Detection of Mule Deer *Odocoileus Hemionus* Fawning Areas by Fusing Multiphenomenological Data

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In the past, gathering data to support research in the biological sciences has traditionally required that people be on site, despite any ecological vulnerability of such sites. Within the last 50 years, the advent of extremely sensitive instrumentation, such as satellite imagery and synthetic aperture radar, has permitted the collection of data from many miles away. This is referred to as “remote sensing.” The primary hypothesis of this paper is that remote sensing may eliminate much of the potential harm caused by traditional field methods for determining ecologically sensitive areas, specifically fawning sites. This study utilized mule deer, *Odocoileus hemionus*, in Fort Carson, Colorado, as a surrogate species for endangered ungulates. We used Landsat5 Thematic Mapper (TM) imagery, vegetation indices, and digital elevation models to explore the advantages and challenges of using remote sensing to assess habitat and landscape use by mule deer. We conducted a maximum likelihood supervised classification in order to characterize fawning sites (determined by GPS-collar outputs) through the use of Landsat5TM imagery. The null-hypothesis testing method showed that multiphenomenological data is highly significant (z-scores > 5) for identifying fawning sites on a regional scale.

**Introduction**

The methodology presented in this manuscript offers the promise of rapid, fine-grain discrimination of ecologically sensitive locations and times within extended areas. The utility of such discrimination is twofold: 1) Comprehensive ecological surveys over large areas can identify sensitive microenvironments that otherwise might be overlooked. 2) To the military/industrial users of the extended areas, it identifies relatively small areas of land and periods of time that need to be avoided, rather than brute-force permanent closures of large blocks of otherwise useful land. This approach will be much more conducive to willing compliance on the part of the landowners.

An ecologically sensitive location, for the purpose of this study, is characterized as an area where an organism chooses to bear their offspring. This is understandably a vulnerable time, especially for species that bear parent-dependent offspring. Where the methods used by previous research present the potential for harm due to human-wildlife interaction, the methods of this particular experiment would almost entirely eliminate that potential, which may have positive implications for extremely endangered species. Ideal study species for this research were those that have
already been identified as selective for such locations, but these species were only determined as ideal through the use of a different methodology from that which was presented in this paper. Mule deer, therefore, were a viable surrogate for endangered hide-strategy ungulates in that they select fawning sites based upon terrain and topography (Long et al. 2009).

The evolutionary history of mule deer has produced specific behavioral patterns associated with the selection of a fawning site (Schwede et al. 1993). Pregnant females isolate themselves from other deer (Downing & McGinnes 1969, Robinette et al. 1977, Ozoga et al. 1982, Schwede et al. 1993, Bishop et al. 2007) and must account for predation, abundance of resources (Pierce et al. 2004), and the avoidance of accidental imprinting on other animals (Lent 1974, Schwede at al. 1993). The mule deer must also account for certain trade-offs, which include the positive spatial correlation that exists between the abundance of resources with the risk of predation (Bowyer et al. 1998, Rachlow & Bowyer 1998, Barten et al. 2001, Hamel & Cote 2007, Long et al. 2009). Female mule deer have developed a complex strategy for finding a fawning site, and because it is difficult for us to mimic their strategy, we must find another way to identify these areas. Recalling that our purpose is to develop a method of determining the characteristics of endangered species through remote sensing, we applied the same level of caution to mule deer.

Because populations of endangered hide-strategy ungulates, such as the Sonoran pronghorn, Antilocapra americana sonoriensis, are declining in different parts of the world (Roldan et al. 2006), there is a motivation to protect all aspects of these ungulates’ reproduction cycle. Since the point of parturition (point of birth) is the time that the pregnant females (and their fawns) are most vulnerable (O’Gara & Harris 1988), the location associated with this critical period became the emphasis of our study. Due to the nature of our study area, Fort Carson, Colorado, the aforementioned factors that have influenced the selection of a fawning site also included the risks associated with military operations, such as tank movements and live-fire exercises, which can readily destroy areas that would otherwise be chosen by a female mule deer for parturition.

**Hypothesis**

Based upon behavioral characteristics of mule deer, Odocoileus hemionus, we believed their selection of fawning sites was directly related to vegetation and the contour of the terrain (to include slope and aspect); for example, in late May, Colorado is still relatively cool; a south-facing slope may provide more warmth as well as a higher concentration of vegetation which provides cover and nourishment. We believed that spectral imagery might be used to detect such sites.

**Study Area and Data**

The study area (Figure 1) is defined by the boundaries of Fort Carson just south of Colorado Springs, Colorado, USA. Fort Carson encompasses 215 square miles and is ecologically managed by the Department of Public Works. Predators of mule deer fawns in Fort Carson include coyotes, black bears, and mountain lions (Pojar et al. 2004). The terrain of Fort Carson is part of the Western border of the Great Plains, which is described as a semi-arid climate (Farahani et al. 1998). This study primarily used these data: 30m-resolution imagery obtained
from Landsat5TM (United States Geological Survey (USGS)), 10m-resolution National Elevation Data (NED) (United States Department of Agriculture (USDA)/National Resources Conservation Service (NRCS) Various dates), and coordinates of 69 estimated mule deer fawning areas in Fort Carson. Additional data that were provided for the purpose of this research included QuickBird imagery. In the following sections we will list the input information that was available to us, briefly assess its theoretical utility, and discuss its utility for this specific analysis.

**Mule-Deer Tracking Data**

Parameters:

- GPS Transponder Collars: Model 4400M, Lotek Wireless, Inc., Newmarket, Ontario, Canada
- Date: May-June 2009-2010
- Temporal (time) Resolution: 6 hours
- GPS Tracking Data: Time and location

These data provided “ground truth” for training of discrimination algorithms using multiphenomenological data.

**Multispectral Data**

1. QuickBird Parameters
   - Date: 19 May 2009
   - Spectral Range: 450 – 520 nm ; 520 – 600 nm ; 630 – 690 nm ; 760 – 900 nm
   - Number of Bands: 4
   - Spatial Resolution: 2.44m

*Figure 1. Study area of Fort Carson, Colorado, USA.*
We performed a maximum likelihood unsupervised classification with Earth Resources Data Analysis System Imagine 9.2 (ERDAS) and determined the basic components of Fort Carson landscape. This imagery, however, was not used in the final fawning-site discrimination task of this study due to its limited coverage. It provided higher spatial resolution (more pixels per unit of surface area), but lower spectral resolution (fewer bands) than the Landsat5TM imagery. For the purposes of this analysis, higher spectral resolution proved to be more valuable than higher spatial resolution.

2. Landsat5TM Parameters
   - Date: 13 July 2009
   - Spectral Range: 450 – 520 nm ; 520 – 600 nm ; 630 – 690 nm ; 770 – 900 nm ; 1550 – 1750 nm ; 2090 – 2350 nm
   - Number of Bands: 7
   - Spatial Resolution: 30m

These spectral data proved to be the most complete due to their coverage of the entire study area. Their lower spatial resolution, as compared to the other spectral platforms noted above, did not prove to be a problem; therefore this imagery was used for the spectral input of this analysis. We did not use the thermal band 6 due to its coarser resolution in comparison with the other bands used to derive classes, and also because thermal data must be integrated with time of day to have significance for this analysis. This could be a useful phenomenology, but it was beyond the scope of this particular effort.

Topographical Data

Parameters:
   - Date: Various
   - File format: National Elevation Data (NED)
   - Spatial resolution: 10m nominal
   - Source: USDA/NRCS- National Geospatial Management Center

These data were reduced to percent slope and aspect using ERDAS Imagine 2011.

Methodology

The following sections describe a three-phase process: 1) gathering ground truth based upon the fawning-site location data; 2) using these data to train multiphenomenological discrimination algorithms; and 3) determining the statistical significance of correlation between the fawning sites and raster data.

Starkey Method

The Starkey method was used to obtain the locations of mule deer fawning sites in the study area of Fort Carson, Colorado. The methodology was named after the process first used to track deer movements at the Starkey Experimental Forest and Range in northeastern Oregon. As described in the R. Long et al. 2009 paper:
Female mule deer (adults ≥ 2 years of age) were captured by project personnel at Starkey during the winters of 2004 and 2005 with panel traps baited with hay (Rowland et al. 1997). Following capture, deer were fitted with Global Positioning System (GPS) collars (model 4400M, Lotek Wireless, Inc., Newmarket, Ontario, Canada) and released back into the study area. Collars were recovered the following winter and most individual deer were monitored for only one year. Deer locations were stored on each GPS collar and retrieved at programmed intervals via an automated retrieval system (Wisdom et al. 2006). A computer queried each of eight cellphone modems located at high points in the study area at regular intervals. Each modem was connected to an ultra-high frequency (UHF) modem at the same location, and every time a connection was established, the UHF modem was directed to retrieve all data stored on GPS collars within line-of-sight of that location (Wisdom et al. 2006). Mean positional error of GPS collars was ≤ 10 m (Wisdom et al. 2006). We obtained location data for 20 female mule deer (10 in 2005 and 10 in 2006) at 50-90 minute intervals 24 hour/day for the duration of our study, giving a total of 27,041 locations [...]

We estimated timing of parturition at 1-week intervals from movement rates (km/hour) of female mule deer. Although we did not directly observe mule deer fawns during our study, cervids commonly exhibit a marked (i.e. ≥ 50%) decline in movement rates immediately following parturition; this well-documented change in behaviour can be used to estimate timing of parturition (Bertrand et al. 1996, Bowyer et al. 1999, Vore & Schmidt 2001, Carstensen et al. 2003, Ciuti et al. 2006).

Figure 2 shows the mean weekly movement rates of 19 female mule deer from six weeks prior to six weeks after the estimated week of parturition (0) at the Starkey Experimental Forest and Range, Oregon, USA, during 2005-2006. Error bars show 95% confidence intervals. The timing of parturition was then used to estimate the location of fawning sites by interpolating the nearest GPS positions (Long et al. 2009).

This methodology as described above was conducted at Fort Carson by a wildlife biologist at the Fort Carson Department of Public Works, Mr. Roger Peyton, and Dr. John Pigage, professor of Biology at the University of Colorado Colorado Springs.
Categorical and Continuous Analyses

Unsupervised classification of QuickBird Imagery

The higher spatial resolution (and lower spectral resolution) of the QuickBird imagery allowed us to create a visual baseline of different land use land cover (LULC) within the study area. We performed an unsupervised classification in ERDAS for 20 classes at 15 iterations. From those 20 classes, we derived seven classes based upon visual analysis of the terrain in both the QuickBird imagery and Google Earth. These seven classes included riparian vegetation, xeric (dry) evergreen, grassland, urban development, rocks/gravel/sand, water, and recently flooded/mud. Of the seven classes, we determined that xeric evergreen interspersed with grassland was the preferred LULC by parturient does.

Supervised Classification of Landsat5TM

Since the Landsat5TM data encompassed the entire study area, we elected to use it for our primary categorical analysis, which proved to be beneficial due to its higher spectral resolution as compared to QuickBird. We divided 69 known fawning sites (FS) into two categories: 40 training sites, or the FS we used to train ERDAS to recognize as significant; and 29 testing sites, or the FS we used to test ERDAS’ training to recognize FS. In ERDAS we then chose 35 non-fawning sites (NFS) that were distributed evenly across the study area (Figure 3). We then drew areas of interest (AOIs) with an approximate 90-meter radius over the training sites, and extracted the raster information through these grouped AOI to distinguish an FS class for the signature editor. To distinguish the NFS class we followed the same process.
Using the signature file thus created by the signature editor, we were able to run a supervised classification using the maximum likelihood parametric rule in ERDAS with the subset Landsat5TM as an input. Although the maximum likelihood parametric rule takes the longest to accomplish, its characteristic of taking the most variables into consideration (Leica Geosystems 2007) is important because of the relatively low spatial and high spectral resolution of Landsat5TM imagery. That is, we anticipated that the does' choice of fawning sites would be based upon subtle characteristics, and the maximum likelihood parametric rule is best at integrating information from all 6 bands we used (we did not use the thermal band 6 as described in “Study Area and Data” above) in the Landsat5TM data. We then used this output to compare to our 29 testing sites. Following standard procedure for confirmatory data analysis in an observational study, we used null-hypothesis testing, meaning that we answered the question “Assuming that the null hypothesis is true, what is the probability of observing a value for the test statistic that is at least as extreme as the value that was actually observed?” (Cramer & Howitt 2004). Null-hypothesis testing was accomplished by deriving a one-sample z-score value and comparing it with the critical z-score value of 1.96, which is representative of a 99% confidence for a two-tailed distribution. Equation 1, the equation for deriving a z-score, is shown below, where \( z \) is the distance from the mean in relation to the standard deviation of the mean; \( \bar{x} \) is the actual sample mean; \( \mu_0 \) is the hypothesized (null hypothesis) sample mean; \( n \) is the sample size; and \( \sigma \) is the population standard deviation.

\[
 z = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}
\]

Eq. 1

**Continuous Analyses of Vegetation Indices and Topographical Data**

Three vegetation indices were selected for continuous analysis to include the baseline Vegetation Index (VI), the Normalized Distribution VI (NDVI), and the Transformed NDVI (TNDVI). These indices were derived from the following equations, respectively:

\[
 VI = \text{NIR} - \text{red}
\]

Eq. 2

\[
 NDVI = \frac{\text{NIR} - \text{red}}{\text{NIR} + \text{red}}
\]

Eq. 3

\[
 TNDVI = \sqrt{\frac{\text{NIR} - \text{red}}{\text{NIR} + \text{red}}} + 0.5
\]

Eq. 4

Instead of creating 90-meter radius AOI around the training FS and NFS, we created AOI that encompassed little more than a couple of pixels (~ 3) using the grow tool function in ERDAS. The rationale for using smaller AOI for

*Figure 2. Point vector layer of FS and NFS overlaying Landsat5TM study area.*
continuous analysis is that we were only interested in the pixel values directly associated with the fawning sites themselves. We extracted the raster information using these AOI into an American Standard Code for Information Interchange (ASCII) file, which we then imported into Matlab. Similar to the significance test of the supervised classification, we used the null-hypothesis method with a one-sample z-score test statistic. The same analysis was performed on the percent slope and aspect rasters derived from the NED in ERDAS Imagine 2011.

Results & Discussion

Supervised Classification of Landsat5TM

Figure 4 shows the results of the supervised classification. 24 of the 29 testing FS points were correctly classified, which represented 83% accuracy. In this study, the “null hypothesis,” \( H_0 \), was that the number of testing FS that were correctly identified would just be the percentage of pixels in the image that have been identified as FS (\( P = 213568/602801 = 0.3543 \)) times the total number of actual testing FS (29). Therefore, \( H_0 \) is confirmed when the number of correctly-identified testing FS = 0.3543*29 ≈ 10.

Note that we made an assumption of statistical independence about the distribution of the observations. Since we trained on one set of 40 deer, but tested on the behavior of another set of 29 different deer, sample independence was assured.

The “alternative hypothesis,” \( H_A \), was that the number of correctly-identified testing FS would be significantly greater than 10. This was the statistical equivalent of the study hypothesis.

The next step was to select a significance level (\( \alpha \)), a probability threshold below which the null hypothesis will be rejected. Common values are 5% and 1%. However, D. H. Johnson of the USGS Northern Prairie Wildlife Research Center points out that “Small values of \( P \) are taken to represent strong evidence that the null hypothesis is false, but workers demonstrated long ago (see references in Berger and Sellke 1987) that such is not the case. In fact, Berger and Sellke (1987) gave an example for which a \( P \)-value of 0.05 was attained with a sample of \( n = 50 \), but the probability that the null hypothesis was true was 0.52.” Our sample size was small (29); we were, therefore, looking to find far smaller values of \( \alpha \). In this study, a single sample set had been extracted from a finite population, so the appropriate statistical measure was the one-sample z-test (Eq. 1), where \( z \) was the distance from the mean in relation to the standard deviation of the mean; \( \bar{x} \) was the actual sample mean, 0.8276; \( \mu_0 \) was the hypothesized (null hypothesis) sample mean, 0.3543; \( n \) was the sample size, 29; and \( \sigma \) was the population standard deviation, 0.0888. The z-score was thus 28.7 and, using an assumed normal distribution, the probability of the null hypotheses was less than 0.0003. We thus believed that our hypothesis of fawning sites being correlated with detectable spectral characteristics was true. We continued to explore other phenomenologies to potentially reduce errors of commission. Our goal was to ensure that a majority of the fawning sites could be localized to a smaller percentage of the map area. Thus, we attempted to demonstrate that VI and topographical data have a statistically significant relation to known FS.
Continuous Analyses of Vegetation Indices and Topographical Data

We derived three different VI from the Landsat5TM (Eq. 2-4). The results were as follows:

Table 1. The table below depicts the mean raster values and standard deviations of the VI data over the entire study area.

<table>
<thead>
<tr>
<th>Vegetation Index (VI)</th>
<th>VI Mean</th>
<th>Fawning Sites Mean</th>
<th>VI Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>VI</td>
<td>21.9095</td>
<td>26.8350</td>
<td>15.5278</td>
</tr>
<tr>
<td>NDVI</td>
<td>0.1814</td>
<td>0.2214</td>
<td>0.1309</td>
</tr>
<tr>
<td>TNDVI</td>
<td>0.8220</td>
<td>0.8456</td>
<td>0.0757</td>
</tr>
</tbody>
</table>

Figure 3. The supervised classification above depicts modeled FS in green, and NFS in pink, overlaid by the actual FS and NFS point vector layer represented by green and red points, respectively.
We had a total of 751 locations (pixels), each of which had three VI values associated with it: VI, NDVI, and TNDVI. 412 of the locations were associated with FS and 339 were associated with NFS. We wished to determine if VIs were significant discriminants of FS.

Using the same methodology as described above, we employed the null-hypothesis method of data analysis. In this case, the null hypothesis, $H_0$, was that the mean values of VI for the FS would be the same as the mean values for all 751 sites:

$$H_0: \bar{x}_{FS} = \bar{x}_{All}$$

The alternative hypothesis, $H_A$, was that FS would cluster either significantly above or significantly below the means (two-tailed analysis):

$$H_A: \bar{x}_{FS} \neq \bar{x}_{All}$$

We chose 99% confidence as we did for the supervised classification. This is a two-tailed test so the critical value is $z = 1.96$. The test statistic is the one-sample z-test; $\bar{x}$ is the actual sample mean; $\mu_0$ is the hypothesized (null hypothesis) sample mean; $n$ is the sample size, 412; and $\sigma$ is the population standard deviation (Table 1). The z-scores are thus 5.6771, 5.7565, and 5.9922 which are significantly greater that our criterion of 1.96. We thus believed that the alternate hypothesis of FS being correlated with VI was true.

We conducted the same methodology upon the percent slope and aspect rasters derived from the NED as described in the “Study Area & Data” section. The results were as follows:

*Table 2. This table depicts the mean raster values, standard deviations and z-scores of the topological FS and NFS features.*

<table>
<thead>
<tr>
<th>Topological Feature</th>
<th>FS Mean</th>
<th>NFS Mean</th>
<th>FS Standard Deviation</th>
<th>NFS Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope %</td>
<td>14.6881</td>
<td>9.2766</td>
<td>12.63</td>
<td>8.74</td>
</tr>
<tr>
<td>Aspect (degrees)</td>
<td>144.2219</td>
<td>162.8321</td>
<td>80.7738</td>
<td>88.6911</td>
</tr>
</tbody>
</table>

We had a total of 4801 locations (pixels), each of which had two topological features associated with it: slope % and aspect (degrees clockwise from true North). 2494 of the locations were associated with FS and 2307 were associated with NFS. We wished to determine if topological features were significant discriminants of FS.

We chose 99% confidence, where $z = 1.96$. The test statistic was the one-sample z-test; $\bar{x}$ is the actual sample mean; $\mu_0$ was the hypothesized (null hypothesis) sample mean; $n$ was the sample size; and $\sigma$ was the population standard deviation (Table 2). The z-scores were thus 10.29 and 5.53, which were significantly greater that our criterion of 1.96. Therefore, we believed that the alternate hypothesis of FS being correlated with topological features was true. Depicted below are visual representations of the slope and aspect distributions (a. and b. of Figure 5) and their corresponding parturition site preferences (c. and d. of Figure 5). Parturition
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site preferences were based upon the ratios between the FS and NFS values in order to better convey the significance of these results.

Figure 4. Graphs a. - d. visually convey our topological feature results.

Female mule deer showed clear preferences and avoidances of particular slope percentages and aspects. In graphs c. and d. of Figure 5, the horizontal line at 1 represents the division at which no preference is shown. That is, if the green plot representing doe preference is equal to 1, then no preference has been shown; therefore, any values on the green plot occurring above the blue line indicate doe preference, whereas any values occurring below the blue line indicates doe avoidance. Doe preference was strongest at 31% slope (18°), and 101 degrees aspect (southeast). Both topographical features showed moderate bimodal distributions, perhaps due to the apparent geographical differences between the northern and southern halves of Fort Carson. Variables associated with fawning areas may not be completely orthogonal due to some vegetation having direct association with certain aspects of slope; however, this does not negatively affect our results. These results are specific to the Colorado terrain, but the methods used can be applied to other locations and species.

Conclusions & Recommendations

Mule deer, *Odocoileus hemionus*, selection of fawning sites is directly related to spectral characteristics, vegetation, and the slope and aspect of the terrain. Analysis of high-resolution
QuickBird imagery indicated a doe preference for xeric evergreen interspersed with grassland. Vegetation indices derived from Landsat5TM showed an extremely high correlation ($z \approx 5$ to $6$) with fawning sites. Categorical supervised classification of Landsat5TM data alone produced a bi-phase map in which $83\%$ of the testing-set fawning sites fell within the $35\%$ potential fawning-site area. Independent statistical analysis of vegetation indices likewise produced a high correlation, as did topographical analysis.

In the topographical analysis, fawning-site selection by slope produced a $z$-score of greater than $10$ and showed the strongest preference at $31\%$. Site selection by aspect (bearing) produced a $z$-score of greater than $5$ and showed the strongest preference at $101$ degrees (southeast). Both topographical characteristics showed moderate bimodal distributions, perhaps due to the apparent geographical differences between the northern and southern halves of Fort Carson.

Multiple phenomenologies have shown strong, independent correlations with known fawning sites determined by radio-tracking collared does. Fusion of these phenomenologies will enable high detection probabilities over smaller map areas. These results are specific to the Colorado terrain and mule deer, but the methodology can be applied to other locations and species.

The utility of this methodology is to detect correlation between multiple phenomenologies and known ecologically sensitive areas. In order to quantify the precautions a land owner/user can employ, we feel that actionable information can be provided to them if a majority of the ecologically sensitive areas can be localized to a small percentage of the map area. From the ecological perspective, providing this information utilizing remotely sensed data and preexisting topographical data will afford a higher degree of micro-ecological protection and a lower degree of potentially harmful human-wildlife interaction. Lastly, its increased speed and affordability make this methodology practical for a far wider variety of research efforts and landscape survey.

For the future, we recommend that a study be performed ranking and comparing high- and low-spectral and spatial resolutions and other potentially significant multiphenomenological data (such as thermal data, elevation data, synthetic aperture radar, ...etc.). This will serve the purpose of isolating the highest correlations between known ecologically sensitive areas and multiphenomenological algorithm outputs.

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**References**


