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EXPLORATION OF METHODS FOR ANALYSES

OF RESOURCE SELECTION USING LOCATION-BASED DATA

A Thesis in

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ABSTRACT

Resource selection functions (RSFs) are commonly used by wildlife researchers to identify resources necessary for the presence or absence of a species in a given area. Resource selection functions can assist decision-makers in protecting necessary resources that can mean the difference between increasing populations or extinction. Hence, it is important that researchers use appropriate RSFs for differing types of data and study designs. The misuse of RSFs is not uncommon, however, and can have negative effects on experiment wise error (i.e., increases in Type 1 error) or give misleading results that lead to poor management plans.

I identified three commonly used RSFs (logistic regression, negative binomial, and discrete choice), and more closely examined two (logistic regression and negative binomial) via the use of Global Positioning System (GPS) and count data. I used logistic regression to assess the selection of agriculture by mule deer in southwest Colorado, and in particular their selection of sunflowers. I then used negative binomial to identify the location characteristics of Pennsylvania captive cervid facilities to address the potential risk that the spread of chronic wasting disease (CWD) poses to wild deer via captive cervid facilities and vice versa.

Resource selection can be used to identify human-related resources that are selected by wildlife and potentially damaged. In southwest Colorado, mule deer (*Odocoileus hemionus*) are a popular game animal, and are economically and environmentally important to the local area. Identification of specific crops and conditions that may increase crop damage can provide cost savings for farmers and wildlife managers by protecting crops most likely to be damaged by mule deer. I used

GPS data and logistic regression to identify selection of specific crops during 8 seasonal/diel periods. Forest, alfalfa and sunflower had the greatest influence on mule deer resource selection. Identification of these specific crops will help wildlife managers implement crop depredation techniques in areas where they will be most beneficial.

Resource selection functions can also be used to identify human selection of resources associated with practices such as placement of captive cervid facilities. Captive cervid facilities in Pennsylvania have a large economic value. They also pose a risk to wild cervid populations via the spread of CWD. I used negative binomial regression to assess the resource selection of captive cervid facility owners in Pennsylvania, and to identify areas where wild deer may come in contact with captive deer and increase the potential for CWD transmission. Agriculture had the most support for areas selected by captive facility owners, and several other covariates had varying effects. Resources that were identified as influential factors to selection by captive facility owners were then used to create a predictive surface of areas most as risk for CWD transmission between captive and wild cervids.

Resource selection functions are a versatile tool in wildlife management. When used appropriately they can provide results that help wildlife managers make the most effective and efficient management plans for resources and animals. There are many places where a researcher can make inappropriate decisions regarding study design and RSF selection and thus produce poor results. In my thesis I discuss the many considerations a researcher must account for when choosing a RSF, and I also give two examples of appropriate RSF analysis using logistic regression and negative binomial.

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I’d like to quote a small, orange, mustached being: “Unless someone like you cares a whole awful lot, nothing’s going to get better. It’s not.”

Chapter 1

Introduction of resource selection functions and their utility

Resource selection analysis is an important tool for wildlife managers. Appropriately designed studies can give managers insight into the resources necessary for a species to be successful in the area of study (Thomas and Taylor 1990, Manly et al. 2002, Thomas and Taylor 2006). The use of modern technologies and methods is extremely important when performing these analyses. There are models that can be used to assess selection of a resource by a species over other available (or unused) resources. Selecting the appropriate model is an important step in the analysis of data, and if inappropriately chosen can lead to multiple issues regarding experiment wise error (Thomas and Taylor 2006). In this chapter I will discuss i) how issues with traditional methods of habitat use have been resolved with resource selection function (RSFs) based on current data collection methods, ii) some topics that should be considered before selecting a RSF for use in research, and iii) briefly compare 3 common models used in RSFs.

Traditional Methods

Earlier methods, such as compositional analysis and Mahalanobis distance, analyzed habitat use by an animal rather than identifying specific resource selection and have been replaced by RSF analyses. Resource selection function analysis provides a measure of resource preference based on what is used or available and in certain circumstances can provide probabilities of use (Boyce et al. 2002, Manly et al. 2002, Thomas and Taylor 2006). Previous methods that analyzed habitat use were also less able to account for various data problems (e.g., lack of independence, parameter heterogeneity), had a high potential for Type 1 errors, and in some circumstances could only handle certain types of spatial data (i.e., discrete or continuous) (Manly et al. 2002, Thomas and Taylor 2006). For example, compositional analysis is only able to assess categorical variables, unless continuous variables were placed into discrete categories (Manly et al. 2002). Most RSF analyses can now account for some lack of independence and heterogeneity, and most can handle all forms of data provided in Geographic Information Systems (Manly et al. 2002).

Data collection methods through the use of Very High Frequency (VHF) and Ultra High Frequency (UHF) satellite transmitters also caused problems with previous habitat use analyses, such as Type 1 error concerns via issues with mapping error, signal bounce, vegetation cover, electromagnetic interference, animal movements, operator error and distance to radio-tagged animals (Millspaugh and Marzluff 2001). These previous telemetry systems also provided far fewer and less accurate locations when compared to more-improved current technologies such as Global Positioning System (GPS) (Millspaugh and Marzluff 2001). An ability to account for temporal and spatial correlation that can be associated with GPS data, and an ability to handle thousands of locations to create very specific resource selection outputs became necessary with more frequent use of GPS units.

Study Designs

Resource selection studies typically fall into three study designs that create different levels of selection (Manly et al. 2002). Johnson (1980) discussed “orders of selection,” in which he describes the different levels at which selection by an animal can occur. First order selection refers to the selection of a geographical range by an individual, and higher orders of selection refer to the selection of specific areas within that geographic area (e.g., home ranges) (Johnson 1980). All orders of selection are based on what the researcher defines as "available" to the animal. What is defined as available to the individual then gives reference to the level of inference that can be made with the final results (i.e., population-level or individual-level). Manly et al. (2002) describes three study designs for resource selection studies that can assist researchers in understanding the level of inference that can be made within their own study. In Design 1, data is collected and analyses are conducted at the population level (Manly et al. 2002). With this design individual animals are not identified, and thus specific inferences cannot be made such as estimating home ranges or identifying differing selection among individuals. In Design 1, availability is also measured at a population level and thus results in lower orders of selection. Examples of this include point counts done for bird species using call back methods or using species-specific presence indicators, such as tracks or territorial markings, and then plotting these points over a specified study area. In Design 2, animals are individually identified (e.g., GPS/VHF/UHF collars, ear tags) but resource availability is still made at the population level such as wildlife management units or *a priori* study areas (Manly et al. 2002). The primary difference between Design 1 and Design 2 is the identification of specific individuals in Design 2 that allows for individual inferences. In Design 3, individual animals are identified through similar methods as Design 2, but the availability of resources is identified separately for each individual (i.e., home range) (Manly et al. 2002). Design 3 can identify the higher orders of selection (third and fourth order selection) because of the specific identification of individual resource use and availability. Researchers should have a thorough understanding on both the order of selection and study design for their research as these study designs are inherently related to the orders of selection that address resource selection in a hierarchical fashion (Johnson 1980).

Unused versus Available

Additional concepts researchers should consider is whether or not they are using "unused" or "available" locations to compare to their used locations as these have different meanings. Defining data within the concepts *use-unused* or *used-available* is the foundation for appropriate selection of the models used in a RSF and then the interpretation of the RSF (Boyce et al. 2002, Keating and Cherry 2004, Thomas and Taylor 2006). The practice of comparing used and unused locations has caused concern, however, because of the inability to truly designate a location as "unused" unless the study is actually able to sample all unused areas (Boyce et al. 2002). Only experimental designs in which used and unused locations can directly be controlled for and observed by the researcher can truly be designated as a *use-unused* study design. However, a majority of resource selection studies are observational rather than experimental, and because of this a *used-unused* study design should be rarely used unless specifically noted in the experimental design.

Final Considerations

Study design, data collection, and experimental unit are important factors in choosing the appropriate model for a RSF (Alldredge and Ratti 1986, Keating and Cherry 2004, Thomas and Taylor 2006). Multiple studies have identified issues with spatial and temporal correlation, pooled data, and controlling for experiment wise error rates (Thomas and Taylor 1990, Thomas and Taylor 2006). The reasons these issues occurred was because researchers did not consider the type of data (e.g., discrete or continuous), order of selection, or study design that appropriately fit the data collected and associated descriptive statistics.

There are numerous models available to analyze data, but with advances in technology certain models have emerged that can better handle problems like temporal or spatial correlation, parameter heterogeneity, and small sample size (Thomas and Taylor 2006). I will discuss the most recent and commonly used methods: logistic regression, negative binomial, and discrete choice.

Logistic Regression

Keating and Cherry (2004) distinguished three sampling designs in which logistic regression typically occurs: *random*, *case-control* and *use-availability*. In the *random* sampling design plots are randomly selected throughout the study area and the characteristics of the plots are measured as either used or not used (use vs. non-use) by the animal. These sampling designs only work when the animal or animal characteristic being studied (i.e., nest, den, roost, or bed site) is common and easily identifiable in the landscape (Keating and Cherry 2004). *Case-control* studies are similar to random sampling designs. However, researchers actively search for and identify used and unused plots and then measure the characteristics of interest for both (Keating and Cherry 2004). For these two sampling designs to be implemented, the animal or characteristic being studied must be easily identifiable to reliably distinguish between presence and absence, otherwise use can be underestimated if locations originally determined as unused were actually used (Keating and Cherry 2004). Again, the ability to truly distinguish a location as “unused” though is questionable in observational studies. *Use-availability* sampling design identifies used locations, but do not specifically identify locations that are unused.

These studies identify what is available to the animal, and could have potentially been used during the study. For example, used locations could be identified by fitting animals with radio telemetry or GPS collars, while availability could be described using a predefined area (e.g. study area, home range) (Keating and Cherry 2004). As previously mentioned, it is important for researchers to identify the order of selection and associated study design when using *use-availability* sampling design for logistic regression to appropriately fit models and also interpret results (Johnson 1980, Johnson et al. 2006).

Logistic regression analysis yields a binary response (use = 1, available = 0), and can be used in certain circumstances to create a RSF in which the relative probability of use is estimated (Manly et al. 2002, Keating and Cherry 2004). Logistic regression can also be used as a resource selection probability function (RSPF), in which true probabilities of use are estimated. A RSPF can only be estimated when comparing used and unused locations (Manly et al. 2002, Keating and Cherry 2004). If logistic regression is used as a RSPF, the extracted values can be modeled using general linear models to produce results and variable coefficients that can be used to create predictive surfaces of resource use (Manly et al. 2002, Keating and Cherry 2004).

Logistic regression also has disadvantages though, in particular its inability to handle overdispersed data. Overdispersed data, or data that does not follow the "iid" assumption (independent and identically distributed data), can cause problems with model precision (Anderson 2008). Overdispersed data is not normally distributed, and data must follow a normal distribution to work with the logistic regression model. Typically when data is treated as if it fits the "iid" assumption and it does not, the sampling variances tend to be too small, and thus create confidence intervals that are too narrow (Anderson 2008). This requirement of normally distributed data is important for logistic regression, and experiment wise error will increase if model precision decreases because of an inappropriate distribution fit.

Logistic regression is a popular method of resource selection by many researchers, and has many benefits such as estimation of a predictive surface. However, researchers must carefully consider distribution of the dataset and the other assumptions of logistic regression before selecting this method to analyze their data as incorrect use of this model can lead to misleading results and poor management plans.

Negative Binomial

Negative binomial regression (NB), in comparison to logistic regression, has more recently been explored for use in wildlife studies (Sawyer et al. 2009, Nielson and Sawyer 2013). This method differs from logistic regression in that use is measured as a continuous variable rather than a binary response (Nielson and Sawyer 2013). Use is a continuous variable because it represents the proportion of animal locations within a sampling unit. Recommendations for sampling units in NB are uniform distribution and have biologically relevant sizes (i.e., dispersal distance, average daily distance moved) (Nielson and Sawyer 2013).

The benefit of using NB is to account for some violations of independence and identically distributed data, although, if data is spatially correlated (i.e., clustering animals) this can still cause precision problems within the NB models. Negative binomial regression accounts for violations of the “iid” assumption through its negative binomial distribution. This distribution allows for the variance to be greater than the mean, which cannot occur in models that depend on Poisson or similar distributions (Nielson and Sawyer 2013).

Although NB accounts for some violations better than other methods, there are still assumptions that must be followed to prevent increased risk of experiment wise error. Like other models, NB assumes animal locations are representative of the population as a whole, and there is spatial independence of locations. Negative binomial also assumes that the distribution of the data must fit one of the negative binomial distributions. Although data must fit the associated distribution of whichever method a researcher uses, NB is unique in that its “normal” distribution accounts for some violations of the “iid” assumption where the variance is greater than the mean. There are also additional versions of NB where some of these assumptions can be further relaxed (i.e., truncated NB or zero-inflated NB) (Nielson and Sawyer 2013).

The benefit of using NB regression is that it provides a measure of intensity of use because of the continuous nature of the response variable, unlike other RSF models (i.e., logistic regression). Like logistic regression, NB can also be used to estimate RSFs or RSPFs, however, it can better account for serial correlation which again is an important consideration for count data. Lastly, literature and supporting software is easily accessible for researchers, and NB is not computationally intensive.

Discrete Choice

Both logistic regression and negative binomial rely upon resource availability being constant over the period of study, and for all individuals of the population to have access to the same resources (Cooper and Millspaugh 1999, Manly et al. 2002). This is not true in all cases, however, and discrete choice models address this issue. Discrete choice models give the researcher the ability to assess selection on a choice-by-choice basis (Manly et al. 2002). It essentially describes the “utility” of a resource to an animal, or how much “satisfaction” a particular resource provides an animal (Cooper and Millspaugh 1999). Although physical traits such as sex or age may be the same, the “utility” or use of a particular resource can be different for each animal because of past occurrences. This unknown difference in individual selection is represented in the discrete choice function as an error term. This error term allows for “utility” or use to be assessed in a probabilistic framework (Cooper and Millspaugh 1999). Discrete choice can assess either discrete or continuous variables and also defines use in a binary sense similar to logistic regression (Manly et al. 2002).

Discrete choice provides an ability to estimate use of a resource based upon its own attributes and the attributes of the other variables in the defined choice set (Cooper and Millspaugh 1999). Discrete choice provides a preferred option for researchers who want to follow a Design 3 study, and make inferences on individual selection of available resources to that same individual. Discrete choice is different from logistic regression and NB because information needs to be collected for the choice set of each individual. Assumptions for discrete choice are similar to logistic regression, and data must follow a normal distribution and not break the “iid” assumption (Cooper and Millspaugh 1999, Manly et al. 2002).

Summary

In the subsequent chapters, I provide an example of logistic and negative binomial regression using two distinct sources of location-based data. In Chapter 2, I assess the selection of agricultural crops by mule deer (*Odocoileus hemionus*) and, in particular, determine if there is a preference for sunflower crop in southwest Colorado. I assessed this selection using logistic regression because of the continuous nature of our GPS points, the accessibility of software that works with logistic regression functions, and the normal distribution of our data. My identification of mule deer preference for sunflower was used to inform local wildlife managers which crops would benefit most from the use of crop damage prevention methods.

In Chapter 3, I identify resource selection by captive cervid facility owners using negative binomial regression. I wanted to identify the resource selection of captive cervid facility owners because of the risk facilities pose to wild deer via disease transmission, and in particular transmission of chronic wasting disease (CWD). I chose negative binomial regression to assess this data because of the abnormal distribution of the count locations, and the ability for negative binomial regression to account for this kind of distribution without affecting the precision of the model. With my results I was able to create a predictive surface of areas most at risk of CWD transmission from captive cervid facilities to wild deer and vice versa because of the increased potential for contact between wild and captive cervids.

Literature Cited

Alldredge, J. R., and J. T. Ratti. 1986. Comparison of some statistical techniques for analysis of resource selection. Journal of Wildlife Management 50:157-165.

Anderson, D. R. 2008. Model based inference in the life sciences: a primer on evidence. Springer Science+Business Media, New York, NY.

Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating resource selection functions. Ecological Modelling 157:281-300.

Cooper, A. B., and J. J. Millspaugh. 1999. The application of discrete choice models to wildlife resource selection studies. Ecology 80:566-575.

Johnson, C. J., S. E. Nielsen, E. H. Merrill, T. L. McDonald, and M. S. Boyce. 2006. Resource selection functions based on use-availability data: motivation and evaluation of methods. Journal of Wildlife Management 70:347-357.

Johnson, D. H. 1980. The comparison of usage and availability measurements for evaluating resource preference. Ecology 61:65-71.

Keating, K. A., and S. Cherry. 2004. Use and interpretation of logistic regression in habitat-selection studies. Journal of Wildlife Management 68:774-789.
Manly, B. F. J., L. L. McDonald, D. L. Thomas, T. L. McDonald, and W. P. Erickson. 2002. Resource selection by animals. Kluwer Academic Publishers, Norwell, MA.
Millspaugh, J. J., and J. M. Marzluff. 2001. Radio tracking and animal populations. Academic Press, San Diego, CA.
Nielson, R. M., and H. Sawyer. 2013. Estimating resource selection with count data. Ecology and Evolution 3:2233-2240.
Sawyer, H., M. J. Kauffman, and R. M. Nielsen. 2009. Influence of well pad activity on winter habitat selection patterns of mule deer. Journal of Wildlife Management 73:1052-1061.
Thomas, D. L., and E. J. Taylor. 1990. Study designs and tests for comparing resource use and availability. Journal of Wildlife Management 54 322-330.
Thomas, D. L., and E. J. Taylor. 2006. Study Designs and Tests for Comparing Resource Use and Availability II. Journal of Wildlife Management 70:324-336.

Chapter 2

Precipitation alters selection of agriculture by mule deer (*Odocoileus hemionus*) in southwest Colorado

Chapter 2 was written in collaboration with Heather E. Johnson, Justin W. Fischer, Matthew Hammond, Patricia D. Dorsey, Charles Anderson, Kurt C. VerCauteren and W. David Walter. I have included this manuscript on the following pages as formatted for a journal.

Abstract

Mule deer (*Odocoileus hemionus*) populations in the western United States provide recreational, ecological and economic benefits to local economies. They can also cause considerable damage to agriculture, and this is particularly concerning when damage is done to lucrative crops such as sunflower. In some cases entire fields have been decimated by local mule deer populations resulting in a need for investigating resource selection and determining strategies for managing deer damage in these agricultural areas. Limited information exists on movements and resource selection of mule deer in agricultural areas and no data exists to understand resource selection of mule deer in response to annual variation in crop rotation and climatic conditions. I tested the hypothesis that mule deer preferentially select for certain crops, and in particular sunflower. My objective was to use home range estimates and resource selection analysis to identify resources used by mule deer, and hence identify crops that would benefit most from crop damage mitigation techniques. I used Global Positioning System collars to monitor 14 mule deer and assess their movement patterns, home range and resource selection in southwestern Colorado, USA. We estimated home ranges for two winter seasons that ranged between 7.68 and 9.88 km^2, and for two summer seasons that ranged between 5.51 and 6.24 km^2. Mule deer selected for areas closer to forest and alfalfa for most periods during 2012, but selected for areas closer to sunflower in a majority of periods during 2013. Considerable annual variation in climate patterns and precipitation levels that affected the availability of sunflower crop during 2012 and 2013 appeared to influence selection by mule deer due to changes in crop rotation and germination success of sunflower. Our results can assist managers in making informed decisions about crop

damage prevention and practices by identifying areas and crops where mule deer damage is expected based on climate conditions and deer presence-absence.

Key words

Climate; crop depredation; home range; mule deer; precipitation; resource selection function; sunflower

Introduction

Mule deer *(Odocoileus hemionus)* are an important game species in the western United States that can also cause large amounts of damage to agriculture crops. For example, damage by a variety of ungulate species, including mule deer, has resulted in as much as US$100 million annually in economic losses (Wagner et al. 1997, Conover 2002, Johnson et al. 2014). State wildlife agencies often have to reimburse farmers for damage caused by deer and other wildlife, which can be expensive for state agencies (Wagner et al. 1997) and can degrade incentives for landowners to maintain habitat for wildlife (Conover 2002). Multiple measures have been implemented to prevent crop damage by deer such as increasing distances between cropland and key foraging areas of deer (Nixon et al. 1991, Hegel et al. 2009), using exclusionary methods such as fencing and repellents (Johnson et al. 2014), and rotating or moving crops that are considered to be favored by cervid species away from areas where they are highly depredated (Yoder 2002, Hegel et al. 2009).

Sunflower depredation by mule deer has become a significant management challenge in southwest Colorado, because it is a lucrative crop that can experience high rates of cervid damage (Johnson et al. 2014). Sunflowers are an important crop in the biofuel industry, and high depredation rates by local mule deer populations can cause fields to be completely decimated. Sunflowers in this region are grown on a rotational basis every 3 – 4 years with other crops that do not receive as much damage by mule deer. Damage by mule deer in Colorado during the 2011/2012 fiscal year resulted in the second highest damage claim ever paid by Colorado Parks and Wildlife at US$292,315 (Colorado Parks and Wildlife 2011-2012). Thus, both farmers and wildlife agencies continuously lose money due to the combination of high depredation rates of various high value crops like sunflower, and the limited information on mule deer populations and their resource selection in this area.

In southwest Colorado several methods (i.e. electric fence, winged fence, polypropylene fence, and a repellent) have recently been explored to prevent crop damage (Johnson et al. 2014), but very little information exists about resource selection by mule deer in this area. Few studies have documented resource selection of mule deer (Marshall et al. 2006, Sawyer et al. 2006, Sawyer et al. 2009, Lendrum et al. 2012), and even fewer have documented landscape-level selection for crops directly using Global Positioning System (GPS) datasets (Walter et al. 2011, Anderson et al. 2012). The few studies that have documented resource selection of mule deer suggested habitat use can be influenced by forage availability, cover, anthropogenic disturbance and water availability (Rost and Bailey 1979, Smith et al. 1989, Nicholson et al. 1997). Mule deer in western Nebraska selected for forested habitats that were near croplands during various seasons (Walter et al. 2011). High quality forage and proximate cover also influence habitat use in arid environments of southern California (Marshall et al. 2006). Despite some examples of mule deer resource selection, direct observation of changing habitat use trends is limited using GPS-monitored deer (Marshall et al. 2006).

A further examination of movements, home range, and resource selection of crops by mule deer in this area is needed to assist wildlife managers in determining the best methods and most important areas to protect and reduce monetary loss. My objective was to use home range estimates and resource selection analysis to identify mule deer crop preference, and in particular if there is a preference for sunflower. Specifically, I (1) determined movements and home ranges of mule deer in an agricultural area, (2) identified resource selection by mule deer in this area where currently no available data exists, and (3) determined variation in selection of crops by mule deer using crop-specific data derived annually for this area. Resource selection studies typically use stochastic National Land Cover Database layers prepared every 3 – 5 years rather than annually created layers used in our analyses that more accurately identifies annual changes in crop rotation of agricultural practices.

Study Area

The study area was approximately 1596 km^2 in size, and was in the vicinity of Dolores County, Colorado, USA (37.736°N, −108.923°E) (Figure 2-1). This area is a mix of public and privately owned properties. Private property was primarily agriculture and public property was primarily native habitat managed by the Department of the Interior's Bureau of Land Management (federal lands) and Colorado Parks and Wildlife (state lands). The elevation in the study area ranged from 1,981m to 2,590 m. The local vegetation was characterized as mountain shrub and woodlands that are interspersed with irrigated and dryland agriculture (Johnson et al. 2014). The primary native vegetation consisted of serviceberry (*Amelanchier alnifolia*), bitterbrush (*Purshia tridentata*), mountain mahogany (*Cercocarpus montanus*), squaw apple (*Peraphyllum* *ramosissimum*), black sagebrush (*Artemisia nova*), pinyon pine (*Pinus edulis*), and juniper (*Juniperus osteosperma*). Mean total annual precipitation was 26.7 cm between 1996 and 2012, which was mostly received during late summer monsoon rains and during the winter as snowfall (Weather Station DVCO1, Colorado Agricultural Meteorological Network 2013). Yearly precipitation totals for our three study years were 30.6 cm for 2011, 15.7 cm for 2012, and 31.3 cm for 2013 respectively.

Methods

Capture and Monitoring

We captured twenty adult female mule deer in September 2011 using a net-gun fired from a helicopter in areas around agricultural fields that had previously experienced crop damage. Each deer received a Telonics store-on-board GPS collar (Product Model: TGW-4501; Telonics, Mesa, Arizona, USA) programmed to collect locations every three hours for two years. All capture and handling methods were in accordance with protocols approved by the Colorado Parks and Wildlife Animal Care and Use Committee (CDOW IACUC No. 05-2011) and within guidelines of the American Society of Mammalogists (Gannon et al. 2007).

Movements and Home Range

We created two seasonal categories related to differences in timing of planting crops and thus variation in germination and sprouting, which influences crop availability and preferences by mule deer. We delineated these two seasons over the two years of the study resulting in four season/year combinations: (1) *winter 2011* from 1 October 2011 to 31 May 2012, (2) *summer 2012* from 1 June 2012 to 30 September 2012, (3) *winter 2012* from 1 October 2012 to 31 May 2013, and (4) *summer 2013* from 1 June 2013 to 30 September 2013.

We determined daily movement distances for mule deer based on 6 – 8 locations collected every three hours for a 24-h period. Mean daily movement distances were determined across all monitored deer and used as the distance an average deer could move during any 24-hour period. We used the 95% movement-based kernel density estimator (MKDE) to estimate seasonal home ranges for each deer using a biased random bridge approach (Benhamou and Cornelis 2010, Benhamou 2011). Unlike traditional kernel density estimator, MKDE can integrate habitat, temporal correlation, and maximum time lags between subsequent locations leading to more refined movement vectors thus improving estimates of home range over traditional estimators (Benhamou and Cornelis 2010, Benhamou 2011, Walter et al. 2015). We excluded locations that were > 24 hours between locations, and we removed locations less than 50 meters apart and considered them inactive due to a mortality event. We did not include habitat in MKDE estimation because we selected to standardize estimation of home range based on temporal duration between relocations regardless of habitat resulting in liberal estimates of home range although less so than most home range estimators (e.g., reference bandwidth smoothing; Walter et al. 2015).

Vegetation Covariates

We identified eight vegetation categories and a road variable believed to influence selection by mule deer in the western US (Rost and Bailey 1979, Austin et al. 1998, Sawyer et al. 2009, Walter et al. 2011). We included roads from the United States Census Tiger/Line ascii files (U.S. Census Bureau, Washington, DC, USA) because roads have been documented to influence resource selection by cervid species in previous studies (Rost and Bailey 1979, Rowland et al. 2000). We used annual crop layers from the Cropland Data Layer (CDL) project that is managed by the United States Department of Agriculture, which utilizes Deimos-1, UK-DMC 2, Landsat TM/ETM+ or Landsat 8, and AWiFS imagery for the production of a 30 m national product (USDA-NASS, Washington, DC, USA). Separate CDL layers were downloaded for each of the three years of our study to most accurately reflect crop rotation for *winter 2011, summer 2012, winter 2012*, and *summer 2013*. Vegetation categories were reclassified into eight categories that were considered important to resource selection by mule deer: (1) s*ummer crops* were defined as crops planted in the spring, grown throughout the summer months, and harvested in early autumn such as dry beans, safflower, triticale, oats, barley, corn, sweet corn, sorghum, and flaxseed, (2) *winter crops* were defined as crops planted in summer or autumn and grown throughout the winter that included rye, speltz, and winter and spring wheat, (3) *other crops* were crops or other CDL categories occurring in either winter or summer and occurred infrequently or in limited areas across the study site, and were considered least important to mule deer resource selection such as watermelon, grapes, and barren land, (4) *alfalfa* because it represented a large portion of the available crops and is known to be consumed routinely by mule deer (Austin et al. 1998), (5) *sunflower* because it was the main crop of interest for this area (Johnson et al. 2014), (6) *forest* included all forest types, which were mostly comprised of pinyon pine and juniper; this category was considered the main cover variable because of the influence forest cover has on the resource selection of cervid species (Ager et al. 2003, Walter et al. 2011), (7) *shrub* included shrubs less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation and likely provided cover to mule deer, and (8) *grass* included all grassland dominated by gramminoid or herbaceous vegetation. We created a 30 × 30-m raster for each covariate by determining distance from each cell to each of the nine covariates. We did not include elevation because a majority of forest cover occurred in lower elevations adjacent to agricultural fields and grasslands likely resulting in both forest and low elevation yielding similar influences on resource selection.

Statistical Analysis

We estimated a population-level resource selection function (RSF) using a mixed-effects logistic regression model (Manly et al. 2002). We examined a correlation matrix for all covariates before modeling to screen for collinearity and covariates with $|r| > 0.7$ during any one period were excluded in all models. *Grass, summer crops, winter crops,* and *other crops* were not included in final models because of collinearity, and because they occurred less frequently within our study area (i.e., collectively about 17%) compared to the remaining vegetation categories. Using logistic regression with use–availability data presents some problems because predicted values are not scaled between 0 and 1 and generally do not reflect true probabilities of resource selection. Logistic regression can provide an informative and unbiased method for ranking habitat use, however, and for comparing relative probability of use (Keating and Cherry 2004, Johnson et al. 2006). We used individual mule deer as a random-intercept in our mixed-effects models to address issues associated with autocorrelation and uneven sample sizes of locations between individuals (Gillies et al. 2006). We modeled diel (night/day) categories separately because of the influence human activity can have on deer behavior (Kilpatrick and Lima 1999, Ager et al. 2003, Walter et al. 2010). We modeled individual

RSFs for each of the eight periods (four seasons, two diel) and chose not to use year or diel as fixed or random effects because we were interested in identifying potential differences in selection of crops and not simply accounting for the effect of year or diel in our data (Boyce 2006). Our study design also considers that various crops are seasonal so some crops were only available during certain seasons and could only be selected by deer during those seasons (i.e., sunflower selection could only occur during the summer seasons because of its absence during the winter seasons).

We used buffered circles to create random points instead of the entire home range to attain a higher order (third order) of selection and specificity as it relates to spatial scale (Johnson 1980, Boyce 2006). We wanted a higher order of selection to identify specific selection among a suite of unique cover and crop categories for each relocation rather than comparing relocations to the same available locations that could be randomly generated within the home range of an animal. The radius of our buffered circles was determined from the mean daily distance moved that included less than six locations per day. We generated five random points within each buffered circle for each used point, and the five random points were considered *available* in our RSF analysis. We included distance to the four vegetation categories and roads in a global model that also included the random effect for each animal. We used second-order bias correction for Akaike's Information Criterion (AICc; Burnham and Anderson 2002) to select the most parsimonious model among a suite of models for each period of analysis. For each period and day/night combination (n = 8), we included all possible combinations of the five variables (n = 32) for model selection with AICc. We used package *adehabitatLT* for movement analysis (Calenge et al. 2015), *adehabitatHR* for MKDE estimation (Calenge and Fortmann-Roe 2015), and *lme4* and *MuMIn* for mixed-effects logistic regression and AICc, respectively, all in Program R (R Foundation for Statistical Computing, Vienna, Austria).

A posteriori analysis of precipitation effects in the area revealed a large difference in the amount of precipitation received during 2012 in comparison to 2013 and the regional yearly average from 1996 – 2012. Total regional precipitation for 2012 was 15.7 cm, and the total for 2013 was 31.3 cm respectively. The average from 1996 – 2012 was 26.7 cm, so precipitation for 2012 was about 41% less than the yearly average and was about 50% less than it was in 2013.

Results

Movements and Home Range

Fourteen of the twenty mule deer equipped with GPS collars were available for our analysis. Three collars failed to release on the scheduled drop date, and three deer perished within three months of being collared so were excluded from the study. We collected a total of 56,811 GPS locations for use in our analysis after removing errors in GPS data due to potential outliers caused by poor GPS fixes (i.e., 2-dimensional satellite fixes). We had a mean 3-dimensional fix rate of 97%, and a mean of 4,057 locations per deer. Mean daily movement distance across all deer in our study was 628 m (± 262 m SD), which is the distance we used for the radius of our buffered circles. The mean winter home range for 2012 and 2013 was 9.88 km^2 (±3.87 km^2) and 7.68km^2 (±2.75 km^2), respectively. The mean summer home range for 2012 and 2013 was 6.23 km^2 (±3.20 km^2) and 5.51 km^2 (±3.22 km^2), respectively.

Resource Selection

Models with the most support indicated that distance to forest influenced nocturnal and diurnal resource selection during both seasons regardless of year (Tables 2-1, 2-2). Negative coefficients and confidence intervals that did not overlap zero indicated strong influence of distance to forest on mule deer resource selection for all seasons and diel periods (Tables 2-3, 2-4). Distance to alfalfa had similar strong effects on mule deer selection during all season and diel periods except for both diel periods during summer 2013 (Tables 2-1, 2-2). During the summer 2012 season and during both winter seasons resource selection of mule deer was driven mostly by minimizing distance to forest and alfalfa along with some combinations of the other covariates (Tables 2-1, 2-2). Negative coefficients for distance to forest and alfalfa along with confidence intervals that did not overlap zero indicated a strong selection for cover (i.e., forest) and a nutritious forage that is available year-round in agricultural areas (i.e., alfalfa; Tables 2-3, 2-4).

Negative coefficients for distance to sunflower indicated that this crop was most influential to mule deer resource selection during the summer 2013 season for both diel periods along with distance to forest (Tables 2-1, 2-2). Negative coefficients and confidence intervals that do not overlap zero indicated strong selection for sunflower occurred during both diel periods for summer 2013 (Tables 2-3, 2-4). Sunflower also influenced selection during both diel periods for winter 2013; however, positive coefficients supported our logic that mule deer avoided areas during winter, which is after sunflower was harvested thus not available. All other vegetation covariates varied in inclusion within the top model, but both distance to roads and shrub tended to have more support during the 2012 season and diel periods which coincided with low precipitation levels in the area (Tables 2-3, 2-4).

Discussion

Our research provides the first reports of movements, size of home range, and selection for agricultural crops by mule deer in southwestern Colorado. Our use of crop-specific data derived annually from remote sensing technology provided detailed information for analysis of resource selection not previously possible with land cover datasets that are typically created in 5 – 10 year increments (e.g., National Land Cover Database). I identified a change in crop selection for mule deer from alfalfa to sunflower over two subsequent summers in response to changes in precipitation levels, which altered plantings and success of germination of sunflower and results in different levels of damage (Johnson et al. 2014). Furthermore, our movement and home range analysis provided detailed information for areas occupied by mule deer throughout the year and potential areas that could sustain crop damage in the future.

Our mean seasonal home range estimates were similar to previously reported home ranges (Nicholson et al. 1997, Kie et al. 2002) although the use of GPS technology compared to very high frequency technology, and differences in estimator differed from other home range studies. Our mean adult female mule deer home ranges during summer (5.51–6.24 km^2) and winter (7.68–9.88 km^2) were similar to mean summer and winter home range for resident adult female mule deer in California of 5.99 km^2 (±1.89 km^2 SD) and 10.28 km^2 (±9.44 km^2 SD), respectively (Nicholson et al. 1997). Kie et al. (2002) documented mean summer and winter size of home range for adult female mule deer also in California of 6.64 km^2 (±3.75 km^2 SD) and 11.38 km^2 (±8.71 km^2 SD), respectively. Although our study was the first to use GPS technology and MKDE to estimate size of home range for mule deer, our apparently smaller home ranges during the summer compared to the winter seasons were similar to other studies (Nicholson et al. 1997, Kie et al. 2002, Walter et al. 2009). Larger home ranges during the winter months are common for cervids due to lack of forage close to cover, and could also be due to lack of native forage or variety of agricultural crops that are available during the summer season but not the winter seasons.

Distance to forest influenced resource selection regardless of season or time of day as expected for mule deer that are associated with forested areas. This also confirmed that cover is preferably selected by deer that are influenced by human activity (Kilpatrick and Lima 1999, Ager et al. 2003, Walter et al. 2009). Forest cover also likely provides relief from effects of solar radiation and precipitation. For these reasons association of our deer with forested habitat was expected. Although most forested habitat in this area was associated with areas of low-elevation riparian depressions, mule deer tended to occupy the periphery of these areas nearest agricultural fields rather than in the center of riparian depressions on public land suggesting that along with cover, easily accessible forage is also important.

Sunflower was selected more frequently by mule deer during the 2013 summer season than other season, and this may have been due to large differences in precipitation levels. Varying precipitation levels during the 2012 and 2013 influenced the planting and germination of certain crops, especially sunflower, in this area and resulted in different levels of sunflower damage (Johnson et al. 2014). As stated previously, the average annual precipitation for 2012 was about 50% less than the average annual precipitation for 2011 and 2013, and about 40% less than long-term annual average that has been recorded since 1996 (Weather Station DVCO1, Colorado Agricultural Meteorological

Network 2013). Johnson et al. (2014) noted that spring seasonal precipitation in 2012 was only 30% of the average spring (March – June) precipitation for this region. This time period is crucial for dryland farming in southwest Colorado, and because of the low precipitation many did not have successful sunflower crops in 2012. Thus sunflower, which is not as drought resistant as other crops like alfalfa, was not as available in 2012 to mule deer as it was in 2013 (Putnam et al. 2016). This may have caused mule deer to select for alfalfa in 2012, but revert back to sunflower in 2013 when it was once again available.

Selection for sunflower in 2013 suggested that precipitation was a key factor in crop selection for this region of Colorado. Furthermore, selection of sunflower during both nocturnal and diurnal hours in summer 2013 suggested that sunflower crop were preferred over alfalfa when available (Tables 2-3, 2-4). These initial results suggested that when present, sunflower is preferentially grazed over alfalfa and other crops; however, when sunflower is absent as it was in 2012, alfalfa remains important forage for mule deer. Distance to alfalfa influenced selection in this region because alfalfa is a perennial crop that provides browsing availability throughout the year, and is usually grown in large quantities (McDonald et al. 2003). It may experience high levels of crop depredation (Austin and Urness 1993, Austin et al. 1998), and our results indicated that it may be the most preferred crop during rotations when sunflower is not planted or during drought years when sunflower does not have enough precipitation to germinate and flourish.

Methods to prevent crop depredation can be expensive and time consuming to implement on an annual basis. The ability to identify crops that need the most protection would greatly reduce the amount of money and time lost by both landowners and wildlife agencies when implementing various crop depredation prevention strategies. To further complicate matters, crop depredation varies annually depending on local precipitation and temperature patterns. This variation directly influences crop rotation, timing of germination and sprouting of plants. This is especially true for areas like southwest Colorado that can have large variation in precipitation levels and temperature and thus crop success. Utilizing crop-specific data derived annually was necessary to achieve our objectives that would not have been possible using static data layers. Appropriate data layers (annually-derived, crop-specific), study design (random locations within buffered circles), and variation among individual animals (random effect) should be considered when detailed resource selection analysis is needed to achieve study objectives (Boyce 2006).

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Literature Cited

Ager, A. A., B. K. Johnson, J. W. Kern, and J. G. Kie. 2003. Daily and seasonal movements and habitat use by female rocky mountain elk and mule deer. Journal of Mammalogy 84 1076-1088.

Anderson, D. E., R. A. Long, M. P. Atwood, J. G. Kie, T. R. Thomas, P. Zager, and R. T. Bowyer. 2012. Winter resource selection by female mule deer *Ococoileus hemionus*: functional response to spatio-temporal changes in habitat. Wildlife Biology 18:153-163.

Austin, D. D., and P. J. Urness. 1993. Evaluating production losses from mule deer depredation in alfalfa fields. Wildlife Society Bulletin 21:397-401.

Austin, D. D., P. J. Urness, and D. Duersch. 1998. Alfalfa hay crop loss due to mule deer depredation. Society for Range Management 51:29-31.

Benhamou, S. 2011. Dynamic approach to space and habitat use based on biased random bridges. PLoS ONE 6:e14592.

Benhamou, S., and D. Cornelis. 2010. Incorporating movement behavior and barriers to improve kernel home range space use estimates. Journal of Wildlife Management 74:1353-1360.

Boyce, M. S. 2006. Scale for resource selection functions. Diversity and Distributions 12:269-276.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Volume 2nd.Springer-Verlag, New York.

Calenge, C., S. Dray, and M. Royer. 2015. adehabitatLT: analysis of animal movements. http://cran.r-project.org/web/packages/adehabitatLT. Accessed February 2015.

Calenge, C., and S. Fortmann-Roe. 2015. adehabitatHR: home range estimation. http://cran.r-project.org/web/packages/adehabitatHR. Accessed February 2015.

Colorado Parks and Wildlife. 2011-2012. FY 11-12 game damage program report - overview.

Conover, M. 2002. Resolving human-wildlife conflicts: the science of wildlife damage management. Lewis Publishers, Boca Raton.

Gannon, W. L., R. S. Sikes, C. The Animal, and M. Use Committee of the American Society of. 2007. Guidelines of the American Society of Mammalogist for the use of wild mammals in research. Journal of Mammalogy 88:809-823.

Gillies, C. S., M. Hebblewhite, S. E. Nielsen, M. A. Krawchuk, C. L. Aldridge, J. L. Frair, D. J. Saher, C. E. Stevens, and C. L. Jerde. 2006. Application of random effects to the study of resource selection by animals. Journal of Animal Ecology 75:887-898.

Hegel, T. M., C. C. Gates, and D. Eslinger. 2009. The geography of conflict between elk and agricultural values in the Cypress Hills, Canada. Journal of Environmental Management 90:222-235.

Johnson, C. J., S. E. Nielsen, E. H. Merrill, T. L. McDonald, and M. S. Boyce. 2006. Resource selection functions based on use-availability data: theoretical motivation and evaluation methods. Journal of Wildlife Management 70:347-357.

Johnson, D. H. 1980. The comparison of usage and availability measurements for evaluating resource preference. Ecology 61:65-71.

Johnson, H. E., J. W. Fischer, M. Hammond, P. D. Dorsey, W. D. Walter, C. W. Anderson, and K. C. VerCauteren. 2014. Evaluation of techniques to reduce deer and elk damage to agricultural crops. Wildlife Society Bulletin:358-365.

Keating, K. A., and S. Cherry. 2004. Use and interpretation of logistic regression in habitat-selection studies. Journal of Wildlife Management 68:774-789.

Kie, J. G., R. T. Bowyer, M. C. Nicholson, B. B. Boroski, and E. R. Loft. 2002. Landscape heterogeneity at differing scales: effects on spatial distribution of mule deer. Ecology 83:530-544.

Kilpatrick, H. J., and K. K. Lima. 1999. Effects of archery hunting on movement and activity of female white-tailed deer in an urban landscape. Wildlife Society Bulletin 27:433-440.

Lendrum, P. E., C. R. Anderson, Jr., R. A. Long, J. G. Kie, and R. T. Bowyer. 2012. Habitat selection by mule deer during mirgation: effects of landscape structure and natural gas-development. Ecosphere 3(9):1-19.

Manly, B. F. J., L. L. McDonald, and D. L. Thomas. 2002. Resource selection by animals: statistical design and analysis for field studies. Volume 2nd.Kluwer Academic Publishers, Dordrecht.

Marshall, J. P., V. C. Bleich, P. R. Krausman, M. L. Reed, and N. G. Andrew. 2006. Factors affecting habitat use and distribution of desert mule deer in an arid environment. Wildlife Society Bulletin 34:609-619.

McDonald, S. K., L. Hofsteen, and L. Downey. 2003. Crop profile for alfalfa in colorado.1-27.

Nicholson, M. C., R. T. Bowyer, and J. G. Kie. 1997. Habitat selection and survival of mule deer: tradeoffs associated with migration. Journal of Mammalogy 78:483-504.

Nixon, C. M., L. P. Hansen, P. A. Brewer, and J. E. Chelsvig. 1991. Ecology of white-tailed deer in an intensively farmed region of Illinois. Wildlife Monographs 118:1-77.

Putnam, D. H., E. S. Oplinger, D. R. Hicks, B. R. Durgan, D. M. Noetzel, R. A. Meronuck, J. D. Doll, and E. E. Schulte. 2016. Sunflower. Alternative Field Crops Manual.

Rost, G. R., and J. A. Bailey. 1979. Distribution of mule deer and elk in relation to roads. Journal of Wildlife Management 43:634-641.

Rowland, M. M., M. J. Wisdom, B. K. Johnson, and J. G. Kie. 2000. Elk distribution and modeling in relation to roads. Journal of Wildlife Management 64:672-684.

Sawyer, H., M. J. Kauffman, and R. M. Nielson. 2009. Influence of well pad activity on winter habitat selection patterns of mule deer. Journal of Wildlife Management 73:1052-1061.

Sawyer, H., R. M. Nielson, F. G. Lindzey, and L. L. McDonald. 2006. Winter habitat selection of mule deer before and during development of a natural gas field. Journal of Wildlife Management 70:396-403.

Smith, D. O., M. Connor, and E. R. Loft. 1989. The distribution of winter mule deer use around homesites. 1989 Transaction of the Western Section of The Wildlife Society 25:77-80.

Wagner, K. K., R. H. Schmidt, and M. R. Conover. 1997. Compensation programs for wildlife damage in North America. Wildlife Society Bulletin 25:312-319.

Walter, W. D., D. M. Baasch, S. E. Hygnstrom, B. D. Trindle, A. J. Tyre, J. J. Millspaugh, C. J. Frost, J. R. Boner, and K. C. VerCauteren. 2011. Space use of sympatric deer in a riparian ecosystem in an area where chronic wasting disease is endemic. Wildlife Biology 17:191-209.

Walter, W. D., J. Beringer, L. P. Hansen, J. W. Fischer, J. J. Millspaugh, and K. C. VerCauteren. 2010. Factors affecting space use overlap by white-tailed deer in an urban landscape. International Journal of Geographical Information Science 25:379-392.

Walter, W. D., D. P. Onorato, and J. W. Fischer. 2015. Is there a single best estimator? Selection of home range estimators using area-under-the-curve. Movement Ecology 3:10.

Walter, W. D., K. C. VerCauteren, H. Campa, III, W. R. Clark, J. W. Fischer, S. E. Hygnstrom, N. E. Mathews, C. K. Nielsen, E. M. Schauber, T. R. Van Deelen, and S. R. Winterstein. 2009. Regional assessment on influence of landscape configuration and connectivity on range size of white-tailed deer. Landscape Ecology 24:1405-1420.

Yoder, J. 2002. Deer-inflicted crop damage and crop choice in Wisconsin. Human Dimensions of Wildlife 7:179-196.

Figure 2-1. Location of mule deer equipped with Global Positioning System collars in southwestern Colorado and southeastern Utah with state and county borders.

Table 2-1. Top models using Akaike's Information Criteria (AICc) adjusted for small sample size with delta AICc < 2.0 for nocturnal locations during summer and winter 2012 and 2013 using mixed-effects logistic regression for mule deer in southwest Colorado. Fixed effects included distance to alfalfa, roads, shrub, sunflower, and forest and random effects were the individual animals.

Model Terms	df	AICc	ΔAICc	Weight
Winter 2012				
Alfalfa + Roads + Shrub + ---- + Forest	6	66525.4	0.00	0.683
Alfalfa + Roads + Shrub + Sunflower + Forest	7	66527.0	1.56	0.312
Summer 2012				
Alfalfa + Roads + ---- + Sunflower + Forest	5	15040.4	0.00	0.335
Alfalfa + Roads + Shrub + Sunflower + Forest	4	15040.4	0.00	0.241
Alfalfa + Roads + ---- + ---- + Forest	5	15041.2	0.82	0.228
Alfalfa + Roads + Shrub + ---- + Forest	6	15041.9	1.48	0.174
Winter 2013				
Alfalfa + Road + Shrub + Sunflower + Forest	7	47363.6	0.00	0.755
Alfalfa + Road + Shrub + ---- + Forest	6	47366.4	2.74	0.192
Summer 2013				
Alfalfa + ---- + ---- + Sunflower + Forest	5	15040.4	0.00	0.230
---- + ---- + ---- + Sunflower + Forest	4	15040.4	0.00	0.230
---- + Roads + ---- + Sunflower + Forest	5	15041.2	0.82	0.153
Alfalfa + Roads + ---- + Sunflower + Forest	6	15041.9	1.48	0.110
Alfalfa + ---- + Shrub + Sunflower + Forest	6	15042.3	1.89	0.089
---- + ---- + Shrub + Sunflower + Forest	5	15042.4	1.98	0.086

Table 2-2. Top models using Akaike's Information Criteria (AICc) adjusted for small sample size with delta AICc < 2.0 for diurnal locations during summer and winter 2012 and 2013 using mixed-effects logistic regression for mule deer in southwest Colorado. Fixed effects included distance to alfalfa, roads, shrub, sunflower, and forest and random effects were the individual animals.

Model Terms	df	AICc	ΔAICc	Weight
Winter 2012				
Alfalfa + Roads + Shrub + Sunflower + Forest	7	55196.4	0.00	0.566
Alfalfa + Roads + Shrub + ---- + Forest	6	55198.0	1.54	0.262
Summer 2012				
Alfalfa + Roads + Shrub + ---- + Forest	6	31204.0	0.00	0.377
Alfalfa + Roads + Shrub + Sunflower + Forest	7	31024.6	0.61	0.277
Alfalfa + ---- + Shrub + ---- + Forest	5	31025.9	1.97	0.141
Winter 2013				
Alfalfa + ---- + Shrub + Sunflower + Forest	6	40409.3	0.00	0.623
Alfalfa + Road + Shrub + Sunflower + Forest	7	40411.3	1.98	0.232
Summer 2013				
---- + ---- + ---- + Sunflower + Forest	4	24478.6	0.00	0.298
Alfalfa + ---- + ---- + Sunflower + Forest	5	24479.7	1.10	0.172
---- + ---- + Shrub + Sunflower + Forest	5	24480.1	1.52	0.139
---- + Roads + ---- + Sunflower + Forest	5	24480.5	1.89	0.116

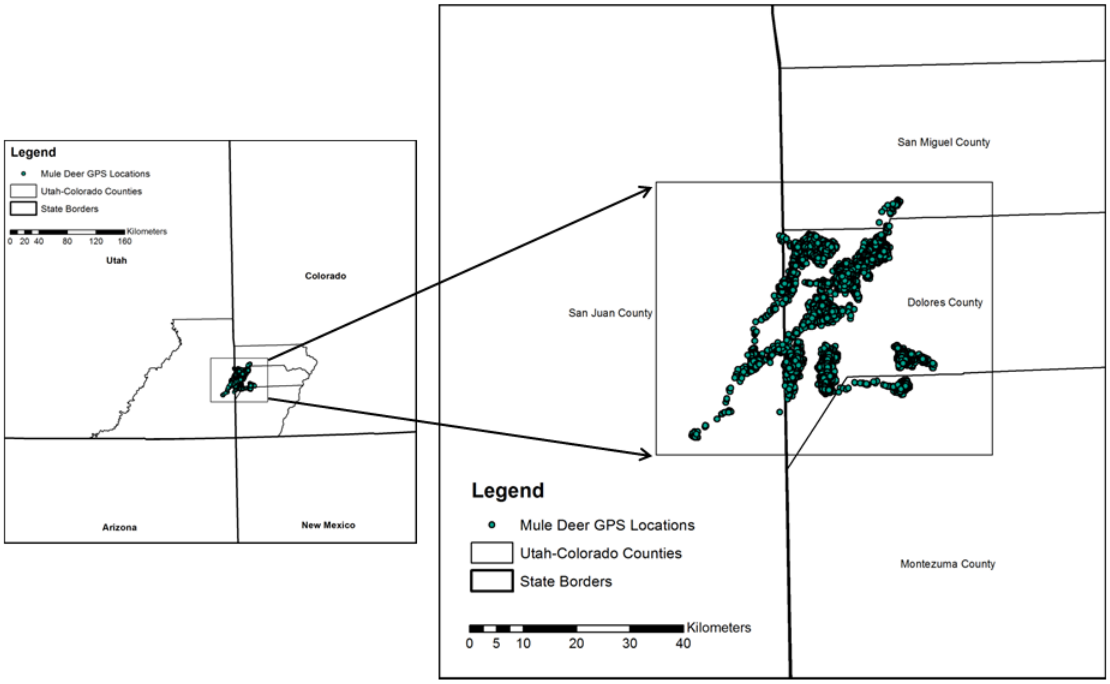
Table 2-3. Parameters, model coefficients (Estimates), standard error (SE), and 95% Confidence Intervals (CI) for summer and winter 2012 and 2013 from the top model during nocturnal hours for selection of crops by mule deer in southwestern Colorado.

Parameter	Estimates	SE	CI
Winter 2012			
Intercept	−1.651	0.010	−1.671 to −1.6307
Forest	−0.335	0.013	−0.361 to −0.310
Alfalfa	−0.090	0.012	−0.1104 to −0.0696
Road	0.035	0.009	0.0156 to 0.0537
Shrub	−0.113	0.012	−0.1364 to −0.0902
Summer 2012			
Intercept	−1.648	0.018	−1.6837 to −1.6116
Sunflower	0.046	0.027	−0.0079 to 0.0970
Forest	−0.349	0.024	−0.3932 to −0.3038
Alfalfa	−0.102	0.028	−0.1547 to −0.0496
Road	0.061	0.018	0.0255 to 0.0971
Winter 2013			
Intercept	−1.653	0.012	−1.6771 to −1.6296
Sunflower	0.034	0.016	0.0034 to 0.0646
Forest	−0.352	0.016	−0.3832 to −0.3213
Alfalfa	−0.123	0.018	−0.1538 to −0.0898
Road	0.034	0.012	0.0109 to 0.0567
Shrub	−0.053	0.015	−0.0818 to −0.0242
Summer 2013			
Intercept	−1.686	0.022	−1.7297 to −1.6425
Sunflower	−0.078	0.021	−0.1189 to −0.0364
Forest	−0.534	0.031	−0.595 to −0.4732
Alfalfa	−0.030	0.022	−0.0725 to 0.0117

Table 2-4. Parameters, model coefficients (Estimates), standard error (SE), and 95% Confidence Intervals (CI) for summer and winter 2012 and 2013 from the top model during diurnal hours for selection of crops by mule deer in southwestern Colorado.

Parameter	Estimates	SE	CI
Winter 2012			
Intercept	−1.636	0.011	−1.6575 to −1.6142
Sunflower	0.029	0.015	−0.0011 to 0.0586
Forest	−0.256	0.014	−0.2829 to −0.2299
Alfalfa	−0.116	0.016	−0.1476 to −0.0853
Road	0.025	0.011	0.0042 to 0.0465
Shrub	−0.095	0.013	−0.1195 to −0.0696
Summer 2012			
Intercept	−1.629	0.015	−1.6579 to −1.6005
Forest	−0.264	0.019	−0.3005 to −0.2276
Alfalfa	−0.057	0.015	−0.0871 to −0.0271
Road	0.029	0.015	0.0006 to 0.0574
Shrub	0.039	0.016	0.0069 to 0.0715
Winter 2013			
Intercept	−1.644	0.013	−1.6697 to −1.6187
Sunflower	0.042	0.018	0.0071 to 0.0767
Forest	−0.294	0.016	−0.3262 to −0.262
Alfalfa	−0.143	0.019	−0.1797 to −0.1066
Shrub	−0.088	0.016	−0.1189 to −0.0566
Summer 2013			
Intercept	−1.639	0.017	−1.6712 to −1.6059
Sunflower	−0.052	0.017	−0.084 to −0.0193
Forest	−0.313	0.021	−0.3532 to −0.2725

Figure 2-1.


Legend
Mule Deer GPS Locations
Utah-Colorado Counties
State Borders
Kilometers
0 20 40 80 120 160
Utah
Colorado
Arizona
New Mexico
San Miguel County
San Juan County
Dolores County
Montezuma County
Legend
Mule Deer GPS Locations
Utah-Colorado Counties
State Borders
Kilometers
0 5 10 20 30 40

Chapter 3

Risk assessment of captive cervid facilities in Pennsylvania

Abstract

Pennsylvania is second only to Texas in number of captive cervid facilities with over 1000 within the state. These facilities can pose a large risk to wild deer populations because of disease transmission issues, and in particular pose a serious threat via the spread of chronic wasting disease (CWD). Current regulations exist to prevent disease spread, but are minimal and often hard to enforce. My objective was to identify areas of use by owners of captive cervid facilities in Pennsylvania, and hence identify areas that are potentially most at risk for CWD transmission between captive and wild deer because of captive facility presence. In order to achieve this objective I will first identify environmental and facility characteristics that are related to CWD transmission and are selected for by captive facility owners, and I will then use these variables to create a predictive surface of areas with a potential for greater risk of CWD transmission from captive to wild deer populations or vice versa due selection of areas by captive facility owners. I used multiple Geographic Information System layers and information from 841 captive facilities to create six variables to include in our models. These variables included elevation, land cover, distance to public lands (federal and state), wild deer density, facility stocking density, and facility deer movements. Wild deer density, stocking density, and movements were all categorized to better represent our data and make for a more appropriate analysis. Land cover was grouped in four categories (i.e., water/wetlands, urban, forest, agriculture). Negative binomial regression was used to assess our 13 *a priori* models. Our regression analysis indicated that agriculture was the most influencing factor affecting areas selected by captive facility owners with positive coefficients and confidence intervals that did not overlap zero. High wild deer density,

average stocking density, and elevation also had varying influence on areas selected by facility owners. Model results were incorporated into a predictive surface to identify areas with the highest risk of CWD transmission in the state that could be attributed to captive facilities. This predictive surface can be used by wildlife managers to better assess where CWD surveillance and monitoring will be most effective.

Key Words

Captive cervid facilities, chronic wasting disease, negative binomial, risk assessment

Introduction

Captive cervid facilities are common throughout the United States with Pennsylvania second only to Texas in the number of facilities with over 1000 facilities that account for over 25,000 cervids (Brooks and Jayarao 2008). These facilities occur for many reasons, such as production and hunting of "trophy" animals, breeding stock, venison, or for small specialty items such as decorative antlers and antler velvet (Coon et al. 2002, Brooks and Jayarao 2008). The captive cervid industry has become a large and successful business in some localities but the relationship between these captive facilities and the spread of diseases such as chronic wasting disease (CWD) has recently become a concern for wildlife managers (Sohn et al. 2002, Williams et al. 2002, Kim et al. 2005).

Interactions of cervid species can account for some local disease spread (Bohm et al. 2007), however, the human-caused (i.e., human transportation of captive cervids) spread of diseases like CWD is a serious concern both internationally and within the United States. The United States and Canada have implemented multiple measures for the captive cervid industry to prevent further spread of CWD (United States Department of Agriculture 2014b;c;a), however, many of these measures are reactive and not pro-active so do not prevent disease transmission (Miller and Thorne 1993). Thus, cases of diseased animals being transported to other states or countries are common, and exacerbate the issue of disease transmission across the world (Miller and Thorne 1993, Sohn et al. 2002, Kim et al. 2005).

Local governments like The Commonwealth of Pennsylvania have taken steps to mitigate further spread of CWD such as mandatory and voluntary herd monitoring programs (Pennsylvania Department of Agriculture 2014). Mandatory and voluntary CWD monitoring programs that include various levels of testing and reporting are now commonly implemented in multiple states to prevent future spread of the disease. These programs also permit inter- and intra-state abilities to transport animals, which gives incentive for captive deer farmers to participate (Pennsylvania Department of Agriculture 2014, United States Department of Agriculture 2014b). Even with this program in place, however, captive herds have tested positive for CWD in Pennsylvania as recently as October 2014. This is an example that even with strict regulations deer with disease continue to be identified, and sometimes even transported among facilities.

Transportation of infected captive cervids is not the only disease issue associated with captive facilities. Multiple studies have found that regulations regarding the care of captive deer species are often minimal, and general practices such as the use of regular vaccines, anthelmintics, and veterinary care are often under or misused by captive facility owners (Bruning-Fann et al. 1997, Brooks and Jayarao 2008). Biosecurity measures such as visual inspections and obtaining herd histories are also infrequently performed (Brooks and Jayarao 2008). Poor husbandry practices lead to higher risks of CWD occurring within captive facilities and can also lead to a higher risk of transmission between captive and wild deer (Miller and Thorne 1993).

Wildlife managers are concerned about the health of the animals in captive cervid facilities because diseases within a captive facility have the potential to spread to wild cervid populations due to poor facility maintenance and enclosures. Spread of these diseases can occur through multiple pathways such as direct and indirect fence line interaction (VerCauteren et al. 2007a;b) or escaped captive individuals (Miller and Thorne 1993, Coon et al. 2002). VerCauteren et al. (2007b) documented direct fence line interaction between captive and wild white-tailed deer, and also wild deer visitation rates of almost one per week in Michigan. VerCauteren et al. (2007a) also documented direct contact through single woven-wire fence between captive and wild mule deer (*Odocoileus hemionus*) and elk (*Cervus elaphus*) in Colorado, however, no direct contact was documented in the areas with captive elk behind double woven-wire fence. The establishment of proper fencing such as double barrier fencing or electric fencing in combination with regular woven wire fencing can reduce contact between wild and captive cervids and would be beneficial in the prevention of disease spread (VerCauteren et al. 2007a;b, Fischer et al. 2011). Many of these regulations are not required, however, and vary state to state (i.e. ≥2.4 m high fencing, double barriers, holding pens for veterinary care) so many facilities do not have adequate structures.

Including captive facilities in risk assessment models is necessary when trying to prevent CWD spread to wild cervids and vice versa. Testing over 25,000 captive cervids in Pennsylvania is not practical. Developing a predictive model to determine where captive facilities and wild deer populations would be more likely to come into contact due to captive facility presence would greatly reduce sampling effort compared to what is currently done and may reduce the likelihood of spread of CWD. My objective was to identify areas of Pennsylvania that are potentially most at risk for CWD transmission between captive and wild deer because of captive facility presence. In order to achieve this objective I first identified environmental and facility characteristics that are related to CWD transmission and are selected for by captive facility owners, and I then used these variables to create a predictive surface of areas with a potential for greater risk of CWD transmission from captive to wild deer populations or vice versa due to selection of areas by captive facility owners.

Study Area

The study area was the state of Pennsylvania where elevation ranges from 979 m above sea level at the highest peak in southwestern Pennsylvania, to sea level at the Delaware Water Gap in eastern Pennsylvania with an overall mean elevation of 335 m. The state varies considerably in geography, but in general lowland areas associated with large bodies of water occur in the Northwest (Lake Erie) and Southeast region (Delaware Water Gap) with the Alleghany mountain range occurring from Southwest to the Northeast region of the state. This diverse geography and large, managed public lands lends to a very diverse mix of forest types (i.e. deciduous, evergreen and mixed), agriculture, scrub/open areas, wetlands/waterways and urban areas. Public lands, including both state and federally owned lands, account for about 14% of the land cover in Pennsylvania with the remainder in private ownership.

Methods

Wild Deer Variable

I used Wildlife Management Unit (WMU) boundaries and deer population estimates created by the Pennsylvania Game Commission (PGC) using the sex-age-kill model to estimate wild deer densities for the state (hereafter referred to as *wild deer density*) (Rosenberry et al. 2011). I then categorized the deer densities into five classes with one being lowest class (low: ≤ 6 deer/km^2, below average: 7 – 9 deer/km^2, average: 10 – 13 deer/km^2, above average: 14 – 17 deer/km^2, and high: ≥ 18 deer/km^2) that were based upon forest regeneration ability (Tilghman 1989, Horsley et al. 2003). I included wild deer density because of the affect high deer densities in combination with white-tailed deer (*Odocoileus virginianus*) biology and behavior have on CWD transmission (Conner et al. 2008, Kelly et al. 2014).

Environmental Variables

I used several Geographic Information System (GIS) layers by landownership for the U.S. Forest Service (~240,000 ha), Pennsylvania Department of Conservation and Natural Resources (~2 million ha), and Pennsylvania Game Commission (PGC; ~1.5 million ha) statewide from the Pennsylvania Spatial Data Access (Penn State Institutes of Energy and the Environment, University Park, PA, USA). I combined all public lands GIS layers to create a distance to variable (hereafter referred to as *distance to public*) because of the ecotones that typically occur along public land borders. Ecotones, especially those created by human activities such as agriculture, have been discussed as potential hot spots of disease transmission for various diseases (i.e., Lyme disease, malaria) because of the type of environmental and biological activities that occur in these transition zones (Despommier et al. 2007).

I used land cover data from the National Land Cover Database (NLCD) (MLRC 2011) and reclassified it into four categories: 1) water and wetlands; 2) developed land, which ranged in intensity from rural to urban; 3) agriculture; and 4) forest which included all NLCD forest categories. Land cover type has been documented to be an important driver of CWD transmission in multiple studies (Farnsworth et al. 2006, Evans et al. 2016).

I also used an elevation layer, which was attained from the United States Department of Agriculture (USDA) Natural Resources Conservation Services and National Cartography and Geospatial Center to include in our analysis (USDA 1998). A greater prevalence of CWD has been found at lower elevations in Colorado where deer concentrate during winter months (Farnsworth et al. 2006).

Captive Facility Variables

I received locations of all known and registered Pennsylvania captive cervid facilities from the Pennsylvania Department of Agriculture (PDA) in 2013. I used 841 captive facilities for analysis after removing captive facilities no longer in operation, facilities for which I could not directly locate a parcel of land, and facilities located within a county from which I did not receive parcel land data. In fall 2013 I initiated contact of County Clerks in Pennsylvania, and I collected GIS parcel layers to associate captive facilities with their appropriate parcels of land. I then created a raster layer across the state that contained the number of captive cervids/acre using the herd size data from the captive facility information and parcel size from the county parcel information (hereafter referred to as *stocking density*). I categorized stocking density into three categories, which were based upon perceived deer health and condition (low: < 5, average: 5 – 15, and high: > 15). I considered low stocking densities to be associated with better health and body condition of deer, and thus considered it more desirable to decrease disease spread in both captive and wild deer (Brooks and Jayarao 2008, Brooks et al. 2015).

I created a layer of movements (hereafter referred to as *movements*) using 150,000 movement records received from the PDA that documented all recorded individual movements into and out of a facility from 2005 to 2015, however, only 49,000 movement records could actually be linked to known animal movements. In particular, I only considered animals that were brought into a facility (e.g., transported in from another facility, born at the facility) or exported within the state because of the potential implications an infected individual would have on wild deer populations in Pennsylvania. Deer that were imported or exported from out of state were not included because geographic reference information was not available for out of state facilities. I categorized the movement layer as low: >35, average: 35 – 60, and high: >60 based on the average amount of movements into a facility for all of the locations over the 10-year period.

Data Preparation

I formatted all raster layers to have a 100 m resolution because of the large study area in ArcMap 10.1 (Environmental Systems Research Institute, Redlands, CA). I then imported all raster layers for analysis into Program R (R Foundation for Statistical Computing, Vienna, Austria). I tested all variables for collinearity with Pearson's test, and were considered correlated with coefficients > 0.5. Forest and agriculture land cover categories, elevation, and distance to public were correlated so were not included in the same models.

I standardized all continuous data to account for difference in sampling techniques of the various layers. I created circular sampling units with diameters of 18 km that were systematically spaced across the counties that I received parcel information, which is representative of the average dispersal distance of female white-tailed deer (Lutz et al. 2015). Dispersal distance was chosen because of the relevance dispersal has on the spread of CWD (Grear et al. 2006, Skuldt et al. 2008). In addition, this diameter provided a sampling circle large enough to effectively sample the entire state, but small enough to recognize differences in the landscape and changes in the number of captive facilities across the study area (Nielson and Sawyer 2013). I then extracted means for each covariate within the 305 circles to include in modeling efforts.

Modeling

I used negative binomial regression models to assess count data because of the overdispersion problems typically found in datasets of this kind (Nielson and Sawyer 2013). Observed count data tends to have variances greater than the mean, and hence does not fit the typical Poisson distribution associated with linear or logistic regression (Manly et al. 2002, Nielson and Sawyer 2013). Additionally, resource selection functions such as logistic regression tend to compare the characteristics of used (use = 1) vs. available (use = 0) locations to assess selection (Manly et al. 2002). Negative binomial instead models use as a continuous variable that compares proportional use of habitat, which works well with discrete data such as the captive cervid data (Nielson and Sawyer

2013, Sawyer et al. 2009). I created 13 *a priori* general linear models that included one to ten fixed effects. I used Akaike's Information Criterion (AIC) values to select the most parsimonious model and models with ΔAIC < 2.0 were considered top models (Burnham and Anderson 2002).

Results

Agriculture was the most supported land cover type selected by landowners to place a captive facility, and was included in three of the four top models (Table 3-1). Positive coefficients and confidence intervals that did not overlap zero indicated that captive facilities were typically located in areas where there is more agriculture rather than forests (Table 3-3). Agriculture was also the only variable in the top model (Table 3-2).

Other variables with support included wild deer density, stocking density, and elevation. Negative coefficients and confidence intervals that did not overlap zero indicated that captive facilities were located away from areas with high wild deer densities (≥18 deer/km^2) (Table 3-2, 3-3). Positive coefficients and confidence intervals that did not overlap zero also suggested that captive facilities were located in areas with other captive facilities that have average stocking densities (5 – 15 deer/acre; Table 3-2, 3-3). Elevation also had support suggesting that captive facilities were preferentially located in areas of low elevation (Tables 3-2, 3-3).

Discussion

Three of the four top models with the most support included agriculture, and agriculture was the only land cover category in any of the most supported models (Table 3-2). Several other variables (i.e., elevation, wild deer density, and stocking density) all had varying effects on captive facility owner selection (Table 3-3). The selection for and against these variables can have a large effect on the spread of CWD among wild Pennsylvania herds.

High wild deer density ($\geq$18 deer/km^2) had a negative effect on areas selected by captive facility owners. Owners tended to select away from high wild deer densities, but there was no indication of selection for or against the other wild deer density categories (i.e., low to above average) (Table 3-3). However, more specific estimates of local wild deer densities might reveal different patterns of use because my estimates were created on the large scale of the WMUs. Additionally, I was unable to collect parcel information for several counties around Pittsburgh in western Pennsylvania, and thus was unable to use those captive facility locations as stated previously in my methods. This area has some of the highest wild deer densities in the state, and also may have revealed different patterns of selection if I was able to include those facilities in my analysis. Selection against high wild deer densities though could be because many areas of high wild deer densities in Pennsylvania occur in urban or suburban landscapes (Etter et al. 2002). Agricultural activities in Pennsylvania tend not to occur in these kinds of heavily human populated landscapes. Thus captive facilities, located more in agricultural or rural areas, also occur outside of high wild deer density areas. Although selection against high wild deer densities by captive facility owners may be beneficial to wild deer by reducing the amount of potential direct and indirect contact between the both wild and captive deer (Joly et al. 2006, Conner et al. 2008, Kjaer et al. 2008, Kelly et al. 2014), more research using specific local wild deer density estimates is needed to best assess captive facility owner use of these areas. Furthermore, the selection against areas of high wild deer density may not be an intentional choice by captive cervid owners, but rather an artifact of other effects such as lack of use of urban areas associated with these high deer densities.

The importance of agriculture to captive facilities is most likely attributed to having access to agricultural infrastructure such as feed stores, veterinary care, and farm hand aid. Agriculture supports a large part of Pennsylvania's economy (United States Department of Agriculture 2016), and most agricultural businesses occur in the central and western part of the state. Even if commercial agricultural resources are not specifically designed to support deer farming, starting a cervid farm in an area in which an agricultural infrastructure currently exists is much easier and cheaper than starting up in an area lacking any such infrastructure. This is a common practice in many other agricultural businesses as well. The selection of agricultural areas, however, has negative implications for CWD transmission. Studies have shown landscapes with less forest cover increase infection rates of CWD among wild deer (Farnsworth et al. 2005, Evans et al. 2016). Thus, wild deer in agricultural areas where less forest cover naturally occurs not only have a greater chance of getting CWD because of the habitats they occupy, but the presence of captive facilities also increases the potential for CWD transmission. Additionally, deer in areas with higher amounts of forest cover also have shorter dispersal distances (Long et al. 2005), and thus may have a smaller influence on the spread of CWD compared to deer in less forested areas that disperse further. Therefore the risk of CWD transmission again is not only affected by deer behavior in this kind of landscape, but also by the higher risk of CWD transmission because of the presence of captive facilities.

The only top model that did not include agriculture indicated that elevation influenced selection of captive facility owners. Specifically, captive facility owners selected for areas of low elevation, which coincides with valleys that agriculture is typically located within Pennsylvania. Selection for lower elevations could also have negative impacts on CWD transmission. In Colorado CWD had a greater prevalence in lower-elevation winter ranges where deer were known to concentrate (Farnsworth et al. 2006). Thus, a high density of both captive facilities and wild deer populations especially during the winter months at lower elevations could prove to be a dangerous combination that increases risk of CWD transmission.

I also found that, captive facility owners also selected areas that had other facilities with average stocking densities. Different stocking densities often connote the type of cervid farm that these facilities represent (Brooks and Jayarao 2008). For example, the lowest stocking densities are often associated with large hunting lodges that maintain deer in large, fenced, wooded areas for the purpose of holding trophy hunts. This is unlike cervid farms that are for hobby purposes that tend to have high stocking densities (Brooks and Jayarao 2008). A majority of cervid farms fall in between these two kinds of facilities, and are moderately sized businesses that sell various kinds of cervid related products or raise breeding and hunting stock to sell to other facilities. These farms tend to have average stocking densities, and make up a majority of the cervid industry (Brooks and Jayarao 2008). It should be noted though that our stocking density estimates were most likely lower than true stocking densities because of our use of the whole parcel area when calculating density. Most cervid farms only use a portion of their land to allow for vegetation regeneration in other areas (Brooks et al. 2015).

Thus, better estimates of captive facility stocking densities may reveal different patterns of use. Stocking densities above the recommended 10 deer/acre can have negative health effects on captive cervid populations (Brooks and Jayarao 2008). These negative effects can result in higher incidents of disease, like CWD, in the captive population, or increase the captive cervid susceptibility to external sources of disease as well (Brooks and Jayarao 2008).

Cervid farmers may also select for areas that have other facilities with average stocking densities because of the ability to get cervid care and business information from other cervid farmers that are already established in these areas. Unfortunately, due to a lack of professional information, such as advice from veterinarians with cervid biology experience, many cervid farmers turn to one another for care and business advice. This can again affect CWD transmission negatively because improper care practices or bad facility maintenance advice can lead to higher risks of CWD infection to captive deer, and thus potentially higher risks of CWD transmission in the area.

The predictive layer created with parameter estimates from the top models shows that the areas of highest risk of CWD spread via captive facilities is in the south central and southeast part of the state (Figure 3-2). This is of particular interest as the first positive case of CWD in a captive cervid facility was a white-tailed deer herd located in Adams and York Counties. Thus, our predictive surface coincides with actual occurrence of CWD in Pennsylvania. The first Disease Management Area (DMA) that was created in Pennsylvania is also located in these counties where this first case of a CWD-positive captive deer occurred. The second DMA is west of DMA 1, and located mostly in Bedford and Blair Counties. This also mostly occurs in a predicted area of medium to high risk where only wild deer have tested positive for CWD. The third and most recent DMA is located in Jefferson County, which is north of DMA 2. This DMA occurs in a low risk area, and does not coincide with the predictive surface. Disease Management Units 1 and 3, however, are likely to be removed from monitoring because the facilities infected with deer are no longer in operation and no infected wild individuals have been identified in these areas unlike DMA 2.

Identification of these highly used areas can assist regulatory personnel of the captive cervid industry and wildlife managers in the control of CWD, and especially when combined with other CWD risk assessment studies. Other risk assessment studies have found that clay content in soil (Walter 2011), landscape variation (Evans et al. 2016, Farnsworth 2005), and the spatial distribution of deer (Farnsworth 2006) also influence CWD prevalence. With our identification of areas more likely to be at risk from captive facilities, wildlife managers can focus on specific facilities for CWD testing as opposed to monitoring every facility statewide. The combination of our results and other CWD risk assessments on wild deer populations will enable a fine scale predictive process in which to sample both wild and captive cervids for CWD. This would be more efficient and could considerably reduce the financial burden on regulatory agencies. Public groups that are affected by CWD (i.e., hunters, captive facility owners) can also use predictive surfaces of risk to help prevent CWD spread attributed to human processes by eliciting more precautionary measures taken by these affected public groups.

Conclusions

Captive white-tailed deer facilities are currently a focus of CWD management because they are considerably linked to wild deer populations (VerCauteren et al.

2007a;b, Brooks and Jayarao 2008). Infection with a disease by either captive or wild deer, could directly lead to transmission to the other that would equally impact the state agency and private industry. Without continued regulation and educational outreach in states that have captive cervid facilities, infection with disease could become detrimental to the economy of a state. Identification of highly selected areas by captive facility owners in combination with other CWD risk assessment studies can help wildlife managers control CWD spread via providing more precise areas to conduct CWD testing protocols.

Literature Cited

Bohm, M., P. C. L. White, J. Chambers, L. Smith, and M. R. Hutchings. 2007. Wild deer as a source of infection for livestock and humans in the UK. The Veterinary Journal 174:60-276.

Brooks, J. W., and B. M. Jayarao. 2008. Management practices used by white-tailed deer farms in Pennsylvania and herd health problems. Journal of American Veterinary Medical Association 232:98-104.

Brooks, J. W., D. Wagner, L. F. Kime, E. Santini, K. F. Martin, and J. K. Harper. 2015. Agricutural alternatives: white-tailed deer production. *in* T. P. S. University, editor. PennState Extension. Ag Communications and Marketing, University Park, PA.

Bruning-Fann, C., K. Shank, and J. Kaneene. 1997. Descriptive epidemiology of captive cervid herds in Michigan, USA. Vet Res 28:295-302.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Volume 2nd.Springer-Verlag, New York.

Conner, M. M., M. R. Ebinger, J. A. Blanchong, and P. C. Cross. 2008. Infectious disease in cervids of North America: data, models, and management challenges. Annals of the New York Academy of Sciences 1134:146-172.

Coon, T. G., H. Campa, III, A. B. Felix, R. B. Peyton, S. R. Winterstein, F. Lupi, M. Schulz, and J. Sikarskie. 2002. Farming captive cervids: A review of social, economic and ecological opportunities and risks in Michigan and North America. North American Wildlife and Natural Resources Conference.Transactions 67:251-268.

Despommier, D., B. R. Ellis, and B. A. Wilcox. 2007. The role of ecotones in emerging infectious diseases. EcoHealth 3:281-289.

Etter, D. R., K. M. Hollis, D. R. Ludwig, J. E. Chelsvig, and C. L. Anchor. 2002. Survival and movements of white-tailed deer in suburban Chicago, Illinois. Journal of Wildlife Management 66 500-510.

Evans, T. S., M. S. Kirchgessnerr, B. Eyler, C. W. Ryan, and W. D. Walter. 2016. Habitat influences distribution of chronic wasting disease in white-tailed deer. Journal of Wildlife Management 80:284-291.

Farnsworth, M. L., J. A. Hoeting, N. T. Hobbs, and M. W. Miller. 2006. Linking chronic wasting disease to mule deer movement scales: a hierarchical bayesian approach. Ecological Applications 16:1026-1036.

Farnsworth, M. L., L. L. Wolfe, N. T. Hobbs, K. P. Burnham, E. S. Williams, D. M. Theobald, M. M. Conner, and M. W. Miller. 2005. Human land use influences chronic wasting disease prevalence in mule deer. Ecological Applications 15:119-126.

Fischer, J. W., G. E. Phillips, D. M. Baasch, M. J. Lavelle, and K. C. VerCauteren. 2011. Modifying elk (Cervus elaphus) behavior with electric fencing at established fence-lines to reduce disease transmission potential. Wildlife Society Bulletin 35:9-14.

Grear, D. A., M. D. Samuel, J. A. Langenberg, and D. Keane. 2006. Demographic patterns and harvest vulnerability of chronic wasting disease infected white-tailed deer in Wisconsin. Journal of Wildlife Management 70:546-553.

Horsley, S. B., S. L. Stout, and D. S. DeCalesta. 2003. White-tailed deer impact on the vegetation dynamics of a northern hardwood forest. Ecological Applications 13:98-118.

Joly, D. O., M. D. Samuel, J. A. Langenberg, J. A. Blanchong, C. A. Batha, R. E. Rolley, D. P. Keane, and C. A. Ribic. 2006. Spatial epidemiology of chronic wasting disease in Wisconsin white-tailed deer. Journal of Wildlife Diseases 42:578-588.

Kelly, A. C., N. E. Mateus-Pinilla, W. Brown, M. O. Ruiz, M. R. Douglas, M. E. Douglas, P. Shelton, T. Beissel, and J. Novakofski. 2014. Genetic assessment of environmental features that influence deer dispersal: implications for prion-infected populations. Population Ecology 56:327-340.

Kim, T. Y., H. J. Shon, Y. S. Joo, U. K. Mun, K. S. Kang, and Y. S. Lee. 2005. Additional cases of Chronic Wasting Disease in imported deer in Korea. Journal of Veterinary Medical Science 67:753-759.

Kjaer, L. J., E. M. Schauber, and C. K. Nielsen. 2008. Spatial and temporal analysis of contact rates in female white-tailed deer. Journal of Wildlife Management 72:1819-1825.

Long, E. S., D. R. Diefenbach, C. S. Rosenberry, B. D. Wallingford, and M. D. Grund. 2005. Forest cover influences dispersal distance of white-tailed deer. Journal of Mammalogy 86:623-629.

Lutz, C. L., D. R. Diefenbach, and C. S. Rosenberry. 2015. Population density influences dispersal in female white-tailed deer. Journal of Mammalogy 96:494-501.

Manly, B. F. J., L. L. McDonald, and D. L. Thomas. 2002. Resource selection by animals: statistical design and analysis for field studies. Volume 2nd.Kluwer Academic Publishers, Dordrecht.

Miller, M. W., and E. T. Thorne. 1993. Captive cervids as potential sources of disease for North America's wild cervid populations: avenues, implications, and preventive management. Transactions of the 58th North American Wildlife and Natural Resources Conference 58:460-467.

Nielson, R. M., and H. Sawyer. 2013. Estimating resource selection with count data. Ecology and Evolution 3:2233-2240.
Pennsylvania Department of Agriculture. 2014. General Quarantine Order; Chronic Wasting Disease Program Requirements for Herd Certification Program and Herd Monitoring Program. Harrisburg, PA.
Rosenberry, C. S., J. T. Fleegle, and B. D. Wallingford. 2011. Monitoring deer populations in Pennslyvania. Pennslyvania Game Commission.
Sawyer, H., M. J. Kauffman, and R. M. Nielson. 2009. Influence of well pad activity on winter habitat selection patterns of mule deer. Journal of Wildlife Management 73:1052-1061.
Skuldt, L. H., N. E. Mathews, and A. M. Oyer. 2008. White-tailed deer movements in a chronic wasting disease area in south-central Wisconsin. Journal of Wildlife Management 72:1156-1160.
Sohn, H. J., J. H. Kim, K. S. Choi, J. J. Nah, Y. S. Joo, Y. H. Jean, S. W. Ahn, O. K. Kim, D. Y. Kim, and A. Balachandran. 2002. A case of chronic wasting disease in an elk imported to Korea from Canada. The Journal of veterinary medical science / the Japanese Society of Veterinary Science 64:855-858.
Tilghman, N. G. 1989. Impacts of white-tailed deer on forest regeneration in northwestern Pennsylvania. Journal of Wildlife Management 53:524-532.
United States Department of Agriculture. 2014a. Cervid health business plan fiscal years 2014 to 2018. Washington, D.C.
A. a. P. H. I. Service. 2014b. Chronic wasting disease (CWD) program standards. Washington, D.C.
United States Department of Agriculture. 2014c. Import requirements of Canada for farmed cervids from the United States of America. Washington, D.C.
United States Department of Agriculture. 2016. 2015 State Agriculture Overview: Pennsylvania. *in* United State Department of Agriculture.
USDA, U. S. D. o. A. N. R. a. C. S. 1998. National Elevation Dataset 10 Meter 7.5x7.5 minute quadrangles. *in* National Cartography and Geospatial Center, Fort Worth, TX.
VerCauteren, K. C., M. J. Lavelle, N. W. Seward, J. W. Fischer, and G. E. Phillips. 2007a. Fence-line contact between wild and farmed cervids in Colorado: potential for disease transmission. Journal of Wildlife Management 71:1594-1602.
_____. 2007b. Fence-line contact between wild and farmed white-tailed deer in Michigan: potential for disease transmission. Journal of Wildlife Management 71:1603-1606.
Walter, W. D., D. P. Walsh, M. L. Farnsworth, D. L. Winkelman, and M. W. Miller. 2011. Soil clay content underlies prion infection odds. Nature Communications 2:1-6.
Williams, E. S., M. W. Miller, T. J. Kreeger, R. H. Kahn, and E. T. Thorne. 2002. Chronic wasting disease of deer and elk: a review with recommendations for management. Journal of Wildlife Management 66:551-563.

Figure 3-1. The Pennsylvania state border with the 48 counties in which I received parcel information and the 841 captive facilities used in analyses.

Figure 3-2. A predictive surface of areas most at risk for CWD spread to wild deer via captive facilities with the counties that I did not receive parcel information (cross hatch) and Disease Management Areas (DMA) 1 – 3.

Table 3-1. Thirteen *a priori* models used in negative binomial regression that included continuous variables (elevation and distance to public lands) as well as categorical data (land cover type, wild deer density, stocking density, and movements of captive cervids).

Models	Parameters	K
1	Elevation + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Distance to Public + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	10
2	Forest + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	9
3	Agriculture + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	9
4	Forest	1
5	Agriculture	1
6	Elevation	1
7	Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	4
8	Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Distance to Public	5
9	Forest + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High)	5
10	Agriculture + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High)	5
11	Forest + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	5
12	Agriculture + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	5
13	Urban	1

Table 3-2. Top models using Akaike's Information Criteria (AIC) with delta AIC < 2.0 for all captive facility locations using negative binomial regression.

Model Number	Model Terms	df	AIC	ΔAIC	Weight
5	Agriculture	3	1176.425	0.00	0.325
3	Agriculture + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	11	1177.186	0.761	0.222
10	Agriculture + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High)	7	1177.218	0.793	0.218
1	Elevation + Wild Deer Density (Below Average) + Wild Deer Density (Average) + Wild Deer Density (Above Average) + Wild Deer Density (High) + Distance to Public + Stocking Density (Average) + Stocking Density (High) + Movements (Average) + Movements (High)	12	1177.853	1.428	0.159

Table 3-3. Parameters, model coefficients (Estimates) standard errors (SE), and 95% confidence intervals (CI) for variables included in the top four models using Akaike's Information Criteria (AIC) with delta AIC < 2.0. Significant variables are indicated with an asterisk (*) based on confidence intervals that do not overlap zero.

Parameter	Estimates	SE	CI
Model 5			
Agriculture	0.465	0.06	0.3358 to 0.5983
Model 3			
Agriculture*	0.4485	0.07	0.3151 to 0.5867
Wild Deer Density (Below Average)	−0.0355	0.21	−0.4436 to 0.3692
Wild Deer Density (Average)	−0.3245	0.21	−0.7271 to 0.0745
Wild Deer Density (Above Average)	0.146	0.31	−0.4506 to 0.7605
Wild Deer Density (High)*	−5.9303	0.3	−1.2804 to −0.0854
Movements (Average)	−0.1439	0.16	−0.4606 to 0.1737
Movements (High)	−0.1442	0.16	−0.4667 to 0.1788
Stocking Density (Average)*	0.4386	0.16	0.1237 to 0.7597
Stocking Density (High)	0.2526	0.3	−0.3106 to 0.842
Model 10			
Agriculture*	0.4526	0.07	0.3192 to 0.5896
Wild Deer Density (Below Average)	0.0643	0.21	−0.3285 to 0.4536
Wild Deer Density (Average)	−0.242	0.21	−0.6426 to 0.1552
Wild Deer Density (Above Average)	0.2391	0.31	−0.3531 to 0.8535
Wild Deer Density (High)	−0.3975	0.29	−0.9561 to 0.1617
Model 1			
Elevation*	−0.4996	0.08	−0.6474 to −0.3534
Wild Deer Density (Below Average)	0.3188	0.2	−0.0846 to 0.7209
Wild Deer Density (Average)	−0.2658	0.2	−0.6638 to 0.1295
Wild Deer Density (Above Average)	0.5482	0.31	−0.056 to 1.171
Wild Deer Density (High)*	−0.9658	0.31	−1.5835 to −0.3496
Distance to Public	−0.1034	0.07	−0.2548 to 0.0496
Movements (Average)	−0.0886	0.16	−0.4003 to 0.2244
Movements (High)	−0.0469	0.16	−0.3661 to 0.2735
Stocking Density (Average)*	0.36561	0.16	0.0496 to 0.6872
Stocking Density (High)	0.472	0.29	−0.0778 to 1.0476

Figure 3-1.

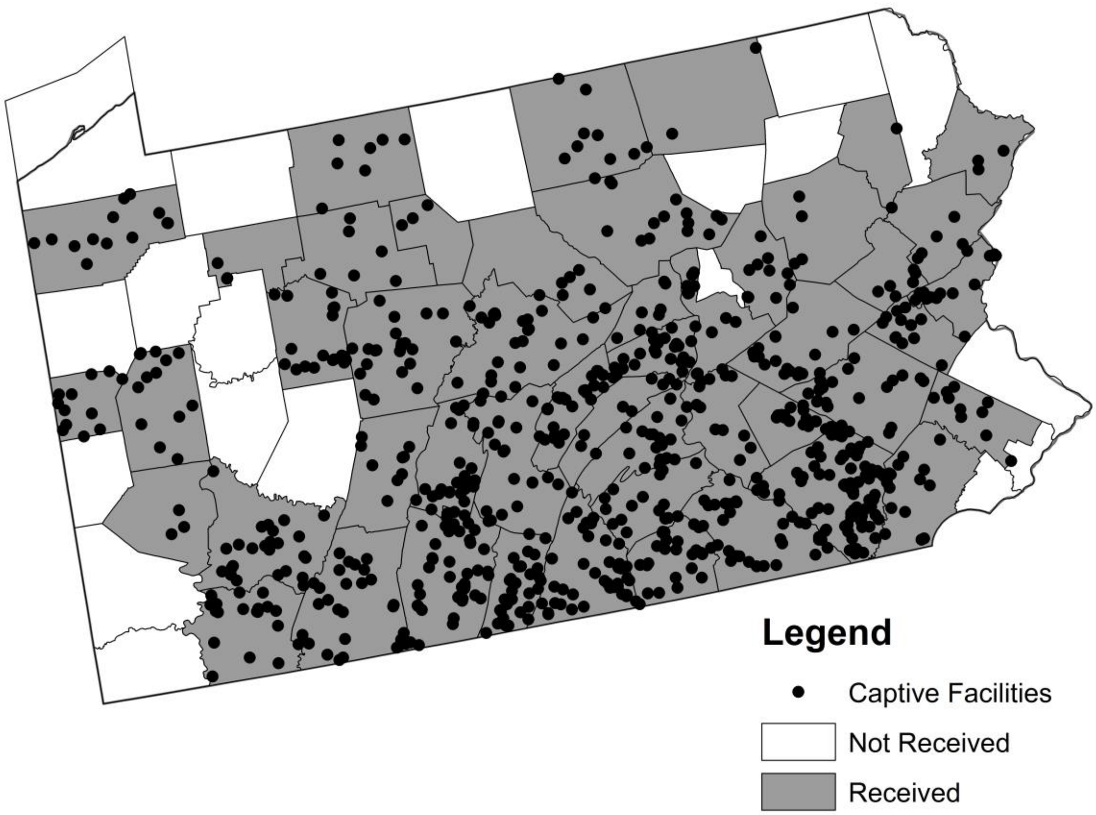


Figure 3-2.