ANALYZING THE EFFECT OF TRAFFIC ON WILDLIFE VIEWINGS IN DENALI NATIONAL PARK: A REGRESSION ANALYSIS

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Abstract. With a large and diverse community of beautiful landscapes and wildlife in Denali National Park and Preserve, visitors flock from all across the globe to explore the park and view the unique species that reside there. Park administration must understand how traffic, especially during nighttime hours, might affect the number of wildlife viewings the following day. In this report, I ask whether nighttime traffic in Denali National Park and Preserve affects the incidence of wildlife sightings from the parks offered tour busses. I construct regression models of 2014 data to answer this main question and also to assess other factors that might explain variation in wildlife sightings. Analyses indicated that the amount of nighttime traffic does not have an effect on wildlife sightings. Specifically, it can be inferred that nighttime traffic at the levels observed in 2014 was not detrimental to wildlife viewing the following day. The nighttime traffic regulations instituted as part of the 2012 Vehicle Management Plan appear adequate to safeguard wildlife viewing opportunities. Other factors, including number of busses, location along the road, and day of year do affect wildlife viewing opportunities for visitors.

1. Introduction

Denali National Park and Preserve, the third largest National Park in the United States, offers visitors amazing mountain vistas, seemingly never-ending arctic taiga, and wildlife roaming through the 6 million acres of protected land. The beautiful lands of Denali can only be accessed by busses that shuttle visitors along the 92-mile road. Exceptions include professional photographers and construction crews, among others, who may be given special permits that allow them to travel the road in personal vehicles. In 2012, Denali staff completed a Vehicle Management Plan in order to control the amount of motorized traffic going through the park. The plan stated that there should be an average of fewer than 3 vehicles per hour recorded at each of the six traffic counters placed in various spots along the road. Additionally, there should be no more than 6 vehicles in any given nighttime hour, with this objective being met 95% of the time. These stipulations were created to limit the effect of nighttime vehicle traffic on animals, with hopes that the daytime viewing of wildlife in the park from the road would not be adversely affected.

In this report, I analyze data collected in 2014 and test for an effect of nighttime traffic on incidence of wildlife viewing the following day. I also test for the influence of other factors on wildlife viewing.

2. Methods

I used a multi-step analysis approach to more fully examine the effect of nighttime traffic and other factors on animal observations. All analyses were conducted in R (R Core Team 2015). The 2014 data set initially contained 47,408 rows, with each row representing a single wildlife observation. Each observation contained the species, bus identification number, geographical coordinates, date, time, and bus destination. Data were also collected on the number of vehicles detected by six traffic counters established at separate points along the road. These counters recorded the number of vehicles that passed the counter every 10 minutes. I reconfigured the data to enable analysis of wildlife observations for each of 111 days of viewing and each of 92 miles of road, resulting in a matrix with 111 x 92 = 10,212 rows (Table 1).

Mile	Day of Year	Date	Wildlife Observations	Busses	Night Traffic	Distance from Counter
1	144	May 24	0	11	6	29
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
92	144	May 24	0	6	5	24
1	145	May 25	0	19	29	
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
92	145	May 25	3	10	3	24
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
1	254	September 11	0	18	0	29
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
92	254	September 11	1	16	0	24

Table 1. Data matrix used in analysis of Denali wildlife viewing data, 2014.

When completed, this matrix contained columns for the mile of the road, the ordinal date, the number of observations in each 1-mile segment of road on a given day, the number of vehicles that were counted by the traffic counter nearest to the specified 1-mile stretch of road the previous night, the number of busses that passed through this bin, and the distance of the bin from the traffic counter (Table 1). A vital aspect of the matrix creation was utilizing the mile marker that was given for each observation, allowing for the allocation of animal counts to the appropriate mile bin.

2.1. **Basic Analyses.** I began with basic summary statistics and exploratory plots. Specifically, I calculated values such as mean, median, and variance by species, day, and location, as well as ANOVA testing, to gain understanding of the amount of sightings occurring in the park. The number of observations by day was plotted to provide a summary of total viewing events. However, total wildlife viewings likely are also dependent on the number of busses that made trips into the park. Thus, I also computed the number of busses per day and the average number of observations recorded per bus each day. To better visualize spatial variation in wildlife viewings, I plotted the number of observations per mile. To account for spatial variation in viewing opportunities, I also plotted the number of wildlife observations on a per bus basis for each mile of road.

To facilitate comparison of the relative magnitude of effects of predictor variables that are measured in different scales and units (e.g., miles and days), I standardized predictor variables by subtracting the sample mean and dividing by the sample standard deviation for each predictor. The standardized variables each have a mean of zero and standard deviation of one. By standardizing variables, it becomes easier and more intuitive to interpret regression coefficients and the effect that each has on the response, measured in standard-deviation units. I standardized all predictors in order to accomplish this task.

2.2. **Multiple Linear Regression.** I fitted a series of regression models to the count data for all wildlife collectively and for selected focal species (caribou, moose, bear, sheep, wolf, and red fox) individually to understand what factors might explain variation in the frequency of wildlife observations. An assumption of multiple regression is that predictor variables are independent. Thus, as a precursor to the regression analysis, the pairwise correlations for all predictor variables were computed. For each response variable, I first ran a multiple linear regression analysis of the daily number of wildlife sightings along each mile of road using the following predictors: number of busses, number of vehicles in the previous night, miles from the beginning of the bus route, and ordinal date.

2.3. **Poisson Regression.** Next I modified my regression analysis to incorporate a distribution more appropriate for count data. Specifically, I fit a Poisson regression model. Linear regression relies on an assumption of normally distributed errors. For data that are discrete counts, a normal distribution is often not appropriate. In contrast, a Poisson distribution often is applicable for count data. An underlying principle of a Poisson distribution is that the mean and variance are equal. To check this assumption, I compared the mean and variance for total counts and counts of focal species.

2.4. **Regression Models to Adress Overdispersion.** For instances in which the count variance was much different from the mean (i.e., a ratio much greater than 1), I fitted count data to a negative binomial distribution, which is commonly used in place of a Poisson when counts are over-dispersed (Zuur et al. 2013). Models were fitted with function glm.nb from the MASS package in R (Venables 2002).

I also more formally assessed over-dispersion by comparing the observed frequency distribution of 0, 1, 2, N wildlife observations per daily mile segment with the frequency expected from a Poisson distribution with the same mean number of observations. When an excess of zeros was evident, fitting a zero-inflated regression model can be a valuable remedy (Zuur and Ieno 2016). This goal was accomplished with function zeroinfl from package pscl in R (Jackman 2015) by assigning a Bernoulli distribution fit to the zero counts (predicting if the observation will be a zero or not) and a negative binomial distribution to the nonzero elements, resulting in zero-inflated negative binomial regression models. As before, I fitted a series of regression models to the count data for all wildlife collectively and for selected focal species (caribou, moose, bear, sheep, wolf, and red fox) individually.

2.5. **Consideration of Spatial Autocorrelation.** It is possible that the number of wildlife viewings at a pair of 1-mile sections of road are dependent on the distance between the sections, even after accounting for variation explained by the predictor variables; specifically, it is possible that road segments close to each other are more likely to covary than a pair of road segments selected randomly. Using function correlog in package pgirmess of R (Giraudoux 2016), I computed Morans I to inspect the amount of spatial autocorrelation that appeared in the residuals of the zero-inflated negative binomial model. The Morans I statistic, similar conceptually to a correlation coefficient, calculates the relationship of a variable with itself a defined number of steps ahead and can be expressed as

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})} \tag{1}$$

with w representing weights applied to the summation and S0 being the sum of all weights. I computed Morans I for several distance bins, tested for significance with randomization tests, and plotted the results as a correlogram that depicts Morans I versus binned distance between road segments.

3. Results

3.1. **Basic Analyses.** The number of wildlife sightings from tour busses varied greatly by species, with caribou accounting for the most sightings, followed by bear (primarily grizzly), sheep, and moose (Figure 1).

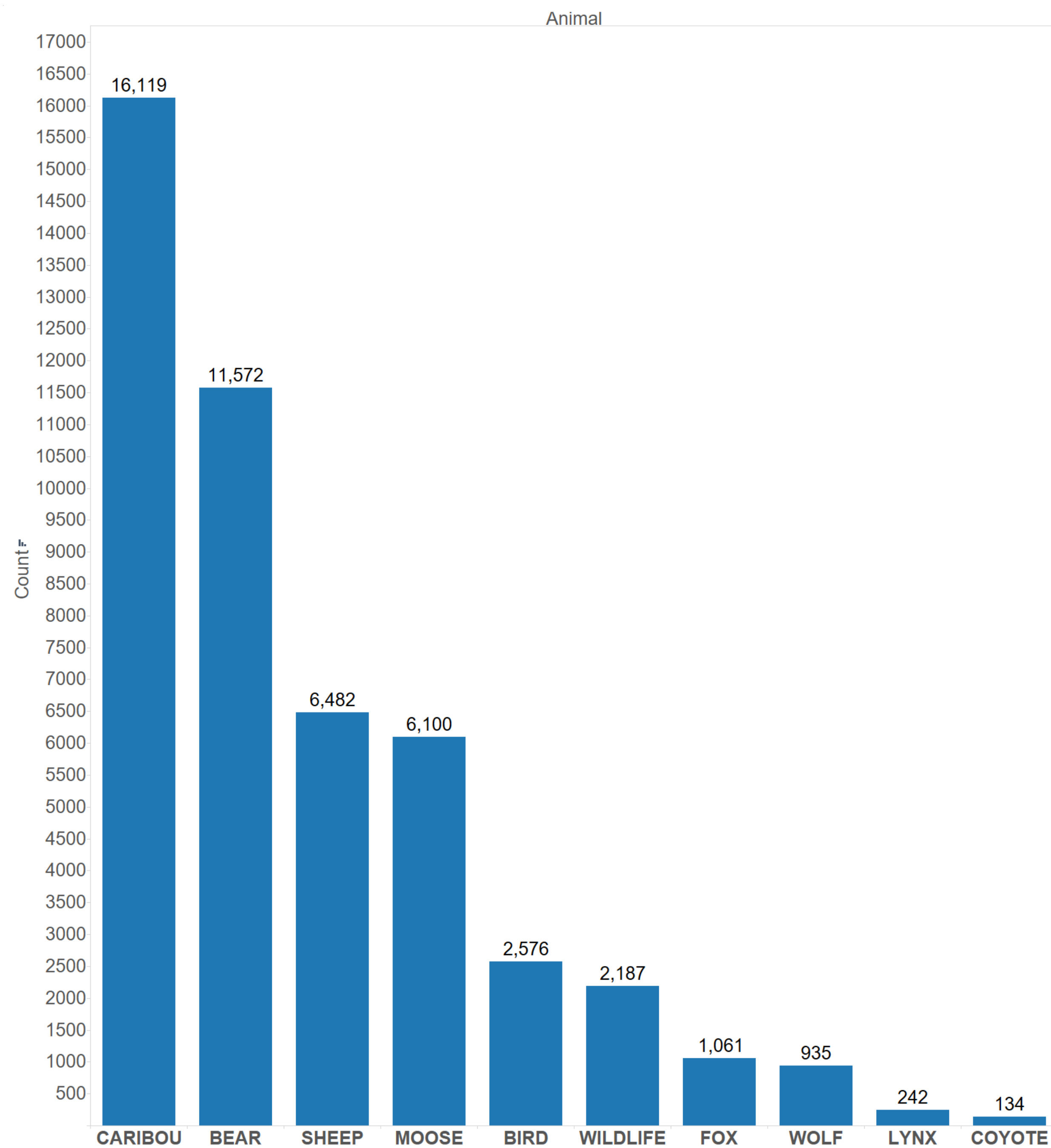

Figure 1. Total number of species observations throughout the 2014 viewing season.

Total wildlife viewings also varied over time, with peaks in mid-June, mid-July, and mid-August and dips at the beginning and end of the viewing season (Figure 2).

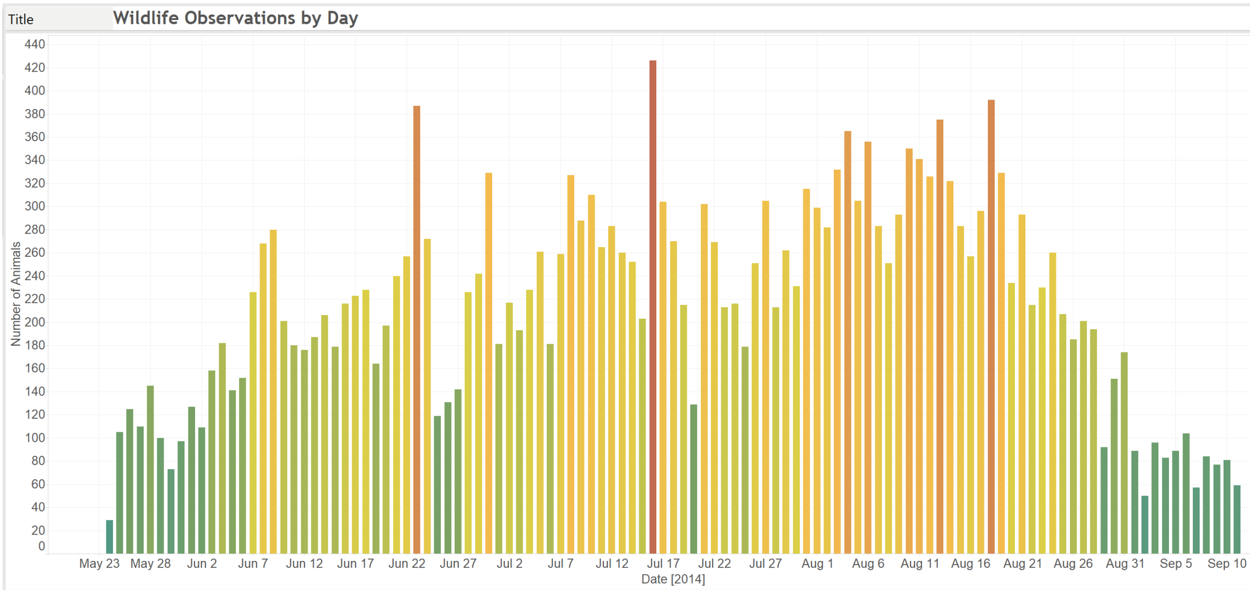

Figure 2. Total number of wildlife observations for each day in the 2014 viewing season.

Variation in the number of wildlife observations on any given day is informative only to the extent that viewing effort remains constant over time. For 2014, the number of busses per day varied from 19 to 63, with general declines at the beginning and end of the viewing season (Figure 3).

Dividing the number of animal observations by the number of bus trips provides a measure of wildlife viewings after correcting for variation in effort, i.e., as viewings per bus. Considerable variation was evident, with viewings per bus ranging from 2.20 to 9.49 (Figure 4). A general increase occurred until August, followed by a decline that concluded with a notable and sustained drop in viewings on the last 11 days of the season (Figure 4).

Busses do not all travel equal distances; more busses stop at shorter distances along the road. Thus, to assess the role of location on wildlife viewings I divided the number of viewings for mile i on day k by the number of busses that travelled through mile i on day k. I then plotted the average of these values for each mile during the entire viewing season (Figure 5). Some of the highest averages occurred near the end of the road. This suggests that, although fewer busses travel to the end of the road, animal observations may be more abundant further along the road.

For additional statistical analyses, I viewed the data through a box plot and ANOVA test, using the original data, rather than the restructured data. To explore the relationship of nighttime traffic and animal observations the next day, I first used a box plot to display the total number of animals observed along the entire road, binned by the amount of traffic the preceding night. The number of animal observations do not seem to depend on the amount of nighttime traffic, at least when subjected to the bin widths I used (Figure 6).

To test this hypothesis more formally, I performed an ANOVA to assess if the number of animal observations was equal across the different binned amounts of nighttime traffic. My ANOVA resulted in a non-significant test ($F = 1.76$, numerator d.f. $= 4$, denominator d.f. $= 570$, $P = 0.14$). Thus, I failed to reject the null hypothesis that the number of animal sightings was equal

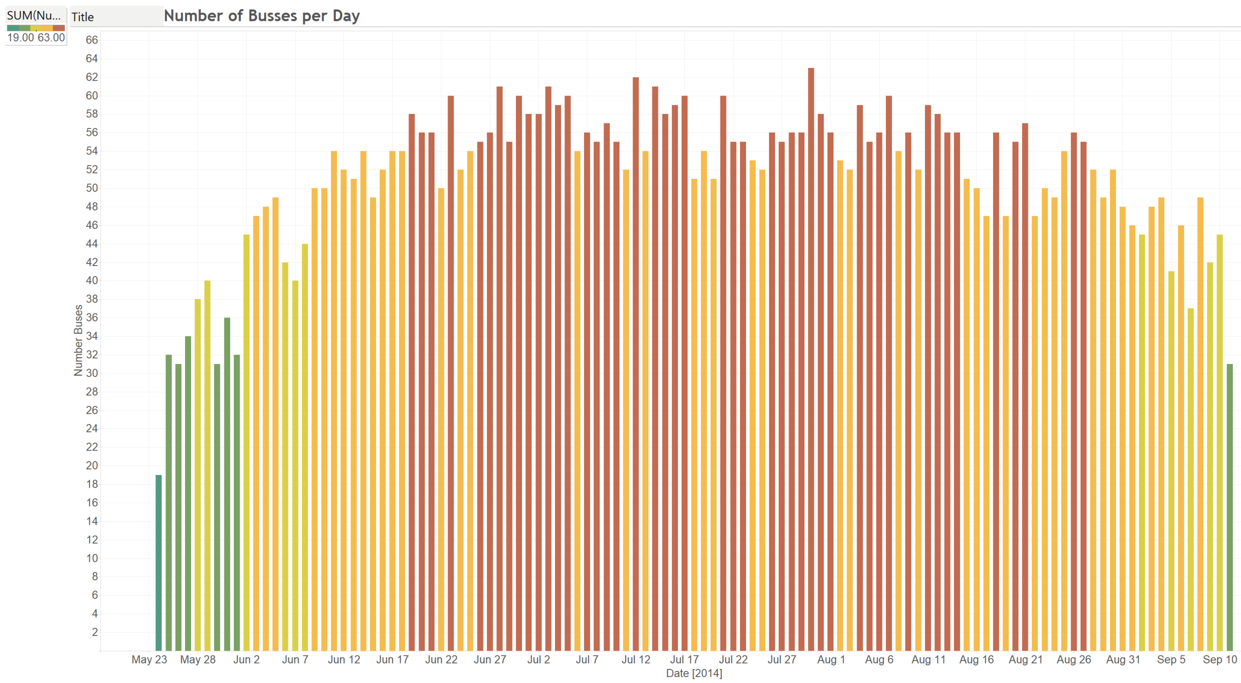

FIGURE 3. Total number of bus trips for each day during the 2014 viewing season.

for different levels of nighttime traffic. This result suggests that there does not appear to be any significant difference in the number of animal sightings for various levels of nighttime traffic. However, ANOVA assumes normality and homogeneity of variances among groups. As seen below, these assumptions were not warranted for the 2014 count data. Moreover, the ANOVA considered data pooled along the entire road rather than mile-specific detections.

3.2. **Multiple Linear Regression.** Through multiple linear regression analysis, I was able to begin to more formally explore the effect that certain variables have on wildlife sightings. Since preliminary analysis suggested that the association between viewings and ordinal date might be unimodal (Figures 3 and 4), I included a quadratic variable represented by

$$Day^2 = (OrdinalDate - \overline{OrdinalDate})^2 \tag{2}$$

Centering on the mean ordinal date for all viewings was done before squaring to reduce collinearity of Day^2 to ordinal date. Once this variable was created, it was then standardized, just as the other predictor variables used in the analysis. An assumption of multiple regression modeling is that predictor variables are independent and hence uncorrelated. To assess the level of multicollinearity, or correlation among predictors, I created a correlation matrix (Figure **??**).

The diagonal of the matrix must always be one, for it represents the correlation of each variable with itself. The correlations between pairs of predictors were rather low, and hence multicollinearity was not viewed as a serious problem in my regression analyses, with one exception. Distance from Counter and Mile were negatively correlated (-0.849). These variables are intuitively related; the traffic counters are spread out along the road, with most counters in the middle section of the road. The beginning and end of the road will then be the farthest locations from the counters, and the end of the road is slightly closer to a counter than the beginning of the road. Consequently, due to the strong correlation, Distance from Counter and Mile were not used simultaneously in models.

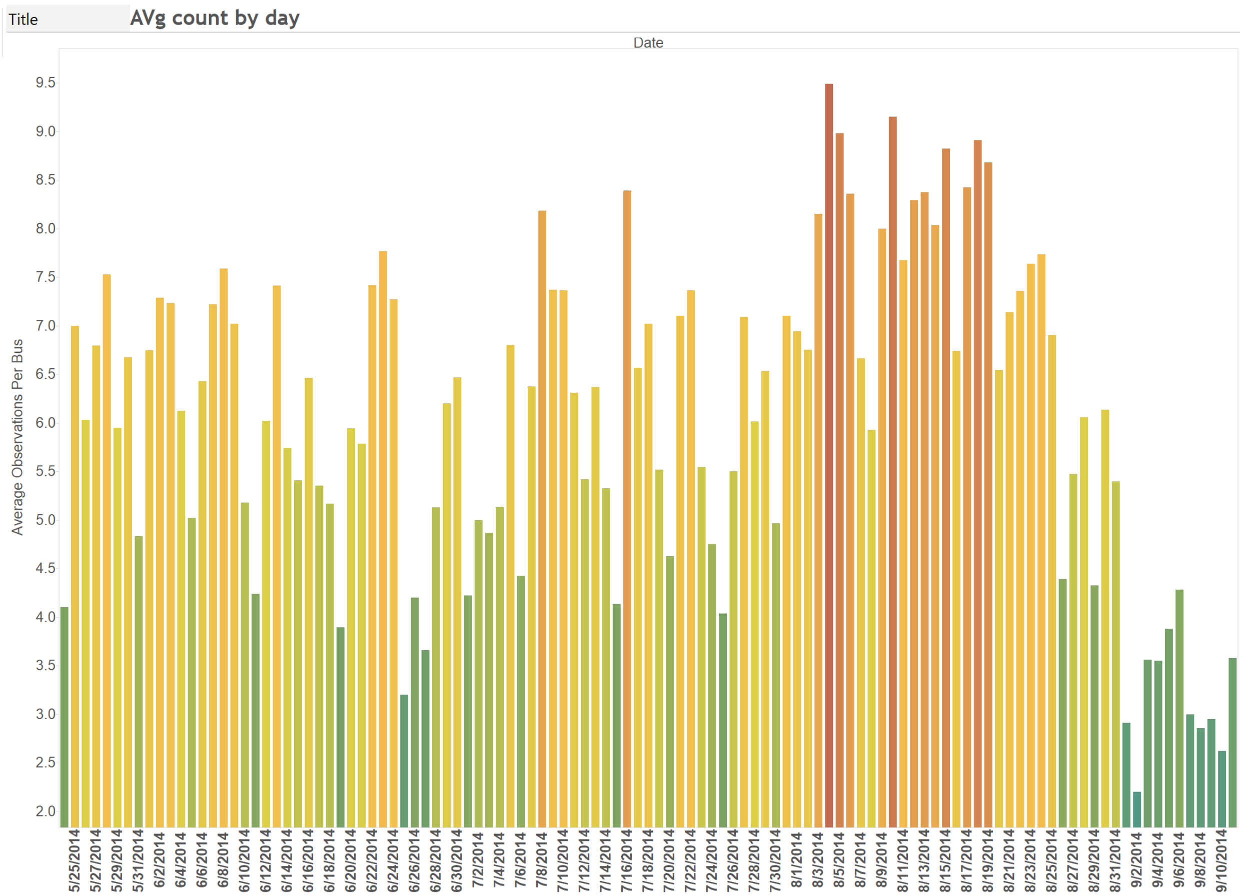

FIGURE 4. Average number of animal observations per bus for each day.

A large sample size, such as in the Denali viewings data set, offers tremendous power to detect significant effects of variables in regression models, even when the size of the effects has little meaning biologically. Even with such large power, the number of vehicles on the road during the previous night did not have a significant effect in the linear model (Appendix Table 1). As noted in the Methods Section, linear modeling may not be the most effective method for predicting animal observations, so next I considered more appropriate regression approaches.

3.3. **Poisson Regression.** Because Poisson regression is more appropriate for count data, I fitted a Poisson regression model to the wildlife viewings. Conclusions were similar to those outlined in Section 3.2 above for multiple linear regression. Once again, number of busses, day of year, quadratic day of year, and mile all made significant contributions to the predictive model, whereas nighttime traffic did not add value to the model (Appendix , Table 2). Use of Poisson regression assumes an underlying Poisson distribution in which the mean and variance are equal. This assumption, however, did not hold for total wildlife viewings, with a mean count of 5.42 per mile per day and variance of 107.48 for animal counts per mile per day. There is considerably more variation in our count data than expected for a Poisson distribution. As a result, I next fitted a regression model to take into account this extra-Poisson variation, also called over-dispersion.

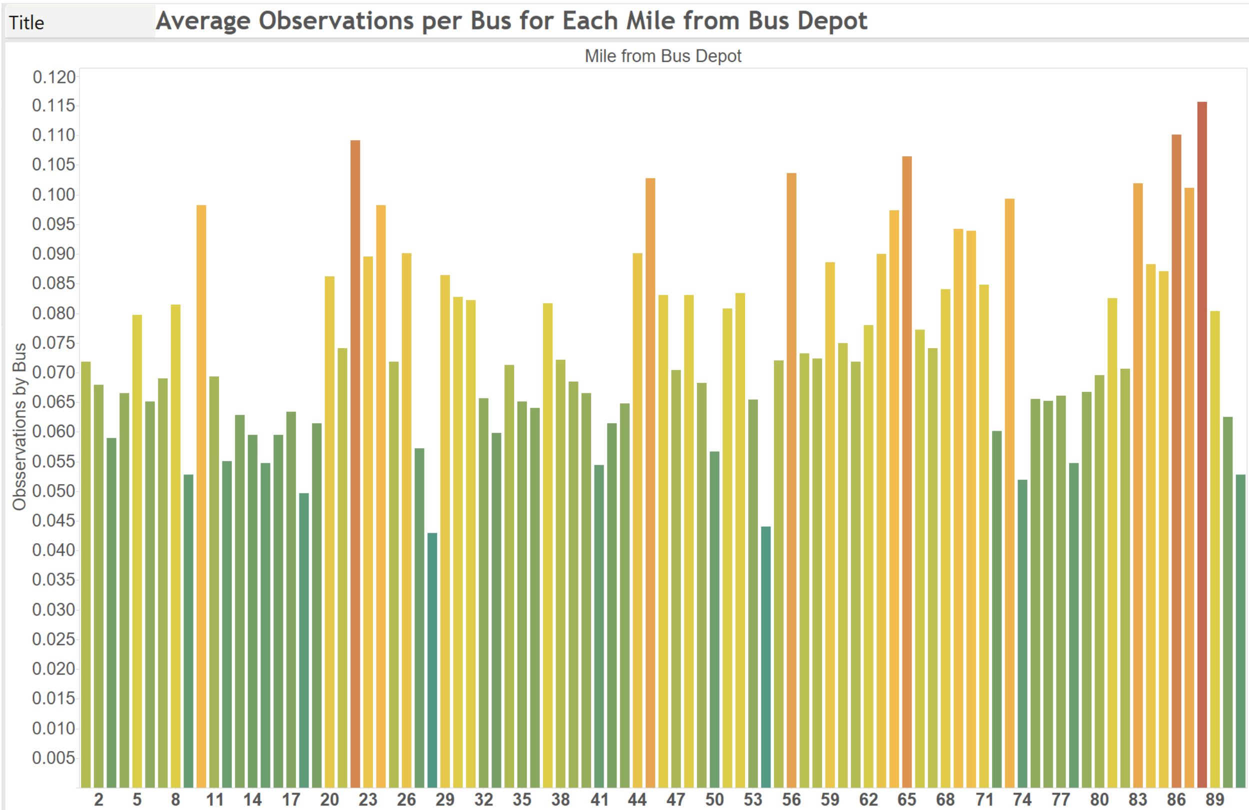

FIGURE 5. Average number of observations for a bus travelling through one individual mile along the road.

3.4. **Overdispersion.** Based on the design of the data matrix (Section 2), many animal sightings (for each mile segment each day) were zero (Figure 8).

A Poisson curve with mean equal to 5.42 was added (in blue) to the histogram for comparison with the Denali data. The data exhibited excessive zeroes and does not follow a Poisson distribution. Considering data for all species combined, I achieved the best model with the greatest support by utilizing a negative binomial distribution, as assessed using both Akaikes Information Criterion and predicted fit statistics. Once again, frequency of nighttime traffic failed to play a significant role in predicting animal observations the next day.

To compare the strength of candidate regression models, I calculated Akaikes Information Criterion (AIC). AIC is a metric that can be used to compare predictive models and is computed as

$$AIC = (-2 * L) + (2 * k) \tag{3}$$

where L represents the maximum log-likelihood value, and k represents the number of parameters in the model (Burnham and Anderson 2002). By calculating AIC for negative binomial, Poisson, and zero-inflated negative binomial distributions fitted to viewings from all species combined, I found AIC to be 44948, 44952, and 44956, respectively. Smaller AIC values indicate better models, so the negative binomial model offers the best approximation to truth for the number of animal counts.

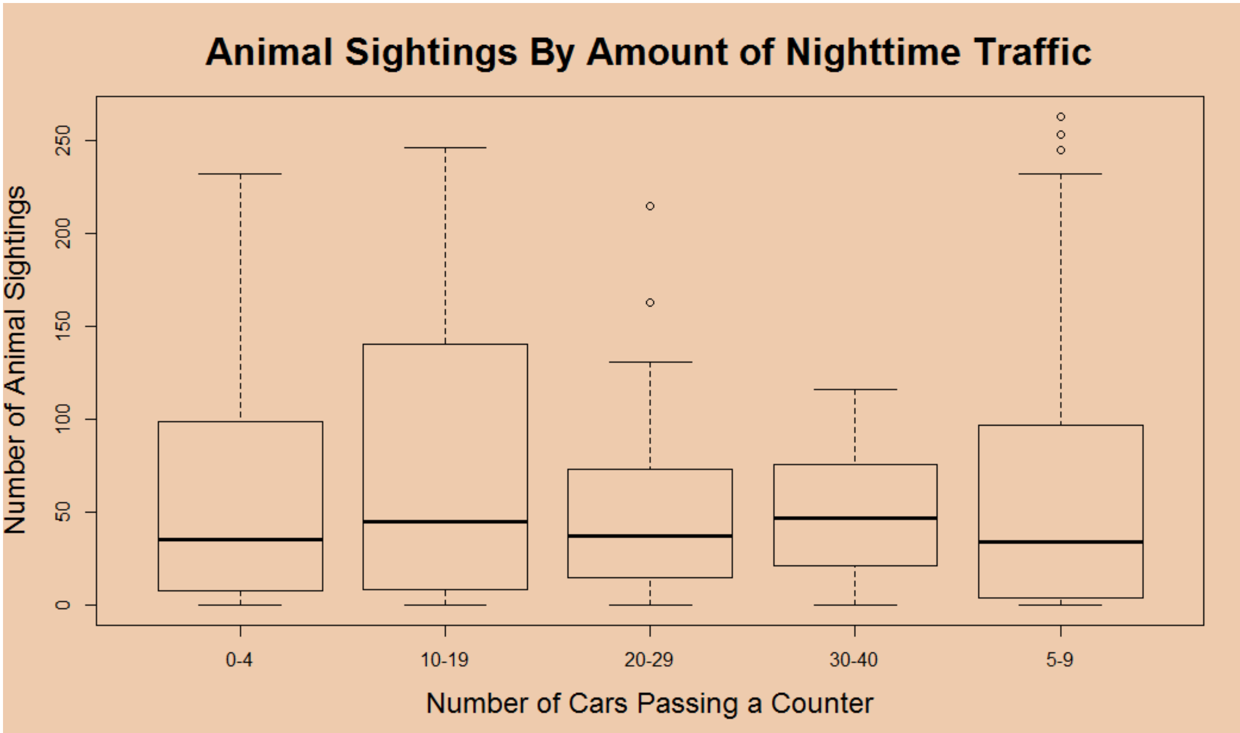

FIGURE 6. Boxplot of the Number of total animal observations based on total nighttime traffic for the previous night.

	Mile	DOY	Count	Busses	NightCars	DistCounter	quad
Mile	1						
DOY	0.007	1					
Count	0.02	0.041	1				
Busses	-0.091	0.272	0.18	1			
NightCars	-0.034	0.114	0.07	0.261	1		
DistCounter	-0.849	-0.033	-0.019	0.054	0.061	1	
quad	0.037	0.091	-0.179	-0.707	-0.399	-0.044	1

FIGURE 7. Correlations among predictor variables used in regression models.

3.5. **Spatial Autocorrelation.** Proceeding with the negative binomial model, I used the models residuals to calculate the Morans I value. When testing the null hypothesis of no spatial autocorrelation, I rejected the null hypothesis for road intervals in the shortest distance class and for several other distance classes (Figure 9).

However, the magnitude of Morans I for residuals from the best regression model was quite small and close to zero (Figure 8), suggesting that spatial autocorrelation was negligible even though it was significant because of the large sample sizes. The correlogram below plots the Morans I values, with possible values falling in the range [-1,1] and values close to 0 representing no autocorrelation.

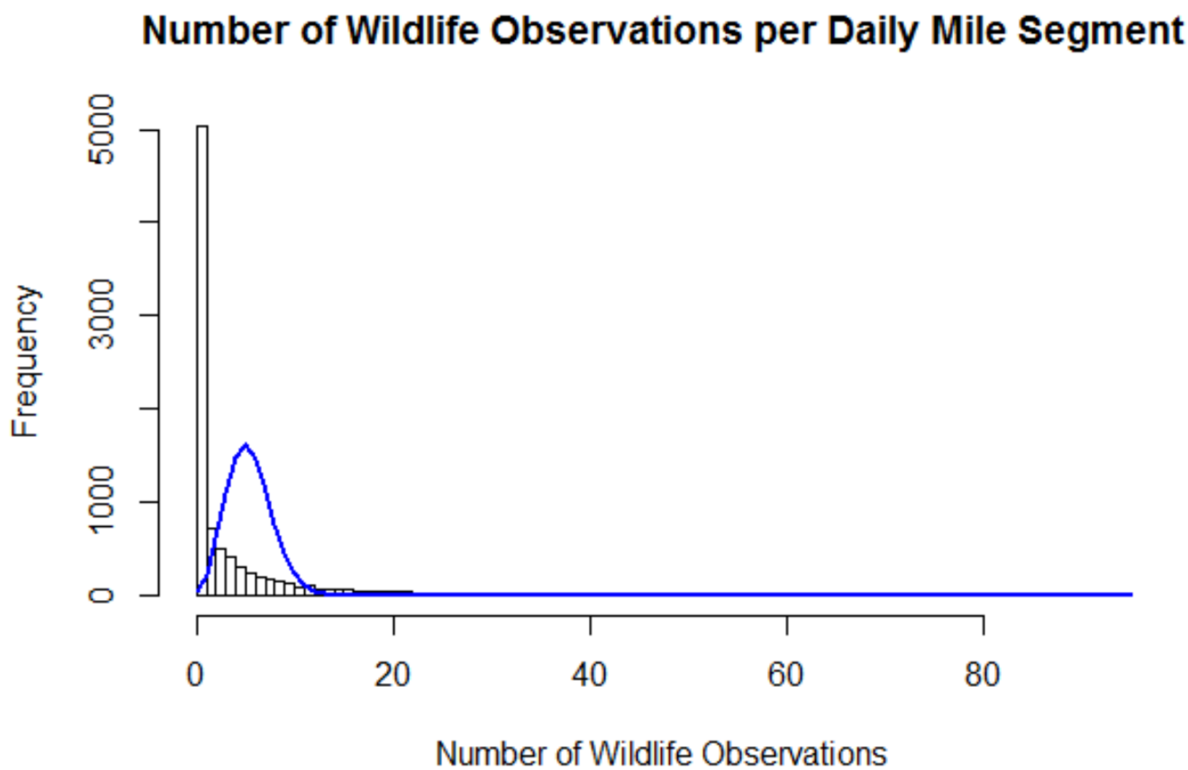

Figure 8. Distribution of animal observations per daily mile, with Poisson curve overlaid.

Note that the ordinate axis in Figure 8 is restricted to the range of [-.2, .2], accentuating what are really very small values for Morans I. Significant points are colored red.

3.6. **Individual Species Regression.** To account for the large amount of daily mile segments of value 0, zero-inflated negative binomial regression was considered to model observations for individual species. However, no improvement was noted in AIC when compared to corresponding negative binomial regression models (Table 2).

Thus, a negative binomial regression is preferred as it is the simpler model. To assess the strength of the negative binomial models in predicting animal observations, Chi-squared goodness of fit tests were performed. This null hypothesis for the test asserts that the data is modeled well by the negative binomial distribution. High p-values for each species suggest that the negative binomial regressions adequately model animal observations (Table 3).

Variance inflation statistics are also listed in the table as c-hat values. This measure is calculated as the sum of squared residuals over the residual degrees of freedom as a measure of overdispersion. Values close to one represent low levels of overdispersion. The c-hat value for the Poisson regression of all species in Section 3.3 was 16.55. The c-hat values in Table 4 indicate dramatic reduction in overdispersion by using the negative binomial models.

I used negative binomial regression to construct predictive models for moose, sheep, caribou, bear, wolf, and red fox observations. Unlike the analyses for all species considered collectively, several variables failed to emerge as significant predictors when data were broken down by species

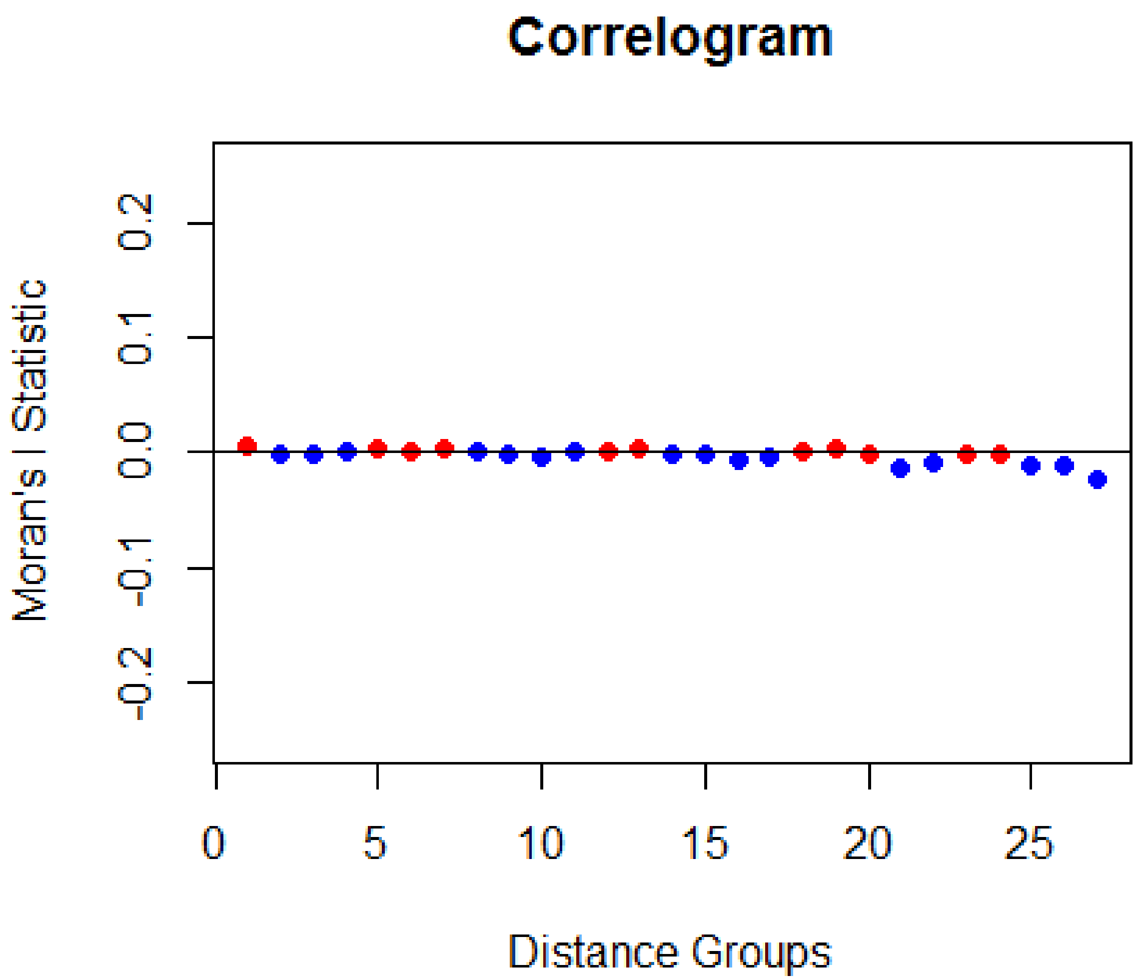

FIGURE 9. Correlogram of Morans I statistic values from the negative binomial regression.

(Table 4). Consistent with prior analyses, nighttime traffic volume did not have a significant negative effect on species-specific viewing. Indeed, the model for sheep suggests a small positive effect of nighttime traffic.

The number of busses that pass through a mile segment is the greatest predictor of wildlife observations, due to the intuitive reason that more effort and eyes yields more opportunities to see wildlife. For all species, except moose, more observations occurred at greater distances along the road. Observations of individual species, except wolves, were also impacted by a seasonality effect, which was quadratic for all species except wolves (Table 5). Caribou, sheep and fox observations were highest at the beginning and end of the season and experienced declining numbers throughout the season.

I plotted predicted values to graphically display selected results of the negative binomial regressions in Table 5. Predicted numbers of animal observations increased with mile segment of the road

	Model AIC	
	Negative Binomial	Zero Inflated Negative Binomial
All Species	44948	44950
Bear	17778	17780
Moose	15491	15493
Sheep	12833	12835
Wolf	5224	5226
Caribou	22501	22502
Fox	5506	5508

Table 2. Comparison of AIC values for negative binomial (NB) and zero-inflated negative binomial (ZINB) regressions.

	Goodness of Fit (P)	chat
All Species	0.408	1.19
Bear	1	1.50
Moose	1	1.40
Sheep	1	1.59
Wolf	1	1.17
Caribou	1	1.15
Fox	1	1.25

Table 3. P-values for goodness of fit tests of negative binomial models and c-hat estimates of overdispersion.

(Figure 10) while fixing the number of busses, day, and the day2 variable at their respective mean values.

Nighttime traffic was varied at four different levels: low traffic (0 vehicles), medium traffic (5 vehicles), high traffic (10 vehicles), and very high traffic (20 vehicles). The predicted numbers of animal observations increase as the busses travel farther along the road, but levels of nighttime traffic have minimal and nonsignificant effects.

Additionally, I predicted animal observations by day in a similar manner as above, but instead with constant nighttime traffic and varying values for day of year. I chose the first quartile, median, and third quartile as the levels, which corresponded to Day 169 (June 18), 197 (July 16), and 223 (August 11). When plotting the resulting predicted values, animal observations increase as mile increases, and observations are highest for July 15 and lowest for August 11 (Figure 11).

4. Conclusion

Negative binomial regression adequately predicted the number of wildlife counts. When considering the main question of the effect of nighttime traffic in the park, vehicles traveling the road during night hours were unimportant in predicting wildlife counts the following day. The limitations on nighttime traffic that are outlined in the Vehicle Management Plan appear adequate to avoid significant negative impact on wildlife viewing based on my analysis of 2014 data. I speculate, from this study, that animals residing in the park have grown accustom to a large amount of traffic. As indicated in the analyses, an increased number of busses yields a greater number of animal

Species	Intercept	Night Traffic	Busses	Mile	Day	Day^2
All Species	1.42 ± 0.018 (< 0.001)	0.02 ± 0.02 (0.34)	1.13 ± 0.03 (< 0.001)	0.17 ± 0.03 (< 0.001)	-0.05 ± 0.02 (0.01)	0.26 ± 0.02 (< 0.001)
Caribou	0.17 ± 0.03 (< 0.001)	0.05 ± 0.04 (0.18)	1.42 ± 0.06 (< 0.001)	0.62 ± 0.05 (< 0.001)	-0.25 ± 0.04 (< 0.001)	0.23 ± 0.05 (< 0.001)
Bear	-0.24 ± 0.04 (< 0.001)	-0.04 ± 0.04 (0.33)	1.66 ± 0.70 (< 0.001)	1.11 ± 0.07 (< 0.001)	0.02 ± 0.04 (0.544)	0.59 ± 0.05 (< 0.001)
Sheep	-1.02 ± 0.05 (< 0.001)	0.11 ± 0.05 (0.04)	2.31 ± 0.09 (< 0.001)	0.84 ± 0.09 (< 0.001)	-0.43 ± 0.05 (< 0.001)	0.94 ± 0.06 (< 0.001)
Moose	-0.76 ± 0.03 (< 0.001)	-0.04 ± 0.03 (0.22)	-0.14 ± 0.06 (0.02)	-0.79 ± 0.05 (< 0.001)	0.10 ± 0.03 (0.004)	-0.15 ± 0.04 (< 0.001)
Wolf	-2.77 ± 0.06 (< 0.001)	0.06 ± 0.06 (0.25)	1.40 ± 0.10 (< 0.001)	0.55 ± 0.08 (< 0.001)	0.14 ± 0.06 (0.02)	0.07 ± 0.07 (0.03)
Red Fox	-2.60 ± 0.06 (< 0.001)	0.11 ± 0.06 (0.06)	1.67 ± 0.10 (< 0.001)	0.93 ± 0.08 (< 0.001)	-0.39 ± 0.06 (< 0.001)	0.52 ± 0.07 (< 0.001)

TABLE 4. Coefficients and standard errors for predictors in the negative binomial regressions fitted to viewing data for individual species in Denali, 2014. P-values given in parentheses.

observations. If higher number of busses does not negatively impact animal observation numbers (Appendix, Figure 12), then one may speculate that species may respond similarly to nighttime traffic.

Variables other than nighttime traffic, including number of busses, mile, and often day of year, were important predictors. The number of busses is intuitively an important predictor as it introduces an effort variable, creating the capacity to see wildlife. Although the variables I included were predictors of wildlife observations, a better understanding could be formed by including more covariates. Precipitation and other weather-related variables may greatly affect opportunities to view species. Including GIS data could offer greater predictive power by indicating terrain and habitat types that cater to the needs of individual species. The variables used in this analysis only have limited association with observations.

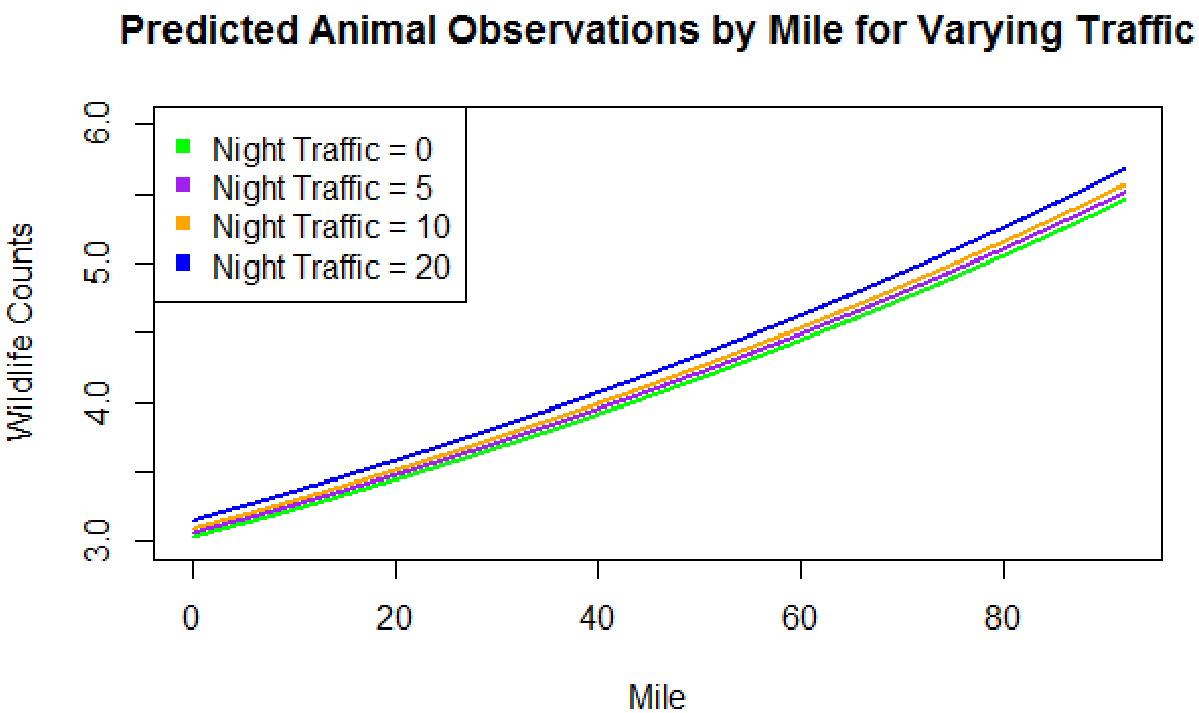

Figure 10. Predicted number of animal observations per mile, accounting for different levels of nighttime traffic.

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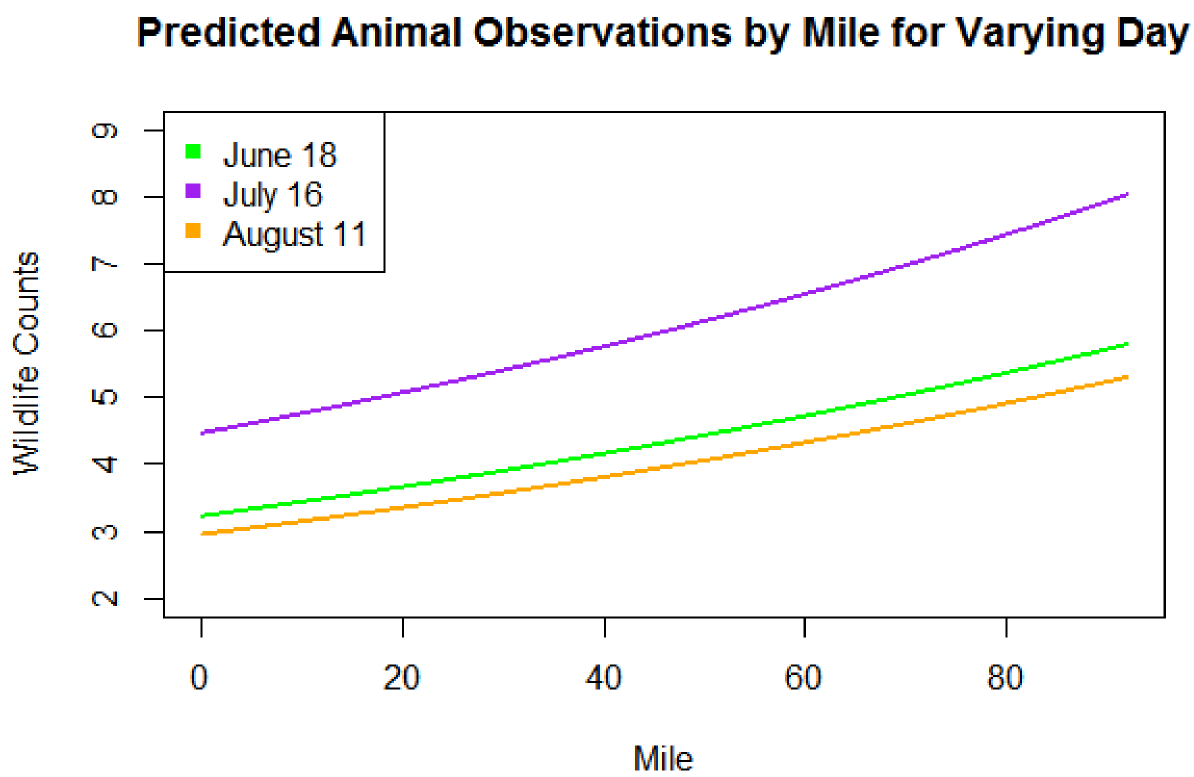

FIGURE 11. Predicted values of animal observations by mile, accounting for different days of the year.

5. Appendix

Table 1. Multiple linear regression indicated that number of busses, day of year, quadratic day of year, and mile all were significant predictors of total wildlife viewings per mile-day, i.e., regression coefficients for these variables were significantly different from 0. Number of vehicles the preceding night was not a significant predictor.

	Estimate	Std. Error	t-value	p-value
Intercept	5.42	0.10	52.96	0
Busses	4.91	0.21	23.74	0
Night Vehicles	0.023	0.11	0.20	0.84
Mile	2.38	0.19	12.46	0
Day	-0.29	0.11	-2.61	0.01
Quad	1.12	0.14	8	0
Dist. Counter	0.07	0.12	0.62	0.54

Table 2. Estimates and standard errors of Poisson regression coefficients for each focal species. P-values are in parentheses.

Species	Intercept	Night Traffic	Busses	Mile	Day	Day^2
All Species	1.49 ± 0.01 (< 0.001)	-0.01 ± 0.01 (0.02)	0.96 ± 0.01 (< 0.001)	0.35 ± 0.01 (< 0.001)	-0.03 ± 0.01 (< 0.001)	0.21 ± 0.01 (< 0.001)
Caribou	0.18 ± 0.01 (< 0.001)	-0.04 ± 0.01 (0.18)	1.30 ± 0.01 (< 0.001)	0.98 ± 0.01 (< 0.001)	-0.09 ± 0.01 (< 0.001)	0.05 ± 0.01 (< 0.001)
Bear	-0.18 ± 0.01 (< 0.001)	-0.01 ± 0.01 (< 0.001)	1.40 ± 0.02 (< 0.001)	1.00 ± 0.02 (< 0.001)	0.15 ± 0.01 (< 0.001)	0.39 ± 0.01 (< 0.001)
Sheep	-0.78 ± 0.02 (< 0.001)	0.15 ± 0.02 (< 0.001)	1.62 ± 0.03 (< 0.001)	0.74 ± 0.02 (< 0.001)	-0.33 ± 0.01 (< 0.001)	0.76 ± 0.02 (< 0.001)
Moose	-0.78 ± 0.02 (< 0.001)	-0.05 ± 0.02 (0.005)	-0.19 ± 0.03 (< 0.001)	-0.87 ± 0.02 (< 0.001)	0.10 ± 0.01 (< 0.001)	-0.08 ± 0.02 (< 0.001)
Wolf	-2.73 ± 0.05 (< 0.001)	0.02 ± 0.04 (0.58)	1.23 ± 0.06 (< 0.001)	0.61 ± 0.05 (< 0.001)	0.24 ± 0.05 (< 0.001)	-0.03 ± 0.05 (0.53)
Red Fox	-2.55 ± 0.04 (< 0.001)	0.07 ± 0.06 (0.06)	1.52 ± 0.06 (< 0.001)	1.04 ± 0.05 (< 0.001)	-0.33 ± 0.03 (< 0.001)	0.49 ± 0.05 (< 0.001)

TABLE 5. Coefficients and standard errors for predictors in the negative binomial regressions fitted to viewing data for individual species in Denali, 2014. P-values given in parentheses.

I assert that increasing the number of busses only leads to an increase in the number of animal observations. In order to assess the validity of this claim, I find the effect of an incremental change in the number of busses. These values were calculated by finding the mean number of observations per bus for each number of busses traveling through a daily mile segment. In order to understand the effect of adding an additional bus, I then found and plotted the change in this average value for each additional bus. It can be concluded that adding busses does not affect the average number of observations in a mile segment per bus.

Figure 1. Effect of adding an additional bus that goes through a mile segment on the average number of observations per bus.

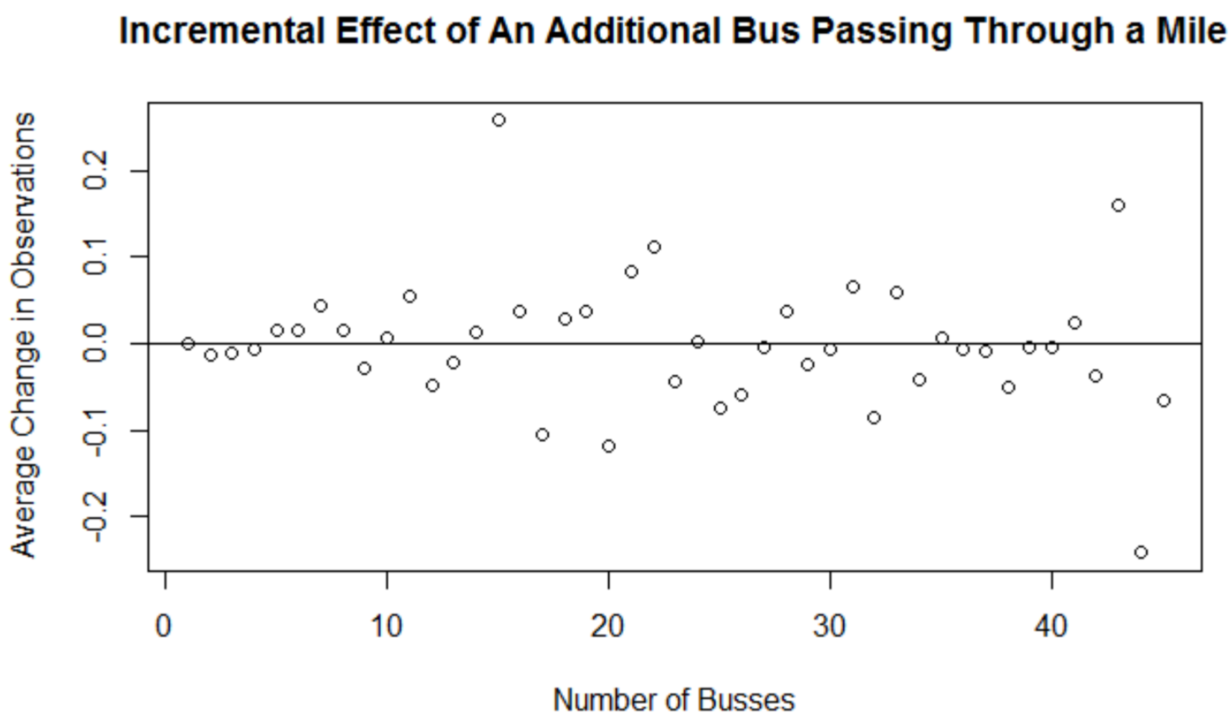
Incremental Effect of An Additional Bus Passing Through a Mile
Average Change in Observations
0.2
0.1
0.0
-0.1
-0.2
0
10
20
30
40
Number of Busses

Figure 12.