### **SUPPLEMENTAL MATERIAL**

## **Correcting for Bias in GPS Collar Transmission**

Anticipating that GPS-collars would not produce data on 100% of expected fix times, and that failure to report data could be biased by some or all of the very covariates of interest, we performed calibration of GPS collars. Using 14 collars from animals that had died or were recaptured, we compared fixes received remotely from the satellite with fixes recorded only on the collar storage device (i.e., store-on-board). Overall, 52.6% store-on-board fixes were transmitted to the satellite and thus formed the data available from the other 20 collars for which we had only transmitted data. To account for potential biases resulting from missing fixes, we adopted a sample weighting approach (Frair et al. 2010) by estimating the probability of a successfully transmitted fix (*Pfix*) via logistic regression models (see below).

To reduce spurious effects resulting from poor GPS location accuracy, we first cleaned the data by removing all GPS location records with PDOP > 4. We further removed all GPS location records that reported elevations < 660 m (the lowest elevation in the study area, Newby and DeCesare 2020). The resulting data set consisted of 9,359 records.

We considered mixed-effects linear models in which *Pfix* was predicted from the binary response variable indicating whether the position was transmitted or not (1 if transmitted, 0 if recorded only on board the recovered collar). We entertained a suite of models with hypothesized environmental predicators including canopy cover, elevation, the cosine of aspect, slope, and topographic position index (TPI, Weiss 2001), all extracted from remote sensing data based on the GPS positions indicated by the collar. In addition, because we suspected that collar model also affected *Pfix*, we considered models in which the 4 types of GPS collars used during the study (Globalstartrack Pro, LifeCycle, SurveyGlobalstar, and LifeCyclePro500) were used as predictors. Finally, because we had only a quasi-random selection of actual collars (and animals) from which to make general inference, we adopted a mixed-model approach treating individual collars as random intercepts. We evaluated models using AIC, as well as whether all predictors in the model significantly improved fit at  $\alpha = 0.05$ . We considered multiple predictors in models only when correlation coefficients were < 0.5. All models were developed using program glmer with binomial error structures, and with individual collar as a random intercept. We considered all possible models consisting of up to 3 predictor variables, including 1st order interaction terms. In some cases, complex models were inestimable.

We evaluated model performance of the top model(s) using program Performance (Lüdecke et al. (2021) implemented in r 4.0.0. Additionally, we performed k-fold cross-validation with  $k = 5$  and data divided into 10 bins using the glm subroutine of program kxv (Brzustowski 2005). As anticipated, *Pfix* was affected by collar type. However, in preliminary models only the Lotek LifeCyclePro500 (overall *Pfix* = 0.229) was significantly different from other collar types (overall mean  $Pfix = 0.582$ ). Thus, collar models were recoded by whether or not they were LifeCyclePro 500 and this simplified binary factor was included as a nuisance variable in all subsequent models.

Model selection, considering only models with significant predictors, is provided in Table S2. The model with canopy closure and TPI (as well as collar model type as a nuisance variable) had almost all model weight and was  $\sim$  24 AIC units better than the  $2<sup>nd</sup>$ -ranking model (only canopy cover). LifeCyclePro 500 GPS collars were predicted to have a





Table S2. Model selection among top-ranked candidate models relating probability of a transmitted GPS fix  $(Pfix)$  to hypothesized environmental covariates. Abbreviations:  $cc =$  canopy cover, TPI = topographic position index, aspect = cosine of aspect. All models also included the binary variable collar model type as a nuisance parameter, and, except for the null model with no environmental covariates, included individual collar as a random intercept. The null model, shown for reference, included only collar type and included no random intercept.



The top model is shown in Table S2.

Table S3. Top model relating probability of GPS fix to predictor variables.

	Estimate	SЕ		
(Intercept)	1.1474	0.1348	8.5140	< 0.0001
Canopy Closure	$-0.0153$	0.0009	$-17.6660$	< 0.0001
<b>TPI</b>	0.0017	0.0003	5.1310	< 0.0001
Collar model	$-1.6919$	0.2395	$-7.0630$	< 0.0001

significantly lower probability of a fix than other collars, but interactions with both canopy cover and TPI were not significant.

Pfix was lower in areas with high canopy cover and within valleys and drainages, and higher on ridgelines and peaks. We found no evidence of overdispersion in the model (dispersion ratio =  $0.997$ ,  $\chi^2$  = 10,620,  $P = 0.582$ , and VIF terms for both variables were 1.01. AUC was 68.3%, and the Hosmer Lemeshow GOF  $\chi^2$  = was 8.938 (df = 8,  $P = 0.348$ ). Approximate conditional *R2* was 0.168, and marginal *R2* was 0.128, suggesting that factors other than the environmental covariates considered (e.g., satellite angle and availability) accounted for most of the variation in fix probability. The mean Pearson correlation coefficient from k-fold cross validation  $(k = 5, 10 \text{ bins})$  was 0.988  $(P < 0.001)$ . Probability of fixes under the top model are illustrated in Figure S1. In RSF modelling, the reciprocal of *Pfix* was applied to each value to correct for habitat-induced biases.



Fig. S1. Probability that a store-on-board GPS fix was transmitted and thus became part of the data set for RSF models, predicted by the top calibration model. Shown are probabilities under a range of canopy cover values, for the lower 95%, median, and upper 95% values of the topographic position index (tpi).





Table S5. Categories of timber harvest type (USFS 2023) used at Stage 1 of the RSF analysis of Cabinet-Salish mountains moose, 2013-2022, and collapsed categories used at Stage 2 in both 2<sup>nd</sup> and 3<sup>rd</sup> order analyses, summer and winter.





Table S6. Names and descriptions of predictor variables used in habitat use analysis of adult female moose, Cabinet-Salish mountains, northwestern Montana. 2013-2022.

Table S7. Top resource selection function models using data from all animals pooled, i.e., the first of stage of the 2-stage RSF approach (Murtaugh ), adult female moose, Cabinet-Salish study area, northwestern Montana, 2013-2022. Significance of predictors not shown because all are highly inflated at this, first stage, because of autocorrelation.



### **I. 2nd order**

a Reference category: Dry mixed conifer b Reference category: Unharvested



# **B. Summer (Table S7, continued)**

aReference category: Unharvested

bReference category: Dry mixed conifer

# **II. 3rd order (Table S7, continued)**





a Reference category: Dry mixed conifer b Reference category: Unharvested



### **B. Summer (Table S7, continued)**

Table S8. Recent burns on the Cabinet-Salish study area, their characteristics, and Manly selection ratios among moose that potentially encountered them.



a Selection ratio could only be approximated because used points but no random points occurred in this burn.

Table S9. Top supported model at the 2nd-stage (Murtaugh 2010) relating percent canopy cover used to maximum daily elevation and hour-of-day, adult female moose, Cabinet-Salish study area, northwestern Montana, 2013-2022. A. Summer. B. Winter.

### **a. Summer**





### **Notes on Figure 11 (main paper) and Table S9**

At first blush, it might appear that a reason for the smooth and continuous parabolic relationships through time might be that characteristics of a location at time  $t+1$  (e.g., 3 am) must have been highly correlated with those characteristics at time t (e.g., 6 am). Statistical problems associated with serial correlation would indeed have been problematic had the data underlying these analyses, figures, and tables come from moose equipped with GPS collars that recorded locations frequently (e.g., hourly). Indeed, a superficial look at Figure 11 would suggest that data obtained at, for example, time interval 0600-0859 came just 3 hours after data obtained at time period 0300- 0559. However, as explained in the main text, about 86% of locations came from collars programmed to collect data every 13 hours, and 14% from collars programmed to collect every 23 hours. With no missing fixes, the minimum time elapsed between a fix at time t and time t+1 (3 hours later in the day) was 26 hours for the 13-hour collars (e.g., fixes at 1 am (the 0000-0259 interval) then 2 pm, then 3 am (0300-0559 interval) the following day. For collars programmed to obtain fixes every 23-hours, the minimum elapsed time between successive times t and t+1 was 20 days



Fig. S2. The relative proportions of locations used by adult female moose in the Cabinet-Salish study area, 2013-2022 by hour of day, and the same proportions used only in shrublands by hour-of-day (both sets of histograms sum to 1.0) Note that use of proportional use of shrublands was greater than overall use during night-time hours, but less than overall during day-time hours.

(because the 23-hour schedule caused the time at which fixes were attempted to recess 1 hour each day, thus requiring 22 days (minus 2 because time periods were 3-hours long) to obtain a fix at the "next" time period. Further, because expected fixes were received at only approximately 53% of expected times, the actual time elapsed between successive fixes was considerably longer. For example, for a 13-hour collar, imagine that fix1 occurred at 1 am (interval 0-0259), and fix2 at 2 pm, (interval 1200-1459) and fix3 at 3 am (interval 0300-0559) (with fix4 at 3 pm (1500-1759 interval), and fix 5 at 4 am (0300-0559 interval). If, however, fix3 was missed, then the

elapsed time between the first 2 "successive" fixes would be 52 hours (fix5 – fix1), rather than 26 hours. For these reasons, we considered the habitat characteristics at "successive" time fixes for each animal independent with no need to consider autoregressive terms in our modeling.

## **LITERATURE CITED (Only In Supplemental Material)**

Brzustowski, J. 2005. k-fold cross-validation for present/available probability models. Free Software Foundation, Boston, Massachusetts, USA.