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LANDSCAPE INFLUENCES ON WHITE-TAILED DEER HARVEST IN NEW JERSEY

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ABSTRACT: *White-tailed deer (Odocoileus virgianus) densities across New Jersey vary widely from urban areas with no deer to a rural community in Hunterdon County where a single herd of over 200 animals was recently documented. This paper examines the relationship between deer harvest (used as a proxy for deer density) and the landscape in an effort to explain this curious distribution. The authors used a GIS and regression analysis to test the predictive power of six different landscape variables (forest cover, forest edge, agricultural land, developed land, forest agriculture edge, forest-developed edge and road density) in an effort to develop a predictive model of deer harvest. The strongest individual predictor was the amount of forest bordering agricultural fields in a given area. A stepwise multiple regression combining these variables explained 58.9% of the variation in deer harvest.*

INTRODUCTION

Deer management in New Jersey has become quite a contentious problem. In 1902, the problem was too few white-tailed deer - Garden State hunters had nearly extirpated them and deer hunting was banned. In the next few years, deer were actually imported from Pennsylvania and Michigan. Today the state deer herd stands at about 200,000 animals (Curran, 2000). While that might at first seem like a success story, there are many problems associated with high numbers of deer. One of the most highly publicized consequences of New Jersey's deer overabundance is the rising number of auto collisions. Officially, the state recorded over 16,000 motor vehicle accidents involving deer in 1999 (Suhay, 2000), and three New Jersey motorists died as a result of accidents involving deer in the same year.

Foresters and ecologists have documented the effects of deer overabundance on forest communities. Tilghman (1989) demonstrated that deer browsing seriously impaired forest regeneration, reduced tree species diversity, and significantly altered understory species composition in a Pennsylvania forest. Browsing by deer significantly inhibits hemlock (*Tsuga canadensis*) regeneration (Alverson and Waller, 1997) and Atlantic white cedar (*Chamaecyparis thyoides*) regeneration (Little and Somes; Zimmerman, *cited in* New Jersey Department of Environmental Protection Division of Fish and Wildlife (NJDEPDFW), 1999). Further, DeCalesta (1994) found that both species richness and abundance of intermediate canopy nesting birds declined significantly as deer density increased. Perhaps the single largest economic impact of New Jersey's deer overabundance is deer damage to agricultural crops. In a recent survey of New Jersey farmers with annual sales above \$10,000, 2,142 respondents reported crop losses in the range of \$5 to \$10 million dollars. The farmers were quite confident in their ability to distinguish deer damage from damage due to other species and attributed 70% of these reported losses to deer (Fritzell, 1998). Estimates of total losses statewide go above \$30 million (Kannapell, 1998). Additionally, 25% of respondents abandoned tillable land due to deer browsing, and 36% ceased growing a more profitable crop (e.g., soybeans) for one less susceptible to deer damage (e.g., hay).

White-tailed deer density varies widely across New Jersey's rapidly changing, fragmented landscape. Highly urbanized areas near New York City and Philadelphia are populated by few deer compared to large herds in the more agricultural northwestern part of the state. The purpose of this paper is to examine these population patterns and to determine the influence of several landscape variables on deer density. If these relationships are strong enough, it will be possible to develop a model that can predict changes of deer density based on changes in the landscape.

METHODS

GIS, Deer, and the Landscape

We used a geographic information system (GIS) to examine the relationship between New Jersey's fragmented landscape and deer harvest, a proxy for deer density. GIS has only recently been utilized in the study of ungulate-habitat relationships. Grossi et al. (1995) used a GIS to show that French roe-deer (*Capreolus capreolus*) movements were influenced by landscape heterogeneity. Chang et al. (1995) used a GIS to show that Sitka black-tailed deer (*Odocoileus hemionus sitkensis*) prefer small clear-cuts near old-growth edges in southeast Alaska. Boroski et al. (1996) used a GIS to determine that cover type and cover interspersion were significant determinants of habitat use by black-tailed deer (*Odocoileus hemionus columbianus*) in northern California. Radeloff et al. (1999) built an interactive GIS allowing foresters and game managers to model habitat suitability and population dynamics of German roe-deer. Finally, Risenhoover et al. (1997) used a GIS to model deer movement in response to landscape features and obstructions. Only rarely have studies examined white-tailed deer densities in the east at a landscape scale of analysis.

Data

This research uses 1995-1996 New Jersey Division of Fish & Wildlife deer harvest data as a proxy for deer density. The Division's divides NJ into 632 36 km^2 (14 mi^2) deer management units (DMU). Data for this season were chosen because of the availability of temporally coincident (1995) land use/land cover data. A popular method for estimating deer populations over large areas utilizes age and sex ratios of harvested deer, sometimes known as "Sex-Age-Kill"(Kelker, 1940). The procedure relies upon field workers to determine the age and sex of each deer checked in. While deer sex determination is not difficult, wildlife biologists determine deer age by dental examination. Few personnel staffing Division deer check stations possess the skills required to determine deer age, therefore this characteristic is listed for fewer than 5% of the deer checked in during the 1995-1996 hunting season. While there are many alternative techniques for enumerating or estimating deer population (e.g., track counts, pellet group counts, drive counts and aerial censuses) the costs/human resources required preclude their use in this analysis. As an alternative, this study relies upon the raw harvest numbers furnished by the Division as a proxy for deer density. Figure 1 shows a dot density map of New Jersey's Deer harvest data at the conclusion of the 1995-1996 hunting season.

A more appropriate question to address with these data might be, "Where is a hunter more likely to bag a trophy deer?" The use of harvest data as a proxy for deer population is not without risk. First, it assumes that the distribution of hunters is similar to the distribution of deer. However, hunter access across the state is variable. Not all landowners are willing to allow regulated hunting on their property. Moreover, in New Jersey hunting is prohibited within 140 m (450 ft.) of buildings that might be occupied by people, unless permission is obtained from the occupants. This regulation tends to exclude large tracts of residential land. Additionally, many NJ municipalities have codes that limit or prohibit firearm discharge within their boundaries. Therefore, a deer harvest indicator as a measure of population may be misleading in two adjacent DMUs where actual deer densities are similar. Finally, hunters must accurately report the location of each kill at the time of deer check-in so that it can be attributed to the proper DMU. Each DMU is part of a regular

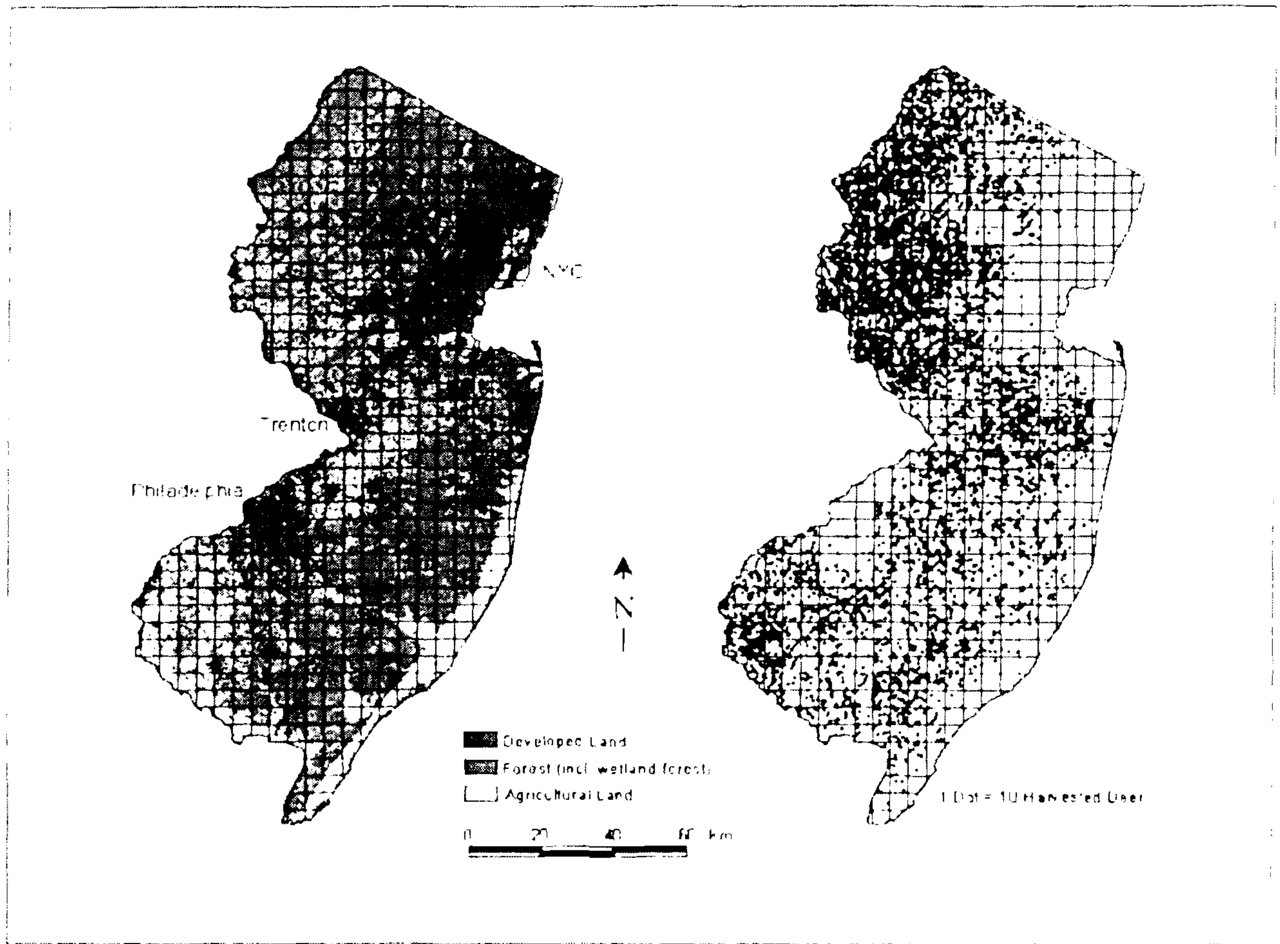

Figure 1. Left: A simplified version of NJ DEPs Land Use Cover based on 1995-1997 aerial photography. Right: Dot density map of NJ Division of Fsh and Wildlife deer harvest data for the 1995-1996 hunting season. Each randomly generated dot represents ten harvested deer.

rectangular grid covering the state and does not conform to features such as roads, fences and streams. This can lead to mistakes in the proper recording of harvest totals by DMU. Raw harvest totals made up the only dependent variable and the use of better population estimates might improve predictive power in this analysis. However, the lack of deer age data made better estimation unfeasible.

The primary independent variable data set used in the analysis is the NJ Department of Environmental Protection (DEP) Land Use/Land Cover Map compiled and interpreted from 1995 and 1997 false-color infrared aerial photography. The resulting GIS map covers the entire state and classifies land according to a modified Anderson scheme (Anderson et al., 1976) with several major categories, e.g., urban, forest, agriculture, wetland, with many more specific sub categories, e.g., coniferous forest, brushland/shrubland, etc. The map has a minimum mapping size of one acre, so actual land use patches smaller in size may not be represented in the final map. Figure 1 contains a reclassified map derived from NJ DEP data showing the distribution of developed, forested and agricultural land that figure prominently in this analysis. As in many wildlife-habitat studies, landscape level data may not represent the same dynamics and variability that finer scale data might reveal.

Analysis

We began the study with a univariate analysis of the harvest data. Next, we independently examined the predictive power of six different landscape variables, using regression analysis to test for linear or curvilinear relationships with deer density. Finally, we used a stepwise multiple regression analysis to find the best combination of independent landscape variables to explain the variation in deer harvest across the state.

The initial part of the analysis examined the relationship between major land use/land cover (LU/LC) classes (forest area, agricultural area, and developed area) versus deer harvest per DMU. These classes were chosen due to their necessity as habitat elements and because they are undergoing rapid change in NJ. Forests are an essential component of deer habitat, providing escape cover, resting areas, and shelter from the elements. The first segment of the (LU/LC) analysis examined two forest maps made up of several subclasses extracted from the NJ DEP dataset. The first layer includes as many classes as possible that might provide deer cover. The second, more exclusive forest class excludes brush, shrub and burned classes in an attempt to capture only mature forest stands that might provide better cover.

Because of their preference for browse in close proximity to cover, white-tailed deer are characterized as an edge species. Therefore we tested forest edge, derived from the two previously discussed forest maps. In each case, all non-forested areas in the respective maps were buffered, creating a 30-meter interior buffer or edge map of both forest classes. Crops such as soybeans, corn, and alfalfa provide a high concentration of nutritious browse, and contribute to a highly productive deer range, so we tested two classifications of total agricultural land cover per DMU. Because higher densities of human development tend to exclude deer, we examined the relationship between developed land and deer density. We also tested the amount of forest edge bordering agricultural land within each DMU, by buffering the more inclusive agricultural land map to a distance of 30 meters and intersecting it with the more inclusive forest edge map. We also examined the amount of forest edge bordering developed land. Finally, we used a U.S. Bureau of the Census TIGER road map to examine the effects of road density and the amount of road bordered by forest.

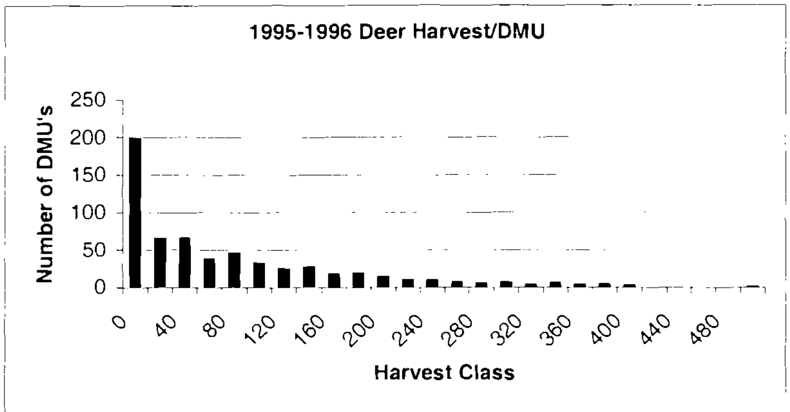

Figure 2. Histogram of harvest for the 632 DMU's during the 1995-1996 hunting season. The mean harvest per DMU was 92.3 animals. NJ Division of Fish & Wildlife.

A combination of several independent variables might better predict deer harvest across New Jersey. The final step in the LU/LC analysis tests this premise by evaluating several combinations of individual variables in a stepwise multivariate regression (SMR). SMR or statistical regression selects the best combination of independent variables that predict the dependent variable or criterion. First, the procedure selects the predictors that have the highest regression coefficients when paired with the dependent variable. Next, the predictors are compared with each other and tested for independence. Variables that are too highly correlated with one another are discarded. Finally, the best predictors are sequentially combined in the final regression equation until the addition of one more variable does not significantly improve ($F >= 0.1$) the coefficient of multiple determination or R^2. As with linear regression, SMR assumes that the data are normally distributed.

RESULTS AND DISCUSSION

During the 1995-1996 season, NJ hunters reported a total harvest of 58,335 deer. Figure 2 shows a frequency distribution for the Division's harvest data. Because many DMU's are highly populated, there are 109 units (17.2%) where hunting is severely limited or prohibited by municipal code and state law, resulting in no reported harvest (the mode). Additionally, the data have a high degree of variance, indicating a wide array of harvest totals from zero in many urban DMU's to a maximum of 502 deer in one western Hunterdon County unit (primarily within Holland Township). Normality is one of the assumptions of regression analysis (McGrew, Jr. and Monroe, 2000) and these data are positively skewed and somewhat platykurtic (i.e., exhibiting a flattened positive tail) apart from the pronounced peak at zero. These factors tend to limit the utility and effectiveness of regression and should be taken into consideration when interpreting the results.

Table 1 summarizes the results of the individual regression analyses, including the coefficient of determination and standard error for each variable. The strongest individual predictor of harvest is the amount of forest edge bordering agricultural edge per DMU. As expected, there is a positive relationship between forest/agricultural edge and deer harvest. This is likely due to the availability of cover in close proximity to highly nutritious crops such as soy beans, corn, and alfalfa. It follows that the greater the amount of edge, the greater the interspersion of these two habitat requirements; and the better the deer range. The coefficient of determination indicates that over 51% of the variation in harvest is accounted for by this edge. Application of a second-order polynomial improved the results only marginally. The predicted values are very similar to the linear regression with the only significant departure being a diminishing harvest as

Table 1. Summary table of coefficients of determination for all predictors

Predictor	R-square	Standard error	Beta (b1, b2)
SMR, Landscape, Statewide	0.589	68.1	
Forest/Agricultural Edge (poly)	0.521	72.2	0.714, -0.128
Forest/Agricultural Edge (linear)	0.515	72.7	0.593
Agricultural Area, All (poly)	0.352	85.0	1.530, -1.317
Forest Edge, All (poly)	0.293	87.7	0.006, 0.501
Forest Edge, All (linear)	0.288	88.0	0.492
Forest Area, All (poly)	0.281	88.5	1.606, -1.451
Forest Edge, Mature (linear)	0.262	89.8	0.472
Agricultural Area, All (linear)	0.231	92.5	0.276
Forest Area, Mature (poly)	0.229	92.0	1.519, -1.406
Agricultural Area, Cropland, Pastureland (linear)	0.221	93.3	0.292
Roadside Forest Edge (poly)	0.134	97.4	0.731, -0.740
Forest Area, All (linear)	0.132	97.3	0.208
Forest/Developed Edge (poly)	0.127	97.5	0.849, -0.648
Developed Area (poly)	0.121	98.1	0.678, -0.948
Road Area (poly)	0.103	98.1	0.571, -0.869
Forest Area, Mature (linear)	0.092	99.8	0.168
Forest/Developed Edge (linear)	0.065	100.8	0.229
Developed Area (linear)	0.051	101.9	-0.216
Road Area (linear)	0.050	101.8	-0.259
Forest Edge, Roadside (linear)	0.033	102.9	0.042

edge approaches maximum. The coefficient of determination and standard error figures are likewise very similar. While the variation in residuals for both regressions is still high, the coefficients of determination are the highest and the standard error calculations are the lowest of any variables tested. Clearly, agriculture/forest edge is the best single predictor of harvest and productive deer range.

The next best single predictor of harvest was the amount of agricultural land per DMU. The linear regressions reveal that there is a weak positive relationship, but change in agricultural land only accounts for approximately 23% of the variation in the better of the two models. A possible cause for this low coefficient of determination is the aggregation of cropland and pastureland classes. All things being equal, a field of soybeans is likely more attractive to deer than a fenced cow pasture. Any stronger correlation between harvest and high nutrition crops might be obscured due to this limitation of data aggregation. Application of a quadratic solution to the more inclusive agricultural layer yields a better goodness of fit. As with the linear models, the quadratic trend line indicates that there is less harvest in non-agricultural areas, but predicts a peak in harvest as agricultural land area reaches approximately 35% of a DMU's total area. Predicted harvest declines as agricultural land approaches 75% of total land use. Drawing conclusions based on this model is risky, but the data suggest that there is higher deer density where agricultural land makes up a substantial portion but not a majority of the land use in a particular DMU.

Following agriculture in importance was the amount of forest edge and forest area per DMU. As one would expect, there is a positive relationship between the amount of forest edge per DMU and harvest. While this relationship is stronger than that between forest cover and harvest, it still only explains approximately 29% of the variation in harvest. The

Table 2. SMR summary of landscape variables

Predictor	Coefficient	Std. Error	Beta
Constant	-1.239	11.069	
Forest/Agricultural Edge Length	0.07838	0.005	0.912
Agricultural Area	-0.001689	0.001	-0.168
Forest/Urban Edge Length	0.02523	0.004	0.448
Road Area	-0.00681	0.001	-0.192
Mature Forest Edge Length	-0.01666	0.004	-0.316
Forest Area	0.002453	0.000	0.346
$R^2 = 0.589$			
$R^2_{adj} = 0.584$			
Standard error = 68.14			

remaining independent variables tested appeared to have little influence on harvest. It is especially difficult to evaluate the predictive power of developed land, given that harvest is prohibited as areas from potential hunting. The amount of developed land per DMU had one of the highest standard errors and one of the lowest coefficients of determination. Similarly, road area (derived by buffering a TIGER road map) per DMU and road area bordering forest, proved to be poor predictors of harvest.

Multivariate Regression

The best single predictor of deer harvest among landscape variables is forest/agriculture edge. However, using several variables in combination can substantially increase predictive power. For this reason, we used a stepwise multiple regression to better predict deer harvest. Table 2 lists the results of the regression analysis.

Forest/agricultural edge length was the best performing single predictor of harvest, accounting for over 50% of the variation ($R^2 = 0.515$). The addition of predictors in a multivariate regression will never decrease the coefficient of multiple determination (Schroeder et al., 1986). However the use of the five additional landscape variables did significantly increase predictive power accounting for nearly 60% of the variation in harvest across the state. Moreover, the standard error of the estimate decreased slightly (from 72.66 down to 68.14).

CONCLUSION

While making predictions regarding deer density based on harvest data is risky, this study shows that the amount of agricultural/forest edge is the single most important landscape influence on harvest ($R^2 = 0.515$). Agricultural area was the next best predictor of harvest ($R^2 = 0.352$). A stepwise multiple regression adding the independent variables agricultural area, forest/developed edge, road length/density, mature forest edge, and forest area moderately increased predictive power ($R^2_{adj} = 0.584$). Better population estimates based on sex and age data might help to improve predictive power further.

From 1986 to 1995 the Garden State saw approximately 16,600 acres of new development each year with farmland seeing the largest part of that change (Hasse and Lathrop, 2001). Drawing conclusions based on this research would seem to predict an overall reduction in the statewide deer herd if this and use trend continues. However, as farm fields are replaced by McMansions, this land becomes excluded from hunted space, which tends to increase the herd. This transition and interaction may be the single most essential factor in understanding and predicting the future of New Jersey's white-tailed deer herd and it is here that more data and more analysis are required.

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