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Diana Alvarez
jiur@southern.edu

Does Bambi Need Privacy? The Impact of Human Recreational Trail Traffic on Abundance and Daily Activity of the White-Tailed Deer (*Odocoileus virginianus*)

Diana Alvarez* and Aaron Corbit, Ph.D*

Abstract

Humans have a significant impact on wildlife populations. Although not as obvious, even non-consumptive recreational activities (i.e. hiking and mountain biking) can impact wildlife. Previous research has suggested that human traffic can impact the movement patterns of the white-tailed deer (*Odocoileus virginianus*). Specifically, as human traffic increases, deer sightings decrease. Also, due to their crepuscular nature, deer peak activity is at dawn and dusk, yet one study reported a decrease in deer sightings in the evening that seemed to correspond to a peak in human traffic. However, the cause-and-effect relationship between human traffic and deer daily movements has yet to be fully established. In this study, we used trail cameras to examine the effect of human traffic on the abundance and daily movement patterns of *O. virginianus* on a private trail system on the campus of Southern Adventist University near Chattanooga, TN. Since our data generated thousands of images, we also tested the efficacy of a simple machine learning algorithm that used the Structural Similarity Index (SSIM) to help us find deer or humans within the images generated by the trail cameras. As with previous research, we found a reduction in deer observations as human traffic increased. We also found that temperature, humidity, and wind speed were inversely related to deer sightings while atmospheric pressure was directly related to deer sightings. While some aspects of our data support the hypotheses that human traffic impacts diel movement patterns of deer, other aspects are inconsistent with this hypothesis so this relationship remains unresolved. Though our machine learning methodology was not very effective, our results suggest that the use of SSIM could prove useful with further refinement. This study adds to our understanding of the ways that non-consumptive, outdoor recreational activities can impact wildlife and may help inform land use policies.

Introduction

Human activity continues to significantly impact natural ecosystems. Due to human impact, the last half of the twentieth century experienced the quickest changes in the function and structure of the world's ecosystems, more than any other period in history (Reid et al., 2005). Excluding Antarctica and most oceanic islands, humans directly influence 83% of Earth's land surface and 98% of arable regions where crops such as rice, maize, and wheat can be cultivated (Sanderson et al., 2002). Human activities with the greatest impact on natural ecosystems include agriculture, urban settlements, construction of roads, and the harvesting of natural resources (Grimm, Grove, Pickett, & Redman, 2000; Sanderson et al., 2002). However, other human activities that don't destroy and displace natural ecosystems to a significant degree can also impact wildland.

One such human activity is outdoor recreation. Outdoor recreation has increased about 7% during the last couple of decades (White et al., 2014). Outdoor recreational activities can be classified into two different types: consumptive and non-consumptive. Consumptive activities involve removing natural resources from the habitat (e.g. hunting and fishing) while non-consumptive activities do not (e.g. hiking and mountain biking) (Knight & Cole, 1995). Although non-consumptive activities do not remove natural resources from the habitat, they can still impact the environment by causing pollution, animal disturbance, and alterations to habitats (Boyle & Samson, 1985). Even something as seemingly trivial as trampling, which means walking heavily or roughly enough to disturb the ecosystem, can have noticeable impacts. One example would be the compaction of mineral soil that would lead to a reduction in the permeability of air and water to the soil, resulting in an increase in runoff and erosion. A less noticeable impact of trampling would be the loss of diversity in functional microbial populations (Sievänen, 2004). In areas with high human recreation, deer are more likely to become used to the presence of humans which can increase the likeliness of predation (Soulard, 2017).

Previous research using trail cameras (Hesler & Corbit, 2018) has suggested that human traffic on recreational trails can impact the behavior of larger vertebrate wildlife. Using data from trail cameras, Hesler and Corbit (2018) found that as human traffic increased wildlife sightings on the trails decreased. This research also suggested that human traffic may alter the diel movement patterns of wildlife. Since the white-tailed deer (*Odocoileus virginianus*) was the most common animal detected in their study and this species is known to have a crepuscular diel pattern, the authors expected to see two daily peaks in wildlife sightings at both dawn and dusk. However, the authors report that the expected evening peak in wildlife sightings was reduced or absent and corresponded with the daily peak in human traffic. While this is suggestive of human influence on the diel movement patterns of wildlife, it is not conclusive. The authors note that white-tailed deer are known to move into more open habitats in the evening (Montgomery, 1963; Beier & McCullough, 1990). Since all the trail cameras used in the study were located within a forested area, the lack of an evening peak in wildlife sightings could have been the result of deer moving into more open areas and away from the cameras instead of in response to human traffic.

A difficulty in using trail cameras in studies, such as the one conducted by Hesler and Corbit (2018), is that this methodology generates thousands of images and abstracting data from these images manually can be a time-consuming process. The use of image processing in machine learning technology has been used to identify species in biological studies (Wäldchen & Mäder, 2018). Applying such technology to the images generated by such studies could significantly increase the efficiency of detecting wildlife and/or humans in these digital images and speed the process of data abstraction.

This study builds on the work of Hesler and Corbit (2018). Using the same recreational trail system and a similar trail camera methodology, we focus on the relationship between human traffic and white-tailed deer (*O. virginianus*) sightings. Our study seeks to confirm the inverse relationship between human traffic and deer sightings suggested by Hesler and Corbit (2018) and to clarify whether the diel movement patterns in deer are impacted by human traffic. This study also tests a simple machine learning protocol that applies the structural similarity index (SSIM) statistic to trail camera images to see if such methodology could make data abstraction from such images more efficient.

Methods and Materials

Location

Like Hesler and Corbit (2018), this study took place on a privately owned recreational trail system located in Collegedale, TN (near Chattanooga). The Bauxite Ridge trail system is one of two major trail systems, collectively known as the Biology Trails, that are owned and managed by Southern Adventist University (SAU). The Bauxite Ridge system, which is east of SAU's campus, was opened in 2016 and contains 12 miles of trails that are utilized for hiking and mountain biking (Hankins, 2013).

This trail system is contained within a forested area and in the Southern Shale Valleys that is located in the Ridge and Valley ecoregion (ecoregion 67; EPA, 2013). This area falls within the Great Valley of Tennessee that lies between the Blue Ridge Mountains and the Cumberland Plateau (Griffith et al., 1997; Arnwine, Broach, Cartwright, & Denton 2000). The region has a temperate climate, and the habitat is known to have a mix of oak-hickory-pine forests (Nature Conservancy, 2003; Amick, 1934; Braun, 1947).

Time

This study was conducted in the Fall of 2019 (October 17 – December 1) to coincide with the breeding season of the white-tailed deer (*O. virginianus)* which are known to be common in this area (Clements et al., 2011).

Camera Placement

Figure 1: Location of camera sites on the Bauxite Ridge trail system.

We distributed 24 trail cameras at 12 different sites (Figure 1). At each site, two cameras were placed on the same tree, but were positioned in opposite directions (Figure 2). This was done to increase the field of view at each site. Camera sites were chosen based on two criteria: distance from the edge of the forest and distance from a recreational trail. Three of the sites were positioned near the edge of the forest and near a trail. Three of the sites were positioned away from the forest edge and near a trail. Three of the sites were positioned near the edge of the forest and away from a trail. And finally, three of the sites were positioned near the center of the forest and away from a trail. The cameras that were placed near a trail had one camera facing the trail and the other camera facing away from the trail. Batteries were checked weekly and SD cards were replaced weekly.

Figure 2: Camera placement at each site.

We used Browning Strike Force BTC-5 Trail Cameras (Browning, Morgan, UT) that made use of infrared LED illumination which allowed nighttime illumination without fear of disturbing the animals. Each camera, after being triggered by motion sensors, was set to take three images in order to increase the chances of capturing images that would allow animal identification.

Data Collection

We visually examined each image to determine the number of humans or deer present. We also considered several climate factors that were suggested from literature to affect deer movement (Tomberlin, 2007). We acquired daily precipitation, temperature, humidity, and atmospheric pressure data from the Southern Adventist University weather station (35.05°N, and 85.05°W) via the Weather Underground website.

Image Processing

We calculated the structural similarity index (SSIM) for each image using Python 3.7 with OpenCV (Howse, 2013) and NumPy libraries (McKinney, 2012). The SSIM compares two images to each other and returns a value between 0 and 1, where 0 is completely dissimilar and 1 is completely identical (Hore & Ziou, 2010). We calculated the SSIM for each image by camera, comparing each image to a reference image from that same camera that did not have deer or humans present.

Statistical Analysis

Since each camera was set to take three images every time it was triggered and deer or humans could linger at a site and trigger the camera multiple times, we estimated the total deer and human sightings per camera per day by counting a new sighting only if the camera had not been triggered for one minute since it was triggered last.

We used a Poisson generalized linear mixed model (PGLMM) to examine what factors affected the number of deer sightings per camera per day. We included the number of human sightings per camera per day as an independent variable as well as several weather variables. These included average daily temperature, humidity, wind speed, cumulative daily precipitation, and minimum daily atmospheric pressure. In order to detect possible trends in deer sightings over the course of the study, we also included the date in the model. This was input as the day of the year where 1 is January first and 365 is December 31. Camera number was used as the grouping variable. Statistical modeling for this analysis was done using Jamovi version 1.2

(Jamovi Project, 2020) and the GAMLj module version 2.0.5 (Gallucci, 2019) with alpha set at 0.05.

To evaluate the time of day that the sightings occurred, we counted the number of sightings for each hour of the day across all the days in the study period for both deer and humans at each camera site. The resulting time-of-day histograms were examined to determine whether they showed deer sightings clustering at both dawn and dusk in a way consistent with the crepuscular pattern known to occur in deer. The presence or absence of this criteria was compared between camera sites and between the four groups each site was placed in (near the edge of the forest and near a trail, away from the forest edge and near a trail, near the edge of the forest and away from a trail, and near the center of the forest and away from a trail) to determine if distance from the trail or distance from the edge of the forest influenced deer diel patterns.

To analyze the effectiveness of SSIM in predicting the presence of a human or deer in an image, we fitted a simple logistic regression model to our data where the dependent variable was whether the image contained a human or a deer (yes/no) and the independent variable was the value of the SSIM. We then applied this model to the SSIM of each image in order to calculate a model-based probability of that image containing a human or deer. Since this model did not generate any probabilities above 0.5, we used the median probability of 0.19 as the threshold. Probabilities greater than 0.19 were considered positive for humans or deer while probabilities less than or equal to 0.19 were considered negative. We then compared the predictions of the model with what we determined via visual inspection of each image using the positive predictive value statistic. Logistic regression modeling and positive predictive value calculation was performed using R version 4.0.2 (R Core Team, 2019).

Results

Over the 45 days of the study, the trail cameras collected a total of 22,330 images. Of those, 2,637 (11.8%) images recorded one or more humans and 1,605 (7.2%) recorded one or more deer. After adjusting for multiple images of the same event and summing total humans or deer per image, we estimated that the cameras had recorded 850 deer sightings and 2,651 human sightings.

Deer Sightings Per Camera Per Day

PGLMM modeling results are shown in Table 1. The model confirmed the inverse relationship between human traffic and deer sightings, with every one person increase in human traffic per camera per day resulting in a 2% drop in deer sightings per camera per day. Several weather variables were also shown to significantly impact deer sightings. Temperature, humidity, and wind speed were inversely related to deer sightings while atmospheric pressure was directly related to deer sightings. We did not detect an increasing or decreasing trend in deer sightings over the course of the study.

Table 1. Results from Poisson Generalized Linear Mixed Model. The dependent variable is the number of deer sightings per camera site per day. Temperature (°C), humidity (%), and wind speed (mph) represent daily averages. Precipitation (in) is cumulative over the day and atmospheric pressure (in) is the lowest daily value. P-values in bold are less than 0.05.

				95% Exp(β) CI			
Names	**Estimate (β)**	**SE**	**Exp(β)**	**Lower**	**Upper**	**z**	***p***
(Intercept)	0.13	0.25	1.14	0.71	1.85	0.54	0.587
Human sightings	-0.02	0.01	0.98	0.96	0.99	-2.92	**0.004**
Temperature	-0.03	0.01	0.97	0.95	0.99	-2.59	**0.010**
Precipitation	0.10	0.08	1.10	0.93	1.30	1.15	0.250
Date	< 0.01	< 0.01	1.00	0.99	1.01	0.14	0.887
Humidity	-0.01	0.00	0.99	0.98	1.00	-2.58	**0.010**
Wind Speed	-0.15	0.05	0.86	0.78	0.95	-2.89	**0.004**
Atmospheric Pressure	0.51	0.25	1.67	1.02	2.74	2.03	**0.042**

Diel Pattern

As shown in Figure 4, most sites didn't have enough deer sightings to give a clear picture of movement patterns. Sites 5, 6, 10, and 12 are exceptions with deer sightings greater than 80. Consistent with the hypothesis that human traffic disrupts the evening peak in deer activity, sites 6 and 12, both of which were far from a trail, do show a peak in deer activity at dawn and dusk consistent with the known crepuscular diel pattern of deer. Also consistent with the human disruption hypothesis, site 5 was near a trail and the evening activity peak appears to be missing. However, contrary to this hypothesis, site 10 lacks the evening activity peak and yet was positioned far from a trail. The relationship between the presence of the evening activity peak and proximity to an open field is also unclear as sites 5 and 10 both lack an evening activity peak, yet one was situated near an open field and the other was not. Hence, the relationship between human traffic and diel movement patterns in deer remains unclear.

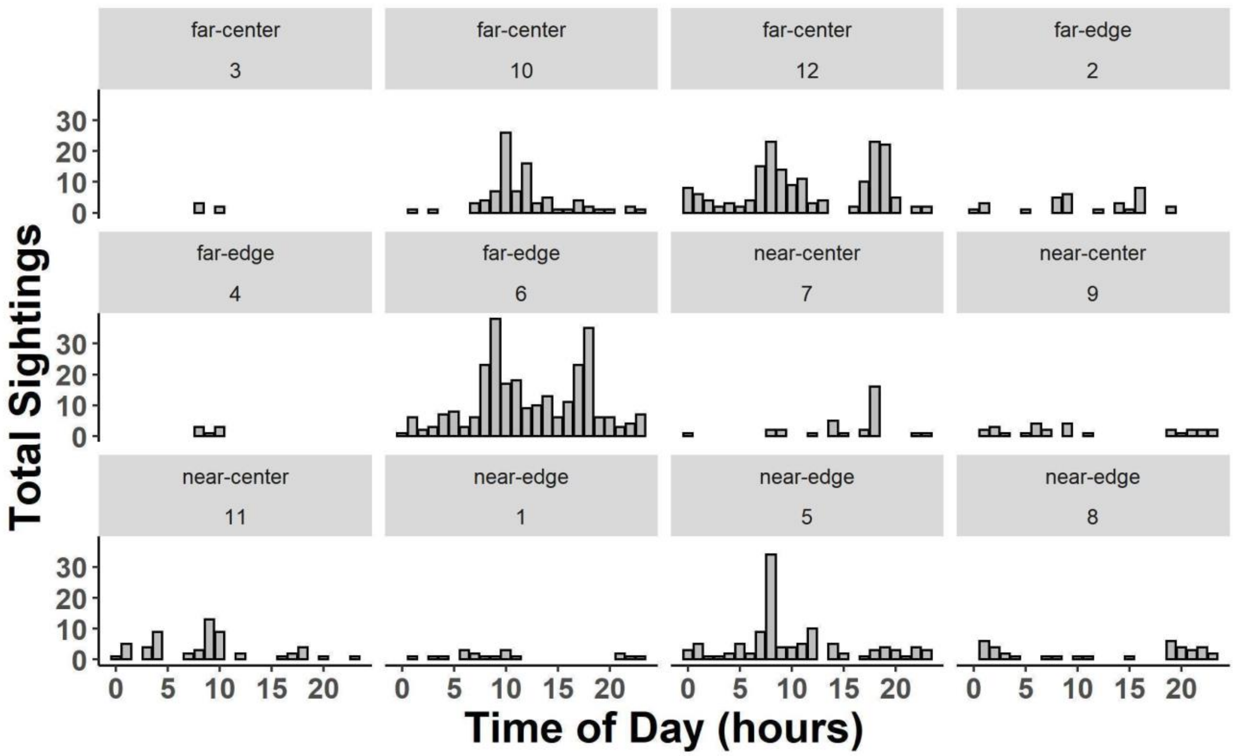

Figure 4. Total deer sightings by time of day for each camera site. Site classification (far = away from trail, near = close to trail, center = away from open field, edge = bordering open field) is listed above each site identification number.

Predicting Based on SSIM

The logistic regression model predicting whether an image contained a human or deer based on SSIM was close to the threshold of significance and indicated that images that were more dissimilar to the reference image were more likely to contain humans or deer (Estimate = -0.33, Odds ratio = 0.72, $z = -1.80$, $p = 0.073$). However, this model did not perform well at identifying images that contained humans or deer. The model was incorrect a majority of the time, generating false positives 48.8% of the time and false negatives 7.0% of the time (Table 2). We calculated a positive predictive value of 19.7% percent, which is not much better than the probability of picking a positive sighting at random (19.0%).

Table 2. Results of a simple machine learning algorithm, based on logistic regression, that used the structural similarity index to predict the presence or absence of deer or humans in digital images obtained from trail cameras.

	Confirmed Sighting	No Confirmed Sighting
Sighting Predicted	2669 (12.0%) True Positives	10893 (48.8%) False Positives
Sighting Not Predicted	1572 (7.0%) False Negatives	7196 (32.2%) True Negatives

Discussion

Our results add further support to the idea that non-consumptive outdoor recreational activities can impact deer behavior. Our findings show that greater human traffic per day is associated with a decrease in the overall number of deer sightings. Our data also suggest that other environmental factors, such as temperature, humidity, wind speed, and atmospheric pressure also impact deer activity. Although we aimed to clarify the relationship between human traffic on recreational trails and deer diel movement patterns, our results were inconclusive. Also, while our implementation of machine learning and SSIM to detect wildlife in digital images was not very effective, our results suggest that this methodology could be useful if developed further.

Influences on deer sightings per day

Our results confirm the major finding from Hesler and Corbit's (2018) study, that increased human traffic decreases wildlife sightings per camera per day. However, our estimates suggest a milder effect. Hesler and Corbit's (2018) statistical model estimated nearly a 25% decrease in wildlife (mostly deer) sightings for every one-person increase in human traffic, while our model only estimated about a 2% decrease in deer sightings. Unlike Hesler and Corbit (2018), who found a slight (3%) increase in overall wildlife sightings over the course of the study, we did not detect such a trend.

As previously mentioned, there were several environmental factors that we examined that had a significant impact on deer sightings. Temperature, humidity, and wind speed were inversely related to deer observations. However, there was no detectable effect of precipitation on deer observations. The relationship that temperature, precipitation, humidity, and wind speed each had with deer sightings in our results were consistent with Tomberlin's (2007) study. However, our results showed that deer observations increased as barometric pressure increased which was contrary to Tomberlin's (2007) study that concluded that deer are most active at moderate pressures.

Diel pattern

Part of the purpose for this research was to further examine the effect of human traffic on the diel movement patterns of deer and to see if we could confirm the hypothesis that deer will alter their daily movement patterns in response to human traffic. While Hesler and Corbit (2018) suggested that deer might avoid areas with high human traffic, especially during later afternoon and evening when human traffic reaches its peak, our results are inconclusive. Although deer may avoid areas with high human traffic, there may also be other factors that affect the movements of deer in and through a particular area other than human traffic and these might have confounded our results.

One factor that could have influenced our results is the habitat the cameras were placed in. Deer, in our study area, are known to rely on mast (especially acorns) and the leaves of broadleaf woody plants in the fall and winter (Johnson et al., 1995) and may spend more time in areas that contain these resources. In our study, two cameras (5 and 10) were placed in areas with a high density of pine trees. The fact that these areas may lack food resources provided by oak and other broadleaf trees may help explain why these two camera sites showed the morning peak in sightings but not the expected afternoon peak.

Machine Learning

Despite the poor performance of our machine learning methodology in identifying images that contained deer or humans, our logistic regression model did provide some suggestion that images that were more dissimilar from the reference image were more likely to contain deer or humans. This suggests the potential usefulness of the SSIM in identifying images that contain wildlife. Further development of machine learning methodologies that use the SSIM could result in algorithms that could detect the presence of wildlife in images with greater accuracy. This could greatly increase the efficiency of data collection from large numbers of images. One method of machine learning for automated species identification that has recently advanced has been the technology for deep learning neural networks (Wäldchen & Mäder, 2018) .

Conclusion

The findings of this study add to the body of evidence that shows that non-consumptive recreation in protected areas can affect the behavior of wildlife. Though we did not find strong evidence that human traffic affects diel movement patterns specifically, we did confirm previous findings that increased human traffic does reduce deer sightings in a particular area. Our results also suggest that the SSIM may be useful in increasing the efficiency of research that must pull data from thousands of images. Overall, our research highlights the fact that human impacts on the natural world can be subtle. Understanding even these small effects can help us determine how we can act in ways that are in greater harmony with the plethora of living things we share this planet with.

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