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Using Accelerometer Data to Remotely Assess Predation Activity of Arctic Wolves

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USING ACCELEROMETER DATA TO REMOTELY ASSESS PREDATION ACTIVITY OF ARCTIC WOLVES

by

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ABSTRACT

Arctic wolves (*Canis lupus arctos*) play an important role in ecosystems located in the far northern regions of the world; however, unlike the gray wolves in Yellowstone National Park, little information is available about High Arctic wolves and their impacts on prey populations. This research uses data received from two GPS radio-collared Arctic wolves located in the Fosheim Peninsula on Ellesmere Island. Each radio-collar was programmed to record a position every 30-60 minutes, as well as the wolf's activity movement (forwards - backwards and left - right), which was generated by an accelerometer housed within the radio-collar. This research project focused on using location clusters and their associated activity data to remotely identify the locations and the frequency of wolf predation events. The activity data can be used to identify potential kill sites because it takes both time and energy for the Arctic wolves to take down and consume their prey, thus clusters of locations with high levels of activity are generated at these places. Over fifty of the cluster sites were visited and assessed for remains of a kill, such as bone remnants, teeth, or hair. A key objective of this study was to identify predictors and develop a statistical model that distinguishes kill sites from non-kill sites, including rendezvous sites, which I also analyzed. I used AIC model selection methods to compare different multinomial logistic regression models that measured the probability a cluster included a kill, a rendezvous, or neither as a function of several variables, including the sum of activity, total timespan of the cluster, average activity, and the initial slope in activity within the first few hours of each cluster, which is the rate at which activity decreased following the establishment of the cluster. The most predictive variable was number of points; other useful predictors included the average distance between each point and the cluster centroid, and the average value in sideways and rotary acceleration (Activity Y) across the cluster lifespan. These three variables comprise

the best-fit multinomial model to distinguish kill and rendezvous clusters, as supported by the AIC results. When excluding the rendezvous clusters, the best-fit multinomial model included the three variables (number of points, average distance, and average in Activity Y) in addition to the slope in activity within the first two hours since cluster formation. Use of accelerometer data and multinomial logistic regression models may help differentiate clusters and enable scientists and wildlife managers to remotely monitor the predatory impact of Arctic wolves.

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Heather Shipp

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INTRODUCTION

Arctic wolves (*Canis lupus arctos*) play an important role in ecosystems located in the far northern regions of the world. Arctic wolves are a subspecies of the grey wolf and tend to have a yearlong white coat; like other wolves, they tend to live and hunt in packs and can have territories that extend across 1,000 square miles or more (Mech 2007). Although research on wolves in areas like Yellowstone National Park is quite common, little is known about High Arctic wolves and their impacts on Peary caribou (*Rangifer tarandus pearyl*) and muskox (*Ovibos moschatus*) populations, which constitute their main prey (Jenkins et. al. 2011). Recently, there has been concern about declining Peary caribou populations, which are endangered and serve as an important food source for local Inuit peoples in Nunavut, Canada (Species at Risk Public Registry 2013). As a result, there is a need to better understand Arctic wolves and their predatory habits.

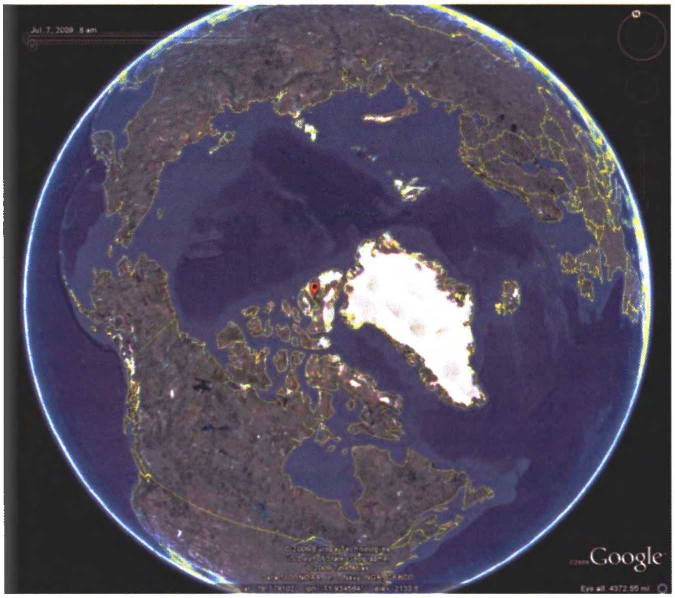

Figure 1: A Google Earth image with the study site on Ellesmere Island shown by the red pinpoint.

Dr. Dan MacNulty, an assistant professor at Utah State University, and his colleagues are currently conducting research on the ecology of High Arctic wolves and their influence on prey populations. The study site is located far north and focuses on Arctic wolves inhabiting the area around Eureka on the Fosheim Peninsula, Ellesmere Island, Nunavut, Canada (Figure 1). The predation patterns and population trends of this Arctic wolf population are being monitored in order to better assess the effects of wolf predation on Peary caribou and muskox populations. Their research builds upon a 20-year record of wolf population dynamics that has been compiled by Dr. David Mech, a leading authority on Arctic wolves (Mech 2005). In addition to measuring wolf abundance and distribution, the long-term goal for their research is to determine how predator-prey interactions between High Arctic wolves, caribou, and muskox will be influenced by ongoing climate change (MacNulty et. al. 2013).

My research project used data recorded by GPS radio-collars on two of four Arctic wolves (440M and 441F), which were used to remotely identify the locations and the frequency of wolf predation events and rendezvous sites. Because capturing and eating prey and provisioning for their pups takes time, clusters of GPS locations are generated at these places and can be used to identify wolf predation events and rendezvous sites (Webb et al. 2008). This study focused on identifying characteristics and patterns in activity data that can be used as predictors to determine whether or not a cluster of locations is indicative of an Arctic wolf predation event or rendezvous site.

The objective of this project was to evaluate the utility of collar accelerometer data for inferring the presence of wolf-killed ungulates at GPS location clusters. Because predation is an energetically-intensive activity, it was expected that location clusters with high levels of activity at the onset of cluster formation were more likely to contain kills. Such a pattern in activity was expected to occur because high levels of motion would be recorded while the wolf was actively taking down the prey, followed by a decline in activity upon making the kill and spending the next several hours eating and digesting, which would result in a negative slope in activity over time. Collar accelerometer data may provide a new tool for scientists and wildlife managers to remotely monitor the predatory impact of large carnivores.

Although statistical models for identifying kill sites have been created for other animals, such as mountain lions (Knopff et al. 2009) and Eurasian badgers (McClune et al. 2014), none have yet been developed for High Arctic wolves. Each model is dependent upon the specific predator and prey species, and therefore, each is relatively unique. Because of this, a model specific to Arctic wolves and their prey (muskox and caribou) was needed to accurately estimate the effects of wolf predation in the High Arctic. Developing a model capable of predicting whether or not a cluster is associated with a predation event can help better assess the impact of Arctic wolves on prey populations. Such a model can also help prioritize the limited time spent in the field.

METHODS

In July 2014, four Arctic wolves, each from a different pack in the Eureka area of Ellesmere Island, were captured and temporarily fitted with a global positioning system (GPS) radio-collar; this technique was pioneered for Arctic wolves by Mech and Cluff (2011). Each radio-collar was programmed to record a position every 30-60 minutes and was equipped with an accelerometer that recorded activity levels, i.e., forward-backward and sideways acceleration (MacNulty et. al. 2013). The data recorded by each GPS radio-collar is transmitted to an Iridium satellite, which can then be received via the Lotek web server. From there, the data can be downloaded from the website to the computer, and can be used in programs such as Microsoft Excel or Microsoft Access.

The location data from the GPS radio-collars were run through an algorithm (Knopff et al. 2009), which identified the different location clusters (hereafter 'clusters'). Each of the clusters indicates a location where the wolf spent some time in one area, and thus each cluster site may potentially be from a kill or rendezvous. Fifty location clusters were visited and inspected for prey remains by Dr. MacNulty and his colleagues. By visiting sites within their study area, they were able to observe whether a kill was made, and collect incidental non-invasive samples, such as hair, teeth, and scat, which were used to determine age, diet, and sex.

At the start of this research project, I used the database software, Microsoft Access 2013, to correctly format the data. I transposed the activity data in Microsoft Excel 2013, then uploaded and added them to the Access file. I identified the first fix of every cluster and used it to determine the time elapsed since the start of the cluster, or in other words, how much time had passed since the cluster first began. Each fix consists of up to five measurements recorded by the GPS radio-collar in five-minute intervals, usually beginning at the top of the hour (for example: measurements for a fix may be taken at 11:50, 11:55, 12:00, 12:05, and 12:10). The time elapsed since the beginning of the cluster (measured in hours) was used for the x-axis in scatterplots, which is further explained in the following paragraph.

After the data had been formatted properly, it was exported as an Excel file. Using this computer program, a scatterplot was created for each cluster to view the change in activity throughout the duration of a cluster. For each scatterplot, the independent variable was the time elapsed since the start of the cluster, which was measured in hours, and therefore was placed as the x-axis. The dependent variable, and thus the y-axis, for all scatterplots was the activity data, which was labelled as 'Activity X+Y' because it was the sum of the value of Activity X (movement forwards and backwards) and the value for Activity Y (movement left to right), as shown in Figure 2. Each of the two different activity values (X and Y) both have a range between 0 and 254; thus, the maximum value possible for the recorded 'Activity X+Y' both on the y-axis was 508.

Figure 2: Picture depicting the different axes measured by accelerometers, with X measuring forward/backward motions, and Y measuring sideway motions. Photograph from "Activity Measurements and Activity Modes".

Scatterplots for over one hundred different clusters were created; however, the remainder of this study focused only on the fifty clusters which were visited, since the results were recorded for each of these clusters whereas all the other clusters have not been assessed for signs of a kill, and therefore could not be confirmed as whether or not they are truly representative of a kill site. Although four High Arctic wolves were radio-collared, the clusters that had been visited and assessed were only made between two of the wolves, which are identified as W440 (male) and W441 (female). The remainder of this research uses this sample of the fifty visited clusters to identify which variables might be indicative of a predation event.

After the scatterplots were made, each was classified as a kill, rendezvous, or null, according to the results that were determined in the field for each cluster. The scatterplots for each of these three different types were compared and contrasted against one another in an attempt to identify similarities in the scatterplots within each category that could be used to differentiate them.

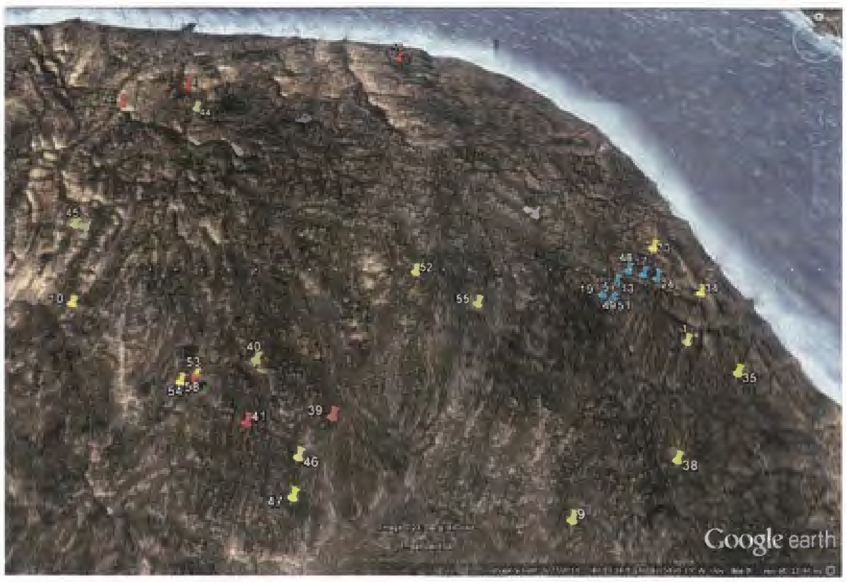

Figure 3: Some of the visited sites of the location clusters on the study site, Ellesmere Island, as plotted on Google Earth.
Red: Kill site Blue: Rendezvous site Yellow = Null site

A screenshot of each scatterplot along with the results and any additional notes from the field were attached to each cluster pin-point plotted at the location coordinates on Google Earth (Figure 3). Each pin point represented a different location cluster. The pins were color-coded according to their type, with kill sites being represented in red, rendezvous sites in blue, and null sites in yellow. This provided an additional visual representation of the Arctic wolves' spatial patterns and distributions across the landscape.

After completing the scatterplots and identifying possible variables indicative of a kill, I analyzed the data using Stata version 13.0. I calculated the slope (beta) and y-intercept (int.) in the Activity X+Y over time for the first three hours of the cluster (labeled as 1hr, 2hr, and 3 hr.) This same process was used separately for both Activity X and Activity Y as well. I recorded these different variables of slope and y-intercept (18 total) for each of the clusters, and later tested these variables as possible predictors of kill sites.

I identified a variety of variables as possible characteristics of activity associated with a kill site, including total timespan of the cluster, the sum of activity, mean activity value, and the initial slope in activity within the first few hours of each cluster. A full list of variables and definitions are provided by Table 1 (page 19-20). I also used Stata to create lowess plots between the different variables of the data. I used lowess plots to help visualize the relationships of different variables between the different types of clusters. The lowess plots helped identify two outliers, which were both rendezvous clusters. Due to this finding, the remainder of the statistical analyses was conducted for all fifty of the visited cluster data as well as only for non-rendezvous sites (the 13 kill clusters plus the 24 other clusters, giving a total of 37 clusters), in case rendezvous sites skewed the data.

The averages of the activity data throughout each cluster were also later calculated. For each cluster, the average activity values within the first three hours were calculated (1hr, 2hr, and 3hr), just like the slopes and intercepts had been. In addition, the total average in activity throughout the entire cluster was also calculated. These were all done for Activity X+Y, Activity X, and Activity Y in each cluster.

Stata was used to create multinomial logistic regression models for the data. 'Null' clusters were identified as '0', Kill clusters were identified as a '1', and Rendezvous clusters were each identified as a '2'. For models that excluded the rendezvous sites, only clusters with a 0 or 1 were used. Various multinomial logistic regression models were tested in an attempt to find the best predictive models for both the data including and excluding the rendezvous clusters. In all analyzes, the 'null' response was the base outcome.

Correlations between variables were evaluated using the "pwcorr" code in Stata (Figure 4). If two different variables had a correlation > 0.50, I used only one of them in each model to avoid possible bias. I used the variable that had the greatest predictive power in models.

Figure 4: A screenshot of an example of the "pwcorr" function used in Stata to test the correlation among variables. Variables being tested: number of points, timespan (hr), average distance (m), initial activity (first activity value recorded), total average in Activity Y, the y-intercept in the Activity X+Y within the first hour, and the slope in Activity X+Y in the first two hours.

```
. pwcorr number_points timespan_hr av_distance_m initial_activity Y_TotalAvg XY_activity_int_1hr XY_activity_beta_2hr
```

	number~s	timesp~r	av_dis~m	initia~y	Y_Tota~g	XY~t_1hr	XY~a_2hr
number_poi~s	1.0000						
timespan_hr	0.5929	1.0000					
av_distanc~m	0.2667	0.4951	1.0000				
initial_ac~y	-0.2063	0.0614	0.2502	1.0000			
Y_TotalAvg	-0.1403	0.1138	0.4146	0.6270	1.0000		
XY_act~t_1hr	-0.2218	0.0692	0.2682	0.9600	0.6745	1.0000	
XY_act~a_2hr	0.0680	-0.3616	-0.2913	-0.3052	-0.2358	-0.2711	1.0000

Based on the multinomial logistics regression models created in Stata, the five best predictive variables were identified. Models of all possible combinations of these variables were then created; if any two variables within a model had a correlation value higher than 0.5 with each other, then only one of the variables was used in any given model. This resulted in 24 different multinomial logistic regression models. AIC values were calculated for both models that included the rendezvous clusters and those that did not. The AIC values account for different numbers of parameters and allow comparison of non-nested models. Furthermore, they provide more definitive results that can be used to indicate which model is most predictive at differentiating types of clusters based on the data.

RESULTS

Thirteen of fifty clusters contained evidence of a kill, thirteen were rendezvous sites, and the remaining twenty-four cluster had no evidence of either, and were thus categorized as 'null'.

When comparing the scatterplots, those that were categorized as 'null' were discernable as not being related to a predation event. Although there was quite a lot of variation within each of the three categories, it was fairly straightforward to predict the result of a cluster from the scatterplot of activity over time across the cluster lifespan. However, it is important to note that there is still a fairly large chance of error.

Clusters with kills or rendezvouses seemed more likely to be mistaken for one another and misclassified. Most rendezvous and kill sites had larger time spans than other clusters, and most rendezvous sites lasted longer than kill sites. Kill sites and rendezvous sites also had a higher number of points recorded within each cluster. However, scatterplots of kill sites usually demonstrated a higher initial activity recorded at the beginning of the cluster (Fig. 5) than those formed form rendezvouses (Fig. 6). Most scatterplots formed from kill sites tended to have a steep negative slope in activity within the first few hours of the cluster, in comparison to sites without kills (Fig 7). This seemed to support the prediction that kill clusters will have high levels of activity at the beginning of the cluster because wolves will be actively taking down prey, followed by a decrease in activity once feeding. However, it is important to note that there is some variation of this within the scatterplots for the thirteen kill clusters.

Figure 5: *A scatterplot of Cluster 23 - One of the confirmed "Kill" sites*

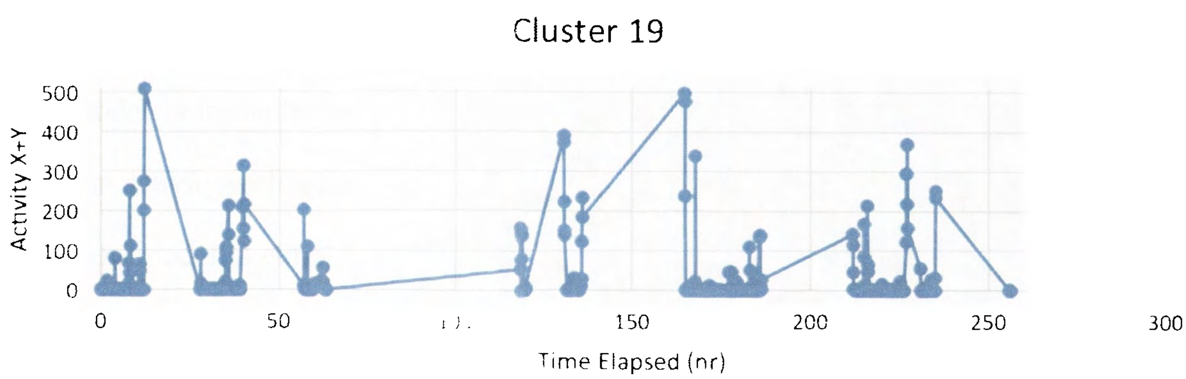

Figure 6: [illegible]

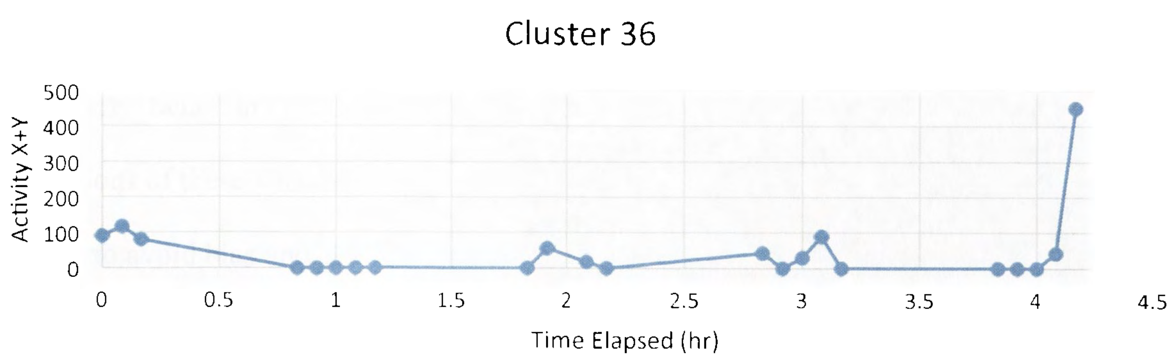

Figure 7: *Cluster 36 One of the "Null" sites*

The multinomial logistic regression models were first created in Stata and were comprised of the different combinations of the variables. The variables and models were primarily assessed by the coefficient values, model likelihood, and the 95% confidence intervals. Variables were deemed a better fit for the cluster data if they had a higher likelihood value, a coefficient number closer to 1 or -1, and if the 95% confidence interval did not include 0 within its range.

Based on these criteria, the variable that was most indicative of the cluster type was the number of points within a cluster (number_points); this was the strongest predictor for both the models with rendezvous clusters and the models without rendezvous. The average distance of the cluster size (av_distance_m) was also a relatively strong indicator for both types of models. For the models, especially the ones that included the rendezvous clusters, the variables of the y-intercept in activity within the first few hours of the cluster were also fairly good indicators based on the model likelihood and coefficient values. However, they had a correlation value higher than 0.5 with some of the other higher-ranking variables, and were thus excluded from additional models tested later on. Based on the results from running the models in Stata, the best variables relating to the activity data were the average in Activity Y throughout the entire cluster (Y_TotalAvg) and the slope in Activity X+Y within the first two hours of the cluster (XY_activity_beta_2hr). Based off of these results, various models were made using different combinations of these variables and were tested using AIC model selection (Table 2 and 4). This was done to avoid bias and account for the different number of parameters in the models.

The AICs produced similar results which support our earlier findings from the scatterplots and from testing different multinomial logistic regression models in Stata. The best-fit multinomial logistic regression model predicting clusters for kills and rendezvous sites included average distance between each point the cluster centroid , number of points within a cluster , and average sideways acceleration throughout the entire cluster (Table 2 and 3). This model had the ΔAIC_C value of 0 between the models that were tested and was weighted 0.37 (Table 2). The next best model was weighted 0.19 and included the same three variables, in addition to the slope in Activity X+Y within the first 2 hours since the cluster began. The variable that was most indicative of the cluster type was the number of points within a cluster (number_points); this was the strongest predictor for both the model with rendezvous clusters (Table 3) and the model without rendezvous (Table 5).

For the best multinomial logistic regression model that included all the responses, a graph was made for each of the three variables (average distance, number of points, and average Activity Y value). Each graph shows the predicted outcome of the probability of it being either a kill or a rendezvous, compared to 'other' clusters, based on the variable, with the 95% confidence interval being represented in each graph by the two dashed lines (Figure 8). For the average distance, there is a negative relationship with the probability of the cluster being a kill; clusters formed as a result of a kill are more likely to have small average distances between points to the centroid (measured in meters), since the wolves will most likely stay close to the carcass, resulting in smaller distances across a given cluster (Figure 8a). On the other hand, the rendezvous clusters demonstrated the opposite trend, showing a positive relationship with the average distance; the probability of the cluster being formed as a result of a rendezvous increases as the average distance increases (Figure 8d). The probability of a cluster being formed either by a kill or by a rendezvous increases as the number of points increases; however, this trend is only seen up to a certain point (Figure 8b and 8e). After about 23 points, the probability of the cluster being a kill begins to decrease, while the probability of it being a rendezvous continues to increase, but at a less rapid pace. As the mean value in Activity Y throughout the entire cluster begins to increase, so does the probability of it being a kill (Figure 8c); conversely, as the probability of it being caused by a rendezvous decreases as the mean value in Activity Y increases (Figure 8f).

In comparison, the AIC showed similar results to the multinomial logistic regression models for clusters excluding all the rendezvous clusters. The best model included the same three variables (average distance, number of points, and average in Activity Y throughout entire cluster duration), in addition to the slope in Activity X+Y within the first two hours since the cluster first started; this model had a ΔAIC_C value of 0 compared to the other tested models and was weighted 0.42 (Table 4 and 5). The next highest model included the same variables but excluded the average distance, and had a weighted value of 0.41.

Graphs were also created for each of the four variables of the best multinomial logistic regression models that excluded the rendezvous clusters (average distance, number of point, average in Activity Y, and slope in Activity X+Y throughout the initial 2 hours since cluster formation). Similar to the graph for the model that did include the rendezvous clusters, the average distance showed a negative correlation with the probability of a cluster being associated with a kill (Figure 9a). The probability of a cluster being formed from a kill increases with the number of points, and anything with it showing a probability of 1 for being a kill for 23 or more points (Figure 9b). The probability of a cluster being associated with a kill event increases as the mean value in Activity Y throughout the entire cluster increases (Figure 9c). The slope in Activity X+Y within the first 2 hours of the cluster formation has a very wide range of values; however, there is a high probability of a cluster being formed from a kill when it has a highly negative slope, and the probability of it being from a kill decreases as the slope becomes less steep and more positive (Figure 9d).

DISCUSSION

Based off of the scatterplots, I predicted that the initial slope in activity within the first few hours of cluster formation would be the strongest indicator of whether or not a cluster included a predation event. This prediction was based on the concept that the wolf would be very active while taking down the prey, which would occur at the start of the cluster, and then, upon making the kill, there would be a steep drop in activity as the wolf spent the next several hours feasting on the carcass and satiating, resulting in a strong negative slope. However, based off of the multinomial logistic regression models, the number of points throughout the cluster was the strongest predictor of whether or not a cluster included a kill (Table 3, Table 5).

Despite implications from assessing the lowess plots, the results from the multinomial logistic regression models did not seem to vary significantly between the models with rendezvous sites and the kill-only models. However, because they have different sample sizes (fifty when included rendezvouses, and 37 when excluded them), the models cannot be compared to each other. Many of the strongest variables for the models that included the rendezvous sites were the same variables as the kill-only models as shown by the AIC results (Table 2 and Table 5).

The best-fit models, for both the rendezvous and kill-only models included the average value in Activity Y measured throughout the cluster. This result was interesting and unexpected because we expected to find that kill clusters had higher averages in activity within the first few hours of the cluster rather than throughout the entire cluster itself. This result in kill sites tending to have high averages in Activity Y (sideways acceleration) throughout the entire cluster may reflect the movement of the wolf eating the carcass throughout the duration of the cluster, rather than attacking the animal at the beginning of the cluster.

The largest challenge of this study was the small sample size. Because there were only fifty cluster sites that have been visited and assessed, and out of those, only thirteen of them were determined to be a kill site, any conclusions that can be made based on this data is somewhat limited. There is also the risk that some of the results are only an attribute of this particular dataset, and may not provide an accurate representation, due to bias caused from the small sample size.

It may be worthwhile to note that identifying predation events based on activity data from one or two radio-collared Arctic wolves may be challenging due to the nature that wolves tend to hunt in packs, and thus tend to share the responsibility of taking down large prey. Thus, it seems plausible that there may be predation events when the individual wolf that has been radio-collared is less involved in making the kill and consequently expending less energy in movement; this would most likely result in a different pattern in activity than if it was more invested or more actively involved in taking down the kill.

The activity patterns estimated from the accelerometer data may also vary somewhat according to the time of year. All of the clusters included in this research project were formed during the summer, primarily throughout July and August. During the summer season, Arctic wolves may have pups, in which case they may make several trips back and forth between the prey carcass and the den where their pups are located. This could be observed in several of the scatterplots for the kill clusters, and may possibly be used as a predictor for clusters with unknown results as an indicator of whether or not it included a kill. However, this pattern was also observed in some of the rendezvous sites. This pattern of going back and forth to the location of the cluster site would be less prevalent in the winter, when wolves are not associating strongly with a den location. This could potentially change some of the variables tested, such as the average value in activity throughout the entire cluster.

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Table 1. Different variables of the data that were recorded or calculated, and later tested in the multinomial logistic regression models. The first column provides the label or code that was used for each variable while using Stata. The second column provides a definition of what each variable measures or indicates.

Variable	Definition
Type	Kill, Rendezvous, Null (nothing)
Parameter	Null = 0, Kill = 1, Rendezvous = 2
number_points	Total number of points recorded in each cluster
timespan_hr	How long the cluster lasted from start to finish, measured in hours (from when the first data were recorded to the last)
av_distance_m	The average distance of points to the geometric center of the cluster, measured in meters.
cluster_radius_m	The largest distance from a point to the geometric center of the cluster, measured in meters.
initial_activity	First single Activity X+Y value recorded for the cluster
sum_activity_first fix	Sum of Activity X+Y values for the first fix within the cluster (usually consisting of five values)
X_Avg1hr	Mean value of Activity X within the first hour of the cluster
Y_Avg1hr	Mean value of Activity Y within the first hour of the cluster
XY_Avg1hr	Mean value of Activity X+Y within the first hour of the cluster
X_Avg2hr	Mean value of Activity X within the first 2 hours of the cluster
Y_Avg2hr	Mean value of Activity Y within the first 2 hours of the cluster
XY_Avg2hr	Mean value of Activity X+Y within the first 2 hours of the cluster
X_Avg3hr	Mean value of Activity X within the first 3 hours of the cluster
Y_Avg3hr	Mean value of Activity Y within the first 3 hours of the cluster
XY_Avg3hr	Mean value of Activity X+Y within the first 3 hours of the cluster
X_TotalAvg	Mean value of Activity X throughout the entire cluster
Y_TotalAvg	Mean value of Activity Y throughout the entire cluster
XY_TotalAvg	Mean value of Activity X+Y throughout the entire cluster
XY_activity_beta_1hr	Slope in Activity X+Y in the first hour of the cluster
XY_activity_beta_2hr	Slope in Activity X+Y in the first 2 hours of the cluster
XY_activity_beta_3hr	Slope in Activity X+Y in the first 3 hours of the cluster
XY_activity_int_1hr	y-intercept value of the slope in Activity X+Y throughout the first hour of the cluster
XY_activity_int_2hr	y-intercept value of the slope in Activity X+Y throughout the first 2 hours of the cluster
XY_activity_int_3hr	y-intercept value of the slope in Activity X+Y throughout the first 3 hours of the cluster
X_activity_beta_1hr	Slope in Activity X in the first hour of the cluster
X_activity_beta_2hr	Slope in Activity X in the first 2 hours of the cluster
X_activity_beta_3hr	Slope in Activity X in the first 3 hours of the cluster

X_activity_int_1hr	y-intercept value of the slope in Activity X throughout the first hour of the cluster
X_activity_int_2hr	y-intercept value of the slope in Activity X throughout the first 2 hours of the cluster
X_activity_int_3hr	y-intercept value of the slope in Activity X throughout the first 3 hours of the cluster
Y_activity_beta_1hr	Slope in Activity Y in the first hour of the cluster
Y_activity_beta_2hr	Slope in Activity Y in the first 2 hours of the cluster
Y_activity_beta_3hr	Slope in Activity Y in the first 3 hours of the cluster
Y_activity_int_1hr	y-intercept value of the slope in Activity Y throughout the first hour of the cluster
Y_activity_int_2hr	y-intercept value of the slope in Activity Y throughout the first 2 hours of the cluster
Y_activity_int_3hr	y-intercept value of the slope in Activity Y throughout the first 3 hours of the cluster

Table 2. The multinomial logistic regression models that were tested using AIC_C values to indicate which model has the strongest indicators for predicting kill and rendezvous sites from other sites. Number of parameters (K), Log-likelihood (LogLike), AIC_C values, differences in AIC_C compared to the best scored model (ΔAIC_C), and weight (Wi) are displayed for each model. The best model, which has an ΔAIC_C of 0 and the highest Wi, is indicated in boldface.

Models	K	LogLike	AICc	ΔAICc	Wi
av_distance_m	2	-49.18	102.61	24.23	0.00
number_points	2	-41.30	86.86	8.48	0.01
Y_TotalAvg	2	-49.67	103.60	25.22	0.00
XY_activity_int_1hr	2	-49.73	103.71	25.33	0.00
XY_activity_beta_2hr	2	-51.68	107.62	29.24	0.00
av_distance_m number_points	3	-39.27	85.05	6.68	0.01
av_distance_m Y_TotalAvg	3	-45.33	97.18	18.80	0.00
av_distance_m XY_activity_int_1hr	3	-45.28	97.09	18.71	0.00
av_distance_m XY_activity_beta_2hr	3	-48.63	103.77	25.40	0.00
number_points Y_TotalAvg	3	-36.85	80.23	1.85	0.15
number_points XY_activity_int_1hr	3	-38.37	83.27	4.89	0.03
number_points XY_activity_beta_2hr	3	-40.06	86.64	8.26	0.01
Y_TotalAvg XY_activity_beta_2hr	3	-49.04	104.61	26.23	0.00
XY_activity_int_1hr XY_activity_beta_2hr	3	-48.64	103.81	25.43	0.00
av_distance_m number_points Y_TotalAvg	**4**	**-34.74**	**78.38**	**0.00**	**0.37**
av_distance_m number_points XY_activity_int_1hr	4	-36.40	81.69	3.32	0.07
av_distance_m number_points XY_activity_beta_2hr	4	-38.73	86.35	7.97	0.01
av_distance_m Y_TotalAvg XY_activity_beta_2hr	4	-44.88	98.65	20.28	0.00
av_distance_m XY_activity_int_1hr XY_activity_beta_2hr	4	-44.76	98.41	20.03	0.00
number_points Y_TotalAvg XY_activity_beta_2hr	4	-36.14	81.16	2.78	0.09
number_points XY_activity_int_1hr XY_activity_beta_2hr	4	-37.31	83.50	5.13	0.03
Y_TotalAvg XY_activity_int_1hr XY_activity_beta_2hr	4	-47.54	103.97	25.59	0.00
av_distance_m number_points Y_TotalAvg XY_activity_beta_2hr	5	-34.21	79.78	1.41	0.19
av_distance_m number_points XY_activity_int_1hr XY_activity_beta_2hr	5	-35.87	83.11	4.73	0.04

Table 3. The best-fit multinomial model predicting the probability that a cluster included a kill or rendezvous site. The coefficient (β), standard error (SE), P-value (*P*), and 95% confidence interval is shown for every variable for each parameter (kill and rendezvous), with the data associated with the 'other' clusters being the base outcome for comparison. The variables within the model included the average distance (meters) between cluster center and each cluster point (Av_distance_m), number of points, and average sideways acceleration across the lifespan of the cluster (Y_TotalAvg).

Parameter	β	SE	*P*	[95% Conf. Interval]	
P(Kill)					
Av_distance_m	-0.011	0.016	0.495	-0.042	0.020
Number_points	0.258	0.121	0.033	0.021	0.496
Y_TotalAvg	0.038	0.015	0.011	0.009	0.068
Intercept	-3.793	1.192	0.001	-6.130	-1.456
P(Rendezvous)					
Av_distance_m	0.023	0.019	0.215	-0.014	0.060
Number_points	0.273	0.121	0.024	0.035	0.511
Y_TotalAvg	0.001	0.024	0.982	-0.046	0.047
Intercept	-4.375	1.261	0.001	-6.846	-1.904

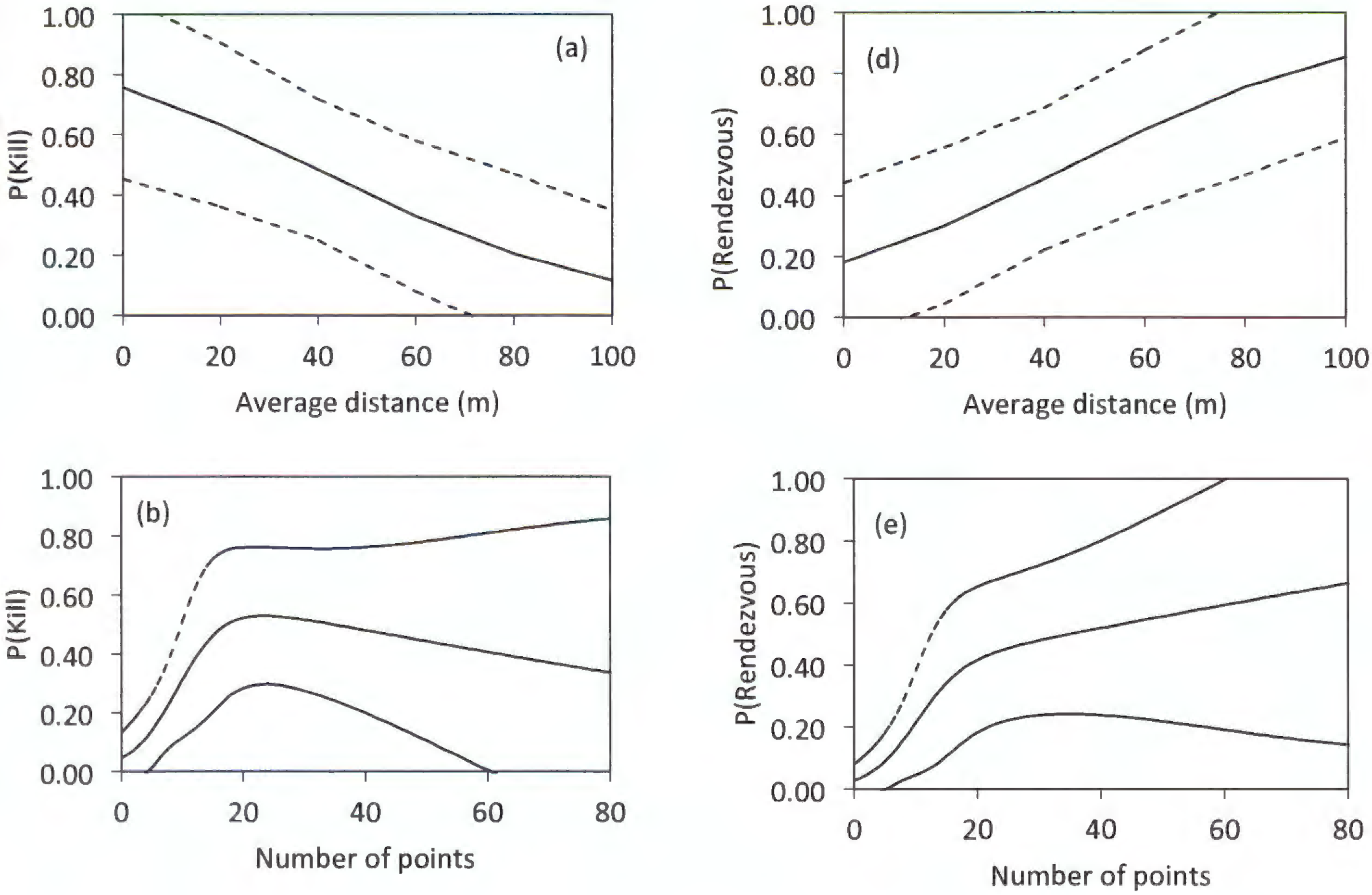
Table 4. The multinomial logistic regression models that were tested using AIC_C values to indicate which model has the strongest indicators for differentiating the kill sites from the 'other sites (excluding rendezvous). Number of parameters (K), Log-likelihood (LogLike), AIC_C values, differences in AIC_C compared to the best scored model (ΔAIC_C), and weight (Wi) are displayed for each model. The best model, which has a ΔAIC_C of 0 and the highest Wi value, is indicated in boldface.

Models	K	LogLike	AICc	ΔAICc	Wi
av_distance_m if Kill<2	2	-23.49	51.34	26.47	0.00
number_points if Kill<2	2	-17.16	38.67	13.80	0.00
Y_TotalAvg if Kill<2	2	-21.27	46.90	22.03	0.00
XY_activity_int_1hr if Kill<2	2	-21.74	47.83	22.97	0.00
XY_activity_beta_2hr if Kill<2	2	-16.08	36.50	11.64	0.00
av_distance_m number_points if Kill<2	3	-17.15	41.04	16.17	0.00
av_distance_m Y_TotalAvg if Kill<2	3	-21.27	49.26	24.39	0.00
av_distance_m XY_activity_int_1hr if Kill<2	3	-21.64	50.00	25.13	0.00
av_distance_m XY_activity_beta_2hr if Kill<2	3	-16.06	38.85	13.99	0.00
number_points Y_TotalAvg if Kill<2	3	-12.77	32.27	7.40	0.01
number_points XY_activity_int_1hr if Kill<2	3	-14.88	36.48	11.61	0.00
number_points XY_activity_beta_2hr if Kill<2	3	-10.70	28.13	3.27	0.08
Y_TotalAvg XY_activity_beta_2hr if Kill<2	3	-14.61	35.94	11.07	0.00
XY_activity_int_1hr XY_activity_beta_2hr if Kill<2	3	-16.05	38.83	13.96	0.00
av_distance_m number_points Y_TotalAvg if Kill<2	4	-11.08	31.40	6.54	0.02
av_distance_m number_points XY_activity_int_1hr if Kill<2	4	-14.84	38.93	14.06	0.00
av_distance_m number_points XY_activity_beta_2hr if Kill<2	4	-10.52	30.28	5.42	0.03
av_distance_m Y_TotalAvg XY_activity_beta_2hr if Kill<2	4	-14.57	38.38	13.52	0.00
av_distance_m XY_activity_int_1hr XY_activity_beta_2hr if Kill<2	4	-16.04	41.34	16.47	0.00
number_points Y_TotalAvg XY_activity_beta_2hr if Kill<2	4	-7.84	24.93	0.07	0.41
number_points XY_activity_int_1hr XY_activity_beta_2hr if Kill<2	4	-10.70	30.65	5.79	0.02
Y_TotalAvg XY_activity_int_1hr XY_activity_beta_2hr if Kill<2	4	-13.52	36.28	11.42	0.00
av_distance_m number_points Y_TotalAvg XY_activity_beta_2hr if Kill<2	**5**	**-6.47**	**24.87**	**0.00**	**0.42**
av_distance_m number_points XY_activity_int_1hr XY_activity_beta_2hr if Kill<2	5	-10.51	32.96	8.10	0.01

Table 5. The values and table generated by Stata of the highest ranking multinomial logistic regression model (av_distance_m number_points Y_TotalAvg XY_activity_beta_2hr), as determined by the AIC_C, when comparing the kill clusters to other clusters, while excluding all rendezvous clusters. The coefficient (β), standard error (SE), P-value (*P*), and 95% confidence interval is shown for every of the four variables within the model, with the data associated with the 'other' clusters being the base outcome for comparison. The variables within the model included the average distance of the cluster (measured in meters), number of points, the mean value for Activity Y throughout the entire cluster, and the slope in Activity X+Y within the first two hours since the beginning of the cluster.

Parameter	β	Std.	*P*	[95% Conf. Interval]	
av_distance_m	-0.046	0.033	0.160	-0.111	0.018
number_points	0.731	0.382	0.056	-0.018	1.479
Y_TotalAvg	0.071	0.034	0.039	0.004	0.139
XY_activity_beta_2hr	-0.034	0.017	0.048	-0.068	0.000
_cons	-9.584	4.124	0.020	-17.666	-1.501

Figure 8. Fitted value plots showing the probability of a kill (left side – graphs a, b, and c) and probability of a rendezvous (right side – d, e, f) for each variable within the highest model for all cluster types (av_distance_m number_points Y_TotalAvg). 95% confidence intervals are represented by the dashed lines.



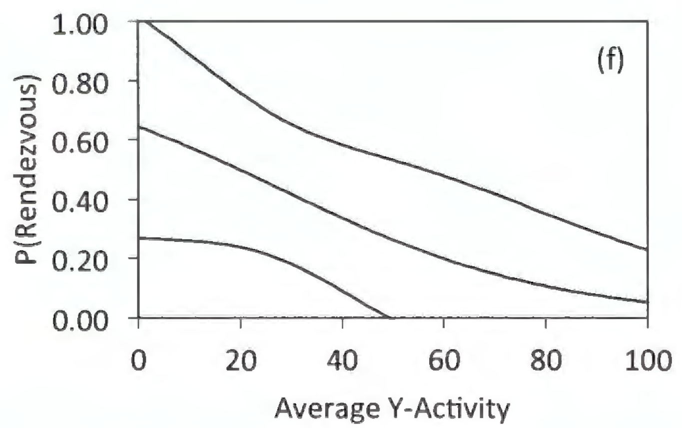
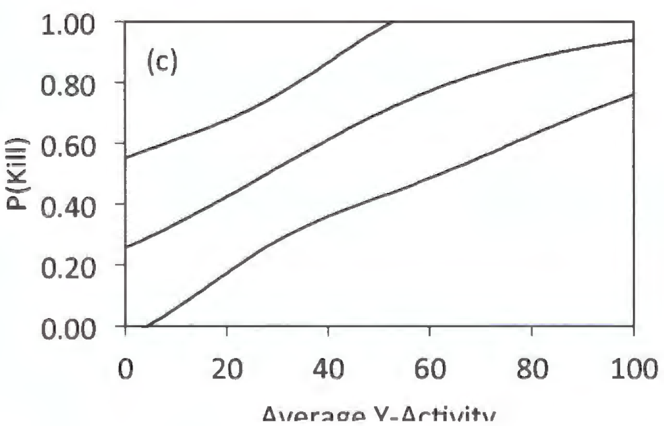
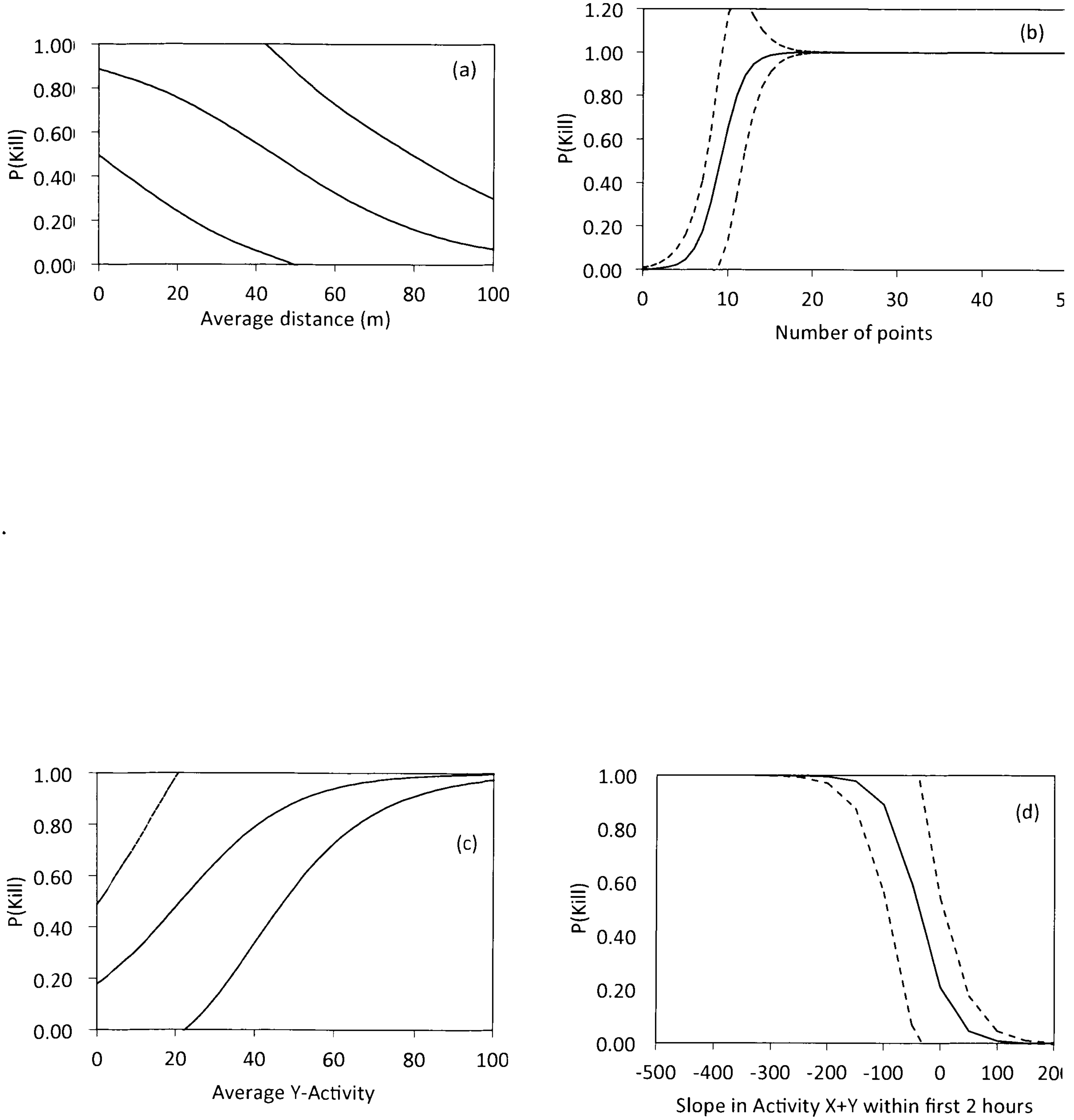


Figure 9. Results for the variables in the best model ((av_distance_m number_points Y_TotalAvg XY_activity_beta_2hr) between kill clusters and other clusters, excluding all rendezvous clusters. Graphs are shown for each variable within the model, with the margin value shown in the black line and the



95% confidence intervals represented by the dashed lines.



REFLECTIVE WRITING

I began my undergraduate research in September 2014, at the beginning of my second year as a student at Utah State University. In high school, I conducted several science projects and started to develop a love and understanding for conducting scientific research. During my sophomore year of high school, I had an internship with Dr. Randy Larsen, a professor at Brigham Young University, and helped with a research project on guzzlers, which are man-made water basins. I later conducted a research project on sinorizhobium bacteria during my senior year of high school. Because of these experiences, I knew that undergraduate research was something I eventually wanted to become involved with. However, as a freshman in college, I was not sure what I wanted to focus on at the time, and I even initially felt intimidated to approach professors whom I did not know about research possibilities.

I first met my mentor, Dr. Dan MacNulty, towards the end of my freshman year during a weekend trip with The Wildlife Society (TWS), one of the clubs in the Quinney College of Natural Resources. The TWS club had their first annual trip to Yellowstone with Dr. MacNulty, to explore his research on the wolves and large ungulates in the park. Throughout those four days, I was able to learn more about his research on wolves and became intrigued with his research, both current and past projects. Because the field trip was held during one of the last weekends of the Spring semester, I did not talk to him at that time about beginning a project; however, at the start of the following semester, I was in Dr. MacNulty's 'Wildland Techniques' class (WILD 2400) and approached him about conducting an undergraduate research project.

After brainstorming several possibilities for research projects, we decided to use the data received from several GPS radio-collars from Arctic wolves that are part of a study Dr. MacNulty was involved with in Ellesmere Island. My research would focus on using the activity data measured by the accelerometers within the radio-collars. An accelerometer measures the motions of the animal, and using activity data to observe and learn about animal behaviors is a relatively new concept.

One of the main goals for this project was to gain experience conducting research as an undergraduate, which would allow me to develop data management and statistical skills, and better prepare me for graduate school and a future career in wildlife biology. I hoped to learn more about the activity patterns of High Arctic wolves and add to the limited understanding of their behaviors and possible effects on prey populations. By conducting this research, I initially aimed to identify criteria to accurately differentiate cluster activity patterns and produce a statistical model. By identifying attributes that characterize a predation event, or when a wolf makes a kill, I would be able to learn about the behaviors of wolves and possibly help Dr. MacNulty prioritize his time in the field, since the study site is in a very remote location far north, which makes time spent in the field expensive and limited.

Overall, I really enjoyed the process of conducting this undergraduate research. I liked learning about the Arctic wolves, even though I was not able to interact directly with them. I was also able to become more familiar with using the programs Excel and Access, and I was able to install and start to learn how to use the Stata computer program. Perhaps the part of my research process that I struggled with the most was conducting the statistical analyses towards the end. Because I took AP Calculus and AP Statistics in high school, I have not needed to take another math class since high school graduation. Most of the statistics used in my research was quite unfamiliar to me, and it was difficult at first to fully understand what the results meant and how significant they were. However, with the help of my mentor, Dr. MacNulty, I was able to learn about these statistics and was better able to interpret my results from the data. Another main challenge with my project was that I had a fairly small sample size to work with; however, this was not something I could change or control.

I have enjoyed having the opportunity to become more familiar with the scientific process of conducting research. I really like connecting my project to the bigger picture and applying what I learn from my research. Although I do not work with the Arctic wolves directly, and all of my work has been computer-based, I still like learning more about their behaviors and activity patterns. I was able to present a poster on my research project at the Research on Capitol Hill, The Wildlife Society Utah Chapter Meeting, and Utah State University's Student Research Symposium. My undergraduate research has helped me connect with faculty and students here at USU, especially within the Quinney College of Natural Resources, and has helped prepare me to pursue a graduate degree in Wildlife Biology; I have enjoyed conducting my undergraduate research project, and I think it would be fascinating to continue in a similar field.

My advice to future students beginning the capstone process would be to find something that you are personally interested in or passionate about. Going through the research process and completing the capstone project will be time-consuming, so find a topic or research question that you want to learn more about and become invested in. As you go along with your project, take thorough and detailed notes; keep these organized so you can refer back to them when needed. Doing so can be a great help later on, especially as you write your final paper. Try to apply your research to other aspects in your life or concepts you are learning in your classes. Before diving into the research, make sure to have at least a general plan in mind and have clear objectives. Take time to develop a structured and logical study design if needed; doing so will help ensure more accuracy and efficiency later on in the process. With that said, it is okay to modify and adapt your project as you go along. Life is unpredictable and classes tend to become more indepth and challenging as you progress through your degree, so plan ahead and get involved with research early on. Do not be intimidated to talk to professors; if he or she is unable to be your mentor, look for other opportunities and do not give up. Even though I have truly enjoyed my college experience, I wish I had become involved in research during my freshman year, especially since I later decided to graduate an entire year early. As you conduct your capstone project, you will most likely encounter some challenges and unanticipated blocks that you may have to adapt to and get around. Although you should try to figure these challenges out for yourself, do not be afraid to ask for some guidance in the process. This is another reason why starting early and keeping ahead of the game is important, because there will almost always be some parts of the process that will take longer than expected.

PROFESSIONAL AUTHOR BIO

Heather Shipp was born and raised in Orem, Utah. Growing up she had many pets, including gerbils, fish, a box turtle, dwarf hamsters, a rabbit, a cockatiel, and her dog, Buddy. She graduated from Timpanogos High School in 2013, and was in the Top Ten of her graduating class of almost 450 students. She chose to attend Utah State University and was selected as a Quinney Scholar by the Quinney College of Natural Resources. Heather is majoring in Wildlife Science and will be graduating on May 7, 2016 with Departmental and University Honors. Due to taking several AP and Concurrent Enrollment classes throughout high school, Heather is graduating one year early, having completed her B. S. degree in three years. Throughout her entire time as an undergraduate student, Heather served as a member of the Student Council of the College of Natural Resources. She also stayed involved by being an active member of The Wildlife Society, and helped compete in and win the Quiz Bowl at the Utah Chapter Meeting in March 2016. During the summer of 2015, Heather spent six weeks in Zakynthos, Greece as a volunteer for a nongovernmental organization called ARCHELON, The Sea Turtle Protection Society of Greece. As an ARCHELON volunteer, Heather helped with the daily monitoring and conservation efforts of loggerhead sea turtles and worked with other volunteers from around the world. After graduation, Heather plans to pursue a graduate degree in Wildlife Biology and continue her love for animals and for learning.