ECONOMIC VALUE OF IMPROVED DEER HUNTING RESULTING FROM PRESCRIBED BURNING IN SOUTHERN CALIFORNIA

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1. INTRODUCTION

In her recent review of the economics of prescribed burning, Hesseln (2000) posed the problem of “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, p. 331-332). Following Hesseln suggestions, in this study we estimate production relationships between prescribed burning and deer harvest by using time-series data and geographic information system (GIS) approaches. Previous work has shown that deer population increases because the quality of forage improves after their habitat is burned (Klinger and others 1989). The deer habitat production models developed were then used to predict the resulting increases in deer harvest from prescribed burning, and subsequently to measure the economic benefits of this environmental improvement (increase in deer harvests) using nonmarket valuation techniques.

The San Jacinto Ranger District (SJRD) is located in southern California’s San Bernardino National Forest between Palm Springs and Idyllwild. As noted by the USDA Forest Service: “Some of the best deer hunting in Riverside County is found in this area. [The area] it is also a very valuable watershed that includes the South Fork of the San Jacinto River” (Gibbs and others 1995, p. 6). The SJRD is an ideal area in which 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 (Gibbs and others 1995, Paulek 1989). The USDA Forest Service has a detailed database of fire history for this area predating the 1970s. The California Department of Fish and Game (CDFG) have hunter deer harvest records for the SJRD dating back to 1974. These two agencies provide the fundamental data sets for modeling a relationship between deer harvest and fire, whether prescribed burns or wildfires. Information from our analysis may be relevant to policy because the SJRD plans to increase the amount of prescribed burning by 50 to 100 percent over the next few years (Gibbs and others 1995, Walker 2001).

The positive effect of prescribed fire on enhancing deer habitat and populations has been shown (CDFG 1998, Klinger and others 1989), but the resulting economic benefits of the treatments have not been quantified. We hypothesized that prescribed burning has a systematic positive effect on deer harvest, and we will use two nonmarket valuation methods to estimate the economic value of additional deer harvest.

2. STUDY AREA

In general, southern California is characterized by a Mediterranean climate, with hot and dry summers and cool, humid winters. There is a significant amount of variation in temperatures and local site conditions in the SJRD. Below 5,000 feet elevation, the dominant vegetation within the SJRD is chaparral. Annual rainfall for

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the chaparral biome is approximately 15 to 16 inches. Areas higher than 5,000 feet tend to be dominated by hardwoods and conifers, such as live oak and Douglas-fir, with annual rainfall reaching up to 30 inches.

The SJRD 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 (CDFG 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 and others 1989). It is hypothesized that increases in quality of forage and fawn survival have improved reproduction, leading to increased numbers of deer. The CDFG noted a significant increase in buck harvest from 1987 to 1996 in hunt locations that had large fires versus hunt locations that did not have large fires (CDFG 1998). To improve deer habitat in California, controlled burns have been underway in all major parks and forests for many years (Kie 1984). Efforts including controlled burning to remove brush have been part of a program to create desirable deer habitat (i.e., chaparral in the open scrubland) and to mitigate the loss of deer habitat resulting from commercial and residential development.

3. TWO APPROACHES TO MODELING PRODUCTION FUNCTIONS

To test whether prescribed burning has a systematic effect on deer harvest we used a macro, or aggregate, time-series approach and a micro, spatial approach. To estimate the economic value of additional harvest resulting from prescribed burning treatments we used two nonmarket valuation methods. By examining prescribed burning effects on deer harvest with two different approaches—a macro, or aggregate, time-series approach and a micro, spatial approach (e.g., GIS)—comparisons can be made between the results for consistency between these two approaches. A macro approach would be able to test the effects of fire, prescribed and natural, across the entire study area over a long period of time. Although more aggregate in geographic space, data availability allows us to test dynamic effects over longer time frames. Using a micro approach provides greater spatial detail to elements such as the influence of a meadow or ridge, but a shorter time frame is covered because of data limitations.

3.1 Multiple Regression Models for Estimating the Production Function

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), total precipitation, temperature, and distance to roads. Thus, multiple regression analysis is an appropriate technique. The simplest form used in this study is ordinary least squares (OLS) regression.

Using OLS, it is not possible to take the log of a zero-valued observation of the dependent variable; but if the negative binomial count data model is used, the probability distribution allows for this—similar to a nonlinear least squares model that circumvents the need for transformations (Hellerstein 1992). Therefore, these features make the Poisson and negative binomial distributions useful in our micro GIS-based analysis since the variable we are trying to explain—deer harvest in 1 of 37 sub-hunting location areas—is a non-negative integer.

However, when modeling the aggregate harvest for all of the SJRD, the mean number of deer harvested is much larger [than 3] and varies between 80 and 157 deer in any given year; therefore, using OLS is an acceptable approach for the macro time-series modeling.

4. ECONOMIC EVALUATION

Wildlife such as deer is commonly considered nonmarket goods in much of the western United States. Although natural resources have use and nonuse values (e.g., existence values), the widespread distribution of deer suggests that the incremental benefits of more deer are use values. For deer, use values are those associated with tangible uses in recreational hunting or viewing benefits. Because of the difficulty in identifying deer viewers, this study focuses on deer hunters.

4.1 Approaches to Production Function Modeling

Two primary methods for estimating a deer harvest production function were applied in this study. Both methods were looking for a statistical relationship between deer harvest and fire, both wildfires and prescribed fires that occurred in southern California's SJRD. The distinguishing difference between the two methods applied is the variation in spatial scale.

The first statistical approach to modeling a production function is based on a time-series regression model to test for a relationship between deer harvest (the dependent variable) and prescribed fire, controlling for other independent variables such as annual precipitation and temperature during the hunting season (table 1). This approach used a data set for SJRD, provided by the CDFG and the USDA Forest Service. The fire records provided data from 1975 to 1996 for wildfire and from 1979 to 1997 for prescribed burns within the SJRD. This ranger district represents the majority of publicly accessible land for deer hunting in Riverside County. Deer harvest data from 1975 to 1998 was provided by CDFG.

A time-series model was established with this data and weather information from the University of Nevada at Reno's Western Climate Center database that contains temperature and precipitation data from the SJRD dating back to 1975. The model attempts to directly explain deer harvest within the SJRD as a function of wildfire, prescribed fire, temperatures during the October hunting

Table 1--Data for modeling a macro time-series production function.

Year	SJRD-Harvest no. deer	Acres Burned: Prescribed Fire	Acres Burned: Wildfires	Oct-Temp ^{0}F	Annual Precipitation inches
1975	105	NA[1]	5231	70.48	19.94
1976	145	NA	0	69.23	27.22
1977	113	NA	3948	74.32	22.63
1978	101	NA	2049	74.32	46.99
1979	148	40.00	1987	70.73	29.62
1980	139	194.10	3,7627	73.68	45.65
1981	155	291.90	1,5016	67.00	15.81
1982	157	228.00	6279	69.42	49.47
1983	143	3,119.90	7206	69.52	56.87
1984	120	971.00	13	64.42	16.96
1985	119	1,311.80	2,1128	67.29	23.58
1986	162	1,309.00	0	65.19	23.92
1987	131	181.50	1432	69.58	23.49
1988	103	1,954.00	1615	75.52	18.25
1989	128	2,009.60	2121	68.65	15.98
1990	104	423.00	119	74.19	19.12
1991	83	0.00	91	72.19	31.49
1992	117	77.70	1458	70.00	23.44
1993	93	383.00	269	69.13	43.64
1994	132	25.40	2,2416	66.68	20.84
1995	82	975.20	7116	73.84	45.09
1996	131	822.00	1,2338	68.10	28.36
1997	126	4.94	NA	69.06	24.96
1998	99	0.00	NA	NA	28.47

[1]NA = not available

season, and total precipitation in a given year (table 1).

The full model (equation 1) is given, and then a lagged model (equation 2) is included that allows for deer harvest to be sensitive to previous years' prescribed fire and wildfire. In past research, the use of burned areas by deer has been shown to increase dramatically during the subsequent years (Klinger and others 1989). Therefore, this model takes into account these subsequent years by using lagged variables.

The SJRD time-series production function model is:

SJRD deer harvest in year$_t$ = func (RxBurn$_t$, WildFire$_t$, TotPrecip$_t$, OctTemp$_t$, Year$_t$), (1)

in which RxBurn$_t$ is the number of acres of prescribed fire in year t, WildFire$_t$ is the number of acres of wildfire in year t, TotPrecip$_t$ is the sum of precipitation for year t, OctTemp$_t$ is the average temperature in October during the hunting season, and Year$_t$ is a trend variable, with 1975 = 1, 1976 = 2, etc.

The lagged model of the SJRD time-series production function is:

SJRD deer harvest in year $_t$ = func (RxBurn$_{t-1}$, WildFire$_{t-1}$, TotPrecip$_t$, OctTemp$_t$, Year$_t$). (2)

Using the log-log form of the production function represents the nonlinear forms of equations 1 and 2. This format allows for a nonlinear relationship, and the coefficients for fire can be interpreted as elasticities: the percent change in deer harvest with a 1 percent change in acres burned.

The second statistical approach taken in this study focused on using a GIS for integrating spatial data into an economic relationship. A similar multiple regression approach was used as in the first method, except that the study area was divided into 37 individual hunting locations reported by hunters. The primary difference in the two models is that the micro GIS approach models deer harvest for 37 small hunting locations, whereas the macro time-series model uses just one large hunting zone that encompassed the SRJD. The micro GIS approach allowed for the incorporation of other influences on deer harvest that varied spatially across individual hunting locations such as distance to roads and elevation.

All of the spatial data for this method came either from the United States Geological Survey (USGS) 1:100,000 digital line graphs (DLG) files or from the USDA Forest Service Arc/Info and Arc/View files, which were provided by the San Bernardino National Forest Supervisor's Office. The data for all the files use the Universal Transverse Mercator (UTM) coordinate system (Zone 11, Datum NAD 27). The scale of the data is at 1:250,000. These spatial data files contain information on prescribed fire, wildfire, elevation, roads, and trails. The CDFG maps and tally sheets provided the hunting location information. The areas on the CDFG maps were aligned with areas on USGS 7.5-minute topographical quads.

All relevant GIS data had to be exported into a spreadsheet format and prepared for regression analysis. A count data model was estimated that regressed deer harvest per hunting zone against prescribed fire and wildfire from 1975 to 1998.

The models developed for the harvest areas had to account for the non-uniform size of each hunting location. Three approaches were used. The first approach measures a percent of the area burned and includes the size of each harvest area as a variable (equation 3). The second approach includes just the size and total number of acres of an area burned (equation 4). The third approach transforms the dependent variable into deer harvest per acre and uses an OLS regression (equation 5).

The model based on percentage of area burned, including lags, is:

$$\text{Deer harvest in year}_t = \text{func}(\text{AvgElev}, \text{LDirtDist}, \text{LTrailDist}, \text{PctRxBurn}_t, \text{PctRxBurn}_{t-1}, \text{PctRxBurn}_{t-2}, \text{PctRxBurn}_{t-3}, \text{PctWildfire}_t, \text{PctWildfire}_{t-1}, \text{PctWildfire}_{t-2}, \text{PctWildfire}_{t-3}, \text{LHvstArea}, \text{OctTemp}_t, \text{Year}_t), \quad (3)$$

where all variables are as described in the next section.

The model with harvest as a function of total size of fire, including lags, is:

$$\text{Deer harvest in year}_t = \text{func}(\text{AvgElev}, \text{LtotalWildfire}_t, \text{LtotalWildfire}_{t-1}, \text{LtotalWildfire}_{t-2}, \text{LtotalWildfire}_{t-3}, \text{LtotalRxBurn}_t, \text{LtotalRxBurn}_{t1}, \text{LtotalRxBurn}_{t-2}, \text{LtotalRxBurn}_{t-3}, \text{LDirtDist}, \text{LTrailDist}, \text{LHvstArea}, \text{OctTemp}_t, \text{Year}_t), \quad (4)$$

where all variables are as described in the next section.

The model based on deer harvest per acre using OLS log-log form is:

$$\text{Log deer harvest per acre in year}_t = \text{func}(\text{AvgElev}, \text{LtotalWildfire}_t, \text{LtotalWildfire}_{t-1}, \text{LtotalWildfire}_{t-2}, \text{LtotalWildfire}_{t-3}, \text{LtotalRxBurn}_t, \text{LtotalRxBurn}_{t-1}, \text{LtotalRxBurn}_{t-2}, \text{LtotalRxBurn}_{t-3}, \text{Ldirtdistance}, \text{Ltraildistance}, \text{LHvstArea}, \text{OctTemp}_t, \text{Year}_t) \quad (5)$$

where all variables are as described in the next section.

5. ESTIMATED PRODUCTION FUNCTIONS

5.1 Macro Time-Series for San Jacinto Ranger District Equations

The basic model between deer harvest in SJRD and both prescribed fire (RxBurn) and wildfire (WildFire) was computed (table 2). Precipitation (TotPrecip), temperature (OctTemp), and year (Year), a trend variable, were also included in the equation. In this linear equation there appears to be no strong statistical significance between the dependent variable and either type of fire. The coefficient on prescribed fire is 0.0009 and has a 0.18 t-statistic, indicating that this variable has minimal effect on deer harvest and is insignificant. The wildfire variable is very similar to the prescribed fire variable: the coefficient is 0.0004 and the t-statistic is 0.92, both insignificant and insubstantial. The only significant variables are October temperature and year.

October temperature (OctTemp) is negative (-3.6472) and has a significant t-statistic of -2.5. This sign is consistent with hunter surveys indicating that when the temperature is high, the deer harvest goes down because deer are bedded to avoid the heat. Year has a 2.8 t-statistic and a negative coefficient of 2.1731. This would indicate that some systematic trend does exist within the data set. Possibly this variable is capturing other influences contributing to the decline in deer population within the SJRD. Total precipitation was expected to have a strong positive effect on vegetation growth and forage availability for deer; however, it does not show up as being significant. The R-squared value for this model is 0.59, and adjusted R-squared is 0.43. These values indicate some ability to explain the effects of fire on deer harvest, as about half the variation in deer harvest is explained by year and October temperature. At this scale and with untransformed variables for deer harvest and fire, there is no indication that the fire variables are related to variation in deer harvest.

A model incorporating a 1-year lag on acres burned was estimated to determine if the year after a fire allows for an increase in deer harvest. This lag is based on the expectation that new vegetation growth occurs in the year after a fire. Previous literature found that the number of deer occupying burned stands of chaparral quadrupled in the first growing season after a burn (Klinger and others 1989). However, a 1-year lag did not make a difference in deer harvest using this model. The 1-year lagged value of prescribed fire (-0.0047) and wildfire (0.0003) were both insignificant, with t-statistics of –0.70 and 0.72, respectively. Values for October temperature and year are almost the same as those in the previous model without a lag. The R-squared values for this model were similar to the previous model, at 0.58 and 0.42.

Table 2--Linear regression model for non-lagged macro time-series for ranger district.

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	4,694.2070	1,535.6420	3.057	0.0092***
RxBurn[1]	0.0009	0.0052	0.185	0.8559
Wildfire	0.0004	0.0004	0.921	0.3736
TotPrecip	0.0361	0.3648	0.099	0.9227
OctTemp	-3.6472	1.4501	-2.515	0.0258**
Year	-2.1731	0.7754	-2.803	0.0150**
R-squared	0.588	Mean dependent variable		124.895
Adjusted R-squared	0.429	S.D. dependent variable		23.758
S.E. of regression	17.947	F-statistic		2.708
Durbin-Watson statistic	1.870	Prob. (F-statistic)		0.026

[1]Prescribed fire **Significant at α = 0.05 ***Significant at α = 0.01

5.2 Log-Log Model for the San Jacinto Ranger District

Taking the log of the dependent variable and the log of the combined wildfire and prescribed burn variable (LnTotFire) results in a statistically significant effect. The coefficient for total fire shows a small magnitude of 0.048, but it has a significant t-statistic of 2.3 (table 3). This appears to be in line with a previous study where the density of deer increased after wildfire (Klinger and others 1989). The sign on this variable is positive, and the coefficient can be interpreted as elasticities by using the log-log form. Therefore, a 1 percent increase in acres burned will lead to a 0.048 percent increase in deer harvest. The other significant variables are October temperature (OctTemp) and year (Year). Again, a negative sign on the October temperature coefficient relates to observations that an increase in temperature results in a decrease in the number of deer harvested. The year variable indicates that a systematic effect exists within the model. This model's explanatory power is better with an R-squared value of 0.68. The Durbin-Watson statistic of 2.07 indicates that autocorrelation is not a problem.

Table 3-- Log-log model for macro time-series for ranger district.

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	41.8087	11.0701	3.7767	0.002***
LnTotFire	0.0487	0.0205	2.3719	0.033**
TotPrecip	-0.0001	0.0026	-0.3666	0.719
OctTemp	-0.0270	0.0107	-2.5362	0.024**
Year	-0.0179	0.0056	-3.1993	0.006***
R-squared	0.677	Mean dependent variable		4.809
Adj. R-squared	0.585	S.D. dependent variable		0.202
S.E. of regression	0.130	F-statistic		6.343
Durbin-Watson statistic	2.066	Prob. (F-statistic)		0.002

**Significant at α = 0.05 ***Significant at α = 0.01

Table 4--Count data model based on geographic information system using total acres burned with lags.

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	62.9643	23.1158	2.7239	0.007***
LAvgElev	-0.2373	0.1307	-1.8154	0.070*
LTotWFires	0.0107	0.0171	0.6249	0.532
LTotWFires (-1)	0.0083	0.0170	0.4877	0.626
LTotWFires (-2)	-0.0277	0.0155	-1.7903	0.073*
LTotWFires (-3)	-0.0247	0.0156	-1.5830	0.113
LTotRxBurns	0.0441	0.0179	2.4609	0.014**
LTotRxBurns (-1)	0.0275	0.0270	1.0193	0.308
LTotRxBurns (-2)	0.0115	0.0222	0.5169	0.605
LTotRxBurns (-3)	0.0115	0.0187	0.6155	0.538
LDirtDist	-0.2338	0.0377	-6.1944	0.000***
LTrailDist	0.3952	0.0418	9.4633	0.000***
LFireDist	0.0727	0.0474	1.5335	0.125
LHuntArea	0.9407	0.0870	10.8128	0.000***
OctTemp	-0.0121	0.0168	-0.7179	0.473
Year	-0.0347	0.0118	-2.9535	0.003***
		Overdispersion parameter		
Alpha:C(17)	-0.281	0.1081	-2.598621	0.009***
R-squared	0.257	Mean dependent variable		1.759
Adjusted R-squared	0.242	S.D. dependent variable		2.611
S.E. of regression	2.273	Avg. log likelihood		-1.618
Restr. log likelihood	-1920.633	LR index (Pseudo-R2)		0.305

*Significant at α = 0.10; **Significant at α = 0.05; ***Significant at α = 0.01

The model in table 3 was also estimated with a 1-year lag. The coefficient on the log of total fire lagged 1 year was 0.01 and had a t-statistic of 0.44, which indicates that the lag is insignificant. The R-squared value did not change from the previous model.

5.3 Summary of Micro Regressions Based on GIS Analysis

Two of the regression models estimated using GIS-derived data—count data and OLS—show that prescribed burns had a statistically significant effect on deer harvest. The count data model based on total fires is used for calculating the marginal benefits of additional burning on deer harvest in the next section because of its superior explanatory power. The low R-squared value (0.18) of a model based on percent of hunting location area burned, and an OLS Log-Log form of harvest per acre (R-squared = 0.13) indicate both equations have relatively low power of explaining deer harvest and are not presented here (results available from the author).

The count data model (table 4) specification uses two separate fire variables: the log of total acres of prescribed fire in the individual hunting area during the time period, and the log of total acres of wildfire in the individual hunting area during the time period. This equation controls for the different size of the individual hunting areas by including a variable for size (acres) of hunting area. Total acres of prescribed fire (LTotRxBurns) are significant during the year of the prescribed fire, but their significance declines over the next 3 years. During the first year, the prescribed fire coefficient is 0.044 with a t-statistic of 2.4. Because this count data model uses the log of the total acres of wildfire variable, it is equivalent to a log-log model. As such, the 0.044 coefficient represents the elasticity. Total acres of wildfire (LTotWFires) were not significant for any of the years in this equation. This model, with an R-squared value of 0.26, has more power to explain the effect of fire on deer harvest than the model based on percent of hunting location area burned and the OLS Log-Log form model of harvest per acre.

5.4 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 used the double-log macro time-series model (table 3) and the micro GIS-based double-log count data models (table 4), as these two models have the highest explanatory power. The resulting predicted change in deer harvest will be valued in dollar terms.

The double-log macro time-series production function model (table 3) is used to estimate the change in deer harvest because of its high explanatory power (68%). The prescribed burning component of the total fire variable in this model is increased to three different levels (1100, 4810, and 8,510 acres, respectively) and the predicted log of deer harvest is calculated at the mean of the other variables. The anti-log of harvest is then calculated to provide the estimate of the deer harvest with that level of prescribed burning (table 5).

Table 5--Comparison of deer harvest response to prescribed burning using the macro time-series model and geographic information system (GIS) micro model.

Macro time-series model				GIS micro model		
Total acres[1] burned	Additional acres burned	No. Deer harvested	Marginal increase in deer harvested	Prescribed Acres burned	No. Deer harvested	Marginal increase in deer harvested
1	NA[2]	83	NA	1	42	NA
1,100	1,100	116	33±3.99[3]	1,100	58	16±4.45
4,810	3,710	124	8±3.99	3,710	66	8±4.45
8,510	3,700	128	4±3.99	3,700	71	5±4.45

[1] Although the variable Total Acres Burned reflects the combined prescribed acres and wildfire acres, for this simulation only, the prescribed burn acres are being changed because prescribed burned is the management variable.
[2] NA = not applicable
[3] Because the dependent variable is the log of deer harvested, the 95 percent confidence interval was computed taking the antilog of the S.E. of the regression (0.13) (table 3) and multiplying it by 1.96 (antilog 0.13 = -2.04 x 1.96 = ± 3.99).

5.5 Applying Results of Micro GIS Production Function Model

The economic implications from prescribed burn programs will be evaluated by using the prescribed burn coefficients (table 4) in the GIS count data model. By using this model it is possible to calculate the additional harvest from additional prescribed burn acres. In table 5, the first row forecasts the estimated number of deer that would be harvested if only one acre of land would burn. By using the current mean number of acres burned in each individual hunting location for the GIS micro model (table 4), 30 acres, and then multiplying this by the total number of individual hunting locations, 37, a SJRD-wide deer harvest level is calculated. The forecast feature in the statistical software package EViews (Quantitative Micro Software 1997) does this. The other variables are set at their mean levels. In the GIS micro model the effect of further increasing prescribed burning is then calculated by increasing the number of acres burned in each hunting location by 100 acres and then 200 acres to provide a wide range of prescribed burning levels in the SJRD. The first level (1,100 acres) is about the average number of acres of prescribed burning over the past 20 years in the SJRD. Maintaining this level of prescribed burning does provide an 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 hunting area (table 5).

The results suggest there is a substantial gain in deer harvest with the first 1,100 acres burned (table 5), 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. In other words, regardless of the spatial level of detail adopted, burning an additional 3,710 acres is expected to result in about eight more harvested deer in the SJRD.

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.

6. VALUATION OF DEER HUNTING

In the SJRD the deer hunting regulation allows for a 1-month hunting season and a one-deer bag limit. According to CDFG, deer hunting is considered one of the major outdoor recreation activities in SJRD every year. Deer hunting offers opportunities for recreational enjoyment and produces economic benefits to the town of

Idyllwild, California. Previous research on deer hunting in California showed that increased success rates and opportunities to harvest a trophy deer (Creel and Loomis 1992) increase the economic value of deer hunting.

Linking hunter trips and success to economic values will result in a bioeconomic relationship that ties fire management decisions to economics. Thus, we estimated the economic value of the additional deer harvest resulting from the prescribed burning program in the SJRD**.** By using both the travel cost method (TCM) and the contingent valuation method (CVM) we can compare the estimates of the change in consumer surplus for harvesting another deer in the SJRD. This economic information will be useful to future policy decisions regarding funding and implementation of a prescribed burning program.

6.1 Contingent Valuation Method

CVM uses simulated (hypothetical) markets to quantify monetary values similar to actual markets (Loomis and Walsh 1997). The method uses survey questions to elicit people's net economic value or consumer surplus for an improvement in environmental or site quality by asking what additional amount they would pay for the specified improvement. Thus, the method aims at eliciting people's willingness-to-pay (WTP) in dollar amounts. In our application, CVM presents hunters with a hypothetical market in which they can pay higher trip costs to receive an increase in deer harvest opportunities. For simplicity in survey design and administration, an open-ended WTP question was asked. In addition, the accumulated evidence to date is that the open-ended format tends to produce conservative WTP estimates relative to dichotomous choice (Schulze and others 1996). Although open-ended questions are more difficult to answer than dichotomous choice questions, hunters who have completed the deer-hunting season at this area are quite familiar with the good they are asked to value (deer). Therefore, we believed that this simplification was acceptable. The basic improvement being valued is the deer hunter's consumer surplus per trip for a guaranteed deer harvest during the season, which is the difference between people's maximum WTP per trip with guaranteed deer harvest (i.e., 100 percent chance of harvesting a deer) and people's current maximum WTP per deer hunting trip (i.e., deer hunting demand with around 9 percent deer harvest success rate). The CVM model is specified as (equation 6):

$$MWTPDeer = MaxWTPKill - MaxWTPCur, \qquad (6)$$

in which *MWTPDeer* is the change in hunter's WTP for increasing deer harvest rate, *MaxWTPKil* is the maximum WTP per trip with certainty of deer harvest, and *MaxWTPCur* is the current maximum WTP per trip.

6.2 Travel Cost Method

The TCM has been a primary indirect approach for valuing environmental resources associated with recreation activity over the past several decades. Clawson (1959) was the first to empirically estimate benefits using a travel cost framework. The basic concept of TCM is that travel cost (i.e., transportation cost, travel time) to the site is used as the proxy for the price of access to the site. When recreationists are surveyed and asked questions about the number of trips they take and their travel cost to the site, enough information can be generated to estimate a demand curve. From the demand curve, net WTP or consumer surplus can be calculated. The explanatory variables that are often included in travel cost demand curves include age, income, family size, educational level, and other socioeconomic variables (Kahn 1995). Since we are interested in the benefits of improvements at just one site with no changes at other sites, a single site TCM demand model will suffice for empirical analyses, and more complex multi-site models such as hedonic TCM (hybrid hedonic travel cost method developed by Brown and Mendelsohn [1984]) or multinomial logit models (sometimes called Random Utility Models [RUMs]) are more costly and complex than warranted.

6.3 Definitions of TCM Price Variable

Besides the travel cost variable or its proxy, travel distance, many articles discuss the inclusion of a travel time variable in the demand function. Knetsch (1963) was the first to point out that the opportunity cost of time is part of travel costs as well. 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 and others (1987), Shaw (1992) and Shaw and Feather (1999) suggest that the opportunity cost of time no longer need be related to the wage rate. These studies suggest that both travel cost and travel time be included as separate variables, along with their respective constraints—income and total time available for recreation.

This study chooses its variables according to the consumer demand theory and past literature (table 6). For instance, private hunting land serves as a substitute (or complement) for public hunting land in SJRD. Hunters were asked neither the distance to substitute sites nor the name of a substitute site for the SJRD deer hunting. Because there are two other deer hunting areas in southern California that could be substitutes, our TCM estimates of consumer surplus may overstate the hunter's net WTP for the SJRD by a slight amount. Hunters 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 data set work a fixed workweek, we assume that the deer hunter maximizes utility level subject to their income and time constraints (Shaw 1992). In other words, time is a constraint like income for time-intensive activities like hunting. Total time budget is constructed for the TCM model according to the demographic time information. For example, for persons who took a paid vacation to hunt, their total time budget (days) is obtained by adding 8 weekend days during the month of the hunting season to the number of weeks of paid vacation of the individual multiplied by 5 days per week, for up to a maximum total of 30 days (31 days in October), which is the length of the hunting season. For persons who took unpaid vacation time or reduced work hours to hunt, their total time budget is 16 days. For those who work their usual amount and hunt when they can, their total time budget is 8 days, the number of weekend days during the October hunting season. Furthermore, the total time budget for the unemployed and retirees is 31 days. In this study, the total time budget ranges from 8 to 31 days, since the deer-hunting season in SJRD lasted for 1 month only.

Table 6--Variables included in regression models and their definitions.

Variable	Definition
<u>Dependent:</u>	
NUMTRIPS	Number of deer hunting trips (primary purpose) taken to the SJRD during 1999 deer-hunting season.
<u>Independent:</u>	
Age	Hunter's age (years)
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 D-19 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 location
PcInc	Hunter income (household)
ToTimeBud	Total time budget (days)
TravTime	One-way travel time (hours)

6.4 Count Data Nature of TCM Dependent Variable

The non-negative integer characteristic in every observation for the dependent variable (i.e., NUMTRIPS) is the so-called "count data." Given the count data form of the dependent variable, a preferred estimation model should be able to control for the integer nature of the dependent variable (Creel and Loomis 1990). In this study, the negative binomial count data model was used to estimate the demand function. The negative binomial is the more generalized form of the Poisson distribution, which allows the mean number of trips to be different from its variance. The negative binomial and Poisson count data models are equivalent to a semi-log of the dependent variable functional form.

The count data TCM model is specified in equation 7:

NUMTRIPS = EXP (C(1) + C(2) x Age + C(3 x DeerKill + C(4) x HuntOpen + C(5) x HuntOrg + C(6) x PrevSeas + C(7) x PrivLand - C(8) x RTravMiles + C(9) x PcInc + C(10 x ToTimeBud - C(11) x TravTime) (7)

In equation 7, we expected the coefficient for DeerKill [C(3)] to have a positive sign, since hunters would likely have taken more hunting trips if the hunting quality had been good. Also, if hunters hunted on the opening day [C(4)], on private land [C(7)], or during previous seasons [C(6)] and belonged to hunting organizations [C(5)], then we expected a positive effect on the number of trips the hunter took, as these variables indicated a strong preference for deer hunting. For those hunters with a higher income level [C(9)] or higher total time budget [C(10)], or both, we expected more hunting trips as well, as a result of less binding income and time constraints. However, round-trip travel distance [C(8)] and travel time [C(11)] are expected to have negative effects on the number of hunting trips because increases in these two variables increase the hunter's expense.

6.5 Calculation of Consumer Surplus in TCM

The consumer surplus from deer hunting is computed from the demand curve as the difference between people's WTP (e.g., the entire area under the demand curve) and what they 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 times the average cost per mile, expressed in RtravMiles * $0.30/mile (see equation 9) (Sorg and others 1985).

6.6 CVM and TCM Comparisons

Literature in CVM and TCM comparisons has usually just compared the average consumer surplus for existing conditions. For example, Carson and others (1996) found in their study that on average, CVM-derived values were usually smaller than revealed preference estimates like TCM. To test the consistency between two valuation methods for nonmarket good, we compared the CVM and TCM in this study for the improvement in deer hunting quality due to the prescribed burning program. A Tobit model was used for the analysis of open-ended WTP responses from CVM because our open-ended dependent variable has only a single bound at 0. The Tobit model uses the open-ended WTP response as the dependent variable in CVM (i.e., people's current WTP), and the independent variables similar to TCM. The same variables are used because both methods are trying to explain consumer surplus. For TCM, this is done via the demand curve. Meanwhile, for CVM, it may be thought of as the inverse demand function.

The CVM Tobit model is equation 8:

MaxWTPCur = C(1) + C(2) x Age + C(3) x DeerKill (8)
+ C(4) x HuntOpen + C(5) x HuntOrg + C(6) x PrevSeas + C(7)x PrivLand - C(8)x RTravMiles + C(9) x PcInc + C(10) x ToTimeBud - C(11) x TravTime

For the same reasons as in the TCM equation, we expected round-trip travel miles and travel time to hold negative signs in equation 8.

6.7 Data for TCM and CVM Models

For cost effectiveness in data collection, a mail questionnaire was used. Hunters were asked about their expenses as well as their willingness-to-pay higher trip costs for the hunting experience on the most recent trip. Specifically, they were asked an open-ended question pertaining to the maximum increase in deer hunting expenses that would have deterred them from taking this trip. Also, the CVM analysis was used to measure hunter increases in WTP associated with increasing deer harvest success, including a 100 percent chance of harvesting a deer during the season. Our WTP estimate from CVM is compensating variation, rather than consumer surplus, but the two measures are nearly identical in most applications since the income effect is quite small for deer hunting.

6.8 Survey Mailing and Response Rate

During the 1999 deer-hunting season, a questionnaire (available on request form author) was mailed to a random sample of deer hunters with licenses for deer in Zone D19, which includes the SJRD. 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. Response rate is, therefore, approximately 47 percent. Among these respondents, 69 did not hunt deer in the San Bernardino National Forest, SJRD.

Table 7—Statistics for variables used in the Travel Cost Method.

Variable[1]	Mean	Median	Maximum	Minimum	Std. Deviation
NUMTRIPS	5.56	4.0	62.0	1.0	6.26
Age (years)	43.0	42.0	80.0	13.0	13.40
DeerKill (Pct)	9.7	0.0	N/A	N/A	0.29
HuntOpen (Pct)	72.3	N/A	N/A	N/A	0.45
HuntOrg (Pct)	35.0	N/A	N/A	N/A	0.48
PrevSeas (Pct)	81.3	N/A	N/A	N/A	0.39
PrivLand (Pct)	15.0	N/A	N/A	N/A	0.36
RTravMiles (miles)	103.80	80.0	800.0	0.5	95.11
PcInc	$33,148.00	$32,500.0	$100,000.0	$833.0	$18,287.00
ToTimeBud (days)	19.78	23.0	31.0	0.0	10.27
TravTime (hours)	1.43	1.2	9.0	0.1	0.98

[1]See table 6 for definition of variables

More than 72 percent of respondents did hunt on opening day. The average deer hunter's age is around 43 years old with a mean income slightly more than $33,000 dollars (table 7).

The distribution of dependent variable observations reflects how many hunting trips the hunter took during the 1999 deer-hunting season:

Number of trips	Number of deer hunters
NA	58
0	2
1-5	207
6-10	53
11-15	13
16-20	10
21-30	6
31-40	0
41-50	1
Above 50	1
Total	**351**

The majority of deer hunters took at least one hunting trip during the season. Two hunters indicated that they did not take any hunting trip in the 1999 deer-hunting season. Fifty-eight hunters did not answer this question because they did not hunt within the SJRD. In addition, more than 80 hunters took more than 6 hunting trips in the 1999 deer-hunting season. One reasonable explanation for this is that those deer hunters live close by the SJRD.

7. STATISTICAL RESULTS OF TCM AND CVM VALUATION MODELS

7.1 Travel Cost Method

A negative binomial count data model was used to estimate the statistical relationship between number of trips and all the independent variables (table 8). There is a negative effect of travel miles (TravMiles), travel time (TravTime), and income (PcInc): increase in travel distance and time results in a decrease in the number of trips the hunter will take. The negative coefficient explains the disutility effect caused by travel time and travel cost increases. Income, in this study, is insignificant. Also, regression results of this study indicate whether a hunter successfully harvested a deer during the hunting season (i.e., DeerKill), whether the individual hunted on opening day (i.e., HuntOpen), whether the hunter hunted in this area in a previous season (i.e., PrevSeas), and whether total time budget (i.e., ToTimeBud) had significant effects on the number of hunting trips hunters take. Indeed, hunters who hunted on opening day, hunted in this area last year, harvested a deer, had a larger time budget, and took more hunting trips. Consistent with economic theory, hunters with longer round-trip travel miles (RTravMiles) and travel time (TravTime) tend to take fewer hunting trips.

Table 8--Estimated negative binomial count data demand equation for the Travel Cost Method.

Variable	Coefficient	Std. Error	Z-Stats	Probability
Constant	1.325	0.216	6.123	0.00
Age	0.001	0.004	0.369	0.71
DeerKill	0.367	0.155	2.370	0.02**
HuntOpen	0.524	0.115	4.564	0.00***
HuntOrg	0.068	0.106	0.639	0.52
PrevSeas	0.285	0.135	2.122	0.03**
PrivLand	0.038	0.132	0.289	0.77
RTravMiles	-0.002	0.0009	-2.490	0.01***
PcInc	-1.00E-06	2.78E-06	-0.360	0.72
ToTimeBud	0.010	0.005	2.099	0.04**
TravTime	-0.289	0.087	-3.334	0.00***

$R^2 = 0.21$, Adjusted $R^2 = 0.17$
Consumer surplus = $134.53/trip
90 Pct confidence interval: $81.13 - $393.59
Marginal consumer surplus per deer harvested = $257.17/deer
90 Pct confidence interval: $155-$752

**Significant at α = 0.05; ***Significant at α = 0.01

Consumer surplus is calculated by using the method of Sorg and others (1985) (equation 9).

Consumer Surplus = -1/β (i.e., coeff. of distance) (9)
*$0.30/mile (i.e., cost per mile).
= 1/0.002230 x $0.30 = 448.43 x $0.30
= $134.53/trip,

in which the $0.30 represents sample average cost per mile.

Finally, the 90 Percent confidence interval is obtained by equation 10:

90 Pct confidence interval on Consumer (10)
Surplus per Trip = 1/(β_{DIST}
$\pm$ 1.64 x 0.000895) x \$0.30/mile
= \$81.13 - \$393.59 per trip

To estimate the benefits of harvesting an additional deer, consider that the average number of trips per hunter is 5.56 trips, and 1 out of 10 deer hunters successfully harvests a deer. Therefore, *average* consumer surplus per deer harvested is 10 x 5.56 x \$134.53 = \$7,480 per deer harvested. To calculate the incremental or marginal value of an additional deer suitable to compare to marginal costs, 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 hunters 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 percent confidence interval (CI) (equation 11) for an additional deer harvested is obtained by applying the 90 percent CI on the value per trip times the additional number of trips taken by the hunter:

90 Pct confidence interval of the value (11)
of harvesting an additional deer =
(1.9116 x \$81.13) - (1.9116 x \$393.59)
= \$155 - \$752 per deer harvested.

7.3 Contingent Valuation Method

In the survey, people were asked their maximum WTP for their most recent trip under current conditions, and their maximum WTP per trip for a 100 percent guaranteed chance to harvest a deer over the season. The consumer surplus and people's maximum WTP per trip were computed (table 9). The CVM estimate of consumer surplus under current low success rate (9 percent) was \$17.59 per trip, while with 100 percent chance of harvesting a deer over the season the consumer surplus estimate rose to \$116.19 per trip. The per-trip figure requires multiplying the mean by the change in number of trips over the season to allow comparison with TCM, since TCM indicates a change of 1.9116 trips when deer harvest is certain over the season. In CVM, therefore, consumer surplus is equal to MaxWTPKill multiplied by 1.9116 trips, or \$222/deer.

Table 9--Results (dollars per trip) using the Contingent Valuation Method.

	MaxWTPKill[1]	MaxWTPCur[2]	MWTPDeer[3]
Mean	116.19	17.59	98.60
Median	50.00	0.00	50.00
Maximum	2300.00	500.00	2300.00
Minimum	0.00	0.00	0.00
Std. dev.	200.24	58.68	191.99

Marginal consumer surplus per deer harvested = \$222/deer,

90 Pct confidence interval: \$178 - \$265

N = 357

[1]Maximum willingness-to-pay for harvesting an additional deer with 100 percent certainty
[2]Maximum willingness-to-pay for harvesting a deer under current conditions
[3]Maximum willingness-to-pay per deer harvested

The 90 percent Confidence Interval on seasonal consumer surplus for harvesting an additional deer is:

= ΔTrips x Mean $\pm$ (t-value@90Pct) x ((St. Dev.) / $\sqrt{n}$)
= 1.9116 x [\$116.18 $\pm$1.64 x (200.2411/$\sqrt{210}$)]
= \$178 - \$265 per deer harvested

7.2 Comparing the Consumer Surplus from TCM and CVM

The marginal consumer surplus of harvesting an additional deer estimated by TCM is \$257 (table 8), and the marginal consumer surplus estimated by CVM is \$222 a deer (table 9). Comparing the 90 percent confidence intervals, TCM has a range from \$155 to \$752, and CVM ranges from \$178 to \$265 per deer harvested.

To estimate the CVM inverse demand curve, 246 observations were used after 103 observations were dropped because of one or more missing variables. The results (table 10) show consistency between the CVM inverse demand function and the TCM demand function for most independent variables except whether the hunter had hunted in this area in a previous season (i.e., PrevSeas), whether the hunter had hunted on private land (i.e., Privland), and round-trip travel miles from home to the hunt location (i.e., RTravMiles). Specifically, the remaining seven variables were either the same sign or insignificant in both TCM and CVM. The comparison results indicate that whether the hunter successfully harvested a deer (i.e., DeerKill) plays a vital role in influencing people's current WTP (i.e., MaxWTPCur) for deer hunting in the SJRD—similar to the TCM demand function. The coefficient on DeerKill) (table 10) offers a second CVM way to calculate the marginal value per deer harvest per hunter. By multiplying \$123/deer/trip with 1.911 trips, marginal value per deer harvest is \$235/deer. This value is still consistent with previous TCM and CVM analyses in tables 9 and 10.

Table 10--Inverse demand curve for the Contingent Valuation Method.

Variable	Coefficient	Std. Error	Z-Stats	Probability
Constant	-143.8908	66.9346	-2.1497	0.032**
Age	-0.0958	1.0850	-0.0883	0.930
DeerKill	123.0983	42.4801	2.8978	0.004***
HuntOpen	15.4554	32.3074	0.4784	0.632
HuntOrg	34.3721	29.8438	1.1517	0.249
PrevSeas	-44.9252	35.8284	-1.2539	0.210
Privland	-19.1205	39.4412	-0.4848	0.628
RTravMiles	0.3784	0.2262	1.6727	0.094*
PcInc	0.0004	0.0008	0.5516	0.581
ToTimeBud	0.7401	1.4302	0.5175	0.605
TravTime	-27.7475	24.8721	-1.1156	0.265

Marginal value per deer harvest = 1.9116 trips x 123.0983 = \$235/deer

*Significant at α = 0.10; **Significant at α = 0.05; ***Significant at α = 0.01

8. APPLICATIONS OF VALUES TO ESTIMATE BENEFITS OF PRESCRIBED BURNING

Both CVM and TCM were used to evaluate the change in deer hunting benefits due to an increase in deer harvest resulting from additional prescribed burning. In the TCM analysis, we found the change in consumer surplus is \$257 with additional trips the hunter took in response to increasing deer harvest. From CVM, we found that the change in consumer surplus is slightly less than the TCM result: \$222 per deer harvested. The mid-point marginal consumer surplus of TCM and CVM, therefore, is \$239.5 per deer harvested, or \$240 with rounding.

The annual deer hunting benefits of prescribed burning additional acres was computed (table 11). While the initial deer hunting benefit in response to prescribed burning of 1,100 acres ranges from \$3,840 to \$7,920 depending on the model, the incremental gains in deer hunting benefits when more acres are burned are quite similar across models. In other words, the annual economic hunting benefits of increasing prescribed burning from its current level of 1,100 acres to 4,810 acres is \$1,920, regardless of the model used. Likewise, when an additional 3,700 acres are burned (to 8,510 acres), the deer hunting benefits are between \$960 and \$1,200 each year, which are fairly similar despite the different modeling approaches.

Table 11--Annual deer hunting benefits from increased prescribed burning: results from macro time-series model and geographic information system (GIS) micro model.

Macro time-series model			GIS micro model		
Additional prescribed Acres burned	Marginal increase in deer harvest	Annual increase in deer hunting benefits	Additional prescribed acres burned	Marginal increase in deer harvest	Annual increase in deer hunting benefits
1,100	33	\$7,920	1,100	16	\$3,840
3,710	8	\$1,920	3,710	8	\$1,920
3,700	4	\$960	3,700	5	\$1,200

9. COMPARISON TO COSTS

The costs of prescribed burning on the San Bernardino National Forest range from $210 to $240 per acre (Walker 2001). This is a much lower total cost per acre than that reported by González-Cabán and McKetta (1986) but substantially higher than the direct costs per acre for southwestern National Forests reported by 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 3,710 acres burned costing $779,100. The deer hunting benefits represent at most about 3.4 percent of the total costs of 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 benefits to adjacent communities of reducing of hazardous fuel would need to make up the difference if the prescribed burning program is to pass a benefit-cost test. If prescribed burning of 1,100 acres prevented as few as two residential structures from burning, the prescribed burn program would likely pass a benefit-cost test. Such an assessment is beyond the scope of this study, however. Many of these multiple-use benefits from a prescribed fire are received for at least 5 years and as many as 10-12 years (Gibbs and others 1995). Thus, a simple annualization of the costs brings the 1,100-acre figure down to $23,100. Deer hunting benefits would cover between 16 and 34 percent of the annual costs of the first 1,100 acres. However, deer hunting benefits would only be minimal (less than 1 percent) compared to further increases in prescribed burning.

10. CONCLUSION

This study evaluated the response of deer harvest and deer hunting benefits to prescribed burning in the SJRD of California. To estimate hunter's benefits or WTP for harvesting an additional deer, the individual observation TCM and open-ended CVM were used. The mean WTP to harvest another deer is about $257 for TCM and $222 for CVM. One reason for such consistency may be that the respondents hunted in the SJRD in previous years. About 80 percent of the deer hunters in SJRD hunted there in the previous season. Also, the changes in number of trips taken for the increase in harvest estimated from TCM were used to scale up both TCM and CVM per-trip benefits to get a seasonal change. Hypothetical bias is a valid criticism of CVM studies. However, because TCM contains no hypothetical bias and the TCM result is consistent with the CVM estimate, it may be that the hypothetical bias in this study was minimal for CVM.

With regard to the response of deer harvest to prescribed fire and wildfire, we compared a macro level time-series model that treated the entire SJRD as one area and a micro GIS model that disaggregated the SJRD into the 37 hunting locations reported by hunters. Both models gave somewhat mixed results, in that some statistical specifications showed no statistically significant effect of prescribed burning or a negative effect of lagged wildfire, or both. However, the better-fitting (68 percent of variation explained) log-log model functional form of the macro time-series model did show a statistically significant effect of the combined prescribed fire and wildfire acres on deer harvest over the 20-year period of 1979-1998. Two of the three micro GIS model specifications indicate that the initial effect of prescribed burning had a statistically significant effect on deer harvest in the 37 hunting locations within the SJRD. Lagged effects of prescribed burning were consistently insignificant in our models, suggesting that most of the benefits occur in the year of the burn. The macro time-series model estimated a larger response to burning of the first 1,100 acres than the micro GIS model did, but for increases in fire beyond 1,100 acres, the two models provided nearly identical estimates.

Combining the average of the TCM and CVM estimated economic benefits with the deer harvest response to fire yields annual economic benefits ranging from $3,840 to $7,920 for the first 1,100 acres burned. For 3,700 additional acres burned, the gain is $1,920 annually, while for another additional 3,700 acres the increase ranges from $960 to $1,200 per year.

The costs of prescribed burning on the San Bernardino National Forest range from $210 to $240 per acre. Thus, the costs to burn an additional 1,100 acres are $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 represent about 3.4 percent of the total costs. Thus, the other multiple-use benefits of prescribed burning, such as providing opportunities for dispersed recreation, protecting watershed, and reducing hazardous fuels in surrounding communities would have to cover the rest. Investigating the extent of these benefits would be a logical next step in evaluating the economic efficiency of prescribed burning in the SJRD.

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

When the wildfire and prescribed fire variables were combined the macro time-series model demonstrated positive and significant effects from total fire. This appears to be in line with a previous study in which the density of deer increased during the growing season after the burn (Klinger and others 1989). A study of prescribed burning in northern California found prescribed burning to have only modest effects of increasing deer habitat use and mentioned that any increases in use are difficult to quantify (Kie 1984).

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 because different fire severities will have different effects on vegetation and soils (Ryan and Noste 1983). Further, including a vegetation and soils layer in the GIS model, rather than using elevation as a proxy, could improve the predictive ability of the GIS-based model as well.

Subject to these caveats, this paper has 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 two of the three GIS models and the positive impact of fire using a macro time-series model. The USDA Forest Service and CDFG can make use of these approaches for future cost-benefit analysis of prescribed burning.

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