Linking GIS and Recreation Demand Models to Estimate the Economic Value of Using Fire to Improve Deer Habitat

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Abstract—*This research combines a Geographic Information System (GIS) based model of deer habitat response to fire with a travel cost method recreation demand model to value the deer hunting benefits of prescribed burning in the San Jacinto mountains of southern California. A statistically significant effect of fire on deer harvest was determined in the GIS based and time-series based production function models. Using the recreation demand model, we estimated the net economic value to hunters of $257 per additional deer harvested. While the initial deer hunting benefit response to the current magnitude of prescribed burning of 1,100 acres ranges from $4,112 to $8,481 depending on the production model, the incremental gains for additional 3,700 acres of prescribed burning are quite similar across production models.*

Introduction

This research compares two models for evaluating the effectiveness of prescribed burning for increasing deer habitat. We also provide a benefit-cost comparison for the San Jacinto Ranger District (SJRD) in the San Bernadino National Forest located in southern California. The methodological contribution begins to answer the challenge posed by Hesseln (2000) in her recent review of the economics of prescribed burning. She stated: "There is a lack of economic models to evaluate short- and long-term ecological benefits of prescribed fire. Without understanding the relationship between economic outcomes and ecological effects, it will be difficult to make effective investment decisions. Research should focus on defining a production function to identify long-term relationships between prescribed burning and ecological effects. Identifying production functions relationships will form the basis for future cost-benefit analysis with respect to prescribed burning" (Hesseln 2000: 331-332). Our study demonstrates two different approaches to estimating production relationships between prescribed burning and deer harvest using time series data and Geographic Information System (GIS) approaches. The production models are linked to the recreational hunting valuation model by including deer harvest as a demand shift variable in the recreational hunting valuation model.

Study Area

The San Jacinto Ranger District (SJRD) is located in Southern California's San Bernardino National Forest near Palm Springs. As noted by the USDA

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Forest Service, "Some of the best deer hunting in Riverside County is found in this area" (Gibbs et al. 1995: 6). The SJRD is an ideal area to demonstrate and compare different approaches to estimating a production function between prescribed burning and deer harvest because prescribed fire has been used for more than 20 years to stem the long-term decline in deer populations since the 1970s (Paulek 1989, Gibbs et al. 1995). Previous research on prescribed burning shows that fire enhances deer habitat and populations (California Department of Fish and Game 1998) but the economic benefits have not been quantified. The results of our analysis should be of some policy relevance as the SJRD plans to increase the amount of prescribed burning by 50% to 100% over the next few years (Gibbs et al. 1995).

In general, Southern California is characterized by a Mediterranean climate, with hot and dry summers and cool, moist winters. There is a significant range of variation in temperatures and local site conditions in the ranger district in the San Jacinto and Santa Rosa Mountains. Elevations in these ranges reach 10,800 feet. The dominant vegetation within the SJRD below 5,000 feet is chaparral. Annual rainfall for the chaparral biome is approximately 15 to 16 inches. Areas above 5,000 feet tend to be dominated by hardwoods and conifers such as live oak and Douglas-fir with annual rainfall of up to 30 inches.

Within the San Jacinto Ranger District, the land is primarily managed by the USDA Forest Service, with small amounts of land administered by the State of California such as the Mount San Jacinto State Park. The land within the San Jacinto Ranger District is an area that evolved with fire as a natural environmental factor. Declining abundance of successional vegetation communities is considered to have the greatest long-term effects on deer populations (California Department of Fish and Game 1998). Historically, fire, either prescribed or natural, has been the primary mechanism for establishing these vegetation communities. Studies in California have noted that after a burn, increased deer numbers can be attributed to individuals moving into the area to feed (Klinger et al. 1989). These increased deer numbers are thought to arise due to increased forage quality and increased fawn survival rates in the recently burned areas. The California Department of Fish and Game has noted a significant increase in buck harvest from 1987 to 1996 in hunt zones that had large fires, versus hunt zones that did not have large fires (California Department of Fish and Game 1998). To improve deer habitat in California, controlled burning has been used in all the major parks and forests for more than a decade (Kie 1984).

Two Production Function Modeling Approaches

The purpose of this study is to test whether prescribed burning has a systematic effect on deer harvest. By examining prescribed burning on deer harvest with two different production models, a macro or aggregate time series approach and a micro, spatial approach (e.g., GIS) can be compared. Using a macro time series approach, we would be able to test the effects of fire, prescribed and natural, across the entire study area over a 20-year time period. Using a micro GIS approach provides greater spatial detail, such as the influence of a meadow or ridge, but this micro data is not available for the 20-year time period. Thus each approach to estimating the production function has its relative strengths and weaknesses.

Estimating a production function that relates deer harvest to acres of prescribed burning must also control for other inputs that influence the production

of deer for harvest. This includes wildfire, elevation (used as a proxy for vegetation data that was incomplete), rainfall, temperature, and distance to roads. Thus, multiple regression is an appropriate technique.

Time Series, Macro Scale Production Function

The macro approach is based on a time series regression model to test for a relationship between deer harvest in the SJRD and prescribed fire, controlling for other independent variables such as annual precipitation and temperature during the hunting season. For this approach we used a dataset for SJRD, provided by the California Department of Fish and Game (CDFG) and the USDA Forest Service. The fire records provided data from 1979 for wildfire and prescribed burns within the San Jacinto Ranger District. This ranger district represents the majority of publicly accessible land for deer hunting in Riverside county. Deer harvest data from 1979 were provided by CDFG. The full model is given by equation 1.1. SJRD Time Series Production Function Model:

$$\text{SJRD Deer harvest in year}_t = \text{func}\,(\text{RXFIRE}_t, \text{WILDFIRE}_t, \text{TOTPRECIP}_t, \text{OCTTEMPt}, \text{YEAR}_t) \qquad [1.1]$$

Where:

RXFIRE_t = the acres of prescribed fire in year t
WILDFIRE_t = the acres of wildfire in year t
TOTPRECIP_t = the sum of precipitation for year t
OCTTEMP_t = temperature in October during the hunting season
YEAR_t = a trend variable, with 1979 = 1, 1980 = 2, … 1998 = 19

We estimate a non-linear form of equation 1.1 using the log-log form. The log-log form allows us to interpret the coefficients for fire effects as elasticity's, i.e., the percent change in deer harvest with a 1% change in acres burned.

To model the aggregate harvest for all of the San Jacinto Ranger District, the dependent variable is the total number of deer harvested in year t. The value of the dependent variable is a relatively large number and varies between 80 to 157 deer in any given year. Because of the relatively large values for the dependent variable, Ordinary Least Squares (OLS) is an acceptable approach for the macro time-series modeling.

Micro GIS Approach to Estimating the Production Function

The approach taken in this study uses a geographic information system (GIS) for estimating the deer harvest-fire production relationship. With the GIS approach, the study area is divided into 37 individual hunting zones delineated by California Department of Fish and Game (rather than treating the entire SJRD as one unit). These hunt areas are defined by topographic features such as steep ridgelines or developed features such as towns or major roads. This allowed for the incorporation of other influences on deer harvest that varied spatially across individual hunting areas such as distance to roads and elevation. Because past research indicates that use of burned areas by deer increases dramatically during the following years, (Klinger 1989) a lagged model as shown in equation 1.2 is estimated. This model tests for these effects during the following years by using a lag on the fire variables.

The first step in the GIS analysis was to identify the necessary layers needed to run a regression between deer harvest and fires. A harvest layer was

constructed, which contains deer harvest by hunt zones and serves as the dependent variable. Then layers were added for the independent variables including acres of prescribed burning, wildfire acres, average elevation, temperature, distance to trails, distance to dirt roads from each hunting zone, and distance to wildfires from each hunting zone. Vegetation type would have been desirable, but this information was incomplete and will not be completed for the entire area until well into the future. Thus elevation was partially used as a proxy for vegetation composition. We developed two models for the harvest areas to account for the non-uniform size of each hunting zone: (1) include the size of the harvest area as a separate independent variable and use total acres of an area burned and, (2) transform the dependent variable into deer harvest per acre, then use an OLS regression. The total area model (with deer harvest a function of total size of fire, including lags) is shown in equation 1.2:

$$\text{Deer harvest in area}_i \text{ in year}_t = \text{func}\,(\text{Avg_Elev}_i, \text{Ltotal_Wildfire}_{i\,t}, \text{Ltotal_Wildfire}_{i\,t-1}, \text{Ltotal_Wildfire}_{i\,t-2}, \text{Ltotal_Wildfire}_{i\,t-3}, \text{Ltotal_Rxfire}_{i\,t}, \text{Ltotal_Rxfire}_{i\,t-1}, \text{Ltotal_Rxfire}_{i\,t-2}, \text{Ltotal_Rxfire}_{i\,t-3}, \text{Ldirt_distance}_i, \text{Ltrail_distance}_i, \text{LHvst_Area}_i, \text{Oct_Temp}_t, \text{Year}_t) \quad [1.2]$$

Equation 1.2 was estimated using a count data model instead of OLS regression because at the micro level harvest in any limited spatial unit is a small non-negative integer variable. Therefore count data models are statistically more efficient because such models are based on probability distributions that have mass only at nonnegative integers (Creel and Loomis 1990). This is certainly the case for deer harvests as hunters cannot harvest a fraction of a deer and the number harvested in each unit is typically 0,1,2,3… rather than 10 or 50. One of the simplest count distributions is the Poisson process. Given the stringency of the mean-variance equality restriction imposed by the Poisson, a more generalized count model like the negative binomial is often more consistent with the data. The negative binomial version relaxes the mean-variance equality of the Poisson. Both the Poisson and the negative binomial yield the equivalent of a semi-log form where the log of the dependent variable is regressed against the explanatory variables.

An alternative specification to account for the different size harvest areas involved transforming the dependent variable into deer harvest per acre. This results in equation 1.3, which is estimated using ordinary least squares regression since this dependent variable is continuous and is not restricted to integer values:

$$\text{Log Deer_harvest per acre in year}_{i\,t} = \text{func}\,(\text{Avg_Elev}_i, \text{Ltotal_Wildfire}_{i\,t}, \text{Ltotal_Wildfire}_{i\,t-1}, \text{Ltotal_Wildfire}_{i\,t-2}, \text{Ltotal_Wildfire}_{i\,t-3}, \text{Ltotal_Rxfire}_{i\,t}, \text{Ltotal_Rxfire}_{i\,t-1}, \text{Ltotal_Rxfire}_{i\,t-2}, \text{Ltotal_Rxfire}_{i\,t-3}, \text{Ldirt_distance}_i, \text{Ltrail_distance}_i, \text{LHvst_Area}_i, \text{Oct_Temp}_t, \text{Year}_t) \quad [1.3]$$

Details of GIS Based Micro Regression Variables

Elevations are based on USGS digital elevation models and act as a proxy for vegetation types, which were not available. However, we do not have an expected sign on elevation, but include it to control for elevation differences among the 37 individual hunting areas within the San Jacinto Ranger District. Based on the literature reviewed above, wildfire and prescribed fire are expected to have a positive sign. The distances to road and trail variables are based on the distances from a central point in each hunting zone. Two

arguments can be made about the sign of this variable, therefore the expectation is left to be ambiguous. One argument is based on accessibility for hunters, where being close to either a trail or road would make hunting easier and more desirable, which would positively effect deer harvest. The second argument is based on the intrusion of the road or trail possibly fragmenting deer habitat. This perspective would lead to a decline in deer harvest because roads cause a break in habitat and pose as a threat from cars.

The distance to fire variable is based on distance from a central point in each hunting zone to the closest fire in that time period. This variable's sign may be either positive or negative.

Harvest area, which takes into account the size of each hunting zone, is expected to have a positive sign. The argument here is that as hunting areas become larger, then the amount of deer habitat increases, which attracts more deer and increases the probability of hunter success. October temperature and year are the other variables used in the models. October is when hunting season is open and, based on hunter's surveys, when temperatures are high the deer tend to bed down and seek cover. Therefore, harvest rates decline, which gives the October temperature a negative sign. Year is a trend variable to capture any temporally varying effects and we do not know whether it would be positive or negative. Table 1 summarizes the description of the variables and their expected sign, if any.

Table 1—Description of GIS based micro regression variables.

Variable	Description	Expected sign on coefficient
Deer harvest	The dependent variable; the number of deer harvested in a designated hunting zone.	
Avg_Elev	Average elevations, based on USGS Digital Elev. Model and re-classed into elevation categories.	No expectation
TOTWFIRES	Total wildfires in a particular year within the San Jacinto Ranger District (-1,-2,-3 are time lags).	+
TOTRXFIRES	Total prescribed fires within the San Jacinto Ranger District for a particular year (-1,-2,-3 are time lags).	+
DirtDist	The distance to the nearest dirt road, in meters from a central location of each hunting zone.	No expectation
TrailDist	The distance to the nearest trail, in meters from a central location of each hunting zone.	No expectation
Fire_Dist	The average distance from a central location of each hunting zone to the central point of a wildfire.	No expectation
HuntArea	The size of each harvest area, measured in acres.	+
Oct_Temp	The average temperature in October, degrees Fahrenheit.	_
Year	A trend variable to look for systematic changes.	No Expectation

Estimated Production Functions

Macro Time Series San Jacinto Ranger District Equations

Allowing for non-linearity proved to be a better predictor of deer harvest than the linear models (linear results available from the authors) so we present the double log model. Results from preliminary regressions also suggested combining the wildfire and prescribed burn into one variable. In table 2, the coefficient for total fire has a small magnitude of .048, but it has a significant t-statistic of 2.3. The sign on this variable is positive and the coefficient can be interpreted as an elasticity due to the log-log functional form. Therefore, a 1% increase in acres burned will lead to a .048% increase in deer harvest. The

Table 2—Macro time series ranger district log-log model. Dependent variable is the log of SJRD deer harvest.

Variable	Coefficient	Std. error	t-statistic	Probability
Constant	41.80865	11.07	3.776	0.002
ln_Totalfire	0.048735	0.0205	2.371	0.032
Total_Precip	-0.00096	0.0026	-0.366	0.719
Oct_Temp	-0.02703	0.0106	-2.536	0.023
Year	-0.01785	0.0055	-3.199	0.006

R-squared: 0.677	Mean dependent var: 4.808
Adj. R-squared: 0.584	S.D. dependent var: 0.202
S.E. of regression: 0.1303	F-statistic: 6.343
Durbin-Watson: 2.066	Prob (F-statistic): 0.002

other significant variables are October temperature and year. The statistically significant negative sign on the October temperature coefficient is consistent with the opinion of hunters that an increase in temperature results in a decrease in the number of deer harvested. The year variable indicates that a systematic time trend effect exists within the model. This model's explanatory power is reasonably good with an R^2 value of .67. The Durbin-Watson statistic of 2.06 indicates that autocorrelation is not a problem. The same model presented in table 2 was estimated with a 1-year lag but this model did not perform well using the lag. The coefficient on the lag of total fire (-1) was .01 and the t-statistic is .44, which indicates the lag is insignificant. The R^2 value did not change from the model with the no lag (results available from authors).

Summary of Micro Regressions Based on GIS Analysis

The two regression models estimated using GIS derived data are presented in this section: one count data and the other OLS, both of which show prescribed burning had a statistically significant effect on deer harvest. As can be seen in table 3a, total acres of prescribed fire is significant during the year of the prescribed fire, and its significance declines over the next three years in the count data model. During the first year, prescribed fire's coefficient is .044 with a t-statistic of 2.4. Since this count data model logs the fire acreage variables it is equivalent to a log-log model. As such, the .044 is the elasticity, which is remarkably similar to the .048 elasticity in the macro time-series model reported in table 2. The total acres of wildfire variable was not significant for any of the years in this equation. The total area count data model has an R^2 value of .25.

Using OLS as an estimator of deer harvest per acre as a function of fire and the other variables provides a similar pattern of signs and significance as the total area count data equation. In this model, a double log form was also used, but this time the dependent variable acts as a controlling measure for the size of each harvest area by dividing harvest in each hunting zone by the number of acres in each zone. The result of this model in table 3b shows that prescribed burning has a statistically significant effect on deer harvest in the first year with a t-statistic of 2.25. Then during the years following the fire, prescribed burning becomes less significant, which corresponds to the previous count data model. The only time wildfire has a significant impact is during the second year following the burn. The sign of the coefficient for wildfire in the second year is negative and less than one, which would imply a negative effect on deer harvest in that year. Distance to dirt roads is also significant,

Table 3a—Count data model based on GIS using total acres burned with lags. Dependent variable is DEERKILL; n = 825. Method is ML - Negative Binomial Count.

	Coefficient	Std. error	t-statistic	Probability
C	62.96425	23.1157	2.7238	0.0065
LAVG_ELEV	-0.237276	0.13070	-1.8153	0.0695
LTOTWFIRES	0.010712	0.01714	0.6248	0.5321
LTOTWFIRES(-1)	0.008299	0.01701	0.4877	0.6257
LTOTWFIRES(-2)	-0.027728	0.01548	-1.7902	0.0734
LTOTWFIRES(-3)	-0.02466	0.01557	-1.5829	0.1134
LTOTRXFIRES	0.044067	0.01790	2.4608	0.0139
LTOTRXFIRES(-1)	0.027531	0.02701	1.0192	0.3081
LTOTRXFIRES(-2)	0.011491	0.02223	0.5169	0.6052
LTOTRXFIRES(-3)	0.011491	0.01866	0.6155	0.5382
LDIRTDIST	-0.233799	0.03774	-6.1943	0
LTRAILDIST	0.395161	0.04175	9.4633	0
LFIRE_DIST	0.072684	0.04739	1.5335	0.1251
LHUNTAREA	0.940678	0.08699	10.812	0
OCT_TEMP	-0.012073	0.01681	-0.7178	0.4728
YEAR	-0.034733	0.01176	-2.9534	0.0031
Overdispersion parameter:				
Alpha: C(17)	-0.2810	0.1081	-2.598	0.0094

R^2: 0.257	Mean dependent var: 1.7587
Adjusted R^2: 0.242	S.D. dependent var: 2.6113
S.E. of regression: 2.2731	Restr. log likelihood: -1920.6
	LR index (Pseudo-R^2): 0.3051

Table 3b—Least squares deer harvest per acre using GIS data model with lags. Dependent variable is LDEERKILLAC; n=825. Method is least squares.

Variable	Coefficient	Std. error	t-statistic	Probability
C	1.341834	1.58826	0.844	0.3984
LAVG_ELEV	-0.009703	0.00927	-1.046	0.2958
LTOTWFIRES	0.001163	0.00120	0.963	0.3357
LTOTWFIRES(-1)	0.000499	0.00116	0.429	0.6678
LTOTWFIRES(-2)	-0.002231	0.00107	-2.086	0.0373
LTOTWFIRES(-3)	-0.001775	0.00109	-1.627	0.104
LTOTRXFIRES	0.002635	0.00116	2.254	0.0244
LTOTRXFIRES(-1)	0.002134	0.00188	1.134	0.2568
LTOTRXFIRES(-2)	0.001333	0.00154	0.862	0.3889
LTOTRXFIRES(-3)	0.001212	0.00130	0.926	0.3546
LDIRTDIST	-0.012952	0.00250	-5.174	0
LTRAILDIST	0.01825	0.00222	8.213	0
LFIRE_DIST	0.005144	0.00320	1.607	0.1084
LHUNTAREA	-0.008678	0.00615	-1.409	0.159
LOCT_TEMP	-0.050413	0.08604	-0.585	0.5581
YEAR	-0.002827	0.00082	-3.436	0.0006

R^2: 0.138	Mean dependent var: -4.532
Adjusted R^2: 0.122	S.D. dependent var: 0.093
S.E. of regression: 0.087	F-statistic: 8.684
	Prob (F-statistic): .0000

a t-statistic of 5.17 and a negative coefficient of -.012. This means that harvest areas farther away from dirt roads have a lower probability of harvesting a deer. The positive sign on the distance to trails variable implies increases in the probability of a deer harvest the farther the hunting area is from a trail. All the other variables in this model fail to be significant indicators of deer harvest,

except for the trend variable, year. Therefore, some unidentifiable systematic temporal change is occurring within the model. Overall this model has a lower level of explanatory power than the total area micro count data model. The R^2 value using OLS is .13 as compared to twice this level of explanatory power in the total area count data model.

Applying the Regression Production Functions

To calculate the incremental effects of different levels of prescribed burning on deer harvest, the acres burned variable is increased from one level to a higher level in the regression model. We use the double-log macro time-series model and the micro GIS-based double-log total area count data models, as these two models have the highest explanatory power. The resulting predicted change in deer harvest will be valued in dollar terms in the next section.

Applying Results of Micro GIS Production Function Model

The results of the "Total Acres Burned" count data model from table 3a provide positive evidence on the desirable effects of prescribed burning programs on deer harvest. The first row in table 4 forecasts the estimated number of deer that would be harvested without having a prescribed burning program. The second row in table 4 represents the current level of prescribed burning. The effect of increasing prescribed burning is calculated by increasing the number of acres burned in each of the 37 hunting areas by 100 acres per hunting area, and then 200 acres per hunting area (for a total of 8,510 acres) to evaluate a wide range of prescribed burning levels in the SJRD. The first level (1,100 acres) is about the average prescribed burning over the last 20 years. Maintaining this level of prescribed burning does provide a significant increase in deer harvest over the no burning level. However, the gain in deer harvest increases more slowly with additional increases in burning in each hunt area.

Table 4—Comparison of deer harvest response to prescribed burning using the macro time series model and GIS micro model.

RX acres burned	Additional acres burned	Macro time series model: # deer harvested	Time series marginal increase in deer harvest	GIS micro model: # deer harvested	GIS marginal increase in deer harvest
1	NA	83	NA	42	NA
1110	1110	116	33	58	16
4810	3700	124	8	66	8
8510	3700	128	4	71	5

Applying Results of Macro Time Series Production Function Model

To estimate the change in deer harvest using the Macro Time Series Production Function Model, the double log model reported in table 2 is used. The total fire variable in this model is increased and the predicted level of deer harvest is calculated at the mean of the other variables. This is done at the same four acreage levels used above.

The results in table 4 suggest there is a substantial gain in deer harvest with the first 1,100 acres burned, especially as calculated from the macro time-series model. However, a very similar diminishing marginal effect is evident from both the macro time-series production function regression and the micro GIS production function regression after burning more than 1,100 acres. That is, regardless of the spatial level of detail adopted, burning an additional 3,700 acres is expected to result in about eight more deer being harvested in the SJRD.

In order to determine the economic efficiency of additional prescribed burning it is necessary to compare the benefits of additional prescribed burning in the form of the economic value of deer harvest against the costs. It is to the development of the valuation data that we now turn.

Valuation of Deer Hunting

According to CDFG, deer hunting is considered to be one of the major outdoor recreation activities in SJRD (Gibbs et al. 1995). Previous research on deer hunting in California showed that increased success rates and opportunities to harvest a trophy deer increase the economic value of deer hunting (Loomis et al. 1989, Creel and Loomis 1992).

Travel Cost Method for Valuation of Deer Hunting

The Travel Cost Method (TCM) has been a primary approach for valuing recreational hunting. The basic concept of TCM is that the travel cost (i.e., transportation cost, travel time) to the site is used as a proxy for the price of access to the site. When hunters are surveyed and asked questions about the number of trips they take and their travel cost to the site, enough information is available to estimate a demand curve. From the demand curve, net willingness to pay or consumer surplus can be calculated (Loomis and Walsh 1997).

Besides variable travel cost or its proxy, travel distance, inclusion of a travel time variable in the demand function is necessary to represent the opportunity costs of time as part of travel costs. Cesario (1976) suggested one-fourth the wage rate as an appropriate estimate of the opportunity cost of time based on commuting studies. For individuals with fixed workweeks, recreation takes place on weekends or during pre-designated annual vacation and cannot be traded for leisure at the margin. In such cases, Bockstael et al. (1987) and Shaw (1992) suggest that the opportunity cost of time no longer need be related to the wage rate. These studies suggest that both the travel cost and travel time be included as separate variables, along with their respective constraints, income and total time available for recreation.

Table 5 contains a list and definition of variables used in the TCM demand model. For this study we chose the TCM variables according to the consumer demand theory and existing literature on deer hunting in California. Individuals who hunt on opening day, belong to hunting organizations, hunted in previous seasons, and had a successful deer harvest may take potentially more hunting trips because such hunters have higher preferences, experience or skill in deer hunting recreation. Because a majority of hunters in our dataset work a fixed workweek, we assume deer hunters maximize utility level subject to their income and time constraints (Shaw 1992). In other words, total time available for recreation is a constraint similar to income for time intensive activities like hunting. The total time budget is constructed for the TCM model using responses to the survey questions regarding availability of

Table 5—Variables included in travel cost model.

Variable	Definition
Dependent variable	
NUMTRIPS	Number of primary purpose of deer hunting trips taken to the SJRD during 1999 deer hunting season.
Independent variables	
AGE	Hunter's age
DEERKILL	Did you harvest a deer in this area during this hunting season? 1= YES, 0 = NO
HUNTOPEN	Did you hunt on opening day of the season? 1= YES, 0 = NO
HUNTORG	Are you a member of a sportsman's organization? 1= YES, 0 = NO
PREVSEAS	Have you hunted in this area in a previous season? 1= YES, 0 = NO
PRIVLAND	Did you hunt on private land? 1= YES, 0 = NO
RTRAVMILES	Round trip travel miles from home to the hunt zone
PCINC	Hunter income
TOTIMEBUD	Total time budget during hunting season
TRAVETIME	Number of hours one-way travel time

vacation time and time periods chosen to hunt (e.g., weekends only versus weekdays). In this study, the total time budget ranged from 8 to 31 days because the deer-hunting season in SJRD lasted for one month only.

Count Data Nature of TCM Dependent Variable

The nonnegative integer characteristic for the dependent variable, number of seasonal trips, is from a count data process. Given the count data form of the dependent variable, a preferred estimation technique would be the negative binomial count model to estimate the demand function (Creel and Loomis 1990). The negative binomial is the more generalized form of the Poisson distribution, which allows the mean of trips to be different from its variance. The count data TCM model is specified in equation 2.2:

$$\begin{aligned} \text{NUMTRIPS} = \text{EXP}\,(&\text{C(1)} + \text{C(2)*AGE} + \text{C(3)*DEERKILL} \\ &+ \text{C(4)*HUNTOPEN} + \text{C(5)*HUNTORG} + \text{C(6)*PREVSEAS} \\ &+ \text{C(7)*PRIVLAND} - \text{C(8)} * \text{RTRAVMILES} + \text{C(9)*}\ \text{PCINC} \\ &+ \text{C(10)*TOTIMEBUD} - \textit{C(11)*TRAVTIME)} \end{aligned} \qquad [2.2]$$

In equation 2.2, we expected the coefficient for DEERKILL (i.e., C (3)) to have a positive sign, because hunters would likely take more hunting trips if the hunting quality has been good. Also, if hunters hunt on the opening day (i.e., C (4)), private land (i.e., C (7)), and/or previous seasons (i.e., C (6)), and belong to hunting organizations (i.e., C (5)), then we expected a positive effect on the number of trips the hunter takes as these variables indicate a strong preference for the deer hunting activity. For those hunters with a higher income level (i.e., C (9)) and/or higher total time budget (i.e., C (10)) we expect more hunting trips as well due to less binding income and time constraints. However, round-trip travel distance (i.e., C (8)) and travel time (i.e., C (11)) are expected to have negative effects on the number of hunting trips because increases in these two variables result in higher hunter's expense.

Calculation of Consumer Surplus in TCM

The consumer surplus from deer hunting is computed from the demand curve as the difference between what people are willing to pay (e.g., the entire area under the demand curve) and what people actually pay (e.g., their travel costs). Because the count data model is equivalent to a semi-log functional form, consumer surplus from a trip is calculated as the reciprocal of the coefficient on round trip travel miles, expressed in RTRAVMILES scaled to dollars using the cost per mile (Creel and Loomis 1990).

Hunter Survey Data

For cost effectiveness in data collection, a mail questionnaire was sent to a random sample of deer hunters with licenses for zone D19, which includes the San Jacinto Ranger District. Of 762 questionnaires mailed to deer hunters in California during the 1999 hunting season, 7 were undeliverable. A total of 356 deer hunters' responses were collected after two mailings. The response rate is approximately 47%. Among these respondents, 69 did not hunt in the San Jacinto Ranger District portion of Zone D19. The response rate of this study is suspected to be low because many of the hunters that did not hunt in the SJRD portion of the D19 Hunt Zone may not have returned the survey.

Statistical Results

Estimation results are summarized in table 6. There is a negative effect of travel miles, travel time, and income on number of trips taken. Income, in this study, is insignificant. The regression results of this study indicate that hunters which successfully harvested a deer during the hunting season (i.e., DEERKILL), hunted on opening day (i.e., HUNTOPEN), hunted in this area in a previous season (i.e., PREVSEAS), and had a larger total time budget (i.e., TOTIMEBUD) had positive and significant effects on the number of hunting trips taken. Consistent with economic theory, hunters with longer round trip travel miles (RTRAVMILES) and greater travel time (TRAVTIME) tend to take fewer hunting trips.

Table 6—Estimated negative binomial count data TCM demand equation. Dependent variable is NUMTRIPS.

	Coefficient	Std. error	Z-stats	Probability
Constant	1.324485	0.2163	6.1226	0.0000
AGE	0.001395	0.0037	0.3684	0.7125
DEERKILL	0.366571	0.1547	2.3695	0.0178
HUNTOPEN	0.524153	0.1148	4.5640	0.0000
HUNTORG	0.067655	0.1058	0.6390	0.5228
PREVSEAS	0.285282	0.1344	2.1217	0.0339
PRIVLAND	0.038041	0.1314	0.2892	0.7724
RTRAVMILES	-0.002230	0.0008	-2.4906	0.0128
PCINC	-1.00E-06	2.78E-06	-0.359	0.7192
TOTIMEBUD	0.010128	0.0048	2.0994	0.0358
TRAVTIME	-0.289315	0.0867	-3.3340	.0009

R^2: 0.2058, Adjusted R^2 : 0.1685
Consumer surplus: $134.53/trip
90% confidence interval: $81.13 ~ 393.59
Marginal consumer surplus per deer harvested: $257.17/deer
90% confidence interval: $154 ~ 752

In table 6 the consumer surplus is calculated by:

$1/\beta$(i.e., coefficient of distance) * \$0.3/mile (i.e., cost per mile).
= 1/0.002230 *\$0.3 = 448.43 * \$0.3 = \$134.53/trip, where the \$0.30 is the sample average cost per mile.

Finally, the 90% confidence interval in table 6 is obtained by the following equation:

90% confidence interval on consumer surplus per trip = $1/(\beta_{DIST} \pm 1.64$ * 0.000895) * \$0.30/mile = \$81.13 ~ \$393.59 dollars per trip

Estimating the Benefits of Harvesting an Additional Deer

The average number of trips per hunter is 5.56 trips and 10% of deer hunters successfully harvested a deer. To calculate the incremental or marginal value of an additional deer harvest we can use the TCM demand equation to predict the extra number of trips deer hunters would take if they knew they would harvest a deer that season. This essentially shifts the demand curve out by the amount of the coefficient on deer harvest. The equation predicts that each hunter would take 1.9116 more trips each season if they knew they would harvest a deer. Therefore, the marginal value of another deer harvested (i.e., marginal consumer surplus) is equal to \$134.53 * 1.9116 = \$257.17 per deer harvested. Finally, the 90% confidence interval in table 6 for an additional deer harvested is obtained by applying the 90% CI on the value per trip times the additional number of trips taken by the hunter: 90% confidence interval of the value of harvesting an additional deer =

1.9116 * \$81.13 ~ 1.9116*393.59 = \$155 ~ \$752 dollars per deer harvested.

Benefits of Prescribed Burning

Table 7 summarizes this study's main conclusion—the annual deer hunting benefits of additional acres of prescribed burning. While the initial deer hunting benefit response to prescribed burning of 1,100 acres ranges from \$4,112 to \$8,481 depending on the model used, the incremental gains for more than the current acreage of prescribed burning is quite similar across models. That is, the annual economic hunting benefits of increasing prescribed burning from its current level of 1,110 acres to 4,810 acres is \$2,056, regardless of the model used. Likewise for an additional 3,700 acres of prescribed burning to

Table 7—Annual deer hunting benefits from increased prescribed burning: macro time series model and GIS micro model results.

RX acres burned	Additional acres burned	Time series marginal increase in deer harvest	Annual increase in deer hunting benefits	GIS marginal increase in deer harvest	GIS Annual increase in deer hunting benefits
1	NA	NA	NA	NA	NA
1110	1110	33	\$8,481	16	\$4,112
4810	3700	8	\$2,056	8	\$2,056
8510	3700	4	\$1,028	5	\$1,285

8,510 acres, the deer hunting benefits are calculated to be between $1,028 to $1,285 each year, fairly similar despite the different modeling approaches.

Comparison to Costs

Discussions with fire management personnel on the San Bernadino National Forest suggested that their prescribed burning costs range from $210 to $240 per acre. This is a lower total cost per acre than reported by González-Cabán and McKetta (1986), but substantially higher than the direct costs per acre for southwestern National Forests in Wood (1988). Nonetheless, if we use the $210 per acre figure, the full incremental costs of burning the first 1,100 acres would be $231,000, with each additional 3,700 acres burned costing $779,100. The additional benefits of deer hunting benefits represent at most about 3.4% of the total costs of performing the first 1,100 acres of prescribed burning. This finding can be used in two ways. First, the incremental costs of including deer objectives in the prescribed burn should not exceed $8,000, as the incremental benefits are no larger than this. Second, the other multiple use benefits such as watershed and recreation, as well as the hazard fuel reduction benefits to adjacent communities, would need to make up the difference if the prescribed burning program is to pass a benefit-cost test.

Conclusion

This study evaluated the response of deer harvest and deer hunting benefits to prescribed burning in the San Jacinto Ranger District in Southern California. To estimate hunter's benefits or willingness to pay (WTP) for harvesting an additional deer, the individual observation Travel Cost Method was used resulting in a mean WTP to harvest another deer of $257. With regard to the response of deer harvest to prescribed and wildfire, we compared a macro level, time-series model which treated the entire San Jacinto Ranger District as one area and a micro GIS model which disaggregated the Ranger District into the 37 hunting areas delineated by California Department of Fish and Game. The macro time-series model estimated a larger response to burning of the first 1,000 acres than the micro GIS model did, but for increases in fire beyond 1,000 acres, the two models provide nearly identical estimates.

Using the marginal willingness to pay for harvesting another deer calculated from the TCM demand model, the deer harvest response to fire yields annual economic benefits ranging from $4,112 to $8,481 for the first 1,100 acres burned. For an additional 3,7000 acres burned, the gain is $2,056 annually, while for a second increase of 3,700 acres (for a total of 8,510) the increase ranges from $1,028 to $1,285 per year. The costs of prescribed burning on the San Bernadino National Forest range from $210 to $240 per acre. Thus the cost to burn an additional 1,100 acres is $231,000, which is an order of magnitude larger than the deer hunting benefits gained. Specifically, the deer hunting benefits of the first 1,100 acres burned represent about 3.4% of the total costs of conducting the first 1,100 acres of prescribed burning. However, there are probably other multiple use benefits such as protecting watersheds and wildfire hazard reduction. These other multiple use benefits of prescribed burning would have to cover the rest of the costs of prescribed burning if the program is to be economically feasible. Investigating the extent of these benefits would be a logical next step in evaluating the economic efficiency of prescribed burning in the San Jacinto Ranger District.

While fire management practices have been identified as having widespread impacts on deer habitats, many other factors that affect deer habitat exist. These other factors include livestock grazing, timber harvesting, urban development, diseases, habitat loss, and annual weather patterns (CDFG, 1998). This study attempted to take into account as many factors as possible, but the amount of data and time available for modeling were a constraint.

Some future improvements in our modeling effort that may better isolate the effects of prescribed burning on deer habitat include controlling for the severity of wildfire as different fire severities will have different effects on vegetation and soils. Furthermore, including vegetation and soils layers in the GIS model, rather than using elevation as a proxy, could improve the predictive ability of the GIS-based model.

Subject to these caveats, we have demonstrated two approaches to estimate a production function relating prescribed burning to effects on deer harvest. We found positive and significant effects on deer harvest for the two GIS models and a positive impact of fire using a macro-time series model. The USDA Forest Service and California Department of Fish and Game can make use of these approaches for future cost-benefit analysis of prescribed burning.

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