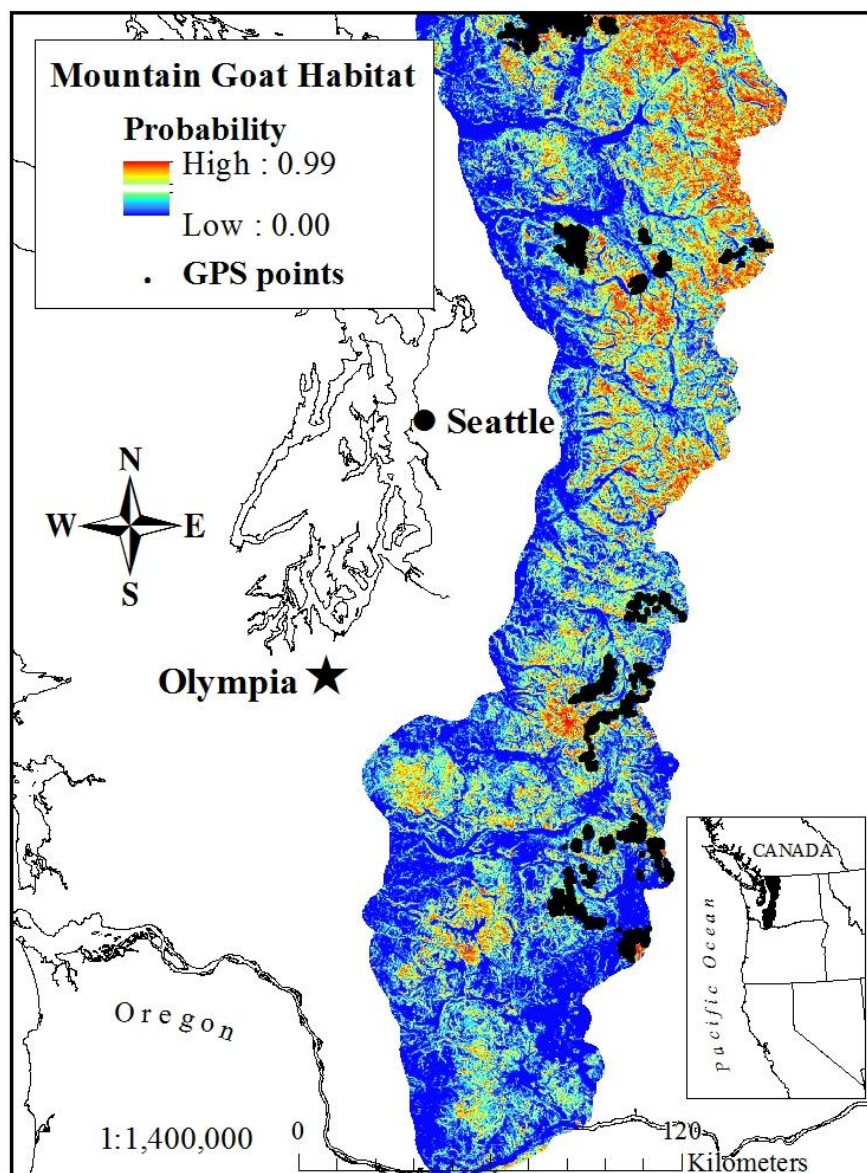
Our primary objective was to map resource selection probability functions (RSPF) [14] at the 2nd order (home range) of habitat selection [15] for annual, summer and winter time periods while increasing the resolution and accuracy of habitat models over previous efforts [16]. Our secondary objective was to incorporate and critically evaluate a GPS bias correction factor. To account for the GPS bias, we developed, applied and evaluated a sample weighting factor based on stationary collar testing for the entire mountain range. The resulting habitat models provided information about the effectiveness of GPS bias correction and the distribution of potential mountain goat habitat in the Washington Cascades. Our models and maps contribute to more effective management and conservation of mountain goats in the Cascades and an example of the widest application of a GPS bias correction model to date.

1.1. Study Area

The study spanned the Washington Cascades (45.6 °N to 49.0 °N and -122.0 °W to -120.0 °W) and was divided into two distinct parts, habitat modeling and bias correction. The habitat modeling portion

of the study focused solely on the Western Cascades (WC; 2.7 million ha; Figure 1). The bias correction model covered both the WC and the Eastern Cascades (EC; 2.6 million ha; Figure 2), naturally divided by the Cascade crest. The spatial extent (Figure 2) of the WC and the EC was defined by the digital product distributed by the Inter-Agency Vegetation Mapping Project (IVMP) [17,18]. We expected to expand the habitat modeling to cover the EC and therefore developed the bias correction model to cover the expected range of mountain goat habitat present in the EC.

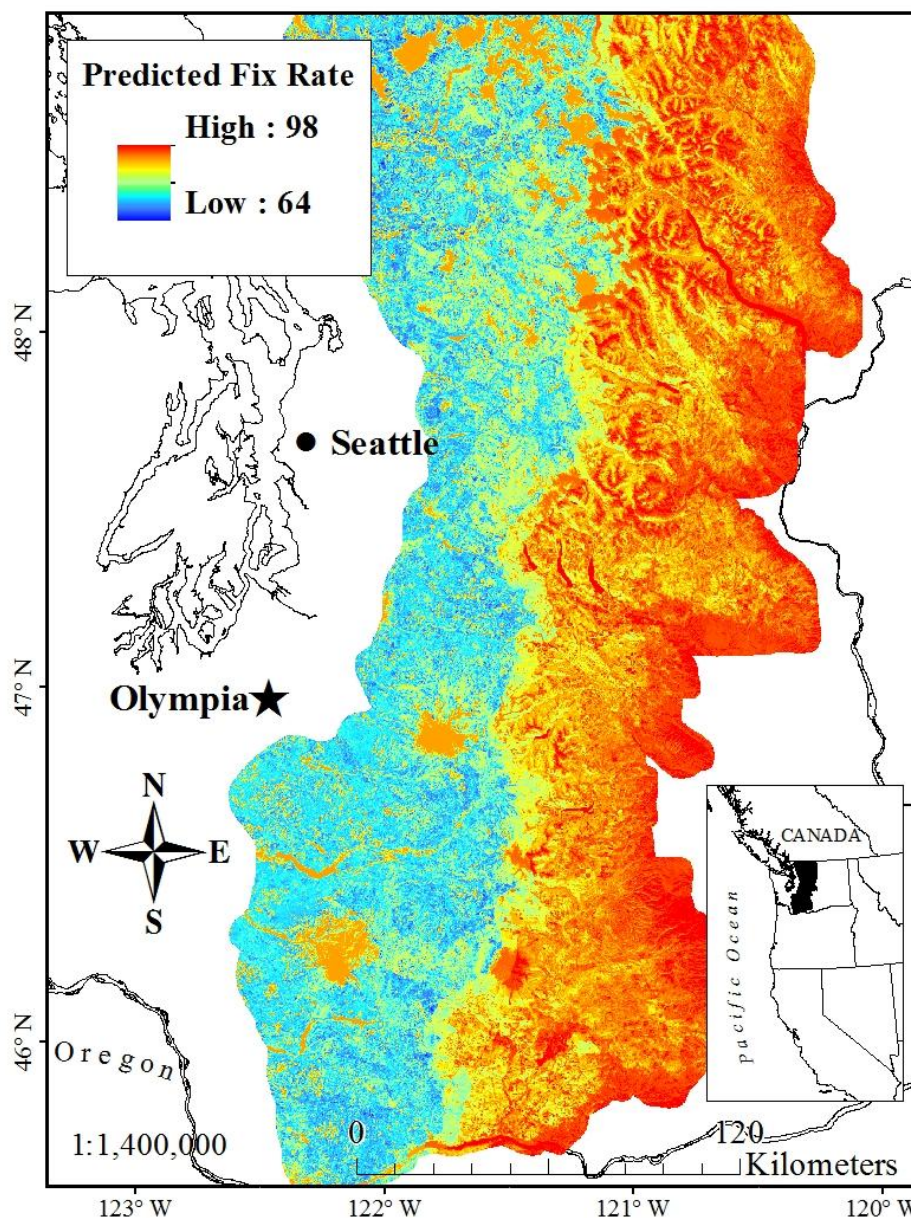
Figure 1. Annual model of mountain goat habitat derived from a resource selection probability function (RSPF) in the western Cascades of Washington, USA (2003–2005) accounting for GPS bias (GPS locations from 38 mountain goats shown for reference).



Mountain goats are native to the Cascade Range occurring both in the WC and the EC. The landscape of the Cascades is characterized by mountainous terrain with massive amounts of topographic relief, numerous glaciers and structurally diverse forest communities. The major

ecological zones occurring in the study area included the montane, subalpine and alpine zones. The combination of physical and vegetative characteristics found in these ecological communities (ranging from dense forests in narrow valleys at lower elevations to treeless ridgelines) provided a wide range of conditions for testing GPS acquisition.

Figure 2. GPS Position Acquisition Rate (P_{ACQ}) bias correction layer, based on stationary field sampling (2004–2005), across the western and eastern Cascades of Washington State, USA, used for sample weighting of GPS fixes from mountain goats.



In the WC, the Pacific silver fir/western hemlock (*Abies amabilis*/*Tsuga heterophylla*) forests are the most common forest community at lower elevations. Common associate over-story species included: Douglas-fir (*Pseudotsuga menziesii*), Red alder (*Alnus rubra*), and Western red cedar (*Thuja plicata*). At higher elevations, Subalpine fir (*Abies lasiocarpa*), Alaska-cedar (*Chamaecyparis nootkatensis*), and Mountain hemlock (*Tsuga mertensiana*) occur. In the EC, Ponderosa pine (*Pinus*

ponderosa) dominates the landscape. Common associates included Douglas-fir, Engelmann spruce (*Picea engelmannii*), Subalpine fir, Western larch (*Larix occidentalis*) and Lodgepole pine (*Pinus contorta*) [19].

2. Methods

2.1. GPS Bias Correction

We followed the experimental design proposed by Frair *et al.* [10] and adopted by Hebblewhite *et al.* [20] and Godvik *et al.* [21] to develop a model to predict the GPS position acquisition rate (P_{ACQ}) based on testing stationary GPS collars for use in sample weighting. During 2004–2005, we benchmarked [22] and tested 24 of the GPS collars that we eventually put on mountain goats. We stratified our sampling based on a range of environmental factors derived with a GIS that we believed *a priori* might influence P_{ACQ} in the WC and EC (Table 1). We stratified our sample sites to cover the majority of combinations of the GIS variables that existed in the WC and EC and compared field measurements with the digital database with a simple correlation. To ground-truth the GIS variables, we recorded elevation ($R = 0.92$), slope ($R = 0.60$), aspect ($R = 0.56$), and percent canopy cover ($R = 0.37$) estimated with a spherical densiometer at each sample site.

Table 1. Strata used for field sampling of GPS bias correction across the Washington Cascades during 2004–2005 based on the Interagency Vegetation Mapping Project (IVMP) data sets.

Variable	Description	Range of Values
Forest type (%)	Open	TVC < 30
	Semi-open	$30 \geq \text{TVC} < 70$
	Conifer	$\text{TVC} \geq 70, \text{CC} \geq 70$
	Mixed	$\text{TVC} \geq 70, \text{CC and BC} \leq 70$
QMD(cm)		0–30
	Western Cascades	31–60
		61–190
Slope and aspect (°)	Eastern Cascades	0–25
		25–190
	Flat	slope < 20
Sky Visibility (%)	Steep north facing slopes	slope > 20 and aspect > 270 or < 90
	Steep south-facing slopes	slope > 20 and aspect > 90 and < 270
Sky Visibility (%)	High	0–60
	Intermediate	60–70
	Intermediate	70–80
	Low	80–100

(TVC = Total Vegetation Cover, CC = Conifer Cover, BC = Broadleaf Cover, QMD = Quadratic Mean Diameter = the diameter at breast height of a tree with the mean basal area of the stand).

All sample sites were located near existing trail networks due to logistic constraints imposed by rugged and inaccessible terrain. Sample sites were >800 m in elevation and spaced ≥ 200 m apart. We

secured GPS units approximately 1 m above ground with bamboo tripods or natural materials found on site. Site selection focused on areas with uniform vegetation characteristics within 30–50 m of the GPS units. We did not attempt to model potential edge effects or fragmentation of forest structure on P_{ACQ} due to the increased complexity of modeling a heterogeneous landscape without first understanding the effects of a homogeneous landscape. Furthermore, sites near the edge of a forest or alpine meadow could have resulted in differences between actual site conditions and the GIS data. We chose areas of uniform vegetation to focus the modeling process on areas that had the greatest chance for discerning the effects of vegetation on P_{ACQ} .

The GPS collars were programmed to attempt a fix for up to 3 minutes every 30 minutes for no less than 24 hours [10] with a maximum acceptable positional dilution of precision (PDOP) 48.6 and an elevation mask of 5° above the horizon, beneath which GPS signals were ignored (Schulte, Vectronic-Aerospace GmbH, personal communication). We defined the sample site position as the average position from all successful fixes. We calculated P_{ACQ} as the percentage of fix attempts that were successful including both 2D and 3D fixes to avoid introducing extra bias [23]. We screened for improbable GPS fix rates (GPS fix rates $< 10\%$) due to suspected collar malfunction or disturbances to the sample site and restricted our analysis to the first 24 hours of data collection at each sample site.

2.2. GPS Bias Correction Variables

We extracted topographic and vegetation predictor variables at 2 spatial resolutions to model P_{ACQ} . We extracted data for a single $25\text{ m} \times 25\text{ m}$ pixel and for a 3 pixel by 3 pixel, or $75\text{ m} \times 75\text{ m}$ square window centered over the pixel that contained the GPS sample site. These two data sets enabled us to examine the relationship between GPS performance and site conditions at two spatial resolutions. We derived topographic predictor variables from a 10 m digital elevation model (DEM) masked to the spatial extent of the IVMP data and resampled to 25 m. We created slope, aspect, sky visibility [11,23–25] data layers.

Vegetation variables for modeling P_{ACQ} were derived from the IVMP data sets [17,18]. The IVMP data set consists of 4 data layers distributed as continuous variables: total vegetation cover (TVC), conifer cover (CC), quadratic mean diameter (QMD), and broadleaf cover (BC). QMD is defined as the diameter at breast height of a tree with the mean basal area of the stand. The IVMP provides these layers as continuous variables, but recommends discrete categorization based on tradeoffs between accuracy and category size; as the number of categories decreases the accuracy increases [17,18]. We classified each vegetation layer based on the distribution of values from sample sites and followed IVMP guidelines on the number of definable classes [17,18]. We classified percent TVC, CC, and BC for both the WC and the EC into 3 classes: 0–60%, 60–90%, and 90–100%; 0–40%, 40–90%, and 90–100%; 0–10%, 10–20%, and 20–100%, respectively. We defined 5 QMD classes for the WC: 0 cm, 0–12.4 cm, 12.4–24 cm, 25–58 cm, and >58 cm. For the EC, we defined 3 QMD classes: 0 cm, 0–12.4 cm and > 12.4 cm. The difference in variable delineation between stratification and modeling was due to the resultant frequency distribution of observations after we completed field work.

To avoid colinearity, we defined 5 vegetation summary predictor variables (TVBC) based on TVC and BC for both the WC and EC. After perfunctory analysis, we found that among the vegetation variables, TVC and CC were highly correlated ($r = 0.88$). Additionally, we found that TVC was the

sum of CC and BC for the majority of sites. We defined the 5 TVBC variables based on the following combination of TVC and BC: TVC (0–60), TVC (60–90) & BC < 10, TVC (60–90) & BC ≥ 10, TVC (90–100) & BC < 10, TVC (90–100%) & BC ≥ 10. In each candidate model, we only considered one of the vegetation variables representing forest type to avoid colinearity.

2.3. GPS Bias Correction Analysis

We used an information theoretic approach with generalized non-linear mixed models to model P_{ACQ} as clustered binary responses [26–30]. Fix attempts at each sample site were coded as successful or not and had the same predictor variables over the course of the entire sampling period. We selected a series of models *a priori* for testing based on expected ecological relevance [31] and performed model selection and fitting in two steps.

First, we used non-linear mixed modeling (PROC NLMIXED; SAS Institute Inc., Cary, NC, USA) for model selection by fitting the candidate models using the logistic link with a single Gaussian random effect at the site level. The NLMIXED procedure fit nonlinear mixed models by numerically maximizing an approximation to the likelihood integrated over the random effects. Therefore, the AICc scores derived from the procedure could be used in model selection and we used AICc scores to rank models for each spatial resolution. However, the procedure estimated parameters for the conditional models. Our primary interest was to derive marginal parameters that had a population-averaged interpretation in the sense that the effect of the covariates was averaged across sites. The conditional models fitted by NLMIXED are equivalent to marginal models with the same covariates and a compound symmetry (CS) covariance structure [32].

In the second step, we used SAS generalized linear mixed modeling procedure (PROC GLIMMIX) to estimate the equivalent marginal models. In addition, we also fit a set of marginal models with the same covariates, but with a first-order autoregressive (AR1) covariance structure. For each selected model, we compared the corresponding marginal models under CS and AR1 covariance structure. We did not use the information theoretic approach to compare the marginal models because this estimation method was not likelihood based.

For each model, we calculated the area under the receiver-operating curve (ROC) for repeated measures [33]. We chose the spatial resolution with the greater area under the ROC [34] for each region, and used the resulting parameter values for predicting P_{ACQ} across the landscape. Finally, to evaluate the predictive power of the bias correction models, we randomly split both the EC and WC datasets, across all animals, into model testing subsets (25%) and model building (75%) and regenerated parameter estimates. We used parameter estimates created with the model building data to predict fix rates in our testing subsets and compared predicted fix rate values to the observed fix rates values at these sites by calculating a coefficient of determination (R_L^2) described by Menard [35].

We used the top models from the optimum spatial resolution to generate a map of predicted GPS fix rates for the EC and WC. The WC and EC bias layer were mosaiced into a single map covering all of the Washington Cascades. We used ArcMap 9.0 Spatial Analyst raster calculator to map predict P_{ACQ} based on Equation (1) [10]:

$$P_{acq} = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)} \quad (1)$$

where P_{ACQ} is the probability of successfully acquiring a GPS fix, β_0 is the intercept $\beta_1 \dots \beta_p$ are coefficient estimates for variables $X_1 \dots X_p$ [10,29]. The final map of predicted P_{ACQ} was then used as a weighting factor during the habitat modeling. Each fix from a GPS-collared goat was weighted by the inverse of P_{ACQ} [10]. In the subsequent habitat analysis (described below), we created habitat models without any weighting and with the scaled weighting factor to evaluate the GPS bias correction factor to assess the influence of the GPS bias correction and also tested the habitat models using data from 9 additional GPS-collared mountain goats that were not used in the development of the habitat models.

Theoretically, the sum of the weighting factor for all fixes should equal the number of attempted fixes. Because this was not true in practice, we scaled the weighting factor. We multiplied the original, “naïve” weight, derived from the P_{ACQ} layer for each telemetry location, by the ratio of the expected attempted number of fixes over the sum of the all the telemetry weights. In this way, the bias correction weighting factor was forced to sum to the total number of fixes we should have obtained from the mountain goats fit with GPS telemetry collars. To understand how the scaling of the weights influenced the results of the habitat models we created habitat models with scaled weights, naïve weights and no weighting using a subset of data (north Cascades). We compared parameter estimates among naïve weighted, scale-weighted, and un-weighted for seasonal and annual habitat models.

In addition to applying our bias correction factor to the mountain goat data, we applied the weighting factor to a “pseudo-habitat” analysis of data that we collected during the bias correction field sampling. At a number of sample sites, the GPS units were left out longer than the 24 hour time period of sampling and recorded additional data. These extra data were treated as hypothetical animal locations and models of habitat selection for this hypothetical situation were developed based on the observed GPS data (with some missing fixes), the expected GPS data (with no missing fixes) and the weighted GPS data. We examined parameter estimates for all the “pseudo-habitat” models in both the EC and WC to gauge how the weighting factor altered parameter estimates toward the expected results, or truth. We created parameter estimates for a single model that included the IVMP data (BC categorized into 3 classes) and a selection of the topographic predictor variables. We did not evaluate diagnostics of the “pseudo-habitat” analysis, since the *a priori* rationale for selecting models to test in an information theoretic approach would have been based on the sample sites stratification. We simply examined how closely the parameter estimates from the “pseudo-habitat” models created with weighted GPS data compared to model created with the observed GPS data and the expected GPS data.

2.4. Mountain Goat Capture and Collars

Mountain goats were captured via aerial and ground-based darting with 0.4–0.5 mL Carfentanil or 50–70 mg xylazine hydrochloride mixed with 0.15–0.25 mg of opiate A3080 and reversed with 3.0 mL Naltrexone or 4.0 mL Tolazine, respectively [36]. Capture methods complied with Washington Department of Fish and Wildlife Policy on Wildlife Restraint or Immobilization. Captured individuals were fitted with GPS telemetry collars (GPS plus collar v6, Vectronic-Aerospace GmbH, Berlin, Germany) programmed to record a fix (3 min max on-time) every 3 hour for 2 yr. Subsequently, GPS data were downloaded remotely via a handheld UHF-receiver.

2.5. Mountain Goat Habitat Variables

We evaluated habitat selection by mountain goats at two resolutions. For each fix, we extracted data at a single resolution for inclusion in the habitat analysis by centering a 75×75 m ($5,625 \text{ m}^2$ or 0.56 ha) window over the 25×25 m pixel containing the GPS telemetry location. We opted to use this extraction window recognizing that over the 3-hour GPS sampling interval, mountain goats likely selected habitats at a range of scales around the resolution of the available digital products used to describe vegetation, which was $25 \text{ m} \times 25 \text{ m}$ (625 m^2 or 0.06 ha). We also expected this 75 m scale to be more realistic given the location error in the GPS data. We evaluated the location error of the GPS units using the 95% circular error probable (CEP) [37].

We developed a series of predictor variables in ArcGIS 9.0 to describe the topographic characteristics of the study area that were relevant to mountain goat ecology. Mountain goats occur in areas that are close to escape terrain and rely on steep slopes, cliffs and escarpments to avoid predation [2,6,38]. We therefore derived predictor variables from a 10-m digital elevation model (DEM). We calculated distance to escape terrain (D2ET) [39] as the distance from the center of each 25-m pixel to the edge of the nearest pixel of escape terrain. We defined escape terrain as areas with slopes $> 35^\circ$ based on an average of previously reported values [38,40-44]. We also created elevation (ELEV) [39], slope and standard deviation of slope (SLSD) layers. We created an aspect layer to evaluate potential differences in habitat selection based on thermal gradients [39]. We used the cosine (ASPCOS) and sine (ASPSIN) of aspect, to test for mountain goats habitat selection along either a north-south or east-west axis because we expected thermal cover, forest type and snow depth to differ primarily along these 2 axes [38].

To assess the influence of vegetation on habitat selection by mountain goats, we defined vegetation variables based on the data layers from the IVMP [17]. We recognize that the IVMP data was not the ideal candidate for assessing relevant features of mountain goat ecology; however, the IVMP provided the largest extent of any available digital product describing multiple characteristics of the vegetation across the entire mountain range. We created 6 classes of TVC: 0–20%, 21–40% (TVC2), 41–60% (TVC3), 61–80% (TVC4), 81–100% (TVC5) total cover, and areas classified as rock and ice (TVC6). We broke the QMD data layers into 4 classes: No cover, 0–30 cm (QMD1), 31–60 cm (QMD2), and 61–190 cm (QMD3). The CC layer was classified into 3 discrete categories: 0–30%, 31–70% (CC2) and 71–100% (CC3). We excluded broadleaf coverage (BC) from the analysis as we did not expect BC to contribute to selection patterns by mountain goats. The final vegetation variables used for model creation also included the number of pixels, or variety (VAR), classified into each of the TVC, QMD and CC classes for each square extraction window at the 75×75 m resolution.

2.6. Mountain Goat Habitat Analysis

We developed 3 temporal habitat models, yearly, winter and summer, based on the use-availability design (type II, sampling protocol SP-A) [14]. We divided the study area into 2 geographic regions, north and south as divided by the US Interstate 90 corridor, a significant barrier to mountain goats [45]. We determined seasons based on elevation shifts of individual mountain goats [13]. We used Hawth's Analysis Tools [46] to generate a matching number of random points with mountain

goat locations per individual. We bound the elevation limits of our analysis with a buffer of 25 m beyond the highest and lowest observed GIS elevations of a mountain goat GPS location. We used weighted logistic regression, with clustering for individual, and Akaike's Information Criteria (AIC) to select a model [31]. Application of the methodology described above for dealing with serially correlated binary data failed to converge when executed with the mountain goat data. We therefore, modeled the probability of a mountain goat location (π) as a RSPF [14] defined by Equation (2) where the sampling probabilities approach zero while ignoring autocorrelation

$$\pi = \frac{e^{[\ln(1-Pa)Pu/Pa]\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n}}{1 + e^{[\ln(1-Pa)Pu/Pa]\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n}} \quad (2)$$

where:

Pa = sample probability of available unit, and

Pu = sample probability of used unit.

We calculated parameter estimates for habitat models, based on a 75% subset of all the GPS data, reserving the other 25% for model testing. To differentiate between habitat and non-habitat along the 0–1 range of predicted probability (π), we determined the cut-point at which the habitat models correctly predicted more mountain goat locations than random locations [34]. With the reserved data, we calculated the percent of the locations that had predictive probabilities greater than the cut-point. We recalculated parameter estimates for the models without the weighting factor to gauge the influence of the bias correction factors on parameter estimation and evaluated the resulting predicted probability for the reserved data.

We also obtained 2 years of additional GPS data, provided by the National Park Service (NPS), on the locations of 9 mountain goats fitted with Vectronic-Aerospace GPS collars in Mount Rainier National Park (MORA; $n = 6$) and the North Cascade National Park (NOCA; $n = 3$). These data were not used in the habitat selection model and were collected after the time period of data used in the habitat models. MORA falls within the extent of the southern region of our habitat model and NOCA falls within the north, thereby offering 2 opportunities to benchmark our models. We plotted the GPS locations of the 9 NPS mountain goats against our habitat model predictions and recorded the percent of fixes classified as in mountain goat habitat. We calculated the percent of correctly predicted mountain goat locations for the all the habitat models with and without the GPS bias correction factor.

3. Results

3.1. GPS Bias Correction

During the summers of 2004–2005, we sampled GPS fix acquisition rates at 543 sites; 324 in the WC and 219 in the EC. At the 324 WC sample sites, we logged 20,788 fix acquisition attempts, 15,552 of which were within the first 24 hrs. This left 5,236 fixes for model evaluation in the pseudo-habitat analysis. At the 219 EC sample sites, we logged 11,081 fix acquisition attempts and retained 10,512 fix attempts from the first 24-hours of sampling, leaving 569 fixes for model evaluation in the pseudo-habitat analysis. The 95 % CEP of the GPS collars based on stationary testing across a range of environments in the WC varied between 83.6 and 77.5 m depending upon the data screening technique [37].

Our sampling strata (Table 1) yielded 144 possible combinations in the WC and 96 possible combinations in the EC. Cross-tabulation of the strata resulted in 81 existing combinations of the 4 stratification variables in the WC study area and 54 existing combinations in the EC. Of the 81 combinations of strata in the WC, we sampled 39 of the combinations that each individually covered more than 0.5% of the study area for a total of 92% of the region. In the WC, the average overall P_{ACQ} from our stationary GPS units was 81.3%. Of the 54 combinations of strata in the EC, we sampled 33 of the 34 strata that each accounted for more than 1% of the study area for a total of 88.9% of the EC. We also sampled a number of the remaining 20 classes that individually represented less than 1% of the study area. Overall, sampling efforts included variable combinations that covered 94.2% of the EC. We over-sampled at lower elevation (<1,000 m) and under-sampled slightly at higher elevations (>1,600 m). Overall, the average P_{ACQ} from our stationary GPS units in the EC was 92.4%.

In the WC, the highest ranked models generally included a measure of forest over-story and in the EC, aspect (Table 2). The coefficients for the 25 m \times 25 m GPS fix rate models for both study areas indicated strong evidence of significance (Tables 3 and 4). Evaluation of the predictive power of the bias correction models by use of the coefficient of determination explained about 30% and 20% for the WC ($R_L^2 = 0.3$) and the EC ($R_L^2 = 0.2$), respectively [35].

The WC model had an area under the ROC of 0.70 based on a 25 m \times 25 m spatial resolution and 0.69 based on a 75 m \times 75 m spatial resolution. For both spatial resolutions, the top EC models included the same variables and had nearly equivalent areas under the ROC (0.68). For the WC model, we opted to use the model based on a 25 m \times 25 m spatial resolution due to the lower AICc score and slightly larger area under the ROC. For consistency sake, the final model on the EC was from the same spatial resolution.

Table 2. Highest ranked models of GPS fix rate (P_{ACQ}) in the Cascades based on 25 m and 75 m spatial resolution for the western and eastern Cascades of Washington during 2004–2005, shown with negative log likelihood ($-LL$), number of parameters (K), Akaike's information criterion ($AICc$), criterion difference (Δ) and weights (w).

Cascade	Resolution	Rank	Model	$-LL$	K	$AICc$	Δ	w
West	25	1	TVC, QMD	5,135.5	5	10,285.0	0	0.51
		2	TVBC, ELEV, SLP	5135	8	10,286.0	1	0.31
		3	TVBC	5,137.5	6	10,287.0	2	0.18
West	75	1	TVC, SLP	5,140.5	5	10,291.0	0	0.38
		2	TVC	5,141.5	4	10,291.0	0	0.38
		3	TVC, QMD	5,140	6	10,292.0	1	0.23
East	25	1	ASP, TVC	2,249.3	5	4,508.6	0	0.65
		2	ASP, TVBC, ELEV	2,247.4	8	4,510.8	2.2	0.22
		3	ASP, TVBC	2,248.8	7	4,511.7	3.1	0.14
East	75	1	ASP, TVC	2,249.5	5	4,509.1	0	0.55
		2	ASP, TVC, SLP, ELEV	2,248	7	4,510.0	0.9	0.35
		3	ASP, TVBC	2,249.4	7	4,512.7	3.6	0.09

(TVC = Total Vegetation Cover, TVBC= Total Vegetation and Broadleaf Cover, QMD = Quadratic Mean Diameter, ASP = Aspect, ELEV = Elevation, and SLP = slope).

Table 3. Parameter estimates for the model of GPS fix rate (P_{ACQ}) at a 25 m resolution for the western Cascades of Washington during 2004 ($n = 317$, Number of fix attempts = 15,552).

Variable	β	SE	t	$P > z $	[L 95%]	[U 95%]
TVC (90–100%)	-1.63	0.18	-9.25	<0.0001	-1.98	-1.28
TVC (60–90%)	-1.31	0.16	-8.04	<0.0001	-1.63	-0.99
QMD (0–12cm)	-0.69	0.13	-2.13	<0.0001	-0.95	-0.43
QMD (13–24cm)	-0.30	0.14	-6.59	0.03	-0.58	-0.02
QMD (25–58cm)	-0.92	0.14	-2.64	<0.0001	-1.2	-0.64
Intercept	3.15	0.12	26.17	<0.0001	3.39	2.91

(TVC = Total Vegetation Cover, QMD = Quadratic mean diameter).

Table 4. Parameters estimates for the model of GPS fix rate (P_{ACQ}) at a 25 m resolution for the eastern Cascades of Washington during 2005 ($n = 219$, Number of fix attempts = 10,512).

Variable	β	SE	t	$P > z $	[L 95%]	[U 95%]
ASP	0.43	0.16	2.67	0.0083	0.11	0.76
TVC (90–100%)	-1.71	0.36	-4.76	<0.0001	-2.43	-0.99
TVC (60–90%)	-0.99	0.36	-2.74	0.0066	-1.72	-0.28
Intercept	3.62	0.33	11.08	<0.0001	2.97	4.27

(ASP = aspect and TVC = Total Vegetation Cover).

The more open forests of the EC had a substantially higher predicted GPS fix rates than the more densely forested WC (Figure 2). The final model yielded predicted GPS fix rates—ranging from 0.64 to 0.98 across the entire study area, which was quite similar to Frair *et al.* [10] whose values ranged from 0.63 to 0.98. As expected, the alpine zones showed high predicted GPS fix rate values with reduced predicted fix rates at lower elevations. In the WC however, the immediate transition zones from alpine to subalpine zone had lower predicted GPS fix rates than those areas lower in elevation. The lowest predicted values across the study area generally fell in this subalpine region with some comparable values in the valley bottoms. The EC model had a regular transition of high to low predicted fix rates moving from high to low elevations.

3.2. Mountain Goats

We acquired 86,826 GPS locations (September 2003–September 2005) from 38 collared mountain goats widely distributed across the WC. Mean P_{ACQ} across all animals for the entire period of study was 65.4% (Standard Deviation (SD) = 13.1%; range = 41.9–85.5%). During the winter, mean P_{ACQ} across all study animals was 60.9% (SD = 17.3%; range = 30.7–90.0%). During the summer, mean P_{ACQ} across all study animals was 78.6% (SD = 11.6%; range = 49.6%–91.0%). The range of GIS

derived elevations from mountain goats fit with GPS collars was 322–3,083 m, which we buffered to 300–3,100 m for our analysis.

Results from model selection based on the information theoretic approach unequivocally selected the global model in all cases, for both weighted and un-weighted analyses. The AIC weights were greater than 0.99 for the global model among each suite of models for the yearly-north, yearly-south, winter and summer analysis. In each case, the global model 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 global models were TVC, CC and QMD.

The yearly models for the north Cascades and the south Cascades (Table 5) show varying direction of effect for the TVC variables and for elevation. The differences in parameter estimates between the weighted and un-weighted models, for both the north and south models, were negligible. Only the QMD variables had differences in parameter estimates close to or greater than 0.1. Note that the QMD variables were also included in the bias correction model developed for the WC (Table 3). The seasonal habitat selection parameters also showed a varying direction of effect for TVC4 and TVC6 among seasons (Table 6). As with the yearly model, differences in parameter estimates between weighted and un-weighted models of seasonal habitat were negligible.

Validation of the yearly habitat models with the 25% of data that were reserved and with the independent data from MORA and NOCA also showed minor differences between weighted models and un-weighted models (Figure 3). The un-weighted north Cascades model correctly predicted 83.1% of the reserved data, 91.6% of the MORA data, and 96.7% of the NOCA data. The weighted north Cascades model correctly predicted 84.2% of the reserved data, 89.4% of the MORA data and 94.5% of the NOCA data. The un-weighted model had a higher classification accuracy of the independent MORA and NOCA data but not the reserved data. The greatest difference in accuracies among the weighted and un-weighted models was less than 2.5%. One might expect that weighting would have a large effect in cases where the fix rate is quite low. However, the average GPS fix rate for GPS-collared mountain goats was only 36.8% in the NOCA and 55.9% in MORA. Only 32% of the study area was classified as “habitat” so the high classification accuracies are unlikely to be due to chance alone. The un-weighted south Cascades model correctly predicted 86.7% of the reserved data, 64.3% of the MORA data, and 66.7% of the NOCA data (less than the proportion of habitat to non-habitat in NOCA). The weighted south Cascades model correctly predicted 86.3% of the reserved data, 65.3% of the MORA data and 67.7% of the NOCA data. The weighted models had slightly higher classification accuracy of the MORA and NOCA data, but not for the reserved data. The greatest difference among the weighted and un-weighted models was only 1%. Overall, the model of mountain goat habitat developed with data from the south Cascades did not perform as well as models created with data from the north Cascades.

Table 5. Parameter estimates (β) and standard errors (se) for mountain goat habitat model of the yearly-north ($n = 22$) and yearly-south ($n = 16$) Cascade regions showing scale-weighted and un-weighted parameter estimates.

Parameter	North Cascades				South Cascades			
	Weighted		Un-weighted		Weighted		Un-weighted	
	β	se	β	se	β	se	β	se
Intercept	-2.1323	0.0808	-2.0601	0.0839	-5.2154	0.1144	-5.1256	0.1182
ASPCOS	-0.7990	0.0153	-0.7994	0.0161	-0.2675	0.0216	-0.2708	0.0224
ASPSIN	-0.3160	0.0138	-0.3112	0.0144	-0.2905	0.0177	-0.2928	0.0184
ELEV	-0.0010	0.0001	-0.0010	0.0001	0.0003	0.0001	0.0003	0.0001
SLOPE	0.0636	0.0013	0.0628	0.0014	0.1313	0.0018	0.1293	0.0018
SLSD	0.0716	0.0031	0.0689	0.0032	0.0828	0.0040	0.0799	0.0041
D2ET	-0.0112	0.0004	-0.0112	0.0004	-0.0019	0.0002	-0.0018	0.0002
TVC2	1.0619	0.0348	1.0779	0.0354	-0.4338	0.0591	-0.4339	0.0598
TVC3	0.7556	0.0324	0.7588	0.0331	-0.5914	0.0474	-0.5870	0.0482
TVC4	0.5257	0.0269	0.4317	0.0284	-0.4154	0.0431	-0.4887	0.045
TVC6	1.4780	0.0394	1.4659	0.0402	-1.0010	0.0512	-1.0303	0.0523
VAR TVC	0.3361	0.0119	0.3178	0.0123	0.1681	0.0164	0.1625	0.0169
QMD1	-0.5724	0.0387	-0.6981	0.0412	-0.6157	0.0577	-0.7444	0.0609
QMD2	-0.7697	0.0420	-0.9136	0.448	-0.8509	0.0611	-0.9655	0.0643
QMD3	-1.158	0.0374	-1.1404	0.0393	-0.7264	0.0563	-0.7460	0.0586
VAR QMD	0.2158	0.0144	0.0152	0.0152	0.1815	0.0203	0.1588	0.0211
CC2	-0.0171	0.0297	-0.0401	0.0305	-0.3736	0.0500	-0.4070	0.0514
CC3	-0.1119	0.0353	-0.1586	0.0368	-0.6882	0.0571	-0.7183	0.0592
VAR CC	-0.1496	0.0170	-0.1475	0.0177	0.2208	0.0244	0.2115	0.0254

(ASPCOS = Cosine of aspect, ASP SIN = Sine of Aspect, ELEV = Elevation, SLSD = Standard Deviation of Slope, D2ET = Distance to Escape Terrain, TVC = 0–20% Total Vegetation Cover, TVC2 = 21–40% Total Vegetation Cover, TVC3 = 41–60%, Total Vegetation Cover, TVC4 = 61–80% Total Vegetation Cover, TVC5 = 81–100%, Total Vegetation Cover, TVC6 = rock and ice, VAR TVC = Variety of Total Vegetation Cover, QMD1 = 0–30 cm Quadratic Mean Diameter, QMD2 = 31–60 cm Quadratic Mean Diameter, QMD3 = 61–190 cm Quadratic Mean Diameter, VAR QMD = Variety of Quadratic Mean Diameter, CC2 = 31–70% Conifer Cover, CC3 = 71–100% Conifer Cover, VAR CC = Variety of Conifer Cover).

Table 6. Parameter estimates (β) and standard errors (se) for summer ($n = 38$) and winter ($n = 35$) models of mountain goat habitat across the whole of the Washington Cascades showing scale-weighted and un-weighted parameter estimates.

Parameter	Summer				Winter			
	Weighted		Un-weighted		Weighted		Un-weighted	
	β	se	β	se	β	se	β	se
Intercept	-2.6865	0.0884	-2.5724	0.0915	-4.8862	0.0833	-4.8201	0.0917
ASPCOS	-0.2384	0.0170	-0.2487	0.0177	-0.8503	0.0181	-0.8532	0.0189
ASPSIN	-0.2307	0.0150	-0.2231	0.0156	-0.3262	0.0153	-0.3259	0.0160
ELEV	0.0005	0.0001	0.0005	0.0001	-0.0007	0.0001	-0.0007	0.0001

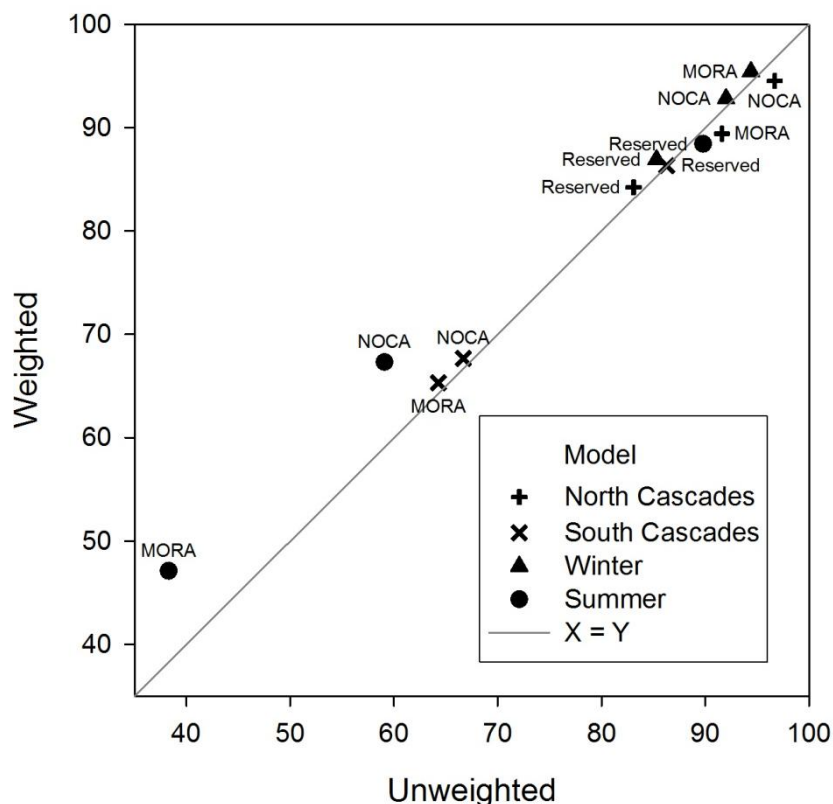
Table 6. Cont.

SLOPE	0.0502	0.0015	0.0485	0.0015	0.1229	0.0015	0.1210	0.0016
SLSD	0.0612	0.0034	0.0594	0.0035	0.0707	0.0034	0.0664	0.0035
D2ET	-0.0096	0.0004	-0.0096	0.0004	-0.0032	0.0003	-0.0033	0.0003
TVC2	0.4019	0.0390	0.4002	0.0395	0.2808	0.0437	0.2930	0.0443
TVC3	0.1673	0.0365	0.1546	0.0372	0.1670	0.0379	0.1760	0.0386
TVC4	-0.0061	0.0341	-0.1178	0.036	0.1552	0.0310	0.0689	0.0325
TVC6	-0.0013	0.0384	-0.0129	0.0391	0.2216	0.0479	0.1923	0.0490
VAR TVC	0.2077	0.0132	0.1993	0.0135	0.3475	0.0133	0.3392	0.0138
QMD1	-0.9395	0.0475	-1.0773	0.0509	-0.3256	0.0438	-0.4462	0.0462
QMD2	-1.2726	0.0530	-1.4009	0.0569	-0.4330	0.0460	-0.5512	0.0486
QMD3	-1.1743	0.0457	-1.1861	0.0479	-0.6904	0.0420	-0.7056	0.0437
VAR QMD	0.1430	0.0171	0.1116	0.0180	0.2728	0.0160	0.2503	0.0168
CC2	-0.2995	0.0353	-0.3168	0.0362	-0.2015	0.0363	-0.2386	0.0373
CC3	-0.2308	0.0434	-0.2656	0.0452	-0.2157	0.0419	-0.2756	0.0435
VAR CC	0.0489	0.0196	0.0474	0.0204	0.0753	0.0191	0.0742	0.0199

(ASPCOS = Cosine of aspect, ASPSIN = Sine of Aspect, ELEV = Elevation, SLSD = Standard Deviation of Slope, D2ET = Distance to Escape Terrain, TVC = 0–20% Total Vegetation Cover, TVC2 = 21–40% Total Vegetation Cover, TVC3 = 41–60%, Total Vegetation Cover, TVC4 = 61–80% Total Vegetation Cover, TVC5 = 81–100%, Total Vegetation Cover, TVC6 = rock and ice, VAR TVC = Variety of Total Vegetation Cover, QMD1 = 0–30 cm Quadratic Mean Diameter, QMD2 = 31–60 cm Quadratic Mean Diameter, QMD3 = 61–190 cm Quadratic Mean Diameter, VAR QMD = Variety of Quadratic Mean Diameter, CC2 = 31–70% Conifer Cover, CC3 = 71–100% Conifer Cover, VAR CC = Variety of Conifer Cover).

Validation accuracies of the seasonal models, created with data from the entire Cascades, also showed little difference between weighted and un-weighted models (Figure 3). The winter model correctly classified 86.9% and 85.3% of the reserved telemetry data, for the weighted and un-weighted models, respectively. The winter model correctly classified 92.8% and 92.0% of the NOCA data and 95.4% and 94.4% of the MORA data for weighted and un-weighted models, respectively. In each case, the weighted winter model had slightly higher classification accuracies, but the greatest difference was less than 2%. The summer model correctly classified 88.4% and 89.8% of the reserved data for the weighted and un-weighted models, respectively. The summer model had accuracies of only 67.3% and 59.1% for the NOCA data and only 47.1% and 38.3%, for the MORA data for the weighted and un-weighted models, respectively. The summer models showed the greatest difference in classification accuracies between the weighted and un-weighted models, but the greatest difference was still less than 10%, and during a time of year when P_{ACQ} was generally higher. The differences in accuracy between the weighted model and the un-weighted model of correctly predicting mountain goat GPS data in optimal mountain goat habitat is minor relative to the overall validation accuracies.

Figure 3. Comparison of validation accuracies of reserved and supplemental data for habitat models of mountain goats in the western Cascades of Washington created with and without a GPS bias correction factor incorporated by sample weighting using scaled weights.



Additionally, evaluating the north Cascades subset of the data based on un-weighted, naïve-weights and scaled weights (Table 7) did not change parameter estimates meaningfully for the seasonal or yearly models. In particular, parameter estimates between the scaled weights and naïve weights were almost identical. The difference between un-weighted parameter estimates and weighted estimates was slightly greater between naïve weights than between scaled weights but still not great enough to alter our interpretation of the ecological significance.

In the pseudo-habitat analysis, the use of weighting did not return the parameter estimates to their expected values (Table 8). However, the observed GPS data, the expected GPS data, and the weighted GPS data showed almost no meaningful change in direction of effect and little difference, if any, in the magnitude between observed and weighted telemetry results. There was greater difference between expected and observed, but arguably not enough to substantially alter resultant models and maps derived from the estimates.

Table 7. Seasonal and yearly parameter estimates (β) for mountain goat habitat models created without weights, with naïve weights and scaled weights models for a subset of the data from the north Cascades.

	Summer (<i>n</i> = 22)			Winter (<i>n</i> = 20)			Yearly (<i>n</i> = 22)		
	Un-weighted	Naïve	Scaled	Un-weighted	Naïve	Scaled	Un-weighted	Naïve	Scaled
Intercept	-6.2723	-6.4559	-6.4559	2.3225	2.429	2.8292	-1.9724	-2.0567	-1.9414
ASPCOS	-0.3181	-0.3072	-0.3073	-1.2837	-1.286	-1.2829	-0.7867	-0.7854	-0.7763
ASPSIN	-0.3469	-0.3636	-0.3635	-0.3465	-0.3456	-0.3469	-0.3133	-0.318	-0.3152
ELEV	0.0034	0.0035	0.0035	-0.0048	-0.0048	-0.0048	-0.0010	-0.001	-0.0009
SLOPE	0.0341	0.0349	0.0349	0.0649	0.0646	0.0633	0.0608	0.0618	0.0624
SLSD	0.1056	0.1091	0.1091	0.0517	0.0548	0.0575	0.0687	0.0713	0.0730
D2ET	-0.0091	-0.0090	-0.0090	-0.0241	-0.0232	-0.0218	-0.0117	-0.0116	-0.0112
TVC2	1.0684	1.0659	1.0659	1.4674	1.4499	1.4947	1.0985	1.0822	1.0871
TVC3	0.5063	0.5116	0.5116	1.0185	0.9973	1.0250	0.7291	0.7235	0.7269
TVC4	0.0754	0.1743	0.1743	0.5860	0.6576	0.6532	0.4178	0.5088	0.5056
TVC6	1.0735	1.0918	1.0916	1.8198	1.8036	1.8286	1.4176	1.4296	1.4556
VAR TVC	0.3045	0.3223	0.3222	0.3004	0.3105	0.3042	0.3341	0.3534	0.3608
QMD1	-0.9868	-0.8562	-0.8562	-0.1574	-0.0446	-0.0526	-0.7014	-0.5754	-0.5828
QMD2	-1.8419	-1.6867	-1.6867	-0.4807	-0.3516	-0.3914	-0.8798	-0.7382	-0.7535
QMD3	-1.7278	-1.6885	-1.6884	-0.9002	-0.8946	-0.9368	-1.0862	-1.0602	-1.0791
VAR QMD	0.0034	0.0428	0.0428	0.2694	0.2917	0.2864	0.1689	0.2018	0.2035
CC2	-0.0587	-0.0482	-0.0482	-0.0707	-0.0301	-0.0147	-0.0530	-0.0268	-0.0273
CC3	-0.0376	-0.0056	-0.0056	0.0005	0.0687	0.0979	-0.1833	-0.1333	-0.1319
VAR CC	-0.0385	-0.0234	-0.0234	-0.1745	-0.1848	-0.1849	-0.1576	-0.1607	-0.1642

(ASPCOS = Cosine of aspect, ASPSIN = Sine of Aspect, ELEV = Elevation, SLSD = Standard Deviation of Slope, D2ET = Distance to Escape Terrain, TVC = 0–20% Total Vegetation Cover, TVC2 = 21–40% Total Vegetation Cover, TVC3 = 41–60%, Total Vegetation Cover, TVC4 = 61–80% Total Vegetation Cover, TVC5 = 81–100%, Total Vegetation Cover, TVC6 = rock and ice, VAR TVC = Variety of Total Vegetation Cover, QMD1 = 0–30 cm Quadratic Mean Diameter, QMD2 = 31–60 cm Quadratic Mean Diameter, QMD3 = 61–190 cm Quadratic Mean Diameter, VAR QMD = Variety of Quadratic Mean Diameter, CC2 = 31–70% Conifer Cover, CC3 = 71–100% Conifer Cover, VAR CC = Variety of Conifer Cover).

Table 8. Parameter estimates (β) for pseudo-habitat analysis of extra data collected during GPS bias correction fieldwork based on models of observed telemetry data, expected data and the weighted telemetry for both the West Cascades (WC) and East Cascades (EC).

	WC			EC		
	Expected	Observed	Weighted	Expected	Observed	Weighted
Intercept	1.0043	1.00854	1.2110	-0.7564	-0.8751	-0.9954
ASPCOS	-0.4033	-0.2532	-0.2527	-0.2056	-0.0932	-0.1155
ASPSIN	0.4664	0.3501	0.3306	0.0035	-0.0037	-0.0001
ELEV	0.0001	0.0001	-0.0001	-0.0011	-0.0010	-0.0009
SLOPE	-0.0291	-0.0233	-0.0225	0.0224	0.0201	0.0208
D2ET	-0.0006	-0.0003	0.0001	NA	NA	NA
TVC2	-2.2519	-2.3051	-2.2892	1.9823	2.0972	2.0547
TVC3	0.0775	0.0414	0.0618	1.3453	1.4541	1.4092
TVC4	-0.5780	-0.0821	-0.1310	1.7015	1.9041	1.9643
TVC5	-0.6561	-0.6060	-0.4162	1.4373	1.6402	1.7205
TVC6	-3.6464	-3.8159	-3.7515	2.0390	1.8385	1.8280
QMD1	1.3984	1.0536	1.0021	-0.7382	-0.7665	-0.8131
QMD2	0.7184	0.5663	0.6171	1.3802	1.1773	1.1782
QMD3	0.2573	-0.0223	-0.1233	0.3801	0.3403	0.4458
CC2	-0.3621	-0.6011	-0.5962	-0.3050	-0.4696	-0.4698
CC3	-0.6493	-0.9752	-1.0002	-0.4281	-0.8254	-0.8364
BC2	-0.5338	-0.7020	-0.6980	0.4730	0.4653	0.4654
BC3	-2.4054	-2.3489	-2.2713	NA	NA	NA

(ASPCOS = Cosine of aspect, ASP SIN = Sine of Aspect, ELEV = Elevation, SLSD = Standard Deviation of Slope, D2ET = Distance to Escape Terrain, TVC = 0–20% Total Vegetation Cover, TVC2 = 21–40% Total Vegetation Cover, TVC3 = 41–60%, Total Vegetation Cover, TVC4 = 61–80% Total Vegetation Cover, TVC5 = 81–100%, Total Vegetation Cover, TVC6 = rock and ice, QMD1 = 0–30 cm Quadratic Mean Diameter, QMD2 = 31–60 cm Quadratic Mean Diameter, QMD3 = 61–190 cm Quadratic Mean Diameter, CC2 = 31–70% Conifer Cover, CC3 = 71–100% Conifer Cover, BC2 = 50–75% Broadleaf Cover, and BC3 = 75–100% Broadleaf Cover)

Despite a negligible influence of the weighting factor on parameter estimates or validation accuracies, the habitat models created probabilistic maps of mountain goat habitat in Western Washington. The final habitat maps displayed the continuous probability of potential mountain goat habitat taking into account the GPS bias correction-weighting factor across the western Cascades that increases the resolution of past modeling efforts from 100 ha [16] to 0.56 ha (Figure 1).

4. Discussion

Overall, we expected a greater influence of the GPS bias correction factor on resources selection analysis and habitat prediction. When benchmarking the habitat models with testing data (25% of locations from study animals) the GPS bias corrected model performed slightly better than the uncorrected model. In 8 of 12 of the comparisons, the weighted habitat model had higher classification accuracies, although the difference was usually only 1–2% (Figure 3). The greatest difference between

habitat models created with and without the bias correction factor was about 8%, but was at the low end of overall classification accuracy. When the habitat models were benchmarked with the data collected from the 9 independent mountain goats, the uncorrected habitat models classified more mountain goat locations in what we described as mountain goat habitat than did the GPS bias corrected model. In addition to slight differences in validation accuracies between weighted and un-weighted models, there was little difference between parameter estimates of weighted *versus* un-weighted models (Tables 5–8). We found this to be the case in each of the comparisons between weighted and un-weighted models.

The lack of difference between the weighted and un-weighted models was unexpected and may be due to a number of factors. If the long-term temporal scale of the observed horizontal movements of mountain goats is fairly limited (no dispersal or long range movements) the amount of GPS data acquired may be enough to adequately characterize the selection of habitats in relation to availability. For example, if a mountain goat remained stationary for an extended period of time, even if the P_{ACQ} was quite low, the selection of that habitat would be constant as long as the number of available locations matched the observed number of locations. In other words, if only one cover type was actually utilized, then the number of observations acquired will not change the selection estimates. This would likely vary as a function of the movement and behavior of a mountain goat in relation to climatic factors (such as snow depth), the age, and sex of collared animals. In other words, the differences between P_{ACQ} among habitats may be negligible based on the behavior of the individual animal, the general ecological relationships of the species to the study area, and perhaps more paramount, the statistical method employed to address the research question of interest. In the future, understanding the consequences of data loss prior to beginning a GPS collaring effort will be helpful in understanding at what magnitude data loss will alter results of habitat analysis beyond acceptability for the question of interest.

Behavior has the additional compounding factor of influencing P_{ACQ} . Our experimental design did not account for activity and this may be why our GPS bias trials had an overall higher P_{ACQ} than the mountain goat data. Presumably, the lower P_{ACQ} exhibited by the collar data depends in part on behavior and the interaction of behavior and habitat. For example, if an animal spends a great deal of time lying down (with the GPS antenna in suboptimal position) in habitats with otherwise good GPS signal reception and a great deal of time foraging in habitats with otherwise poor GPS signal reception, the interaction could result in no differences in P_{ACQ} among these habitats. Our GPS bias correction model was not designed to account for the variation of P_{ACQ} from mountain goat telemetry data due to activity.

It is also possible that our analysis was flawed in that the scale of the GIS data may not capture the actual environmental factors that influence acquisition of GPS satellite signals. Nevertheless, our model diagnostics were comparable to other published studies advocating this modeling approach. The goodness of fit of our GPS bias correction model was low to acceptable (WC: $R_L^2 = 0.296$, $ROC = 0.70$ and EC: $R_L^2 = 0.202$, $ROC = 0.68$) which was comparable to other studies that reported similar metrics. D'eon *et al.* [23] and D'eon [47] incorporated canopy cover and available sky in a model with a fix rate $R^2 = 0.229$ whereas Lewis *et al.* [37] reported fix rate $R^2 = 0.028$ – 0.099 for models including sky visibility and canopy cover. Hebbelwhite *et al.* [20] reported the area under the $ROC = 0.81$ for a

model predicting the probability of obtaining a successful fix based on collar manufacturer, aspen, closed conifer, and topographic position in narrow valleys or steep slopes. Hebbelwhite *et al.* [20] also reported a range of ROC scores between 0.71 and 0.75 for models based on individual collar manufacturers. Frair *et al.* [10] reported an area under the ROC of 0.683 for P_{ACQ} based on a model including collar type, vegetation class, percent slope, and the interaction of slope and vegetation. Only Frair *et al.* [10], Hebbelwhite *et al.* [20] and our study accounted for the lack of independence between successive fixes at each trial site in their analysis. Even though we expanded upon the statistical approaches advocated in the literature to deal with binary data that is serially correlated and clustered, our habitat analysis showed little difference between models created with a bias correction factor *versus* those created without a bias correction factor. Our study is the largest reported effort to correct for the GPS bias issues using the sample weighting approach. Our bias correction model included hundreds of sample sites and was applied across the widest geographic extent yet reported, but did not markedly change model predictions and improved predictions by only a few percent.

More studies are addressing how the GPS bias correction models actually influence the results of a habitat selection [10,21,48]. Frair *et al.* [10] addressed the question of how bias correction changed the results based on 10 iterations of simulated 30% data loss based on P_{ACQ} . Frair *et al.* [10] found that sample weighting reduced Type II error rates and corrected the coefficient bias. We found, like Godvik [21], that our parameter estimates did not change in a meaningful or explainable manner in any of the comparisons we made including: among yearly models (both north and south), among seasonal models, among models scaled to correct for the expected number of telemetry locations we should have acquired, and among models with known selection ratios. Likewise our pseudo habitat analysis did not correct the biased parameter estimates back to the original, true estimates.

Despite the negligible differences between habitat models created with or without a GPS bias correction factor, the amount of telemetry data accrued allowed us to create habitat maps that performed well and matched with our expectations of the distribution of mountain goat habitat (Figure 1). The habitat models however, suffer from some flaws. Notably, the modeling did not account for the lack of independence between successive GPS fixes from an individual mountain goat, nor were the vegetation data provided by the IVMP optimum for discerning mountain goat habitat. The habitat models however do not provide insightful ecological interpretations of habitat selection by mountain goats due to the number of variables included in the final models. Nonetheless, the resultant models, when displayed in a GIS provide a more detailed depiction of the habitat available to mountain goats in the western Cascades based on a large number of observations over the course of two years. In particular, the data acquired during the winter time provided the most comprehensive data set for analysis of habitat selection by mountain goats during this difficult study period. These data can assist with future management, conservation and research plans to meet the multiple goals of the numerous authorities and interest groups of the region.

The performance of our GPS bias correction model poses some questions and highlights additional avenues of research. If this approach to correct habitat induced GPS bias is to be continued, the foremost imperative of research needs to be a critical evaluation of how a GPS bias correction model and weighting scheme can produce an unbiased result. Further simulation studies, like those of Frair *et al.* [10] and Nielson *et al.* [48] are the most likely means of addressing the limitations and problems of this method. Such studies may clarify which variables in a GPS bias correction model

have more of an influence on fix success rates and if the bias correction factor can adjust habitat selection estimates back to actual values obtained from real-world data. Simulation studies will also help understand the magnitude of the GPS bias correction problem in habitat analysis [48]. More simulation exercises may help assess at what point, and to what extent, data loss alters parameter estimates of habitat selection models beyond some statistical threshold of significance or acceptability. The challenge remains however, to demonstrate correction of habitat coefficients from real-world data. When employing the stationary collar sampling design, the time interval should match those of collars deployed on wildlife [12] and the influence of animal behavior on P_{ACQ} needs to be addressed for the specific species of interest [11,49]. The decision to pursue a bias correction model in future studies by other researchers shouldn't be ignored, but carefully consider in light of our results. We concluded that the weighted sampling approach yielded virtually no difference between bias corrected and un-corrected results. If data loss is great enough based on initial returns from deployed collars, research may need to investigate the causes and implications (via simulation of habitat models based on differing rates of data loss) of the bias. If there is a high enough fix success, obviously the entire point is moot.

Our habitat models ignored the inherent autocorrelation of GPS data from wildlife. Application of the modeling technique we developed here to deal with the autocorrelation in the bias data resulted in a failure of the computer algorithm to converge when applied to the mountain goat data. Furthermore, the ecological justification for application of the methodology for dealing with the bias data does not necessarily apply to wildlife since successive locations from free roaming animals may have variable distances, times, and related predictor variables. The ongoing development of statistical and modeling techniques to capitalize on the lack of independence between successive GPS fixes from free ranging wildlife in habitat and space use studies [50], will refine the ability to develop ecologically meaningful habitat models and to deal with the large amount of data accrued by GPS collars.

5. Conclusion

We applied and critically evaluated the results of a state-of-the-art methodology for addressing GPS bias correction, issues of scale (resolution), mapping of environmental variables, and habitat selection based on GPS data. We conducted the largest-scale application of GPS bias correction methodology supported by the literature and applied GPS technology to a pressing management and conservation issue. Without GPS technology, acquiring the location and movement data of this detail on mountain goats across the entire Cascade mountain range was simply impossible. The sheer volume of data accrued through GPS telemetry of free ranging wildlife defies the imagination and with decreasing hardware cost and weight will continue to define the future of wildlife tracking and monitoring. We now have a much greater understanding of the habits of mountain goats in the Cascades and how the landscape supports the species. The enormous gains in data made possible by GPS technology, however are with limits and offer future avenues of research and discourse.

Acknowledgements

This work was part of a cooperative research project on the mountain goat (*Oreamnos americanus*) in conjunction with Sauk-Suiattle Indian Tribe (C. Danilson), the Washington Department of Fish and

Wildlife (Wildlife Science and Aquatic Lands Enhancement Account (ALEA) Volunteer Cooperative Grant Program), Western Washington University, Seattle City Light Wildlife Research Program, Biological Resource Division of the USGS, the US Forest Service and the US National Park Service, the US Environmental Protection Agency, and the US Fish and Wildlife Service. We would like to thank J. Rachlow and O. Garton from the University of Idaho for contributing to the long-term support of mountain goat research in Washington State. We also thank the anonymous reviewers who provided comments and feedback to improve the manuscript.

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