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Economic Value of Big Game Habitat Production from Natural and Prescribed Fire

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Abstract

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A macro time-series model and a micro GIS model were used to estimate a production function relating deer harvest response to prescribed fire, holding constant other environmental variables. The macro time-series model showed a marginal increase in deer harvested of 33 for an increase of 1,100 acres of prescribed burn. The marginal deer increase for the micro GIS model was 16. An additional 3,710 acres of prescribed burn would produce an additional eight deer harvested regardless of the model. For an additional 3,700 acres more of prescribed burn the marginal increase in deer harvested is four and five deer respectively for the macro time-series and micro GIS models. Using the Travel Cost Method the change in consumer surplus or net willingness-to-pay was $257 per additional deer harvested due to the additional trips in response to increasing deer harvest. The consumer surplus estimate using the Contingent Valuation Method was $222. Depending on the production function model used the initial deer hunting benefit response to a prescribed burning of 1,100 acres ranges from $3,840 to $7,920. An additional increase of 3,710 acres of prescribed burning would produce benefits of $1,920 regardless of the model used. An extra 3,700 acres more would produce only between $960 and $1,200 depending on the model. When compared to the cost of conducting the prescribed burning, the benefits derived from an increase in deer harvest represent no more than 3.4 percent of the total costs of the first 1,100 acres.

Retrieval terms: contingent valuation, deer hunting benefits, fire economics, prescribed burning costs, travel cost method, willingness-to-pay

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In Brief

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Retrieval terms: contingent valuation, deer hunting benefits, fire economics, prescribed burning costs, travel cost method, willingness-to-pay

On the San Jacinto Ranger District (SJRD) of the San Bernardino National Forest in southern California prescribed burning is an important resource management program. Prescribed burning is used to provide many multiple use benefits including improved deer habitat, opportunities for dispersed recreation, and reduced hazardous fuels in the chaparral that surround several residential communities and associated watersheds.

The main objective of this research was to quantify the economic value of the improved deer hunting resulting from prescribed burning. Previous prescribed firework has shown that fire positively enhances deer habitat. Enhanced deer habitat increases deer population hence better hunting. Two approaches were used to estimate a production function relating deer harvest response to prescribed burning, holding constant other environmental variables. We compared a macro level, time-series model that treated the entire SJRD as one area, and a micro geographic information system (GIS) model that disaggregated the Ranger District into the 37 hunting locations reported by hunters. Both modeling approaches gave somewhat mixed results in that some statistical specifications showed no statistically significant effect of prescribed burning. 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.

All technical information on prescribed fire and fire effects was obtained from USDA Forest Service personnel in the SJRD and California Department of Fish and Game and was used in development of the hunter's survey questionnaire used in this work.

During the 1999 deer hunting season, a mail questionnaire was sent to a random sample of deer hunters with licenses for deer in Zone D19, which includes the SJRD. Of the 762 questionnaires mailed to deer hunters in California, a total of 356 deer hunters' responses were collected after two mailings for a response rate of approximately 47 percent.

Two of the three micro GIS model specifications showed that the initial effect of prescribed burning on deer harvest in the 37 hunting locations within the SJRD was statistically significant. Lagged effects of prescribed burning were consistently insignificant in our models, suggesting that most of the response occurs 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 of more than 1,100 acres, the two models provided nearly identical estimates.

The net economic value of the resulting additional deer hunting benefits was estimated by using the Travel Cost Method (TCM) and the Contingent Valuation Method (CVM). By using TCM analysis, we found the change in consumer surplus or net willingness-to-pay (WTP) is $257 per additional deer harvested due to the additional trips the hunter took in response to increasing deer harvest. From CVM, we found the change in consumer surplus of $222 per additional deer harvested. The mid-point marginal consumer surplus of TCM and CVM, therefore, is $240 per deer harvested.

The initial deer hunting benefit response to the current magnitude of prescribed burning of 1,100 acres ranges from $3,840 to $7,920, depending on the model. However, the incremental gains for additional prescribed burning are quite similar across models: the annual economic hunting benefits of increasing prescribed burning from its current magnitude of 1,100 acres to 4,810 acres is $1,920, regardless of the model used. Likewise, for a second increase of 3,700 acres of prescribed burning to 8,510 acres, the deer hunting benefits are calculated to be between $960 and $1,200 each year, which are fairly similar despite the different modeling approaches.

The costs of prescribed burning on the San Bernardino National Forest range from $210 to $240 per acre. Using the information in this research, 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 a prescribed burn of 1,100 acres should not exceed $8,000, as the incremental benefits are no larger than this. Second, the other multiple use benefits—such as watershed, recreation, and 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. For example, if prescribed burning 1,100 acres prevented as few as two residential structures from burning, the prescribed burning program would likely pass a benefit-cost test. However, such an assessment was beyond the scope of this study. Nonetheless, we can conclude that incremental deer-hunting benefits from prescribed fire appear to be relatively small, compared to the cost of prescribed burning in the SJRD.

Introduction

Estimating the impact of fire on resources and the economic consequences of it is very difficult. This difficulty arises because of the multiple outputs of the forest and the strong interdependence between the present output choice and the capital stock level of natural resources (González-Cabán 1993). The problem is further complicated because the effects of fire on the production stream of many goods and services from the forest, particularly nonmarket outputs, is largely unknown (SAF 1985).

This research makes a methodological contribution to the development of models for evaluating ecological effects of fire as well as providing results for the San Jacinto Ranger District (SJRD) in the San Bernardino National Forest located in southern California. In her recent review of the economics of prescribed burning, Hesseln (2000) posed the problem as "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). To make a first modest step in the direction suggested by Hesseln, this study estimates production relationships between prescribed burning and deer harvest by using time-series data and geographic information system (GIS) approaches. Previous work has shown an increase in deer population as a result of forage quality improvement from burning their habitat (Klinger and others 1989). The 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 SJRD is located in southern California's San Bernardino National Forest between Palm Springs and Idyllwild, California. As noted by the USDA Forest Service: "Some of the best deer hunting in Riverside County is found in this 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 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). Previous research on prescribed burning shows that fire positively enhances deer habitat and populations (CDFG 1998), but the economic benefits have not been quantified. 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) has hunter deer-harvest records for the SJRD 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 will use two nonmarket valuation methods to estimate the economic value of additional deer harvest.

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. Elevation in the SJRD ranges from 3,500 feet up to 10,800 feet. Below 5,000 feet elevation, the dominant vegetation within the SJRD is chaparral. Annual rainfall for 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.

Within the SJRD, primarily the USDA Forest Service manages the land, with small amounts of land administered by the Bureau of Land Management (BLM) as well as the State of California. Mount San Jacinto State Park lies on the northeastern boundary of the SJRD and is owned by the State of California. There are two state game refuges, one located in the Mount San Jacinto State Park and the other in the southern portion of the Ranger District around the Santa Rosa Mountains. Hunting is prohibited within the refuges.

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). These increased deer numbers have been thought to improve reproduction due to increased forage quality and an increase in fawn survival rates. The CDFG has 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 the 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.

Two Production Function Modeling Approaches

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 cover a longer time frame, and hence test long dynamic effects. Using a micro approach provides greater spatial detail to elements such as the influence of a meadow or ridge, but a less temporal time frame is covered because of data limitations. Thus, each approach to estimating the production function has its relative strengths and weaknesses.

Literature Review

Deer Habitat and Prescribed Burning

There have been just a few studies indicating the positive results of fire on deer habitat and populations. In one northern California study it was reported that the number of deer in stands of pure chaparral that were burned by fire quadrupled during the first growing season after the burn, then gradually decreased to pre-burn levels over the next 4 years (Klinger and others 1989). These increased deer numbers were attributed to the movement of deer into the burned stands where forage quality was improved and fawn survival rate was up. Using prescribed fire to benefit deer should occur during the season when the greatest likelihood of achieving the desired plant response will occur. According to the CDFG, dry season burns tend to result in better regeneration of shrub species from seed than wet season burns. Fire adapted shrub species, such as chaparral, respond best to prescribed burns during the time of year when fire occurs naturally, usually in late summer or early fall.

In arid regions such as southern California, vegetation change does not conform to traditional patterns. Vegetation is always in a state of flux due to harsh environmental factors and extreme events such as fire that cause a sudden shift in vegetation composition. Fire can cause the germination of seeds that would otherwise be dormant and create changes in relative abundance of vegetation such as chaparral. In the southern California area, there are different types of chaparral: seeding species and sprouting species. According to a past study (Zedler and others 1983) on the impacts of fire in chaparral, fires can produce a varying degree of results depending on the species of chaparral. This implies that fire regimes in chaparral produce a variety of responses in vegetation communities depending upon the type of species that exist (Zedler and others 1983). In terms of deer harvest, this difference in chaparral vegetation may suggest that certain areas will be more productive for hunting after a fire, depending on what type of vegetation was burned, e.g., the sprouting or seeding species. The biotic zonation in the San Jacinto Mountains where the SJRD is located includes coastal sage scrub up to 2,500 feet, hard (lower and upper) chaparral from 2,500 to 5,000 feet, yellow pine forest from 5,000 to 8,000 feet, lodgepole pine forest from 8,000 to 9,500 feet, and subalpine and alpine forest from 9,500 to 11,000 feet.

Prescribed burns have become a management tool for improving chaparral for deer habitat. As a result, the use of prescribed fire has become a technically viable solution for improving the carrying capacity of chaparral deer ranges such as those in southern California. Hence, it is important to document and quantify the magnitude of the benefits from prescribed burning compared to its costs.

Deer hunting is considered a necessary element of deer management (Paulek 1989). Hunting is a tool to restrict deer herds to the carrying capacity of their range. This type of herd restriction prevents "boom or bust" cycles among populations and helps maintain a balance of forage across a deer herd's range. Deer hunting also provides economic activity to local economies in California. A recent study using survey data compared the economic contribution of deer hunting in 1997 to a previous survey in 1987 in northeastern California. The results indicated that hunters' expenditures (not adjusted for inflation) in Lassen, Modoc, and Plumas counties have dropped significantly, from $5.4, $4.7, and $0.76 million, respectively, in 1987 to $0.83, $0.55, and $0.17 million, respectively, in 1997 (Loft, 1998). Nonetheless, even in 1997, deer hunters in these three counties still accounted for an estimated $1.5 million in local expenditures.

Geographic Information Systems

A geographic information system (GIS) is a system for working with spatial data. The Environmental Systems Research Institute (ESRI) (1995) describes GIS as an organized collection of computer hardware, software, geographic data, and personnel designed to efficiently capture, store, update, manipulate, analyze, and display all forms of geographically referenced information.

GIS can also be described by its ability to carry out spatial operations, known as queries, through linking different data sets together. These functions are what make a GIS a powerful tool for data analysis. Typically, a GIS links different data sets to reveal some new or unknown relationship (Chou 1997). For example, in the case of fires, it is possible through a GIS to discover how many acres were burned in a particular region by examining overlaying datasets in a spatial context.

In order to design a digital database, some key questions must be answered: What will be the study area or boundary? What types of data files or layers (e.g., vegetation cover, prescribed burned areas, roads, etc.) will be needed in order to solve the problem? What attributes are needed for each layer and how will these attributes be stored? After these questions are answered, then spatial data should be obtained for inputting into the database and making it usable. The last part of building a spatial database involves specifying what necessary attribute information will be needed by the various data layers and then adding it on. This is usually done by relating a common item or joining the attributes onto a particular data layer.

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 regression. This can be improved upon for modeling deer harvest, especially at the micro level where harvest in any small spatial unit is a non-integer variable, by using a count data model. Count data models are based on probability distributions that have mass only at non-negative integers, and it is impossible for the distribution to have a fractional outcome or a negative outcome (Hellerstein 1992). This is certainly the case of deer harvest, as hunters cannot harvest a fraction of a deer. The classic example of a count distribution is the Poisson process. The counts described consist of numerical quantities, *Lambda*, which is the mean number of events per unit of progression (specified as an exponential link function that ensures nonnegativity) and is equal to the variance. As *Lambda* increases, the Poisson distribution approaches the normal distribution, with a decreasing probability mass at zero (Forsythe 1999).

Given the stringency of the mean variance equality restriction imposed by the Poisson distribution, a more generalized count model, such as the negative binomial distribution, is often more consistent with the data. The negative binomial version allows the variance to move freely. Both the Poisson and the negative binomial distributions yield the equivalent of a semi-log form where the log of the dependent variable is regressed against the explanatory variables.

Using ordinary least squares (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 non-linear least squares that avoids 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. The number of harvested deer recorded in specific hunting areas tends to be small, such as 0, 1, and 2 or 3, rather than larger numbers like 10, 20, or 50. Therefore, the count data is more efficient with the distribution mass at small integers than OLS (Hellerstein 1992).

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

Economic Evaluation

Wildlife such as deer are commonly considered nonmarket goods in much of the western United States. Although natural resources have both 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 difficulty in identifying deer viewers, this study focuses on deer hunters.

Kahn (1995) categorizes two major techniques for estimating nonmarket goods: indirect and direct techniques. Indirect techniques (revealed preference approaches) can be used to analyze decisions or actions in response to changes in an environmental amenity to reveal the value of the amenity. Indirect techniques such as hedonic pricing and travel cost models are mostly useful for estimating the use value of nonmarket goods. Direct valuation techniques elicit values (stated preference approaches) from individuals through survey methods, which can be used to measure both use and nonuse values. In this study, we will apply both the Contingent Valuation Method (CVM) and the Travel Cost Method (TCM) to estimate the use-value in deer hunting. Although there is a substantial amount of literature comparing TCM and CVM estimates of the value of a recreation day (Carson and others 1996), there are fewer comparisons for a change in recreation quality.

Production Function Modeling Approaches

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 GIS-based approach can be considered a micro, spatial scale examination, while the macro time- series approach looks at the entire SJRD at a more aggregate level, using the entire ranger district as one unit of observation in each year. This more aggregate or macro method tests a time-series relationship between deer harvest and fire in SJRD. The GIS-based method disaggregates fewer years of fire data and deer harvest into a much finer level of spatial detail, breaking the SJRD into the 37 hunting locations reported by hunters (see *appendix II* for a general map of SJRD).

Time-Series, Macro Scale Production Function

The first statistical approach 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 dataset for SJRD, provided by the CDFG and the USDA Forest Service. The fire records provided data from 1975 for natural wildfire but only from 1979 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 were 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 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 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:

$$[1] \quad \textit{SJRD deer harvest in year}_t = \textit{func}\ (\textit{RxFire}_t, \textit{WildFire}_t, \textit{TotPrecip}_t, \textit{OctTemp}_t, \textit{Year}_t)$$

$RxFire_t$ is the acres of prescribed fire in year t, $WildFire_t$ is the acres of wildfire in year t, $TotPrecip_t$ is the sum of precipitation for year t, $OctTemp_t$ is the temperature in October during the hunting season, and $Year_t$ is a trend variable, with 1975 = 1, 1976 = 2, etc.

The SJRD time-series production function lagged model is:

$$[2] \quad \textit{SJRD deer harvest in year}_t = \textit{func}\ (\textit{RxFire}_{t-1}, \textit{WildFire}_{t-1}, \textit{TotPrecip}_t, \textit{OctTemp}_t, \textit{Year}_t)$$

Using the log-log form represents the non-linear forms of equations 1 and 2. This format allows for a non-linear 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.

Micro GIS Approach to Estimating the Production Function

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 (*see appendix I*). Thus, the primary distinction to the macro time-series model is that with the GIS-based micro model, deer harvest was modeled for 37 smaller hunting locations instead of by using just one large hunting zone that encompassed the SJRD. This 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 prescribed fire, wildfire, elevation, roads, and trails information. 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.

The function of the GIS portion of this project was to provide the detailed data at a micro level, which could be used to regress the relationship between deer harvest and prescribed fire or wildfire. Using a spatial database to identify

Table 1—*Data for macro time-series production function model.*

Year	SJRD-Harvest	Acres Burned: Prescribed Fire	Acres Burned: Wildfires	Oct-Temp	Annual Precipitation
	No. Deer			°F	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

and describe a spatial pattern and distribution between deer harvest and fires is very useful. The focus of building a GIS was to provide data on variables to estimate the deer production function.

The first step was to identify the necessary layers needed to run a regression between deer harvest and fires. A hunting layer was constructed for the regression model, which contains deer harvest by hunting locations. Then layers were added for the independent variables, including prescribed burn, wildfire, average elevation, temperature, distance to trails, dirt roads and roads from each hunting location, and distance to wildfires from each hunting location. Vegetation type would have been desirable, but this information was incomplete and will not be completed for the entire area until the distant future.

The next step in constructing a spatial model is deciding on how to determine the delineation of geographic units (Chou 1997). Decisions on size of geographic units must balance consistent data availability as well as meaningful units. Although a 640-acre section grid had some attractive features, deer harvest data at that level of resolution was only available for 4 years. Further, deer herd movement may often be larger than a 640-acre section. Therefore, we relied upon deer harvest locations reported by hunters within the SJRD. These hunt locations are defined by topographic features, such as streams, steep ridgelines, or sometimes features created by people, including towns or major roads. These locations were often much larger than a single section and encompassed areas where deer herds and hunters might move within but not between areas. In addition, CDFG had a much longer time-series of deer harvest at the harvest location level as compared to the section level. Because of the different size of each harvest location, some basic assumptions had to be made when calculating distances to roads, trails, or recently burned areas. These assumptions included finding a central point within each harvest location to serve as a point to calculate distances. Therefore, all distance calculations are based on averages from a central point. In addition, regressions accounted for the size of the hunting location as one of the explanatory variables.

All relevant GIS data had to be exported into 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 burned from 1975 to 1998.

The models developed for the harvest areas had to account for the nonuniform 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 includes just the size and total 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 percent burned, including lags, is:

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

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

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

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

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

Description of GIS-Based Micro Regression Variables

Elevations (AvgElev) (meters) are based on USGS digital elevation models (DEMs) and act as a proxy for vegetation types that were not available. However, we do not have an expected sign on elevation, but simply wish to control for elevation differences between the 37 individual hunting areas within the SJRD. Both fire variables, wildfire (WildFire) and prescribed fire (RxBurn) (total acres/year), are expected to have a positive sign (Kie 1984, Zedler and others 1983).

The distance (meters) to road (LDirtDist) and trail (LTrailDist) variables are based on the distances from a central point in each hunting location. Two arguments can be made about the sign's direction. One argument is based on accessibility for hunters, in which having a close proximity to either a trail or road would make hunting easier, more desirable, and would positively affect deer harvest. The second argument is based on the intrusion of deer habitat by a road or trail. This perspective would lead to a decline in deer harvest because roads cause a break in habitat and pose a threat. Therefore, the expectation is ambiguous.

The distance (meters) to fire variable (LDistFire) is a measure of how close fire comes to burning into the interior of the hunting area's vegetation. A value of zero would indicate a fire in that year burned into the center of the hunt area. This variable sign may be either positive or negative.

Harvest area (LHvstArea) (acres) accounts for the size of each hunting location and is expected to have a positive sign. The rationale is that as hunting areas become larger, then the amount of deer habitat increases, which attracts more deer; therefore, the probability of hunter success increases. October temperature (OctTemp) (degrees Fahrenheit) and year (Year) are the other variables used in the GIS models. October is when hunting season is open, and based on hunters' surveys, when temperatures are high 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 does not carry any expected sign.

Estimated Production Functions

Macro Time-Series 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) have also been included in

Table 2—*Non-lagged macro time-series ranger district linear model.*

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	4,694.2070	1,535.6420	3.057	0.0092
RxBurn[1]	0.0010	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

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 this variable has minimal effect on deer harvest and is insignificant. Wildfire 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 is negative 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 2.17. 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 0.58, and adjusted R-squared is 0.42. 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 harvest and fire variables, there is no indication that the fire variables are related to variation in deer harvest.

A 1-year lag-on-acres-burned model 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 the first growing season after the 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. October temperature and year are almost the same as 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.

San Jacinto Ranger District Log-Log Model

Taking the log of the dependent variable and the log of the combined wildfire and prescribed burn variable (LTotFire) 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

Table 3—*Macro time-series ranger district log-log model.*

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	41.8087	11.0701	3.7767	0.002
LTotFire	**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

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 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-square value of 0.67. The Durbin-Watson statistic of 2.06 indicates that autocorrelation is not a problem.

The same model (*table 2*) 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 the lag is insignificant. The R-squared value did not change from the previous model.

Summary of Micro Regressions Based on GIS Analysis

Three regression models were estimated by using GIS-derived data (*tables 4, 5, 6*). Two of these regression models—count data and OLS—show 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.

Percent of Hunting Location Area Burned, Micro Model

This model describes the relationship between deer harvest (dependent variable) in each of the 37 hunting locations as a function of average elevation (AvgElev), the distance to dirt roads (LDirtDist) and trails (LTrailDist), the percentage of hunting area experiencing a prescribed fire (PctRxBurn) and wildfire (PctWildfire) in the time period considered and the size of each hunting location (LHuntArea), the temperature in October (OctTemp) of that year, and year (Year) (*table 4*). The significant variables with t-statistics over 2.0 are distance to trails and dirt roads, the size of the harvest area, and temperature in October. Wildfires for year one—the year during which the fire occurred—have a t-statistic of 1.8, which is considered statistically significant at the 10 percent level. However, the coefficient on the wildfire is negative (-1.6), which would indicate that fires decrease the probability of harvesting a deer in that year. The rest of the wildfire and all of the prescribed fire variables for each hunting area are not considered significant for any of the years using this percent-burned method. According to these fire variables across time, their insignificance demonstrates that differences in deer harvest cannot be attributed to fire. In this model, the distance to dirt roads, distance to the nearest trail, the size of a hunting area and the temperature statistically influence deer harvest in October. The R-squared value of 0.18 and the adjusted R-squared value of 0.17 indicate this model has relatively low explanatory power of deer harvest (*table 4*).

Micro GIS-Based Equation Using Total Acres Burned

The second count data model (*table 5*) presents a different specification by using 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 hunting area (acres) size variable. Total acres of prescribed fire (LTotRxFires) are significant during the year of the prescribed fire, and its 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 logs the fire acreage variables, it is equivalent to a log-log model. As such, the 0.044 is the elasticity. Total acres of wildfire (LTotWFires) were not significant for any of the years in this equation.

Table 4—*Count data model based on GIS with percent burned with lags.*

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	2.7350	13.2598	0.2063	0.837
LAvgElev	-0.1989	0.1337	-1.4872	0.137
PctRxBurn	1.6726	1.5733	1.0631	0.288
PctRxBurn (-1)	1.5721	1.5961	0.9850	0.325
PctRxBurn (-2)	2.1253	1.4669	1.4488	0.147
PctRxBurn (-3)	-0.3572	1.7741	-0.2013	0.840
PctWildfire	-1.6569	0.8893	-1.8631	0.063
PctWildfire (-1)	-1.1365	0.8064	-1.4094	0.159
PctWildfire (-2)	-0.4622	0.7290	-0.6340	0.526
PctWildfire (-3)	-1.5480	0.8390	-1.8451	0.065
LDirtDistance	**-0.2429**	**0.0386**	**-6.2893**	**0.000**
LTrailDistance	**0.4096**	**0.0426**	**9.6125**	**0.000**
LFireDist	0.0426	0.0467	0.9118	0.362
LHuntArea	**0.9377**	**0.0882**	**10.6355**	**0.000**
OctTemp	**-0.0343**	**0.0147**	**-2.3412**	**0.019**
Year	-0.0035	0.0065	-0.5416	0.588
	Overdispersion parameter			
Alpha:C(17)	-0.1999	0.103823	-1.925655	0.054
R-squared	0.186	Mean dependent variable		1.759
Adj. R-squared	0.170	S.D. dependent variable		2.611
S.E. of regression	2.379	Avg. log likelihood		-1.629
Restr. log likelihood	-1922.63	LR index (Pseudo-R^2)		0.300

This model has more explanatory power of the effect of fire on deer harvest than the previous model based on a percent burn of each harvest area. This total area count data model R-squared value of 0.25 and the adjusted R-square 0.24 is almost 40 percent greater than the percent burn count data model.

Micro GIS-Based Equation Using OLS Log-Log Form of Harvest Per Acre

This equation was used as an alternative method to account for the different sizes of hunting location. Using OLS regression 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 the dependent variable acted as a control measure for the size of each hunting location by dividing harvest in each hunting location by the number of acres in each location. The results of this model (*table 6*) show that prescribed burns (LTotRxFires) have a statistically significant effect on deer harvest in the first year with a t-statistic of 2.25. During the years after the fire, prescribed burn areas become less significant, which corresponds to the previous count data model. The only time wildfire has a significant impact is during the second year (LTotWFires(-2)) after 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 (LDirtDist) is also significant, a t-statistic of 5.17 and a negative coefficient -0.013. This may mean that hunting locations further away from dirt roads have a lower probability of the occurrence of hunters harvesting a deer or possibly that many hunters

Table 5—*Count data model based on GIS 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
LTotRxFires	**0.0441**	**0.0179**	**2.4609**	**0.014**
LTotRxFires (-1)	0.0275	0.0270	1.0193	0.308
LTotRxFires (-2)	0.0115	0.0222	0.5169	0.605
LTotRxFires (-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-R^2)		0.305

Table 6—*Least squares deer harvest per acre using GIS data model with lags.*

Variable	Coefficient	Std. error	t-Statistic	Probability
Constant	1.3418	1.5883	0.8448	0.398
LAvgElev	-0.0097	0.0093	-1.0461	0.296
LTotWFires	0.0012	0.0012	0.9632	0.336
LTotWFires (-1)	0.0005	0.0012	0.4293	0.668
LTotWFires (-2)	-0.0022	0.0011	-2.0862	0.037
LTotWFires (-3)	-0.0018	0.0011	-1.6276	0.104
LTotRxFires	0.0026	0.0012	2.2548	0.024
LTotRxFires (-1)	0.0021	0.0019	1.1349	0.257
LTotRxFires (-2)	0.0013	0.0015	0.8620	0.389
LTotRxFires (-3)	0.0012	0.0013	0.9262	0.355
LDirtDist	**-0.0130**	**0.0025**	**-5.1748**	**0.000**
LTrailDist	**0.0183**	**0.0022**	**8.2132**	**0.000**
LFireDist	0.0051	0.0032	1.6072	0.108
LHuntArea	-0.0087	0.0062	-1.4098	0.159
LOctTemp	-0.0504	0.0860	-0.5859	0.558
Year	**-0.0028**	**0.0008**	**-3.4364**	**0.001**
R-squared	0.139	Mean dependent variable		-4.533
Adjusted R-squared	0.123	S.D. dependent variable		0.093
S.E. of regression	0.087	F-statistic		8.684

do not venture very far from roads. This lower probability may be due to poaching along roads and/or to lower deer populations as a result of roads fragmenting habitat. The positive coefficient on the distance to trails variable (LTrailDist) implies that having a distant proximity to trails increases the probability of a deer harvest. 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-squared value by using OLS is 0.13 and the adjusted R-squared value is 0.12 compared to twice this level of explanatory power in the total area count data model (*table 5*).

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 2*) and the micro GIS-based double-log count data models (*table 5*), as these two models have the highest explanatory power. The resulting predicted change in deer harvest will be valued in dollar terms.

Applying Results of Macro Time-Series Production Function Model

The double log Macro Time Series Production Function Model (*table 3*) is used to estimate the change in deer harvest. This model has a high explanatory power given that it explains almost 68 percent of the variation in deer harvest. As will be recalled in this model, the lag effect proved insignificant. Therefore, the prescribed burning component of the total fire variable in this model is increased to three different levels (1100, 4810, and 8510 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 7*).

Applying Results of Micro GIS Production Function Model

The results of both the count data model (*table 5*) and the least squares model (*table 6*) provide positive evidence on the desirable effects of prescribed burning programs on deer harvest. Because the count data model has nearly double the R-squared value of the least squares model, the economic implications from prescribed burn programs will be evaluated by using the prescribed burn coefficients (*table 5*), the GIS count data model. By using this model it is possible to calculate the additional harvest from additional prescribed burn acres on deer harvest. In *table 7*, 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 5*), 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 acres of prescribed burning over the last 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 hunt area (*table 7*).

Table 7—*Comparison of deer harvest response to prescribed burning using the macro time- series model and 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	83	NA	1	42	NA
1,100	1,100	116	33±3.99 [2]	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] 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).

The results suggest there is a substantial gain in deer harvest with the first 1,100 acres burned (*table 7*), 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.

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 has offered opportunities for recreational enjoyment as well as produced 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 bio-economic 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.

Valuation Methodologies

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 a 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 formats tend 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 goods (deer) they are asked to value. Therefore, we felt 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):

$$[6] \quad MWTPDeer = MaxWTPKill - MaxWTPCur$$

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

Travel Cost Method

The TCM has been a primary indirect approach for valuing environmental resources associated with recreation activity over the last 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.

Definitions of TCM Price Variable

Besides variable travel cost 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 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 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.

This study chooses its variables according to the consumer demand theory and past literature (*table 8*). For instance, private hunting land serves as a substitute (or complement) for public hunting land in SJRD. Hunters were not asked the distance to substitute sites nor to identify if there was 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 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 dataset work a fixed workweek, we assume the deer hunters maximize 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 a person who took a paid vacation to hunt, his/her total time budget (days) is obtained by 8 weekend days during the month of the hunting season plus 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, which is the length of the hunting season. For a person who took unpaid vacation time or reduced work hours to hunt, his/her 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, for those unemployed and retirees, their total time budget 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 8—*Variables included in Regression Models and their Definitions.*

Variable	Definition
Dependent:	
NUMTRIPS	Number of primary purpose of deer hunting trips taken to the SJRD during 1999 deer hunting season.
Independent:	
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 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
ToTimeBud	Total time budget.
TravTime	Number of hours one-way travel time

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 integer nature of the dependent variable (Creel and Loomis 1990). In this study, the negative binomial count model was used to estimate the demand function. 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 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:

$$
[7] \quad NUMTRIPS = EXP\,(C(1) + C(2) \text{ x } Age + C(3) \text{ x } DeerKill + C(4) \text{ x } HuntOpen + C(5) \text{ x } HuntOrg + C(6) \text{ x } PrevSeas + C(7) \text{ x } PrivLand - C(8) \text{ x } RTravMiles + C(9) \text{ x } PcInc + C(10) \text{ x } ToTimeBud - C(11) \text{ x } TravTime)
$$

In equation 7, we expected the coefficient for DeerKill [C(3)] to have a positive sign, since hunters would likely take more hunting trips if the hunting quality had been good. Also, if hunters hunted on the opening day [C(4)], private land [C(7)], and/or previous seasons [C(6)] and belong 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 the deer hunting activity. For those hunters with a higher income level [C(9)] and/or higher total time budget [C(10)], 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 of these two variables increase 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 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 x $0.30/mile (see equation 9) (Sorg and others 1985).

CVM and TCM Comparisons

Literatures in CVM and TCM comparisons have 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 nonmarket good valuation methods, 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 only has 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:

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

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.

Data for TCM and CVM Models

For cost effectiveness in data collection, a mail questionnaire was used. There were six sections along with one demographic section. The first section gave a brief introduction of the questionnaire and then asked about the number of hunting trips taken this season to the SJRD and prior hunting experiences in the SJRD. The second section gathered information on the land ownership of the area hunted, weapon type used, and information on deer harvest characteristics if the hunter had been successful. The third section asked about the hunter's involvement in opening day of the hunting season. Section four inquired about the travel distance and travel time to the hunting area. The fifth section asked questions about the hunter's expenses as well as the hunter's WTP higher trip costs for the hunting experience on the most recent trip. Specifically, hunters were asked an open-ended question pertaining to the maximum increase in deer hunting expenses before they would not have taken 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. The sixth section asked about the characteristics of the hunter's preferred hunting area. The final section of the survey detailed demographic information such as age, income, family size, educational level, and other socioeconomic variables from the respondents.

Survey Mailing and Response Rate

During the 1999 deer hunting season, a mail questionnaire (*appendix I*) was sent 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.

Descriptive Statistics

More than 72 percent of respondents did hunt on opening day. The average deer hunter is around 43 years old, with a mean income slightly more than $33,000 dollars (*table 9*).

Table 9—*Statistical information of TCM variables.*

Variable[1]	Mean	Median	Maximum	Minimum	Std. Deviation
NUMTRIPS	5.56	4.0	62.0	1.0	6.26
Age	43.0	42.0	80.0	13.0	13.40
PctDeerKill	9.7	0.0	NA	NA	0.29
HuntOpen (Pct)	72.3	NA	NA	NA	0.45
HuntOrg (Pct)	35.0	NA	NA	NA	0.48
PrevSeas (Pct)	81.3	NA	NA	NA	0.39
PrivLand (Pct)	15.0	NA	NA	NA	0.36
RTravMiles	103.80	80.0	800.0	0.5	95.11
PcInc	$33,148.00	$32,500.00	$100,000.00	$833.00	$18,287.00
ToTimeBudget	19.78	23.0	31.0	0.0	10.27
TravTime	1.43	1.2	9.0	0.10	0.98

[1] See *table 8* for definition of variables

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 indicate 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 70 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.

Statistical Results of TCM and CVM Valuation Models

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 10*). There is a negative effect of travel miles (RTravMiles), 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

Table 10—*Estimated negative binomial count data TCM demand equation.*

Variable[1]	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 - 393.60
Marginal consumer surplus per deer harvested = $257.17/deer
90 Pct confidence interval: $155 - $752

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 took. Indeed, hunters who hunted the 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) tended to take fewer hunting trips.

The consumer surplus is calculated by using Sorg and others' (1985) method (equation 9) in which the $0.30 is the 30 cents per mile sample average cost per mile.

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

Finally, the 90 percent confidence interval (*table 10*) is obtained by equation 10:

[10] *90 percent confidence interval on Consumer Surplus per Trip = 1/(βDIST ± 1.64 x 0.000895) x $0.30/mile = $81.13 - $393.59 per trip*

Estimating the Benefits of Harvesting an Additional Deer

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 each hunter would take 1.9116 more trips each season if hunters knew they would harvest a deer. Therefore, the marginal value of another deer harvested (i.e., marginal consumer surplus) is equal to \$134.53 x 1.9116 = \$257.17 per deer harvested. Finally, the 90 percent confidence interval (CI) in *table 10* 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:

[11] *90 percent confidence interval of the value of harvesting an additional deer = 1.9116 x \$81.13 - 1.9116 x 393.59 = \$155 - \$752 per deer harvested.*

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 11*). The CVM estimate of consumer surplus under current low success rate (9 percent) conditions 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 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 (at the mean) multiplied by 1.9116 trips, or \$222/deer.

Table 11—*CVM results (dollars per trip).* [1]

	MaxWTPKill	MaxWTPCur	MWTPDeer
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

[1] See *table 8* for definition of variables

The 90 percent Confidence Interval (C.I.) on seasonal consumer surplus for harvesting an additional deer is:

$$[12]\quad \textit{90 pct C.I.} = \Delta Trips \times Mean \pm (t\text{-}value@90Pct) \times ((St.\ Dev.)/\sqrt{n})$$
$$= 1.9116 \times [\$116.19 \pm 1.64 \times (200.2411/\sqrt{210})]$$
$$= \$178 - \$265 \text{ per deer harvested,}$$

in which Δ is the change in number of trips when deer harvest is certain.

Comparing the Consumer Surplus from TCM and CVM

The marginal consumer surplus of harvesting an additional deer estimated by TCM is \$257 (*table 10*), and the marginal consumer surplus estimated by CVM is \$222 a deer (*table 11*). Comparing the 90 percent confidence intervals, TCM has a range from \$154 to \$752, and CVM ranges from \$178 to \$265 per deer harvested.

Table 12—*CVM inverse demand curve.*

Variable[1]	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

[1] See *table 8* for definition of variables

To estimate the CVM inverse demand curve, 246 observations were used after 103 observations were dropped due to one or more missing variables. The results (*table 12*) 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 the variable "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 whether the hunter harvested a deer (i.e., DeerKill) (*table 12*) 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 analysis in *tables 10 and 11*.

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 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 benefit of additional acres of prescribed burning was computed (*table 13*). While the initial deer hunting benefit response to prescribed burning of 1,100 acres ranges from $3,840 to $7,920 depending on the model, the incremental gain for more than the current acreage of prescribed burning is quite similar across models. In other words, the annual economic hunting benefit 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 for an additional 3,700 acres of prescribed burning, to 8,510 acres, the deer hunting benefit is between $960 and $1,200 each year, which is fairly similar despite the different modeling approaches.

Table 13 *Annual deer hunting benefits from increased prescribed burning: macro time-series model and GIS micro model results.*

Macro time-series model			GIS micro model		
Additional 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
NA	NA	NA	NA	NA	NA
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

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 reported by González-Cabán and McKetta (1986) but substantially higher than the direct costs per acre for southwestern National Forests reported 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 3,710 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 hazardous 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. 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.

Conclusion

This study evaluated the response of deer harvest and deer hunting benefits to prescribed burning in the SJRD of California. To estimate hunters' 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 due to the respondents' hunting 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 trips 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. 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 and/or a negative effect of lagged wildfire. 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 3,710 additional acres burned, the gain is $1,920 annually, while for an 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 fuel 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 that affect deer habitat exist. 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.

The macro time-series model demonstrated positive and significant effects from total fire when both wildfire and prescribed fire variables were combined. This appears to be in line with a previous study where the density of deer increased the growing season after the burn (Klinger and others 1989). A study of prescribed burning in northern California found prescribed burning to only have 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 others 1983). Furthermore, 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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Appendix 1. Survey instrument used in the study

HOW WAS YOUR DEER HUNTING SEASON?

SECTION I: YOUR DEER HUNTING TRIPS THIS SEASON

INSTRUCTIONS:

1. If you hunted for deer in the San Jacinto Mountains region shown on the enclosed map please complete all the relevant questions in the booklet.

   If you did not hunt there, please answer the questions on the inside back cover and then put the booklet in the postage paid envelope to mail back to us.

2. If you hunted in the San Jacinto Mountains please locate on the map, where you went deer hunting on the most recent trip this season. Please write the general area NAME in the spaces below.

By "area" we mean the place where you parked your vehicle and started hunting. The purpose is NOT to find out your special hunting spot, but rather to determine the hunt area characteristics you prefer so public agencies and landowners can manage for those desired characteristics.

Area name/landmark: ______________________________

Nearest road: ____________________________________

Please draw a small circle on the map of the general area where you spent most of your time hunting on your most recent trip. This is important for us to determine if there is any relationship of your hunting to our management practices.

When answering the remaining questions please think only about your hunting trips to this area.

1. How many trips from home for the primary purpose of deer hunting did you make to this area during this deer hunting season?
   (For the purposes of this survey, a trip is defined as journey from home to your hunting area or hunting camp and then back home again).

   _____ # of Trips

2. How many days did you actually hunt deer on a typical hunting trip this season to this area?

   _____ # Days per trip

3. Have you hunted in this area in a previous season?
   (Please circle your answer) YES NO

   If YES, how many years have you hunted in this area?

   _____ Years

4. How satisfied were you with hunting in this area? On a 1-10 scale, where 1 is not at all satisfied, 5 is somewhat satisfied and 10 is completely satisfied, please rate this area.

   _____ Rating

SECTION II: LAND OWNERSHIP IN THE HUNTING AREA

1. DID YOU HUNT ON PRIVATE LAND? YES NO
(Please circle your answer)

If you answered YES please answer 2a below, otherwise go to 2b.

2a. If private land, how was access obtained?

Private but open to public access	YES	NO
Requested and obtained free access	YES	NO
Paid for access	YES	NO

If you paid for access, how much did you pay? $ __________

Was this fee?

Seasonal Daily
(Please circle one)

2b. DID YOU HUNT ON PUBLIC LAND? YES NO (Go to Q#4)
(Please circle your answer)

If you hunted on Public Land, what kinds? (Please check)

____San Bernadino National Forest (U.S.F.S.)

____ U.S. Bureau of Land Management

____Department of Fish & Game Lands

____ Other Public Land or Not Sure

____ Native American Lands

3. Did you hunt in a designated Wilderness Area?

YES NO
(Please circle your answer)

4. About how far from a road did you spend most of your time hunting?

____ Miles

5. What type of weapon did you hunt with?
(Please check all that apply)

____ Rifle

____ Bow

____ Muzzle Loader

____ Shotgun

____ Pistol

6. During this hunting season, did you kill a deer in this area? (Please circle) YES NO

6a. If YES, what kind did you harvest? (Please check)

two point buck _____

three point buck _____

four point or larger buck _____

SECTION III: WHAT ABOUT OPENING DAY?

1. Did you hunt on opening day of the D-19 season? (IF NO, Go to Section IV below) YES NO

1a. If YES, How many deer did you personally see on opening day? ____# deer

1b. How many of these deer were bucks (including spikes)? ____# bucks

1c. How many hours did you hunt on opening day? ____ # hours

SECTION IV: TRAVEL TO YOUR HUNTING AREA

1. About how long did it take you to travel (one-way) from home to your hunting area? (If less than an hour, please use a fraction.) ____ # Hours one-way travel time

2. About how many miles was this hunting area from your home? (Please write down one-way mileage.) ____ One-way Miles

3. Including yourself, how many licensed hunters were in the vehicle that you traveled in to the hunting area? ____ # of Hunters in vehicle

SECTION V: EXPENSES FOR THE MOST RECENT HUNTING TRIP

These next few questions ask about your current expenses for deer hunting in D-19. This information is used by resource management agencies in land management planning decisions affecting deer populations and habitat. Please answer these questions for your most recent deer hunting trip.

Area name of most recent trip ______________________________
(Please write area name)

1. How much did you personally spend on transportation? $ __________

2. How much did you spend on food and beverages? $ __________

3. How much did you spend on lodging or camp fees? $ __________

4. How much did you personally spend on supplies such as ammo, safety vests, maps, stove fuel, etc., specifically for this trip? $ __________

5. How much did you spend on other expenses? (Do not include hunting license, deer tags, access fees) $ __________

TOTAL DEER HUNTING EXPENSES FOR THIS TRIP TO THIS AREA

$ __________
(Please add amounts above)

6. Was this trip worth more than you actually spent? YES NO

6a. IF YES, What is the maximum increase in your trip costs you would have paid for each trip to hunt this specific area?

$__________ per trip

If your answer to 6a was zero, please tell us why.

_____ The trip was not worth more than I spent.

_____ I cannot afford the higher trip cost.

_____ It is unfair to expect me to pay more.

_____ Other (Please explain)

7. Prior to the start of the season, what did you think your chances of harvesting a deer was in this zone? For example, did you think there was a one in four chance or 25% chance?

_______chances in 100 or _______% chance of harvesting a deer.

7a. Now suppose everything about the most recent hunting trip to this zone was the same except that your chances of harvesting a deer were twice as high as you wrote down in Q#7.

What is the maximum increase you would pay per trip to hunt this specific area under these improved conditions?

$__________ per trip

7b. What if hunting success in this area could be increased to the point where you would be almost certain to harvest a deer in this hunt zone each season?

What is the maximum increase you would pay per trip to hunt this specific area if you knew you would be virtually certain to harvest a deer during the season?

$__________ per trip

SECTION VI: CHARACTERISTICS OF THE AREAS IN WHICH YOU HUNTED

To assist public land management agencies in providing the type of hunting experience you desire, it is important for us to know what features of a hunting area are important to you.

	(Circle One)	
1. Do you prefer to hunt in areas that have mature forests overhead but open understory?	YES	NO
2. Do you prefer to hunt in areas that have been recently burned? (e.g., had burned this calendar year).	YES	NO
3. Do you prefer to hunt in areas that had been previously burned? (e.g., burned 2 or more years ago).	YES	NO
4. Do you prefer to hunt in areas with dense vegetation?	YES	NO

DEMOGRAPHICS

These last few questions will help us understand how representative our sample is. Your answers are strictly confidential and will be used only for statistical purposes. You will not be identified in any way!

1. Are you: _____ Male _____ Female

2. What is your age? _____ Years

3. Are you a member of any hunting or sportsman organization? _____ Yes _____ No

4. What is your Zip Code? __________ Zip Code

5. How many weeks of paid vacation do you receive each year? _____ Weeks

6. How many hours do you normally work for pay each week? _____ Hours

7. During this Fall deer hunting season:
   (check all that apply)
   ____ Did you take a paid vacation to hunt?
   ____ Did you take unpaid vacation time or reduced work hours to hunt?
   ____ Did you work your usual amount and hunt when you could?
   ____ Were you unemployed?
   ____ Were you retired?

8. Please circle the highest number of years of education you have completed.
   (Circle one number)

1 2 3 4 5 6	7 8 9	10 11 12	13 14 15 16	17 18 19 20
Elementary	Jr. High	High School	College or Vocational	Graduate or Professional

9. To the best of your knowledge what was your household income before taxes last year?

_____ under $4,999	_____ $25,000-29,999	_____ $50,000-59,999
_____ $5,000-9,999	_____ $30,000-34,999	_____ $60,000-69,999
_____ $10,000-14,999	_____ $35,000-39,999	_____ $70,000-79,999
_____ $15,000-19,999	_____ $40,000-44,999	_____ $80,000-99,999
_____ $20,000-24,999	_____ $45,000-49,999	_____ Over $100,000

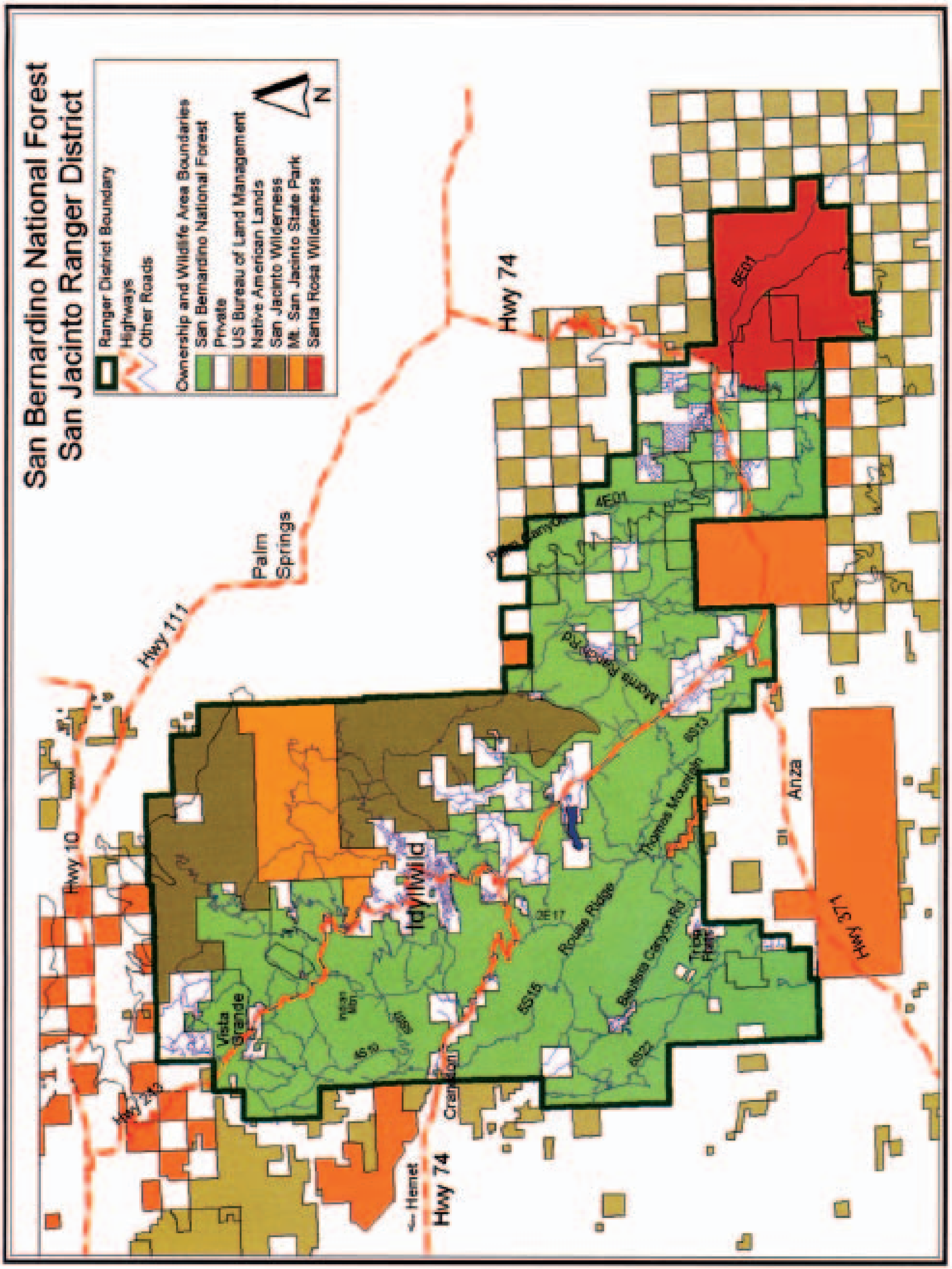
10. How many persons contribute to this income? ____ # of persons contributing

Thank you very much for completing this survey.
If there is anything else you would like to tell us regarding this study or your answers, please feel free to write them on the back of the questionnaire.

Please put the completed survey in the enclosed postage paid, self addressed envelope and mail to us.

Don't forget to enclose the MAP indicating where you hunted.

Appendix 2. San Bernardino National Forest



The Forest Service, U.S. Department of Agriculture, is responsible for Federal leadership in forestry. It carries out this role through four main activities:

- Protection and management of resources on 191 million acres of National Forest System lands;
- Cooperation with State and local governments, forest industries, and private landowners to help protect and manage non-Federal forest and associated range and watershed lands;
- Participation with other agencies in human resource and community assistance programs to improve living conditions in rural areas; and
- Research on all aspects of forestry, rangeland management, and forest resources utilization.

The Pacific Southwest Research Station

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Economic Value of Big Game Habitat Production from Natural and Prescribed Fire

United States
Department
of Agriculture
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