Project Completion Report
Rocky Mountains Cooperative Ecosystem Studies Unit (RM-CESU)

Project Title: ESTIMATING GRIZZLY BEAR USE OF LARGE UNGULATE CARCASSES WITH GPS TELEMETRY DATA

Project Code: P12AC10875 MSU-249

Type of Project: Research

Funding Agency: National Park Service

Partner University: Montana State University

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Project Summary,

Overview: GPS data has become the standard method of data collection for large mammal telemetry studies. This approach has provided substantial increases in data collected for wildlife habitat studies, yet proportional gains in ecological insights from such studies continues to lag behind the technology. The increased volumes of data collected by GPS collars come with substantial analytical challenges that result from the added complexity of storing, filtering, and analyzing the data (e.g., millions of records, unknown behavioral conditions at animal locations, and non-independence of observation; Cagnacci et al., 2010). In response to these challenges there has been a growing trend of increasingly sophisticated statistical models (e.g., hierarchical mixed effects models, generalized estimating equations) to handle the complex data structure. At the same time, without the need to manually track animals in the field, less information about animals' behaviors associated with locational data is being collected. Without this behavioral information of what animals are "doing," the default approach has been to treat all GPS locations as equal, and assess wildlife habitat relationships (e.g. habitat selection) from a behaviorally homogenous dataset. When different behaviors have opposing patterns, complete pooling of data without regard for animal behavior can results in the incorrect assessment of the importance, strength and form of habitat selection studies (Roever et a., 2013).

This project developed a novel approach using grizzly bear GPS data and records of behavioral observations to recent field visits to randomly selected GPS locations and to demonstrated that relatively simple analytical techniques (e.g., basic trigonometry, cluster analysis, and multinomial regression) can be used to accurately quantify GPS data into different behavioral categories meaningful to grizzly bear management and ecology. The project further demonstrated, as a cases-study, that using this approach to reduce the GPS data set from all locations (i.e., pooled homogenous behavior) to a single behavior type (e.g., the use of large ungulate carcasses) allowed for the testing of the an a priori ecological hypothesis: that fall use of ungulate carcasses has increased from 2000-2011, a period associated with the decline of white bark pine within grizzly bear habitat in the Greater Yellowstone Ecosystem (GYE).

Methods:

Bear Capture and Handling:

Bears were captured following handling procedures reviewed and approved by the Animal Care and Use Committee of the U.S. Geological Survey, Northern Rocky Mountain Science Center; Procedures conformed to the Animal Welfare Act and to U.S. government principles for the utilization and care of vertebrate animals used in testing, research, and training. Appropriate Federal and NPS research permits were also obtained. Bears were fitted with Telonics GENIII or GENIV (Telonics Inc., Mesa Az.) For ground truthing studies Telonics spread –spectrum technology was used to facilitate remote downloads and follow-up visits as detailed in Schwartz et al. (2009), and Fortin et al. (2011). For bears not involved in ground truthing studies remote downloads were unnecessary and Telonics store-on-board collars were used.

GPS Data Handling:

GPS acquisition scheduled varied during the period of study from approximately 0.5 hours to 3.5 hours and successful fix acquisition rates varied across individuals. Because our focus was on the spatial clustering of GPS locations (i.e., not while the animal is actively moving) we approached the handling missing GPS locations (i.e., failure to acquire a GPS location) from what is ultimately a conservative perspective. Using a modified version of the "fill in" approach of Friar et al. (2004), missing locations were randomly allocated within a rectangle defined by the previous and subsequent successful GPS locations buffer missed locations. We considered this approach conservative because the "filled-in" locations only entered the analysis when they were buffered by true locations that were within the same cluster. While it is possible that the animal left the cluster and failed to acquire a positions continuously while not at the cluster, behavior driven factors (i.e. laying down on antenna while resting) are much more plausible assumptions for missing locations based on empirical data (Schwartz et al., 2010). Nevertheless, we flagged these "assumed" positions to allow for the assessment of their contribution to clusters that were predicted to be carcass use.

We clustered data spatially (i.e. ignoring time) using the DBScan algorithm (Ester et al. 1996). This algorithm relies on the density-based notion of clusters, does not require specifying the number of clusters to find a priori, and excels at finding clusters of arbitrary size and shape. The algorithm requires two parameters: the local search neighborhood (ε) and the minimum number of points required to qualify as a cluster (γ). We used a fixed value of $\varepsilon = 20$ meters and allowed γ to vary as a function of GPS acquisition interval ($\gamma = 7$ / GPS acquisition interval in hours) which resulted in minimum cluster sizes of 2 locations for a 3.5 hour interval and 14 locations for 0.5 hour.

For model development, we culled the full GPS dataset to locations identified as clusters by the DBScan algorithm. Using an iterative process for each GPS bear-year, clusters were given individual unique id numbers and a suite of quantitative variables were created including temporal attributes describing each cluster. Although temporal information was not considered a parameter for the original clustering of GPS data, we accounted for it explicitly when quantifying the attributes of individual clusters. We combined GPS cluster information with data from two independent field studies which visited locations of recently downloaded bear GPS data (< 10 days old) to quantify bear activity at GPS locations during randomly selected 24 hour periods between mid-May and mid-October (see Fortin et al., 2013 and Schwartz et al., 2009). This resulted in a subset of 174 GPS clusters where the food source, or more accurately the behavior, that resulted in the clustering of GPS data was estimated from evidence gathered at the GPS locations in the field.

Parameterization of predictive model:
The site visit field data was collected for detailed analyses of grizzly bear diet ecology and the number of behaviors and food types recorded were too fine-scaled for our general interest in the use of large ungulate carcasses. Accordingly, we lumped together cluster information collected in the field into 5 groups (old-carcass, carcass, low-biomass carcass, resting, and area-of-interest), each representing a unique “type” of GPS cluster.

We used the MASS package (Venebeles and Ripley, 2002) of program R (R Core Team, 2013) to perform multinomial logistic regression to estimate the probability of a cluster being associated with each of 5 the five categories whereby the total probability for a cluster summed to 1. Our modeling framework was strictly focused on maximizing predictive accuracy rather than explaining the relative importance of the covariates and therefore we do not interpret model covariates but rather focus on the overall predictive accuracy of the fitted model and the application of these fitted values to further analyses. We developed a global model based on a suite of cluster covariates (12) that made ecological sense and to protect against over-fitting of the data used the stepAIC function in the MASS package to identify a reduced model using both backward and forward AIC selection to determine which terms should be dropped from the model. We specified our global model as the upper limit of model complexity and an intercept only model as the lower limit for the stepwise AIC model selection.

We extracted the predicted values from the estimated models and selected the cluster category with the highest predicted probability as the estimated cluster type. We evaluated classification accuracy for each cluster category as the proportion of observations correctly classified. We examined the Type I and Type II errors relative to the predict category and discuss these errors relative to the field observations.

Case Study: Trends in large-ungulate carcass use in the Greater Yellowstone Ecosystem

Using the 302 bear-GPS years from 2002-2011 we applied our clustering algorithm to reduce the full data set to a subset (5413) of spatial clusters distributed across years. We used the same approach described above to create the cluster attributes from the top predictive model and appended the predicted probabilities for each cluster type. Using the subset of clusters that were predicted to be large ungulate carcasses, we developed an index of monthly carcass use from May through October for each year from 2002-2011. This index explicitly accounts for the number of bear-GPS days on the air for each month which varied across years.

We used multiple linear regression to test the hypothesis of there being an increase in the carcass use index over time during fall months.

H_1: Time trend in carcass index for fall months but not non-fall months

Using an information theoretic approach we compared two models to address the support for month as a predictor variable of the carcass index.

1. $\hat{Y}_i = \beta_0 + \beta_1(year) + e_i$
2. $\hat{Y}_i = \beta_0 + \beta_1(year) + \beta_2(month) + e_i$

Because there was support for an increasing trend across years for fall months (September and October, see results section) we tested the hypotheses that the increases in the carcass index during fall months was not simply a function of more bears being located in areas open to hunting and having access to elk gut piles (H_2). Using GIS and spatial information on hunting units in the study area we calculated the proportion of estimated carcasses that were in areas open to hunting during each month (prop_hunt). We also tested a two hypotheses related to whitebark pine (H_3 and H_4) using annual mortality adjusted cone count (macc), and if masting year was good or bad (GB).

H_2: For fall months, time trend is not a function of sampling more bears in hunt areas over time
H_3: For fall months carcass index is a function of median cone count (i.e., mast > time)
H_4: For fall months carcass index is a function of mortality adjusted cone count (adjusted) & year (i.e., mast & time)

<u>Fall only dataset (H_2 – H_4):</u>

3. $Y_i = \beta_0 + \beta_1(year) + e_i$
4. $Y_i = \beta_0 + \beta_1(macc) + e_i$
5. $Y_i = \beta_0 + \beta_1(GB\_1) + e_i$
6. $Y_i = \beta_0 + \beta_1(prop\_hunt) + e_i$
7. $Y_i = \beta_0 + \beta_1(year) + \beta_2(macc) + e_i$
8. $Y_i = \beta_0 + \beta_1(year) + \beta_1(month) + e_i$
9. $Y_i = \beta_0 + \beta_1(year) + \beta_2(\mathrm{GB}) + e_i$
10. $Y_i = \beta_0 + \beta_1(year) + \beta_2(prop\_hunt) + e_i$
11. $Y_i = \beta_0 + \beta_1(year) + \beta_2(prop\_hunt) + \beta_3(\mathrm{GB}) + e_i$
12. $Y_i = \beta_0 + \beta_1(year) + \beta_2(prop\_hunt) + \beta_3(month) + e_i$

Results:

Predictive model:

The top predictive model correctly classified 88% of the carcasses identified in the field as large ungulate carcasses, our category of primary interest. Only 1 of the 174 clusters (type = inactive/resting) was categorized differently by the a priori model containing 12 parameters and the stepwise AIC selected model which selected 9 parameters. The ability of our approach to classify small biomass carcasses and old carcasses correctly appears to be rather low. However, some of these errors are more likely due to sample error in the field (e.g. calling a mule deer carcass low biomass, while our statistical model predicts it to be a large ungulate carcass). None of the incorrectly classified “inactive” or “area of interest (AoI)” clusters were attributed to the large biomass category (see table below).

		OBSERVED						
		Inactive	AoI	high biomass carcass	low biomass carcass	old carcass	total	percent
MODEL PREDICTION	Inactive	76	4	0	9	4	93	0.82
	AoI	2	27	1	1	5	36	0.75
	high biomass carcass	0	0	28	3	1	32	0.88
	low biomass carcass	1	1	2	7	1	12	0.58
	old carcass	0	0	1	0	0	1	0
	total	79	32	32	20	11	174	
	percent	0.96	0.84	0.88	0.35	0		

Case Study:
For the case study application of this approach to large ungulate carcass use in the GYE, there was considerable support for model #2 which included month over Model #1 (year only) given the data. The year only model has nearly zero model probability

MODEL	K	AICc	Delta_AICc	AICcWt	Cum.Wt	LL
mod 2	8	-349.6564	0.0000	1	1	184.2400

mod 1	3	-326.9363	22.7201	0	1	166.6825

The table of coefficients shows that only months #9 and month #10 that are significant predictors of carcass index. We used this quantitative evidence as support for using a restricted dataset (months 9 and 10) to test the remaining hypotheses about whitebark pine and spatial relationship to hunting, which are also only biologically meaningful for the fall period.

Coefficients:

	Estimate	Std. Error	t	value Pr(>|t|)
(Intercept)	-4.8187405	1.0771256	-4.474	4.10e-05 ***
year	0.0024083	0.0005368	4.486	3.93e-05 ***
factor(month)6	0.0025408	0.0053412	0.476	0.636251
factor(month)7	0.0046663	0.0053412	0.874	0.386256
factor(month)8	0.0025381	0.0053412	0.475	0.636606
factor(month)9	0.0202601	0.0053412	3.793	0.000383 ***
factor(month)10	0.0260894	0.0053412	4.885	9.96e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.01194 on 53 degrees of freedom
Multiple R-squared: 0.5403, Adjusted R-squared: 0.4882
F-statistic: 10.38 on 6 and 53 DF, p-value: 1.385e-07

There was considerable model selection uncertainty given the data and the candidate set of models in this analysis:
Model selection based on AICc :

Model	K	AICc	Delta_AICc	AICcWt	Cum.Wt	LL
mod 7	4	-110.30005	0.0000000	0.33634114	0.3363411	60.48336
mod 3	3	-109.93962	0.3604377	0.28087427	0.6172154	58.71981
mod 9	4	-108.64518	1.6548749	0.14703762	0.7642530	59.65592
mod 8	4	-107.83043	2.4696209	0.09783824	0.8620913	59.24855
mod 10	4	-107.18640	3.1136552	0.07090198	0.9329932	58.92653
mod 11	5	-105.52726	4.7727951	0.03093006	0.9639233	59.90649
mod 12	5	-104.32923	5.9708233	0.01699152	0.9809148	59.30747
mod 4	3	-104.09242	6.2076354	0.01509417	0.9960090	55.79621
mod 6	3	-100.13260	10.1674503	0.00208423	0.9980932	53.81630
mod 5	3	-99.95463	10.3454267	0.00190677	1.0000000	53.72731

The top model (model #7) $\hat{Y}_i = \beta_0 + \beta_1(year) + \beta_2(macc)$ carried 34% of the model weights and roughly 90% of the cumulative model weight was captured by the top 4 models. However, models #8-10 (AICc rankings 3-5) all contained one additional parameter, were within 2 delta AIC units of the top model, and have virtually identical log-Likelihoods. Accordingly there is lack of improvement in fit and these more complex models are not supported, or alternatively are "uninformative (Burnham and Anderson, 2002, Anderson 2008). Discounting the uninformative models the evidence ratios show that the highest ranked model containing the proportion of carcasses in hunting areas (model #10) had 0.11 times the support of model # 3 (ranking =2) and 0.09 times the support of model #7 (ranking = 1). The year and mortality adjusted cone count (macc) predictors had slope estimates with 85% confidence intervals (Arnold, 2010) that did not include zero for all models they were included in; all other predictors had slope estimates with 85% confidence intervals that contained 0 (Figure 1).

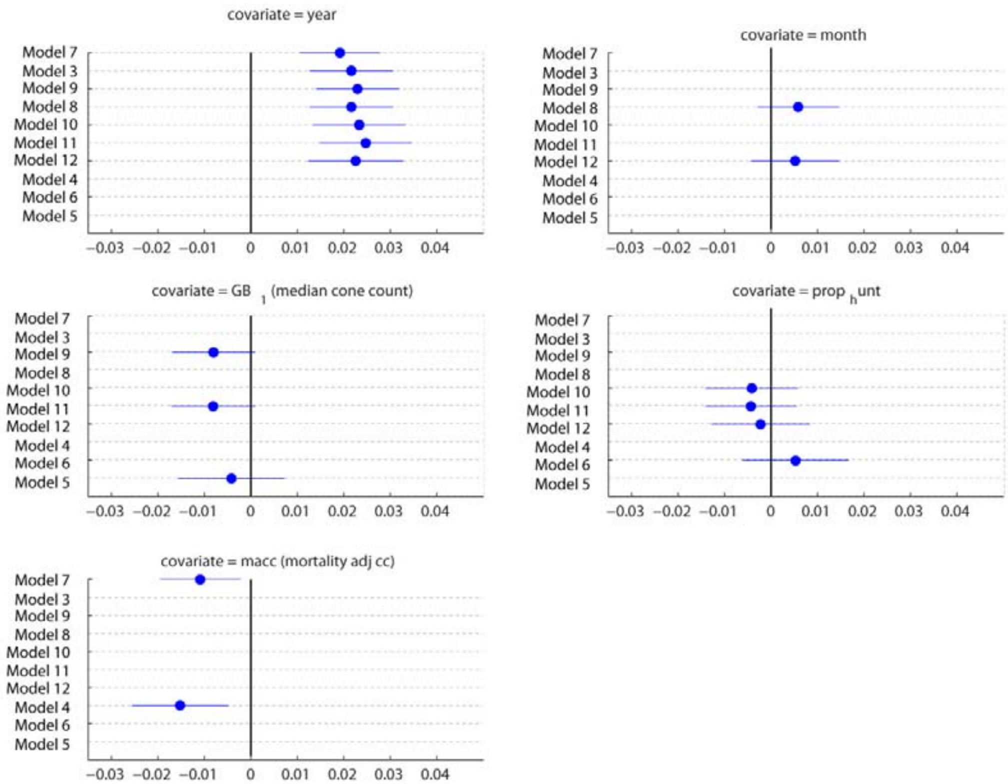

Figure 1. parameter estimates and 85% confidence intervals for the candidate model set.

Evidence ratios comparing the top model to the prop_hunt model (ER = 109) suggests there is approximately 0.009 times the support for the prop_hunt model relative to the top model. Thus there is little quantitative evidence to support the hypothesis that the increase in the predicted carcass index is simply a function of more carcasses (i.e. collared bears) being located in areas with access to hunting and elk gut piles in later years of the time series. Given the data and set of candidate models, the most quantitative support is for the H_3 hypothesis that predicted carcass index is a function of year and the mortality adjusted cone count (macc).

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-6.4791975	2.0460064	-3.167	0.00564 **
year	0.0032500	0.0010194	3.188	0.00538 **
macc	-0.0010236	0.0005653	-1.811	0.08790 . ---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01275 on 17 degrees of freedom
Multiple R-squared: 0.4988,   Adjusted R-squared: 0.4399
F-statistic: 8.46 on 2 and 17 DF, p-value: 0.002818

Table 1; output from linear model of year and macc

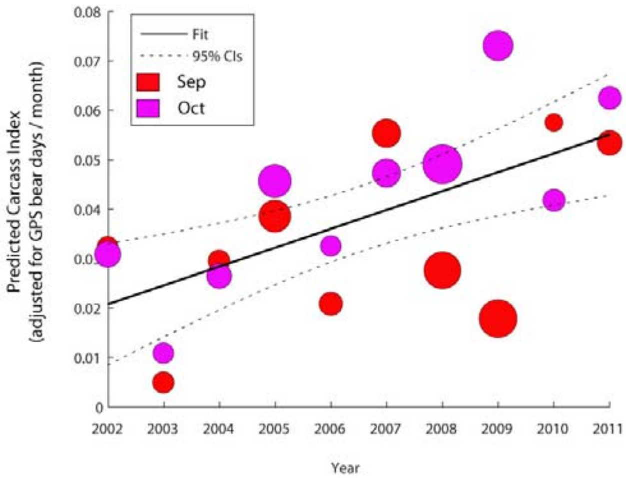

Figure 2. Linear model fit to fall carcass index data.

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Products:

Presentations:

Estimating Grizzly Bear Use of Large Ungulate Carcasses with GPS Telemetry Data. Presenter: Michael R. Ebinger, U.S. Geological Survey lecture to visiting students. Bozeman, MT. 2013

Estimating Grizzly Bear Use of Large Ungulate Carcasses with GPS Telemetry Data. Presenter: Michael R. Ebinger, The International Association for Bear Research and Management (IBA) international conference. Provo, Utah, 2013

Publications:

Ebinger, M.R., M. A. Haroldson, F. T. van Manen, J. K. Fortin, S. R. Podruzny, J. E. Teisberg, K. A. Gunther, S. L. Cain, and P. C. Cross. 2014. **Estimating Grizzly Bear Use of Large Ungulate Carcasses with GPS Telemetry Data.** *In prep.*

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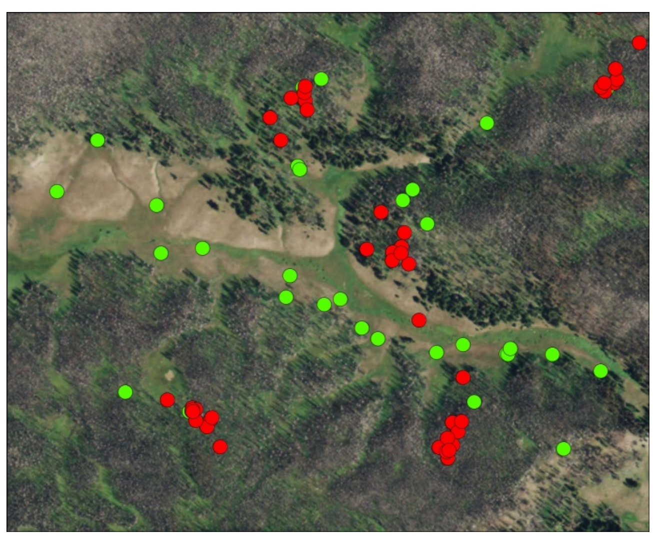
Computer Programs:

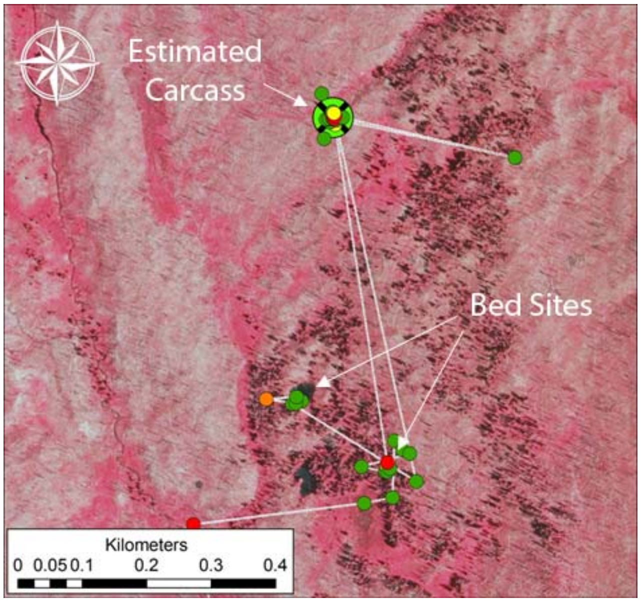
The NPS was provided with the computer programs (Matlab & R) that allow grizzly bear GPS data to be classified into the behavioral groups as used in this study. There are two primary uses for these programs:



(1) The programs allow the GPS data to be dichotomized two behavioral groups: “active” and “non-active” for use in grizzly bear habitat studies. The figure on the right shows an example of this outcome for a single bear with red points indicating “inactive” locations and green points indicating

"active" locations. Notice the concentration of green points in the meadow and on the meadow edges and the higher degree of clustering for the red locations.

(2) The programs allow clusters of GPS data to be partitioned in classes associated with large ungulate carcass use, bedding areas, and other unspecified clusters.



Lessons Learned from this project:

- This study produced a number of findings related to the study of grizzly bear ecology and management in YNP and the Greater Yellowstone Ecosystem (GYE).
- We have learned that simply analyzing the grizzly bear GPS data is likely to be less powerful and possibly lead to misleading conclusion related to management and conservation compared to analysis behavior specific subsets of the GPS data set (e.g. habitat selection of bedding sites and active locations using separate datasets).
- We have learned through the set of protocols and computer code provided how to conduct these analyses on existing and future NPS grizzly bear GPS datasets.
- This work has demonstrated that is important to continue to collect GPS data using collars that record activity at the time of GPS acquisition in order to continue to use these tools.

Other RM-CESU agencies or research partners who participated in this project:

Inter-agency Grizzly Bear Study Team

Michael R. Ebinger. University of Montana / Montana State University