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RH: Wildey and Bickford 2024 • Mule Deer Habitat Selection and Density

**Near and Deer: Individual and Population Responses of Mule Deer to Human Recreation**

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**ABSTRACT** Outdoor recreation extends human influence on landscapes beyond built environments but is often thought to be compatible with wildlife conservation. Human capability as a highly efficient predator creates a strong selective force on wildlife, analogous to natural predation risk, regardless of trophic level. Behavioral responses of wildlife have been observed across taxa but linking these changes in individual behavior to population-level responses represents an important step in understanding and mitigating the impact of our everyday presence on ecosystems. Here we present results of an integrated step selection analysis (iSSA) of the habitat selection exhibited by ten mule deer (*Odocoileus hemionus*) in response to environmental and human factors and the possible impact on population density. Mule deer in our study area had differential habitat use and movement characteristics with time of day and intensity of human disturbance. Mule deer increasingly selected for forest land cover as human presence increased. Deer showed different movement responses with increasing human presence depending on the time of day. Changes to habitat selection and movement patterns have important implications for habitat management of winter range and potential costs to deer populations. Pairing our movement data with camera data, we found evidence for a low density of mule deer on our winter range compared to winter ranges across Colorado possibly caused by human recreation. Low densities of mule deer has implications for the role density-dependent effects play in modifying the impact of recreation. Our study provides critical information on the role human recreation plays in modifying the effectiveness of habitat management on deer winter ranges and possible scenarios this may scale up to impact mule deer populations.

**KEYWORDS** camera traps,Colorado, density dependence, habitat selection, human recreation, integrated step selection functions, mule deer, *Odocoileus hemionus,* time to event modeling

Humans play many roles in ecosystems locally and globally. One of the simplest but most profound impacts we have is through our presence, as our capabilities as highly efficient predators has been found to affect wildlife in many ways (Darimont et al. 2015, Larson et al. 2016). These effects are felt even when our activities are non-lethal, as is the case with recreation (Smith et al. 2021). Importantly, these impacts transcend individuals to influence populations, and communities (Larson et al. 2016). Uncovering how impacts at these different hierarchical levels are related, and when negative consequences scale up is important for mitigation, however these mechanisms are understudied (Marion et al. 2020, Wilson et al. 2020).

Protected natural areas often face a dual mandate to conserve natural resources and provide recreational opportunities, which garner public support and serve as a financial incentive for land conservation (Reed and Merelender 2008). Recent reviews have identified a need to more accurately measure the magnitude of recreation, in part to help identify thresholds at which negative effects transition to long term impacts (Larson et al. 2016, Marion et al. 2020). Determining these thresholds, and the mechanisms by which they occur, can inform the balance of needs between recreation and conservation (Marion et al. 2020, Wilson et al. 2020).

In response to human presence, animals may flee, hide or increase their vigilance behavior. These interruptions disrupt fitness-enhancing behaviors such as foraging, parental care or mating (Frid and Dill 2002). Individuals may take a more proactive response avoiding risk across the landscape by altering their spatiotemporal niche (Lesmerises et al. 2017, Ladle et al. 2019, Suraci et al. 2019). Increasing nocturnal activity (Gaynor et al. 2018, Naidoo et al. 2020, Sévêque et al. 2020), and/or changing the type of habitat selected or altogether avoiding habitat near trails (Muhly et al. 2011, Coppes et al. 2017, Ladle et al. 2019, Smith et al. 2018) have all been observed. Such changes are also reflected in decreases or increases to movement rates, depending on the species and chosen response (Tucker et al. 2018, Doherty et al. 2021).

Interruption of fitness- enhancing behaviors, alteration of spatiotemporal niche, and increased movement costs provide possible mechanisms of individual changes scaling up to populations. The relationship between impacts at the individual-level and population-level is not always straightforward, as modulators like density dependence and habitat quality can alleviate or aggravate expected effects (Tablado and Jenni 2017). Density-dependence theory predicts populations well below carrying capacity experience less competition for forage and are in better body condition, potentially mitigating the negative impacts of recreation at the individual level (Stewart et al. 2005, Bowyer et al. 2014). Improved habitat quality could allow for the compensation of energetic losses at the individual-level through more nutritious and abundant forage.

Habitat management to improve habitat quality for overwintering mule deer (*Odocoileus hemionus*) is a common practice, with research supporting the idea that winter habitat is limiting populations declining range-wide (Unsworth 1999, Bishop et al. 2009, Bergman et al. 2014, Bergman et al. 2015, Bombaci and Pejchar 2016). To alleviate some of these challenges, habitat management has focused on deer winter range with thinning of pinyon-juniper forest intended to improve winter forage (Bombaci and Pejchar 2016, Miller at al. 2019). These efforts have been shown to increase overwinter fawn survival, an important bellwether for mule deer populations although a corresponding increase in deer density was not observed (Bishop et al. 2009, Bergman et al. 2014, Bergman et al. 2015).

Research on how human recreation affects mule deer is rather limited and its interaction with habitat management has not previously been considered. Multispecies camera studies have detected temporal responses of mule deer to recreation, documenting decreases in daytime activity during times of increased human presence but not observing shifts in space use away from cameras with the highest human activity (George and Crooks 2006, Reilly et al. 2017). Return times to specific sites have also shown to be impacted, with human presence typically a more important factor in determining the timing of these recursive movements than the presence of predators or competitors (Visscher et al. 2023). Previous telemetry research determined deer increased movement rates slightly during periods of biking, hiking, and horseback riding in comparison to a control but did not observe a change in flight responses between treatment and control, suggesting deer might be responding to recreation with fine-scale changes in habitat use (Wisdom et al. 2004). This previous work demonstrates behavioral responses of mule deer to recreation, however whether these more nuanced behavioral changes are, or are not, transmitted to populations can better inform management efforts for mule deer and possibly other species showing similarly nuanced responses.

Here we examine mule deer responses to recreation on winter range in Salida, Colorado. The goal of this study was to investigate behavioral changes of mule deer to human recreation and the link to possible population level change in deer density. Our objective was to 1) identify if mule deer are which habitats they’re selecting avoiding areas near trails, or changing when they are most active in response to human presence on trails, 2) assess how these changes relate to habitat management actions, 3) obtain an index of deer density across our study area as a product of environmental factors, and 4) explore whether behavioral alterations at the individual level can amplify to changes in deer density at the population level.

**STUDY AREA**

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Our study area was near Salida, Colorado, USA (approximately 38° 30´ 8" N and 106° 0´ 41" W). Salida sits in the Arkansas River Valley and is an outdoor recreation hub for a variety of outdoor activities including mountain biking, hiking, whitewater rafting, skiing and snowboarding. Elevation ranged from 2180m – 2465m. Mean annual precipitation is 282mm, mean annual minimum temperature is -1.26° C and mean annual maximum temperature is 15.98° C (Oregon State University PRISM Climate Group 2012). Land cover type varied from developed land on the edge of town to agricultural lands, grasslands, and pinyon-juniper forest in the foothills. The Methodist Mountain trail network is on Bureau of Land Management property south of Salida, Colorado. Methodist Mountain is the northern terminus of the Sangre de Cristo range which is characterized by pinyon dominant pinyon-juniper forest with cottonwood (*Populus deltoides*) growth along major washes and interspersed patches of gambel oak (*Quercus gambelii*). Habitat management has been performed for the purposes of fuel reduction, habitat management, and watershed improvement (Miller et al. 2019). This involves thinning of pinyon juniper forest on flat ground accessible to machinery. This thinned habitat appears on land cover classification layers as “shrub” habitat as opposed to surrounding “forest” habitat. The managed habitat promotes the growth of shrub species such as golden currant (*Ribes aureum*), mountain mahogany (*Cercocarpus ledifolius*), and rabbitbrush (*Ericameria spp.*). Our study area serves as a winter range for a migratory population of mule deer who migrate about 11km southwest to summer range across the San Luis Valley.

**METHODS**

**Field methods**

Six mule deer were captured using clover traps baited with corn and alfalfa, and four were free darted from a vehicle and chemically immobilized (April 2021 and November 2021 – February 2022). Capturing, handling and radio-tagging procedures were approved by the Institutional Animal Care and Use Committee at Colorado State University-Pueblo (Protocol #: 000-000A-028). Ten deer had a Cellular Tracking Technology (CTT) GPS-GSM Solar-powered CTT®-ES400 ear tag placed in their ear (Cellular Tracking Technologies, Cape May, New Jersey), with a cattle tag placed in the opposite ear. Locations were taken every 2-4hrs depending on solar charge of the batteries; for analysis purposes 4 hour location intervals were used. Nine deer total, three males and six females, and 1,354 locations were ultimately used for this analysis.

We arranged 36 cameras in a grid pattern at a spacing of ~400m for a totral grid area of ~5.6km. 6 LTL Acorns LTL-5310A and 31 Bushnell Prime Low Glow Trail Cameras. Cameras were set to motion trigger and took 5 photos per trigger for Bushnell cameras and 3 pictures per trigger for Acorn cameras, with a 1-minute quiet period and high sensitivity setting. Specific camera locations were randomized within a 100m buffer of the center of each grid cell using QGIS, following recommendations for *a priori* rules when deploying cameras for our specific analysis (Loonam et al. 2021). Microsite selection involved placing cameras along a corridor of travel established by humans or animals within 30m of randomized point. Hiking trails were used if they were present within the microsite search area for camera placement. Cameras were placed at knee height, 5m off path of travel at a 30 degree angle to maximize exposure time of animals crossing the camera frame. Cameras were deployed from April 2022- August 2022 and checked once approximately halfway through deployment. Trail camera photos were uploaded to Wildlife Insights for processing photos using an artificial intelligence model trained on 35+ million images (Ahumada et al. 2020). Wildlife Insights was used to filter out blank images, which can be identified 88% of the time with an error rate of less than 2% (Wildlife Insights). Photos tagged as containing an animal were reviewed for identification, while a subset of blank images was reviewed for quality assurance.

**Covariates for analysis**

Trailheads at either end of the study area were equipped with infrared trail counters from which human activity was estimated. A TRAFx trail counter (TRAFx Research Ltd., Canmore, Alberta, CA) was placed on the actual trail while a TRAFx vehicle counter (TRAFx Research Ltd.) was placed on the parking lot recording the number of cars. While this does not count the exact number of trail users from one end of the trail network, we assume it is an accurate index of human activity originating from that trailhead. Trail counters recorded the number of people per hour. We summed the number of users from each trailhead and created a rolling average of trail users from the current hour and the previous 3 hours to match our GPS fix interval. Distance to trail for each location was also included as a covariate to test for avoidance of the trail network resulting in loss of habitat.

We included layers of terrain ruggedness index (TRI), aspect and landcover type to model habitat selection. TRI was chosen to not only represent rugged terrain but also as a proxy for predation risk from mountain lions, a primary predator of mule deer, as has been done in other studies (Kohl et al. 2019, Smith et al. 2019). Aspect, measured in radians, was cosine transformed to represent “northness”, as deer may preferentially select warmer south-facing slopes in winter (Sawyer et al. 2006, Anderson et al. 2012, Coe et al. 2018).  Land cover classes were modeled using the most recent landcover data from the National Land Cover Database (NLCD) in 2019 (DeWitz 2021). Landcover classes were simplified into forest, shrub, herbaceous, developed and wetland land cover types. Thinned forest from habitat management was represented by the shrub land cover class from the NLCD. Land cover types associated with human development were considered as available habitat for mule deer in our analysis and not excluded, due to the presence of a resident deer population in the town of Salida indicating this habitat could be used. Wetland habitat represented riparian vegetation along a stream. Time of day for each location was classified as day, night or crepuscular using the time\_of\_day function in R package animal movement tools (Signer et al. 2019), and then used to subset data to evaluate the temporal aspect of habitat selection. All continuous variables were scaled and centered for analysis.

*Environmental Covariates - Density Estimate*

Relative human activity was measured as weekly detections of humans at camera sites. Previous research has recognized the importance of scale in species-habitat relationships (McGarigal et al. 2016, Moraga et al.2019), therefore we included measurements of variables at multiple scales to account for the scale of effect (Moraga et al. 2019). An estimate of slope at camera site and mean slope within 100 meters of camera site was derived from a digital elevation raster. Landcover classes were extracted from the National Land Cover Database for 2019 (DeWitz 2021) and simplified in the same manner as for the habitat selection portion of the study. Forest and shrub land cover was modeled as a percent land cover within three different buffer distances of camera locations — 100m, 250m, and 385m. Distance to herbaceous cover, assumed to be a proxy for high quality forage for mule deer based on our habitat selection study, was also included as a variable. Trails in the study area were digitized and trail length was measured at the grid cell scale and within 100m of camera locations. All continuous variables were scaled and centered for analysis.

**Habitat selection statistical analyses**

We analyzed deer spatiotemporal habitat selection using integrated Step Selection Analysis (iSSA) which simultaneously estimates a component modeling habitat selection free of movement constraints and a component estimating a likelihood of selection based on movement parameters in a homogeneous environment (Avgar et al. 2016). This analysis compares used steps, those taken by the animal, to available steps, calculated by combining a random step length and turn angle sampled from distributions fit to the empirical observations of step length and turn angles. The model calculates a probability of use between 0 and 1 as the response variable based on the binary used (1) and available (0) points (Fieberg et al. 2021). Used steps were paired with 20 available steps in this analysis (Avgar et al. 2016, Fieberg et al. 2021). We fit a von Mises distribution to observed turn angles and a lognormal distribution to observed step lengths as a heavy tailed distribution better fit the probability of larger step lengths.

We used a mixed Poisson regression to calculate population level estimates of habitat selection. A Poisson regression, with stratum-specific intercepts fixed at a large variance, is likelihood equivalent to the conditional logistic regression that is traditionally used in iSSA (Muff et al. 2020). But the Poisson regression allows for the incorporation of random slopes that are computationally and mathematically challenging when fit with conditional logistic regression models (Muff et al. 2020). This allowed us to account for dependence among locations from the same individuals and variation in responses to different habitat and human-related covariates. Mixed models were compared to fixed effect models using information criteria to ensure the incorporation of random effects produced the best performing models. Regression analyses were run using the R package glmmTMB (Brooks et al. 2017).

Models fit to data included a null model that contained only attributes of movement representing how an animal would move free of selection for habitat. Parameters included cosine-transformed turning angle, cosine-transformed turning angle squared, log step length and the squared log step length. Cosine-transformed step length converts this circular variable into a variable where 1 represents no change in turn angle and -1 indicates a 180° change in direction, with left and right turns represented by 0. This allows us to account for the tendency of movement in the same direction. Cosine-transformed turning angle squared was added as a covariate after initial data exploration indicated deer exhibited a tendency to persist in direction of travel (1) or travel in the exact opposite direction (-1). Log step length and squared log step length were included because the estimated coefficients of these step length parameters can be combined with the estimated parameters of our observed lognormal step length distribution to update our step length distribution (Avgar et al. 2016). Furthermore, we can include interactions with these movement parameters to allow movement distributions to change depending on environmental conditions (Fieberg et al. 2021). Movement parameters interacted with human activity were used to update step length distributions from the model to explore changes in movement patterns in response to human activity.

The null model with just movement parameters explained above was fit to test if models involving habitat selection parameters could outperform a model assuming movement irrespective of habitat selection (Fieberg et al. 2021). A habitat model was fit incorporating habitat covariates (land cover classes, cosine-transformed aspect, terrain ruggedness index) and a human activity model was fit with main effects of, and an interaction between, rolling average of human activity and distance to trail. Two variations of a global model were fit, the first of which included interactions between movement characteristics and rolling average of human activity. We used this interaction to investigate how movement behavior changed in response to changes in human activity. The second global model contained an interaction between rolling average of human activity and forest habitat selection. The five models were fit on the whole (pooled) dataset, a dataset for points at night and a dataset for points during the day. Continuous variables were scaled and centered. Analysis was not done with the crepuscular time period due to a small sample size caused by the small window of time classified as crepuscular. Models were evaluated using Akaike Information Criterion (AIC) (Burnham and Anderson 2002).

To compare and visualize deer movement patterns in relation to human activity between different time periods including crepuscular times, we used a linear mixed effects regression in R package nlme (Pinhiero and Bates 2023), with a log-transformed response variable of mean movement rate (meters/hour) over each time period of each day for each individual. We tested a model with an interaction between human activity and time of day versus a model with just the main effects of human activity and time of day. Since human activity could not be incorporated at the hourly level, we used a daily measurement of human activity as an explanatory variable. Human activity measurements for movement rates at night corresponded to the previous day's value of human activity. We included a random effect for individual deer and the main effect of sex in both models. Models were checked for fit with residuals and qq plots and evaluated using Akaike Information Criterion (AICc) (Burnham and Anderson 2002).

*Time-to-event Camera Analysis*

Time-to-event modeling (TTE) (Moeller et al. 2018, Loonam et al. 2021), is a part of a relatively new set of models using camera viewsheds to estimate abundance of unmarked populations. TTE specifically allows us to leverage movement data from mule deer telemetry, in combination with captures of our study species on trail cameras to estimate abundance (Moeller et al. 2018). TTE and similar statistical approaches (space-to-event, random encounter models) sample the landscape as opposed to modeling unmarked animals and therefore do not carry the same difficult assumptions as other models to estimate unmarked populations of animals (Loonam et al. 2021a, Moeller et al. 2022). More specifically, TTE models the distribution of animals in the collective viewshed of all the cameras as a Poisson distribution and utilizes the connection to the exponential distribution, representing the amount of time it takes for a Poisson distributed event to occur (Loonam et al. 2021a). Therefore, we measure the number of sampling periods it takes for an animal to appear during a sampling occasion to then estimate abundance. These measures are repeated across time and across space at multiple cameras allowing us to model heterogeneous density at individual cameras based on environmental factors (Moeller et al. 2018, Loonam et al. 2021a). Time-to-event models have been shown to have more precise estimates than space-to-event or random encounter models (Morin et al. 2022), and estimated densities are comparable to more intensively derived density estimates (Loonam et al. 2021).

An estimate of speed is required to define the sampling period as the time it takes to cross the viewshed of a camera (Moeller et al. 2018, Loonam et al. 2021). Estimation of speed is non-trivial, as movement rate measured in discrete time is dependent on sampling rate with coarse time scales under-estimating speed and very fine time scales over-estimating speed (Noonan et al. 2019, Poulin et al. 2021). Over- and underestimating speed has been shown to cause a linear bias in density estimates from TTE models (Loonam et al. 2021a, Santini et al. 2022). To solve this, we calculated speed using continuous time movement modeling which has shown to be robust to variable sampling rates (Noonan et al. 2019), while also calculating movement rate from more frequent (<1hr) locations, estimating density from both movement rates. Viewshed area was estimated as 45m², based on ex situ measurements of camera detection area used in other TTE modeling applications (Loonam et al. 2021). Other measures of trail camera viewshed area include a total viewshed area of 87m² area with detection reduced to 22-65m² depending on direction of animal movement in a controlled test (Apps and McNutt 2018), and 106m² used in similar space-to-event modeling (Ausband et al. 2022). To account for uncertainty in camera viewshed we estimated density at three different measurements of viewshed area, sampling camera viewsheds from a normal distribution centered around 45m², 65m², and 80m², all with a standard deviation of 5m².

A time frame from April 14, 2022- May 15, 2022 was chosen for an overall density estimate for the study area. This timeframe was chosen to match the timing of our habitat selection study on deer winter range, with the earliest migration date found among collared deer to be May 15. To separately investigate heterogeneous density among cameras, the entire deployment period (April 2022-August 2022) was used to maximize data available for estimation of density at individual cameras. When the assumption of a closed population is violated, TTE models estimate average abundance across the duration of the survey (Loonam et al. 2021). Following the recommendations of Moeller et al. 2019, fewer number of sampling periods per occasion were used for modeling density at individual cameras, accounting for animals in the immediate vicinity of the camera (Moeller et al. 2018). Heterogeneous density was modeled at individual cameras using generalized linear models with a gamma distribution and identity link function. Given the small sample size, environmental (slope and land cover at different scales, distance to herbaceous cover) and human factors (trail density at different scales and relative human activity at the camera) were tested individually before combining the environmental layers that best predicted the data, as measured by ΔAIC, with human factors.  Models were checked to ensure assumptions were met and evaluated using Akaike Information Criterion for small sample sizes (AICc) (Burnham and Anderson 2002).

**RESULTS**

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**Pooled iSSF model**

The best fit model for the pooled dataset was the global model containing an interaction between forest land cover and rolling average of human activity (“Global 2” model, Table 1). Due to a large difference in ΔAIC and model weight, we proceeded with inference from this model. The posterior estimates for the effects of all covariates can be seen in Figure 2. The interaction for forest land cover and rolling average of human activity was found to have a strong, positive effect on selection, meaning as the rolling average of human activity increased, selection for forest habitat as compared to shrub habitat increased. Herbaceous and wetland landcover types also have a strong positive effect on selection in relation to shrub habitat. There is a weak, positive effect of forest habitat on selection. Lastly there is a strong, negative effect of distance to trail on selection implying selection for areas closer to trail.

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**Day iSSF model**

The global model including interactions between human activity and movement characteristics was the best fit model for the day dataset (Table 2). In terms of habitat selection, we found a weak, negative effect of herbaceous land cover on selection, while we see a weak, positive effect for forest land cover on selection (Figure 3). Suggesting a minor avoidance of herbaceous land cover and selection for forest land cover during the day. There is a significant, positive effect of wetland land cover, meaning wetland habitat along a riparian corridor was preferred during the day (Figure 3).

We also see significant interactive effects with movement characteristics. Interactions between log step length and human activity and squared log step length x rolling average were significant. Using the beta coefficients from our model we can update our step length distribution to facilitate interpretation of this interaction on movement behavior. Doing so produces Figure 4 illustrating that as human activity increases the step length distribution changes and deer are move less.

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**Night iSSF model**

For our nighttime model set, the global model with an interaction between movement characteristics and human activity once again was the best fit model similar to the day dataset (Table 3). There was a strong, positive effect of herbaceous land cover type on selection), indicating deer selected for herbaceous land cover at night. There was also a significant interaction between human activity and log step length (Figure 3). Similar to our day iSSF model, we can update our step length distribution with the beta coefficients from our interaction terms to ease interpretation. This indicates a greater likelihood of longer step lengths with increasing human activity at night implicating deer move more at night with increases in human activity (Figure 5), albeit this is a smaller effect when compared to the step length distribution for the daytime analysis.

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**Movement rate regression**

The model including an interaction between daily human activity and diel period was the best fit model. Daily human activity had a strong, positive effect on movement rates, and deer movement rate was smaller at night compared to crepuscular times of day, while daytime movement did not differ significantly from crepuscular time periods (Figure 6). Male deer had higher movement rates and the effect of human activity interacting with time of day was significantly negative for both day and night in comparison to crepuscular times of day (Figure 6). Figure 7 shows the effect of this interaction, with deer increasing their movement rate most during crepuscular periods of the day in response to human activity and also showing increases in movement rate during the night in response to human activity. Meanwhile we see a decrease in deer movement in response to human activity during the day (Figure 7).

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**TTE modeling**

Overall deer density estimates on the study area dependent on camera viewshed estimates were 4.21 deer/km² for a viewshed area of 45m², 3.42 deer/km² for a viewshed area of 65m² and 2.87 deer/km² for a viewshed area of 80m² (Figure 8). As parameters estimates for camera viewshed area increased, density estimates for mule deer decreased.

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Overall deer density estimates dependent on movement rate estimates for mule deer were 13.91 deer/km² at a movement rate of 41 meters/hr, 4.61 deer/km² at a movement rate of 106 meters/hr and 1.80 deer/km² at a movement rate of 208 meters/hr (Figure 9). The movement rate of 208 meters/hr was estimated from an average movement rate of continuous time movement models fit to the movement data of 9 deer. As deer movement rate increased, estimates of deer density decreased.

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Data was sufficient to estimate densities at 21 individual cameras. Four models had a ΔAICc < 2 (Table 4) and were model averaged to get final parameter estimates. All four models contained either trail density at a grid cell scale, or relative human activity. The full model average resulted in no strong effect of any of the covariates and camera-level density (Figure 10). The intercept, or average density at cameras, was 0.613 deer/km², trail density at the camera grid level had a non-significant, negative effect; relative human activity had a non-significant, negative effect and slope had a weak, non-significant, negative effect.

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**DISCUSSION**

**Deer habitat selection and movement patterns**

With both our pooled dataset and separate day/night datasets, the models that best explained the data incorporated anthropogenic and habitat factors. Our model for the pooled dataset indicated a change in habitat use with increasing human activity, as indicated by a significant interaction between rolling average of human activity and forest habitat in reference to shrub habitat. The shrub habitat, increasingly avoided by deer with human activity, is indicative of areas where forest management has been implemented for fuel reduction and habitat management (Miller et al. 2019). This involves mastication of pinyon and juniper trees in areas flat enough for heavy machinery, resulting in thinned, open savannah-like habitat. A loss of foraging opportunities could result from this shift in habitat preference, with the shrub habitat providing a greater abundance and diversity of browse for mule deer (Bombaci et al. 2016, Miller et al. 2019). Habitat management of winter range for mule deer may be rendered less effective with increasing human recreation as potentially important cover habitat is removed and productive foraging habitat is perceived to be riskier. Thoughtful consideration of the goals of pinyon-juniper management may be needed to balance the needs of wildlife management along with other benefits of this practice (Miller et al. 2019). However, compromise may exist in the patch size and arrangement of treatments. Short et al. 1977 examined deer use across different thinning treatments finding that small patch cuttings (≤0.5km) were used more often by deer and that the arrangement of treatment patches near undisturbed woodland was important for use. Further examination of this question could help resolve equivocal results on the utility of pinyon-juniper habitat management to mule deer population health.

This change in habitat preference as a result of human presence has also been observed in other wildlife species (Cristescu et al. 2013, Smith et al. 2019). Competing mesocarnivore species in high use open spaces, showed greater habitat overlap between a generalist carnivore – coyote – and more specialized carnivores, gray fox and bobcat, than low use open spaces (Smith et al. 2018). Grizzly bears showed changes in selection for resting sites depending on level of human activity (Cristescu et al. 2013). This pattern suggests niche compression due to human activity (Gilbert et al. 2022) could be at play on our study area, if deer are facing competition from other herbivores, such as elk, simultaneously altering habitat selection in response to human presence. Further research of competition with other ungulate/herbivore species from niche compression could reveal an indirect pathway impacting mule deer, or competing ungulate species, initiated by increased human presence. Greater intraspecies competition could also result from increased human presence as well if individual deer are seeking a similar solution to human presence.

Mule deer also show divergent responses to increasing human activity depending on the time of day. During the day, deer moved less in response to increasing human activity while at night and during dawn/dusk they moved more. Changes to activity patterns of mule deer, and specifically reducing daytime activity, have been found in camera studies looking at deer response to human activity on trail networks (George and Crooks 2006, Reilly et al. 2017, Nix et al. 2018, Lewis et al. 2021). The only other telemetry study examining this question found slightly increased hourly movement rates for deer when looking at activity patterns during four recreation activities in comparison to a control and suggested, as we found, that deer might be seeking different habitat in response to high human activity (Wisdom et al. 2004). On a global scale, human footprint has been shown to reduce terrestrial mammal movements and increase wildlife nocturnality (Gaynor et al. 2018, Tucker et al. 2018), while a different review found that human disturbance changed animal movement across taxa, with disturbance caused by human activities like recreation causing a greater effect than habitat modification (Doherty et al. 2021).

There was a negative effect of distance to trail on deer habitat selection, indicating selection for areas near trails and no indirect loss of habitat caused by human recreation. This is also reflected in camera work indicating no spatial avoidance with an increase of human activity on trail networks (George and Crooks 2006, Reilly et al. 2017, Lewis et al. 2021). Previous telemetry work similarly did not find avoidance of trail by mule deer unlike elk (Wisdom et al. 2004), indicating the possibility that elk could be more sensitive to human presence. However, indirect loss of habitat has been found for mule deer on winter range in response to natural gas drilling (Sawyer et al. 2006). Distance to trail was modeled as a linear response in my model set. It is possible the relationship between habitat selection and distance to trail is more complex, resulting in selection for an intermediate distance from trail. A lack of spatial avoidance may not be a reliable indicator for a lack of effect either, as suitable, alternative habitat may not exist or be accessible (Gill et al. 2001). Deer are already constrained by snow and human development on winter range, possibly limiting alternative, suitable habitat. Many of the individual deer in this study also utilized habitats where farther from trail meant closer to humans, such as developed land cover, actively managed and fallow agriculture fields, and riparian habitat. The trail network could in fact allow deer to balance foraging risk tradeoff by offering a less risky habitat in comparison to open fields to utilize during the day for refuge. Deer could also prefer similar biophysical characteristics we use for trails that we did not consider in this model, coincidentally causing this preference for areas near trails. Deer could also be habituated to the repeated stimuli of recreation showing decreased responses in terms of avoidance, as ungulate populations in areas of high human presence have shown weaker flight responses (Stankowich 2008)

Potential foraging habitat, represented by wetland and herbaceous land cover, did have a positive effect on selection, with these land cover types creating a strong enough draw to overcome proximity to human development dependent on time of day. It is important to remember that habitat selection parameters should be interpreted as relative intensity of use, meaning that all other factors being held equal deer will choose wetland or herbaceous cover over forest landcover (Fieberg et al. 2021). In reality, herbaceous and wetland habitat is an order of magnitude rarer in availability than shrub or forest habitat. Selection does not indicate where an animal is likely to be found most of the time, but where it selects for with all other variables held constant and different habitat being equally available (Fieberg et al. 2021). Taken this way, we can interpret deer as being choosy about what habitat they are in when they are far from the trail and balancing their risk of foraging closer to developed habitat when far from trail by utilizing these habitats during times of human inactivity. The potential non-linearity of selection in response to distance from trail could also resolve the seemingly contradictory conclusions from distance to trail and selection of herbaceous and wetland habitat. Utilization of wetland and herbaceous habitat during different times of day, analyzed in our separate day/night datasets further clarify how deer balance selection based on time of day associated with differing behaviors and human activity.

During the day deer selected for wetland habitat, while at night we see selection for herbaceous habitat. Importantly, herbaceous landcover covariates seem to be time dependent, with a weak, negative effect for selection during the day but positive effect of selection at night. Contrasting habitat selection estimates based on time of day suggests a spatiotemporal strategy to balance needs for cover and foraging, with deer preferring habitats offering more cover during the day and habitats associated with better forage at night. This indicates the ability of mule deer to spatiotemporally avoid risk in an important habitat type more closely associated with humans, akin to balancing forage-risk tradeoffs with natural predators active during different times of the day such as wolves and mountain lions (Kohl et al. 2019, Smith et al. 2019).

**Measurement of recreation**

Human recreation involves both human presence and human infrastructure. While both can have an impact on wildlife, infrastructure is often measured and serves as a proxy for recreation with only 6.7% of studies remotely monitoring recreation activity (Larson et al. 2016). Human activity is also commonly measured as a binary with high and low use areas, but this may not put a specific number to human activity or track changes over a continuum of activity (Larson et al. 2016). Use of infrared trail counters for tracking human presence fulfills the need for better measurements of human activity needed in recreation research (Marion et al. 2020). Trail counters provide a valuable metric down to the hour, and measure trends over longer periods of time than was needed for this study, making it possible to monitor long term recreation trends. Trail counter data provides a useful tool for managers looking to manage trail traffic and detect thresholds at which human presence might become significantly more damaging (Monz et al. 2013, Larson et al. 2016). Our research using both measures of human activity (trail counter data) and infrastructure data (distance to trail) disentangles the two components human recreation brings, isolating the effects of changes in human presence while accounting for infrastructure associated with recreation.

**Deer density estimates**

Time to event modeling is part of a relatively new set of models still under development, with separate simulation studies finding an overestimation (Santini et al. 2022) or an underestimation (Moeller et al. 2018) of density, depending on the animal movement model used in simulations. Uncertainty and bias in estimates can also be introduced when assumptions of the model are not met, and we follow recommendations in consideration of these violations (Gilbert et al. 2021). Previous research into TTE models indicated they are robust to some assumptions but suffer decreased accuracy and bias when movement rate was poorly estimated, when cameras are placed non randomly with respect to habitat, and with inaccurate measurements of camera viewshed area (Moeller et al. 2018, Loonam et al. 2021, Santini et al. 2022, Moeller et al. 2023). However, previous studies found TTE models to have comparable estimates of density to more established methods (Moeller et al. 2018, Loonam et al. 2021a). We attempted to account for uncertainty in movement rate using two estimates of movement rate from discrete movement data, including intervals between locations less than 2 hrs (41 meters/hr), less than 1 hr (106 meters/hr) and using a continuous time movement model robust to the resolution of location data (208 meters/hr) (Noonan et al. 2019). With density estimates decreasing with movement speed, we suspect, if anything, a positive bias in density (Loonam et al. 2021a, Santini et al. 2022). At the landscape level, cameras were placed systematically, and were then placed randomly within grid cells, while trails were targeted within proximity of randomized locations. Cameras were placed randomly at 2 of 3 scales, and followed recommendations of *a priori* rules for camera deployment (Loonam et al. 2021). Cameras placed randomly at microsite scales could be impractical with camera viewsheds potentially being obstructed and censored from analysis (Loonam et al. 2021). We would expect our non-random placement of cameras along travel corridors, would increase detection rate and would once again bias estimates high (Loonam et al. 2021). We attempted to account for uncertainty surrounding camera viewshed area estimates by including density estimates at three different parameter values, finding a decrease in density estimates with an increase in camera viewshed area. Given our conservative estimate of camera viewshed area, we again suspect this may overestimate deer density, while other studies have similarly used a single value to represent viewshed area across all cameras (Moeller et al. 2018, Loonam et al. 2021, Ausband et al. 2022, McMurry et al. 2023). Considering our attempts to account for uncertainty in estimates in our area and movement rate parameters, previous findings indicating comparable estimates of TTE models to other estimates of density, and the violation of all these assumptions more likely leading to overestimation of density, we feel confident in our density estimates reflecting a low density of mule deer on our study area in comparison to other winter ranges.

Density of mule deer on our study area was estimated using time to event modeling resulting in estimates of 1.8-13 deer/km² depending on different estimates of camera viewshed area and movement rates. We focused our density estimates in pinyon-juniper habitat as we were most interested in the density of deer this predominant winter range habitat type could support and this is where recreation took place. Density estimates for other winter ranges in Colorado include estimates ranging from 4-14 deer/km² to 20-84 deer/km² across the Uncompahgre Plateau (Bergman et al. 2015). Earlier mule deer density estimates from the same range were <2 to >30 deer/km², with chosen study sites having densities that varied between 31-59 deer/km² regularly reaching 85 deer/km² (Bishop et al. 2009). Elsewhere in Colorado, mule deer density estimates on a winter range impacted by natural gas development were ~6-14 deer/km² (Northrup et al. 2021), while earlier estimates on the same range were ~40-80 deer/km² before natural and intended reductions brought densities down to ~20 deer/km² (White and Bartmann 1998). By comparison, our estimate of mule deer density is on the low end for reported densities in comparison with other winter ranges comprised of pinyon-juniper habitat, and in line with estimates of deer densities on winter range with high intensities of energy development (Northrup et al. 2021). Furthermore, while our model average results were non-significant, our top models of density estimates at individual cameras repeatedly contained human activity and trail density. With these factors explaining the data better than any other included covariates; suggesting trail density, and relative human activity may play a role in decreases in density.

While our density estimate is low compared to values from other winter ranges, this is not necessarily a reflection of human disturbance. Low densities could simply reflect timing of surveys, our density estimate took place in late spring (April-May) immediately prior to deer migrating to summer range, with deer less constrained by snow during this time of year and therefore potentially less concentrated than if surveys had been conducted earlier in winter. Additionally, lower density could be an artifact of past conditions or events that reduced density, as well as a product of limitation on summer range, although as previously discussed mule deer in Colorado are thought to be limited by winter habitat (Bishop et al. 2009, Bergman et al. 2015, Northrup et al. 2021). Lower density could also be due to poor habitat quality regardless of human activity potentially limiting nutritional carrying capacity of the range (Northrup et al. 2021). Nevertheless, the notion of anthropogenic caused habitat degradation, loss or avoidance has been suggested as a mechanism limiting carrying capacity, supporting the evidence of our individual camera density modeling (Forrester and Wittmer 2013, Johnson et al. 2017). Unfortunately, the scope of these competing hypotheses is beyond the capabilities of our study but the possibilities to expand beyond the framework of our study to answer these questions will be discussed later.

**Density dependent impacts**

Regardless of the cause, low densities raise questions about density dependence, which can modulate the impact of recreation (Tablado and Jenni 2017). For large-bodied, long-lived species like mule deer, whose life history is characterized by small litter sizes, multiple reproductive efforts, and high adult survival rates, density-dependence plays a critical role in population dynamics (Bowyer et al. 2014, Bergman et al. 2015). Increasing competition for resources at higher densities leads to worsening nutritional condition causing decreases in reproduction and survival metrics contributing to lower population growth rates (Bowyer et al. 2014, Monteith et al. 2014). With lower densities of mule deer, improved nutritional condition and reproductive rates of adult females, in addition to improved survival rates of juveniles could counteract some of the negative behavioral consequences of human recreation. While this has not been shown in ungulates, reduced densities of woodlarks in highly disturbed sites exhibited density dependent responses of larger chick masses, higher post-fledgling survival, and lower rates of starvation related nestling mortality compared with high bird density, less disturbed sites (Mallord et al. 2007). However, recreation is often associated with habitat degradation (Tablado and Jenni 2017), providing a possible mechanism for reductions in carrying capacity of disturbed landscapes to lower densities (Bergman et al. 2015). Additionally, human disturbance during calving season has been shown to impact reproductive rates of elk, indicating the timing of disturbance could cause a density-independent effect on wildlife, although elk density was not considered in these studies (Phillips and Aldredge 2000, Shively et al. 2005). Determining the impacts of recreation at the population level within the context of density dependence population dynamics will be important to understanding whether recreation simply impacts density, resulting in a smaller population with improved vital rates, or if recreation might additionally lower carrying capacity resulting in lower density populations with poor nutrition and vital rates. Measuring nutritional carrying capacity (Montieth et al. 2014) as a component in future study designs provides a pathway to answer these questions.

Density dependence has also been theorized to change habitat selection (Rosenzweig 1981, Avgar et al. 2020). While rarely investigated in wild populations of large mammals, changes in habitat selection have been documented, although with contrasting results (Merrill et al. 2020, Smith et al. 2023). The specific change in habitat selection is dictated by how resources are coupled in space, with habitat providing forage often attracting predators as well, creating a forage-risk tradeoff (Verdolin 2006). Under scenarios with low densities and decreased competition for food resources, mule deer may be able to meet foraging requirements while prioritizing safer habitat. Under these circumstances the selective force of avoiding predation is greater than that to acquire better food, while the per capita predation rate is also higher with less conspecifics around (Lehtonen and Jaatinen 2016, Visscher et al. 2016). Higher densities increase competition for lower quality forage in safer habitats and the consequences of a poor diet become more severe, changing the calculus and leading to an increased selection for forage. This relationship between density and habitat selection was documented with elk wintering in Yellowstone National Park (Smith et al. 2023). Other research into density dependent habitat selection and the tradeoff between forage and risk in elk found a higher selection for forage and safety at low densities. The speculation being that human activity was providing a refugia from wolf predation allowing elk to select safe habitat with quality forage (Merrill et al. 2020). Assumed low density on our study area could indicate deer are able to use safe habitat while meeting forage requirements akin to Smith et al. 2023 or deer could be the beneficiary of humanity as a refuge from natural predation while exploiting high quality forage, which has been described in previous studies (Berger 2007, Leighton et al. 2010, Lesmerises et al. 2017). However, this is still a new area of inquiry with uncertainty about how these relationships might translate across species, ecosystems, and different levels of human activity, but density dependent habitat selection should be considered when developing recommendations to mitigate impacts of recreation.

**Conclusions and future study**

While mule deer density can possibly provide numerical feedback indicating the severity of recreation impacts, recruitment or fawn survival could provide an earlier indication of a decline in population health for mule deer (Monteith et al. 2014). Earlier detection of deleterious effects through physiological and energetic mechanisms are important to understand to enable earlier action and detect thresholds where impacts move beyond behavioral changes. It is possible with accelerometer data to construct a landscape to understand energetic costs associated with human disturbance as has been done with mountain lions in California (Nickel et al. 2019).

Mule deer have shown a capability of adapting to human disturbance in increasingly urbanized areas as illustrated by resident populations of deer being those closest to human development (Robb et al. 2019). Our population demonstrates that deer who summer in comparatively natural habitats can still depend on increasingly urbanized winter ranges. Mule deer migration is culturally transmitted and declines in ungulate migration have been associated with increasing human development, possibly due to constraints to movement caused by anthropogenic barriers or availability of preferred forage within human environments (Bolger et al. 2008, Robb et al. 2019). Increasing human presence on winter ranges could contribute to a loss of migratory individuals by amplifying fear effects to impact populations or the desensitization of deer to human presence, either way resulting in losses of migratory deer. Simultaneous influences of human development and recreation must be considered, these two different aspects of humanity have differing effects, but synergy between them could amplify the problem. Barriers and potential loss of foraging habitat near town through conversion to higher intensities of human development could act in concert with increasing trail presence to further constrain deer between deep snow at higher elevation, human development, human presence on trail, and natural predators. Loss of migratory movements can eliminate typical dual-range migrants or other variations in migration, such as multi-range migrants or partial migrants, decreasing diversity in migration behavior and limiting available strategies to adapt to a changing world (van de Kerk et al. 2021). The outcome of these changes to mule deer winter range and potential consequences to migratory behavior requires more study.

Most research examining mule deer responses to recreational activity has looked at immediate behavioral responses, such as probability of fleeing and fleeing distance (Taylor and Knight 2003) or used camera traps to examine activity patterns and occupancy patterns (George and Crooks 2006, Muhly et al. 2011, Reilly et al. 2017, Nix et al. 2018, Lewis et al. 2021) with only one other study using telemetry data (Wisdom et al. 2004). This was surprising given that cervids are the most studied group of wildlife in terms of recreation research (Marion et al. 2020). Our study provides important, detailed examination of deer habitat selection and movement considering multiple strategies mule deer may use to cope with human presence. Changes in the selection of managed habitat, increased movement costs, and loss of foraging opportunities may broaden impacts of human presence from individuals to populations of migratory deer increasingly constrained on their winter range. Additionally, we observed evidence for possible population level consequences from recreation in the form of reduced deer density in relation to documented estimates on other winter ranges.

Further study could build on our research using TTE modeling as a less intensive and invasive method for estimating density (Moeller et al. 2018, Loonam et al. 2021), while following further development of TTE study design (Moeller et al. 2023). Maximizing data derived from collared individuals including survival, reproduction and nutritional condition can help identify nutritional carrying capacity, revealing the role recreation plays in the limitation of wildlife species and other density-independent impacts recreation might have at the population level. With density estimations not being particularly sensitive and having high variability from year to year collecting this supplemental data will provide support for the mechanisms we propose may be important in this population (Bergman et al. 2015). Our work represents a snapshot in time with low density possibly caused by a variety of reasons that we were not able to distinguish. Longer term study following the trends of recreation over time can resolve this uncertainty present in our study design. There is still a lot we don’t know about the severity of recreation impacts, as the magnitude can be modulated by other factors such as density dependence outlined above. Understanding the behavioral pathways leading to population ramifications and ecological changes will help us determine when we should strive to mitigate behavioral changes caused by recreation and when changes may be less impactful, in order to better direct conservation efforts (Wilson et al. 2020).

**MANAGEMENT IMPLICATIONS**

While resident urban deer demonstrate the ability to adapt to human environments, resident deer are more closely associated with human development (Robb et al. 2019). Shifts in the balance of migratory and resident individuals towards residents have been documented (Hebblewhite and Merrill 2000, Middleton et al. 2013), portending poor outcomes for migratory portions of deer populations. A review of flight responses of ungulates found a robust yet weak effect of habituation at higher levels of recreation (Stankowich 2008). Reduced response to human presence may be a good outcome for deer allowing them to maintain normal behaviors, although this desensitization may lead to increased human-wildlife conflict (Thompson and Henderson 1998), increased disease prevalence (Farnsworth et al. 2005) and loss of migratory behavior (Robb et al. 2013). Similar research into energy development did not find habituation by mule deer with respect to decreased avoidance of well pads, also observing a concomitant decline in the population over 15 years of development (Sawyer et al. 2017). However responses may differ between these two disturbance types, as the most active phase of natural gas development includes noise and artificial light beyond heavy traffic volumes and human activity (Northrup et al. 2021). Unlike energy development which experiences a predictable rise and fall of disturbance over the course of development peaking with drilling and extraction (Northrup et al. 2021), the story of development for recreation is often one of escalating disturbance, with this shifting baseline requiring continuous adaptation. Indeed, more trail development is planned for our study area. Many wildlife management agencies have implemented seasonal closures of deer winter ranges to improve winter condition of mule deer through decreased disturbance. Part of our study area has an unlocked gate across the trail with signage requesting trail users avoid the trail from December 1st to April 15th. Seasonal closures have similarly been suggested to improve elk reproductive success during calving season (Phillips and Alldredge 2000, Shively et al. 2005). Efforts to mitigate disturbance on mule deer have the ancillary benefit of providing protection for species more sensitive to human disturbance.

Off-trail recreation is also an unaccounted for presence on the study area with hikers accompanied by off leash dogs being regular enough to establish several social trails through otherwise trail-less control areas. Quantifying the magnitude of this problem and limiting its extent may be important as mule deer have shown stronger avoidance responses to both off trail recreationists (Miller et al. 2001, Taylor and Knight 2003), and humans accompanied by dogs (Miller et al. 2001, Lenth et al. 2008).

The results of our habitat selection analysis and observation suggest herbaceous and riparian wetlands land cover provide an important foraging habitat for mule deer, providing a partially human-derived benefit that counteracts the negative impacts of recreation. Preventing the transition of this type of landcover to higher intensity development may be important for continuing to subsidize resources for this deer herd, as has been argued for the conservation of other species (Guitierrez-Gonzalez et al. 2015, Kreye and Pienaar 2015), although this may cause a clash with future housing needs (Wondra 2022).

The size and arrangement of thinned pinyon-juniper could contribute to mitigation with greater cover afforded by unmanaged habitat close to better forage in shrub habitat (Short et al. 1977). Current treatment areas already conform to suggested patch sizes for treatment potentially providing this mitigation. However more formal testing of patch size and arrangement should be conducted to investigate this idea to better inform future habitat management efforts.

Finally, the most effective form of mitigation may be education of recreationists. Taylor and Knight 2003 assessed visitor perceptions along with research into ungulate flight behavior, finding that ~50% of recreationists did not believe recreation was impacting wildlife. Recreationists believed they could approach wildlife closer than observed flight distances without causing harm and that other recreation types are responsible for major disturbance (Taylor and Knight 2003). Research on visitor perception of wildlife impacts was difficult to find, indicating a need for future research. Increasing awareness about potential negative consequences of recreation on wildlife could foster more responsible stewardship and perhaps hold the greatest potential in mitigating our impact, facilitating experiences that inspire us to conserve wildlife.

Snow and climate at high elevation constrains available habitat forcing migration to winter ranges where snow depths can increase movement costs and obscure nutritionally limited forage (Northrup et al. 2021). Winter range is under additional threat from human development, as humans often seeking similar biophysical traits in habitat to wildlife (Leu et al. 2008, Johnson et al. 2017). Mule deer winter range in Colorado has experienced greater residential and energy development than summer range correlating with declines in recruitment (Farnsworth et al. 2005).

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**ETHICS STATEMENT**

Capturing, handling and marking procedures were approved by the Institutional Animal Care and Use Committee (IACUC) at Colorado State University Pueblo (Protocol #: 000-000A-028) .

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Figure Captions

Figure 1: Study area overlaid with the Methodist mountain trail network, telemetry locations for 9 deer from 2021-2022, randomized camera locations and associated grid cells, and land ownership. Inset map depicts location of study area within Colorado.

Figure 2: Coefficient estimates of covariates from the top ranked model of deer habitat selection for the pooled dataset analysis. Habitat covariates include land cover types: developed, forest, herbaceous and wetland as well as terrain ruggedness index (TRI) and cosine aspect. Distance to trail and rolling average of human activity are the human covariates. This model includes interactions between rolling average of human activity and forest land cover selection.  Asterisks (\*) represent estimates where confidence intervals did not overlap zero.

Figure 3: Coefficient estimates of covariates for the top-ranked model of deer habitat selection for both the day and night dataset analyses. Habitat covariates include landcover types: developed, forest, herbaceous and wetland as well as terrain ruggedness index (TRI) and cosine-transformed aspect. Distance to trail and human activity measured at the interval of locations (Rolling Average=RA) are the human covariates. These models include interactions between human activity metrics and movement characteristics.  Asterisks (\*) represent estimates where confidence intervals did not overlap zero. Estimates for the day step selection analysis are represented in orange and estimates for the night step selection analyses are represented in blue.

Figure 4: Update step length distributions for the day step selection analysis, modeled as a lognormal distribution, incorporating the interaction between rolling average of human activity and step length parameters. Rolling average of human activity is modeled at three levels with the corresponding change in probability density function represented by orange (low human activity), blue (medium human activity), and green (high human activity). As human activity increases the probability of smaller steps increases.

Figure 5: Update step length distributions for the night step selection analysis, modeled as a lognormal distribution, incorporating the interaction between rolling average of human activity and step length parameters. Rolling average of human activity is modeled at three levels with the corresponding change in probability density function represented by orange (low human activity), blue (medium human activity), and green (high human activity). As human activity increases the probability of smaller steps increases.

Figure 6: Coefficient estimates for the top ranked model of diel movement rate of deer. Covariates include human activity measured as the daily average, time of day including day and night, sex, and an interaction between human activity and time of day factors. Asterisks (\*) represent estimates where confidence intervals did not overlap zero.

Figure 7: The effect of time of day and human activity, measured at a daily temporal scale, on movement rate of mule deer, measured in meters per hour. Increasing human activity results in an increase in movement rate during dawn/dusk and night, while resulting in a decrease in movement during the day.

Figure 8: Density estimates for the study area based on varying estimates of the camera viewshed area parameter.

Figure 9: Density estimates for the study area based on varying estimates of the deer movement rate (speed) parameter.

Figure 10: Coefficient estimates from the full model average of top ranked models explaining deer density estimates at individual cameras

Tables

Table 1: Model Selection table for full mule deer (*Odocoileus hemionus*) dataset modeled with an integrated step selection function. Global 2 model represents a model with an interaction between forest land cover and rolling average of human activity, global represents a model with interaction between movement characteristics (log step length, log step length squared) and rolling average of human activity.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **Model Selection** | | | | | | | |
| **Models** | **K** | **AICc** | **Δ AICc** | **Likelihood** | **AICc Wt** | **LL** | **Cum. Wt** |
| Global 2 | 15 | 29,598.62 | 0 | 1 | 0.97 | −14,784.30 | 0.97 |
| Global | 16 | 29,605.44 | 6.82 | 0.03 | 0.03 | −14,786.71 | 1 |
| Habitat | 12 | 29,612.01 | 13.39 | 0 | 0 | −14,794.00 | 1 |
| Human | 7 | 29,634.41 | 35.79 | 0 | 0 | −14,810.20 | 1 |
| Control | 4 | 29,643.26 | 44.64 | 0 | 0 | −14,817.63 | 1 |
|  |  |  |  |  |  |  |  |

Table 2: Model selection table for the diurnal subset of telemetry data for mule deer (*Odocoileus hemionus*) modeled with an integrated step selection function. Global 2 model represents a model with an interaction between forest land cover and rolling average of human activity, and the  global model contains an interaction between movement characteristics (log step length, log step length squared) and rolling average of human activity.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **Model Selection- Day** | | | | | | | |
| **Models** | **K** | **AICc** | **Δ AICc** | **Likelihood** | **AICc Wt** | **LL** | **Cum. Wt** |
| global | 16 | 13,609.83 | 0 | 1 | 1 | −6,788.89 | 1 |
| global2 | 15 | 13,676.19 | 66.37 | 0 | 0 | −6,823.08 | 1 |
| habitat | 12 | 13,695.43 | 85.61 | 0 | 0 | −6,835.71 | 1 |
| human | 7 | 13,709.38 | 99.55 | 0 | 0 | −6,847.69 | 1 |
| control | 4 | 13,746.63 | 136.8 | 0 | 0 | −6,869.31 | 1 |

Table 3: Model selection table for the nocturnal subset of telemetry data for mule deer (*Odocoileus hemionus*) modeled with an integrated step selection function. Global 2 model represents a model with an interaction between forest land cover and rolling average of human activity, the global model contains an interaction between movement characteristics (log step length, log step length squared) and rolling average of human activity.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| **Models** | **K** | **AICc** | **Δ AICc** | **Likelihood** | **AICc Wt** | **LL** | **Cum. Wt** |
| global | 16 | 12,427.25 | 0 | 1 | 1 | −6,197.60 | 1 |
| human | 7 | 12,444.06 | 16.82 | 0 | 0 | −6,215.03 | 1 |
| global2 | 16 | 12,449.57 | 22.32 | 0 | 0 | −6,208.76 | 1 |
| habitat | 12 | 12,459.93 | 32.68 | 0 | 0 | −6,217.95 | 1 |
| control | 4 | 12,464.49 | 37.24 | 0 | 0 | −6,228.24 | 1 |

Table 4: Model selection results for the generalized linear models of mule deer (*Odocoileus hemionus*) density estimate at individual cameras. Model evaluation is based on Akaike’s Information Criterion for small sample sizes (AICc). The total number of parameters is represented by K. The scale at which the covariate was assessed is in parantheses such as in Shrub (100m) and Trail Density (Grid), which represents the scale of the camera grid.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | **K** | **AICc** | **Δ AICc** | **Likelihood** | **AICc Wt** | **LL** | **Cum. Wt** |
| Trail Density (Grid) | 3 | 65 | 0 | 1 | 0.25 | −28.80 | 0.25 |
| Human Activity | 3 | 65.22 | 0.22 | 0.9 | 0.23 | −28.90 | 0.48 |
| Human Activity + Slope | 4 | 66.42 | 1.41 | 0.49 | 0.13 | −27.96 | 0.61 |
| Human Activity + Trail Density (Grid) | 4 | 66.76 | 1.76 | 0.42 | 0.11 | −28.13 | 0.71 |
| Shrub (100m) + Human Activity | 4 | 67.09 | 2.09 | 0.35 | 0.09 | −28.30 | 0.8 |
| Trail Density (Grid) + Slope | 4 | 67.76 | 2.75 | 0.25 | 0.06 | −28.63 | 0.87 |
| Trail Density (Grid) + Human Activity + Slope | 5 | 69.01 | 4 | 0.14 | 0.03 | −27.50 | 0.9 |
| Distance to Herbaceous | 3 | 69.17 | 4.17 | 0.12 | 0.03 | −30.88 | 0.93 |
| Slope (100m) | 3 | 69.21 | 4.2 | 0.12 | 0.03 | −30.90 | 0.96 |
| Trail Density (Grid) \* Human Activity | 5 | 70.21 | 5.21 | 0.07 | 0.02 | −28.11 | 0.98 |
| Trail Density (Grid) + Human Activity + Distance to Herbaceous | 5 | 70.23 | 5.23 | 0.07 | 0.02 | −28.12 | 1 |