Journal of Forest Economics 16 (2010) 113–126

Contents lists available at ScienceDirect

Journal of Forest Economics

journal homepage: www.elsevier.de/jfe

Spatial allocation of forest recreation value

Kenneth A. Baerenklau[a,*], Armando González-Cabán[b], Catrina Paez[a], Edgar Chavez[a]

[a] Department of Environmental Sciences, Geology Building #2460D, University of California, Riverside, CA 92521, USA
[b] USDA Forest Service, Pacific Southwest Research Station, Forest Fire Laboratory, Riverside, CA 92507, USA

ARTICLE INFO

Article history:
Received 24 March 2009
Accepted 4 September 2009

JEL classification:
Q23
Q26
Q51
Q57

Keywords:
Non-market valuation
Travel cost method
Geographic information system
Viewshed analysis

ABSTRACT

Non-market valuation methods and geographic information systems are useful planning and management tools for public land managers. Recent attention has been given to investigation and demonstration of methods for combining these tools to provide spatially-explicit representations of non-market value. Most of these efforts have focused on spatial allocation of ecosystem service values based on land cover types, but recreation value has yet to be considered. This article presents an objective method for spatially allocating forest recreation value that is based on readily available data, demonstrates the method for a Southern California study site, and discusses the policy relevance of the method and how it might be extended to other applications and tested with additional primary survey data.

© 2009 Elsevier GmbH. All rights reserved.

Introduction

From a planning and management perspective, non-market valuation methods and geographic information systems (GIS) are potentially very useful analytical tools for public land managers. For many years, non-market valuation methods such as travel cost analysis, hedonic pricing, and contingent valuation have been used in a variety of contexts to help inform natural resource management decisions. Notable applications include the Glen Canyon Dam (Bishop et al., 1987), Hell's Canyon (Krutilla and Fischer, 1975), Mono Lake (Loomis, 1987), the Spotted Owl (Hagen et al., 1992), Kootenai Falls (Duffield, 1982), and the Kakadu Conservation Reserve (Imber et al., 1991). The USDA maintains average "unit day values" for different recreation activities on public lands

* Corresponding author. Tel.: +1 951 827 2628.
E-mail address: ken.baerenklau@ucr.edu (K.A. Baerenklau).

1104-6899/$ - see front matter © 2009 Elsevier GmbH. All rights reserved.
doi:10.1016/j.jfe.2009.09.002

(USDA, 2006) and is a proponent of the "benefits transfer" method for inferring values from previous valuation studies when a new study cannot be conducted (USDA, 2005). Originally the province of academic economists, these and other non-market valuation methods were thrust into the public policy spotlight in the 1980s and 1990s following the passage of federal legislation which legitimized their use by government agencies to determine appropriate levels of compensation from liable parties in natural resource damage cases.

During roughly the same timeframe, the development and proliferation of GIS software has enabled public land managers to characterize and monitor landscape features more accurately and precisely and to develop more detailed land management plans. An example, which also motivates this work, is the USDA Stewardship and Fireshed Assessment (SFA) process which utilizes GIS-based fire modeling software to generate estimates of the costs of fire prevention and mitigation efforts and the effects of those efforts on fire behavior. The SFA process enables more effective allocation of costly fuels treatment efforts throughout varied landscapes and under changing environmental conditions.

More recently researchers have begun combining these tools to derive spatially-explicit representations of landscape values (e.g., Eade and Moran, 1996; González-Cabán et al., 2003; Troy and Wilson, 2006). This is a promising innovation because valuation methods traditionally have limited spatial elements.[1] For example, the travel cost method might be used to determine the value of access to a backcountry trailhead. Explanatory variables in the travel demand regression might include features of the trail and the landscape, but traditionally there is no attempt to allocate the access value to the landscape in a meaningful and informative way. That is to say, a recreation trip is valuable presumably because the user experiences an appealing landscape; but a traditional analysis does not attempt to ascertain the specific values of each piece of the landscape. Spatially allocating the recreation value of a forest to the landscape is an essential part of any GIS-based benefit-cost analysis, and a desirable part of overall planning and management efforts (van der Horst, 2005), but researchers have only begun to investigate methodologies for doing so. This article presents an objective method that is based on readily available data, demonstrates the method for a Southern California wilderness area, and discusses its policy relevance and how it might be extended to other applications and tested with additional survey data.

Study site

This study specifically examines backcountry recreation during 2005 in the San Jacinto Wilderness in the San Bernardino National Forest in Southern California (Fig. 1). The wilderness, covering 13,350 hectares (ha), is located within a 2.5 hour drive of most of the greater Los Angeles, San Diego, and Palm Springs metropolitan areas and attracts roughly 60,000 backcountry visitors each year. Another 350,000 ride the Palm Springs Aerial Tramway into the Mt. San Jacinto State Park but do not enter the backcountry. The Pacific Crest Trail traverses the wilderness from north to south, and elevations range from 1800 to 3300 meters. In 2006 the Esperanza Fire severely burned a large area just to the northwest of the wilderness.

Backcountry access is regulated by two US Forest Service Ranger Stations and one State Park office. Horses are allowed but bikes and motorized vehicles are prohibited. Day hiking is by far the most popular activity in the backcountry. Day hikers enter the backcountry via several vehicle-accessible trailheads located on the north, west, and south sides of the wilderness (regulated by a Ranger Station and the State Park office, both in Idyllwild), or by riding the tram and then hiking in from the east side (regulated by a Ranger Station in Long Valley). Table 1 presents some statistics for the ten trailheads for which we have data and which account for nearly all day use visitors.

Backcountry visitors are required to obtain a permit in either Idyllwild or Long Valley, but the Forest Service estimates the compliance level is around 75% (Melinda Lyon, personal communication,

[1] Eade and Moran and Troy and Wilson both use benefits transfer and GIS to spatially allocate ecosystem service values primarily based on land cover types. González-Cabán et al., also allocate value based on land cover. Eade and Moran's method for allocating tourism value is similar to the method presented here.

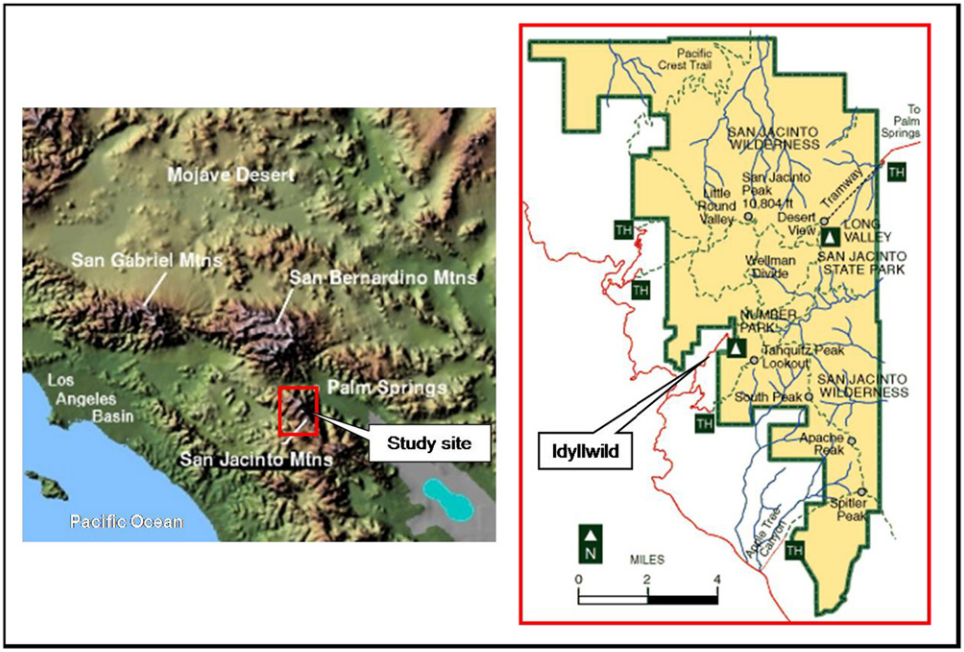

Fig. 1. Maps of Southern California and the study site (image credits: 〈gorp.away.com〉, 〈en.wikipedia.org〉; modified by the authors).

Table 1
Summary statistics for trailheads.

Trailhead name	Sample number of users in 2005[a]	Minimum number of users from any ZIP code[a]	Median number of users across ZIP codes[a]	Mean number of users across ZIP codes[a]	Maximum number of users from any ZIP code[a]	Starting elevation (m)	Distance to first trail junction (km)	Average slope (%)
Fuller ridge	330	0	0	0.56	18	2365	8.0	4.2
Seven pines	196	0	0	0.33	15	1928	6.1	11.3
Marion mountain	1391	0	0	2.37	40	1964	4.0	16.3
Deer springs	4793	0	2	8.18	356	2097	3.7	−9.8
Devil's slide	8428	0	4	14.38	855	1956	4.0	12.7
Ernie maxwell	269	0	0	0.46	21	1956	3.7	−5.9
Spitler peak	182	0	0	0.31	30	1781	4.7	6.6
Fobes trail	47	0	0	0.08	8	2090	1.6	−5.0
South ridge	2143	0	0	3.65	534	2303	6.4	3.9
Long valley	16,439	0	13	28.05	1,024	2576	0.5	0.6

[a] Includes users originating from a ZIP code within 2.5 hours of the wilderness and who submitted a complete day use permit. Does not include an additional 11,000 documented visitors for various reasons (e.g., multiple-day users, insufficient permit information for statistical analysis).

USDA Forest Service, March 2007). Data needed to perform a standard count data travel cost analysis is available from permit receipts maintained by the Forest Service and State Park offices. Each permit lists the date of the trip, the number of people in the group, the entry and exit points, and the home address of the group leader. Most wilderness areas maintain similar records which helps explain the popularity and usefulness of travel cost models for estimating recreation value (Hilger and Englin, in press; Shonkwiler and Englin, 2005; Moeltner, 2003; Englin and Mendelsohn, 1991).

A unique issue we must address in this application of the travel cost method is the existence of the tramway. The large number of riders and the non-trivial ticket price ($21 per adult in 2005) suggest this is a valuable means to access the wilderness. However we do not have the data needed to estimate this value: there is not enough variability in ticket prices nor do we have any information about visitors who ride the tram but do not enter the backcountry. Therefore we cannot separate the value derived from the tram ride itself from the value derived from the forest landscape via the Long Valley trailhead; rather we can only determine the value of the combined experience for riders who also enter the backcountry (for whom we have the necessary data from hiking permit receipts).

Because our primary interest is in spatially allocating forest landscape value, we proceed as follows. First, intuition suggests that much of the value of a tram ride is the ride itself, during which time visitors primarily experience views of the Coachella Valley and Palm Springs; only a small part of the landscape that is relevant to this study can be seen by these visitors. Therefore we omit this demand for forest access and instead base our estimates only on the visitors who use the backcountry trails. This may cause us to understate the value of the landscape near the tramway, but it should not affect our value estimates for the remaining majority of the forest. Second, we assume that the primary interest of visitors who access the backcountry trails via the tram is the forest experience rather than the tram ride. Therefore we allocate the entire surplus associated with the Long Valley trailhead to the forest, even though some (unknown) amount of it should be allocated to the tramway. This means we treat the monetary and time costs associated with riding the tram as part of the total cost of accessing the Long Valley trailhead. This likely overstates the value of the forest landscape that can be accessed from Long Valley; however our approach is no different from the standard assumption that there is no benefit associated with driving to a trailhead, even though some people may gladly pay the cost of a scenic drive without ever leaving the car to participate in an outdoor activity such as hiking.

Estimation of forest access value

We estimate the access value for each trailhead using a multiple-site zonal travel cost model (e.g., Moeltner, 2003; Weber and Berrens, 2006). A zonal model typically uses ZIP codes as the unit of analysis and thus facilitates incorporation of census data as explanatory variables in the regression. Zonal models suffer from potential aggregation bias but, compared to other approaches based on individual data, are less prone to model specification bias and have performed well in Monte Carlo tests (Hellerstein, 1995). They also do not require costly surveys of individual visitors but rather utilize existing recreation permit data to establish the aggregate demand for access from each ZIP code.[2] Because ZIP codes differ both in terms of demographic characteristics and distance from the relevant recreation sites, functions can be estimated that describe how demand varies with respect to access cost (i.e., the price of the recreation activity) while controlling for relevant demographic factors. The overall goal of the statistical analysis is to estimate a set of demand functions that is consistent with economic theory and thus permits calculation of welfare measures (i.e., access value).

A popular approach for obtaining economically rational estimates for multiple recreation sites is an incomplete demand system (Englin et al., 2006, 1998; Shonkwiler, 1995). The theory supporting the use and estimation of incomplete demand systems has been developed by LaFrance and Hanemann (1989), LaFrance (1990), and von Haefen (2002). An incomplete demand system approach specifies the parameter restrictions on the observable demand functions that are necessary to insure

[2] The issue of survey cost is non-trivial, particularly when the resource of interest draws a large and diverse population of users, as is the case here. Implementation of a survey that would generate a dataset of similar size and geographic breadth as the one obtained here through the use of permits would be prohibitively expensive. Therefore the existence of permit data has enabled researchers to address questions for which surveys are ill-suited due to the scale of the desired analysis.

the integrability of the demand system and thus the ability to derive theoretically consistent welfare measures from the demands.[3]

Although many functional forms are permissible for incomplete demand systems, a semi-logarithmic form is particularly useful in conjunction with count data travel cost models because it restricts demand to be non-negative and is easily incorporated into standard count data statistical frameworks such as the Poisson and Negative Binomial. The semi-log specification used here assumes that an individual's demand for trips is given by (von Haefen, 2002):

$$x_j = \alpha_j(\mathbf{q})\exp\left(\sum_{k=1}^{J}\beta_{jk}p_k + \gamma_j y\right), \forall j \tag{1}$$

where x_j is demand for trips to site $j \in \{1,\ldots,J\}$; α_j is a "demand shifter" that is a function of observable variables $\mathbf{q}$; p_k is the cost to access site k; each β is an estimable parameter describing the effect of the cost to access site k on the demand for trips to site j; y is individual income; and γ_j is an estimable parameter. By assumption, individual demands for different sites are uncorrelated, although correlation may be incorporated as in Hilger and Englin (in press), Signorello et al. (in press), and Shonkwiler (1999).

One set of parameter restrictions which guarantees integrability of the demand system described by Eq. (1) is (LaFrance, 1990; von Haefen, 2002):

$$\begin{aligned} &\alpha_j(\mathbf{q}) > 0,\ \forall j \\ &\gamma_j = \gamma,\ \forall j \\ &\beta_{jk} = 0,\ \forall j \neq k \\ &\beta_{jj} < 0,\ \forall j \end{aligned} \tag{2}$$

Imposing these restrictions on Eq. (1) gives:

$$x_j = \exp(a_j(\mathbf{q}) + \beta_j p_j + \gamma y),\ \ \forall j \tag{3}$$

where $a_j(\mathbf{q}) \equiv \ln(\alpha_j(\mathbf{q}))$ and each β_j is restricted to be negative.

A quasi-indirect utility function that can be derived from this system of demands is (LaFrance, 1990; von Haefen, 2002):

$$\phi(\mathbf{p},\mathbf{q},y) = -\frac{1}{\gamma}\exp(-\gamma y) - \sum_{j=1}^{J}\frac{\alpha_j(\mathbf{q})}{\beta_j}\exp(\beta_j p_j) \tag{4}$$

This utility function can be used to obtain a welfare measure called "equivalent variation" which represents the equivalent monetary loss experienced by an individual when access to a recreation site is denied (i.e., when the price of access is sufficiently high that no trips are demanded).[4] Equivalent variation (v) is defined as:

$$\phi(\mathbf{p}^0,\mathbf{q},y+v) \equiv \phi(\mathbf{p}^1,\mathbf{q},y) \tag{5}$$

where $\mathbf{p}^0$ is the baseline set of access prices and $\mathbf{p}^1$ is the set that "chokes-off" demand to one or more sites. Combining (4) and (5) and rearranging gives (Englin et al., 1998):

$$v \equiv \frac{-1}{\gamma}\left[\exp(-\gamma y) - \gamma\sum_{j=1}^{J}\frac{\alpha_j(q)}{\beta_j}\left(\exp(\beta_j p_j^0) - \exp(\beta_j p_j^1)\right)\right] - y \tag{6}$$

Empirical use of Eq. (6) requires an assumption about the functional form of $a_j(\mathbf{q})$; information about the variables $\mathbf{q}$, p, and y; and a statistical framework for estimating α, β, and γ. As in previous studies, we assume $a_j(\mathbf{q})$ is linear in $\mathbf{q}$: $a_j(\mathbf{q}) \equiv \delta'\mathbf{q}$; thus $\alpha_j(\mathbf{q}) \equiv \exp(\delta'\mathbf{q})$. Information about the explanatory

[3] Integrability specifically refers to the ability to integrate the system of demand equations to obtain a quasi-indirect utility function that is consistent with the observed behavior. See Varian (1992, p.125).

[4] For an overview of equivalent variation and other related welfare measures, see Varian (1992, p. 161).

Table 2
Definitions and summary statistics for variables used in the regression analysis.

Variable name	Variable symbol	Variable description	Mean	Median	Standard deviation
Travcost	pij	Roundtrip travel cost from ZIP code to trailhead ($2005)	69.85	67.92	23.96
Intercept	$q_{1,i}$	Trailhead-specific constant term	1	1	0
Prop12	$q_{1,i}$	% of ZIP code residents voting “yes” on proposition 12[a]	64.15	62.16	9.77
White	$q_{3,i}$	% of ZIP code residents who are white/Caucasian	62.67	65.10	21.17
M1839	$q_{4,i}$	% of ZIP code residents who are male, ages 18–39	16.64	16.10	5.21
M4059	$q_{5,I}$	% of ZIP code residents who are male, ages 40–59	12.85	12.33	3.18
M60	$q_{6,i}$	% of ZIP code residents who are male, ages 60 and over	6.81	5.98	3.85
F1839	$q_{7,i}$	% of ZIP code residents who are female, ages 18–39	15.89	16.27	3.75
F4059	$q_{8,i}$	% of ZIP code residents who are female, ages 40–59	12.96	12.69	2.85
F60	$q_{9,i}$	% of ZIP code residents who are female, ages 60 and over	8.53	7.87	4.32
Urban	$q_{10,i}$	% of ZIP code residents living in urbanized areas	90.02	100.00	26.44
College	$q_{11,i}$	% of ZIP code residents with a Bachelors degree	24.16	20.09	16.56
PCinc	y_i	Average per-capita income for the ZIP code ($2005)	24,264	20,385	14,208
Pop	n_i	Total ZIP code population in 2000[b]	31,640	29,269	21,194

[a] Safe neighborhood parks, clean water, clean air, and Coastal Protection Bond Act of 2000.
[b] Not used as a regressor.

variables is obtained following conventional methods as in Moeltner (2003) and Weber and Berrens (2006). We combine the hiking permit data for 2005 with the most recent census data (US Department of Commerce, 2000) to construct a dataset containing the number of backcountry trips taken from each of the 586 ZIP codes within a 2.5 hour drive of the wilderness and certain population characteristics of each ZIP code that are likely to help explain variation in recreation demand across ZIP codes (e.g., race, gender, age distribution, education level, income).[5] The price of a trip from each ZIP code is estimated to be the sum of driving costs and time costs. Driving costs are a function of distance (derived from Google Maps), the average per-mile cost of operating a typical car ($0.561/mile; AAA, 2005), and the average number of passengers per vehicle (1.5; authors' dataset). Time costs are a function of travel time (derived from Google Maps) and the opportunity cost of time which is evaluated at one-third of the average hourly per-capita income for each ZIP code (a standard assumption in the literature; Hagerty and Moeltner, 2005). For tramway users, the ticket price and one hour of wait and ride time are added to these amounts. When necessary, costs are adjusted to 2005 dollars using the US Consumer Price Index. We also augment our dataset with voting records on an environmental initiative from the 2000 election (California Secretary of State, 2000) to help control for variation in environmental attitudes across ZIP codes. Table 2 summarizes the variables used in the regression analysis.

To estimate the model parameters, we specify that individual demand for each site follows an independent Poisson distribution (Cameron and Trivedi, 1986):

$$\Pr(x_j = x_j{*}) = \frac{\exp(-\lambda_j)\lambda_j^{x_j^*}}{x_j^*!} \tag{7}$$

with mean and variance both equal to λ_j.[6] We parameterize λ_j using a slightly simplified version of Eq. (3) that assumes the marginal effect of the price of a trip is invariant across sites (i.e., β_j=β, $\forall j$):

[5] To avoid the need for a truncated analysis, ZIP codes from which no trips were taken are included in the dataset.

[6] A well-known drawback of the Poisson model is the restriction that the mean equals the variance. A negative binomial specification relaxes this restriction but tends to over-predict the number of trips taken to each site, thus inflating the welfare estimates (e.g., Englin et al., 2006; von Haefen and Phaneuf, 2003a). We found similar results: a negative binomial specification predicted 3.4 times the actual number of trips and increased welfare estimates by 24% relative to the Poisson, which correctly predicted the total number of trips. von Haefen and Phaneuf (2003b) have suggested the Poisson therefore is preferable for policy purposes.

Table 3
Estimation results.

Variable name	Coefficient symbol	Variable description	Estimate	Standard error	*P*-value
Travcost	β	Roundtrip travel cost from ZIP code to trailhead ($2005)	−0.0529	0.0037	<0.01
Intercept	$\delta_{1,1}$	Trailhead-specific constant term – fuller ridge	−11.1973	0.6243	<0.01
Intercept	$\delta_{1,2}$	Trailhead-specific constant term – seven pines	−11.9620	0.6334	<0.01
Intercept	$\delta_{1,3}$	Trailhead-specific constant term – Marion mountain	−10.1339	0.6204	<0.01
Intercept	$\delta_{1,4}$	Trailhead-specific constant term – Deer Springs	−9.1559	0.6249	<0.01
Intercept	$\delta_{1,5}$	Trailhead-specific constant term – devil's slide	−8.4752	0.6249	<0.01
Intercept	$\delta_{1,6}$	Trailhead-specific constant term – Ernie Maxwell	−11.9890	0.6378	<0.01
Intercept	$\delta_{1,7}$	Trailhead-specific constant term – spitler peak	−12.0211	0.6550	<0.01
Intercept	$\delta_{1,8}$	Trailhead-specific constant term – fobes trail	−13.1070	0.6672	<0.01
Intercept	$\delta_{1,9}$	Trailhead-specific constant term – south ridge	−9.8284	0.6650	<0.01
Intercept	$\delta_{1,10}$	Trailhead-specific constant term – long valley	−6.7094	0.5722	<0.01
Prop12	$\delta_{2,}$	% of ZIP code residents voting "yes" on proposition 12	0.0051	0.0072	0.24
White	δ_3	% of ZIP code residents who are white/caucasian	0.0299	0.0029	<0.01
M1839	δ_4	% of ZIP code residents who are male, ages 18–39	0.0593	0.0065	<0.01
M4059	δ_5	% of ZIP code residents who are male, ages 40–59	0.0244	0.0335	0.23
M60	δ_6	% of ZIP code residents who are male, ages 60 and over	0.0992	0.0325	<0.01
F1839	δ_7	% of ZIP code residents who are female, ages 18-39	−0.0157	0.0167	0.17
F4059	δ_8	% of ZIP code residents who are female, ages 40–59	0.0002	0.0001	0.02
F60	δ_9	% of ZIP code residents who are female, ages 60 and over	−0.0457	0.0277	0.05
urban	δ_{10}	% of ZIP code residents living in urbanized areas	−0.0135	0.0301	<0.01
college	δ_{11}	% of ZIP code residents with a Bachelors degree	0.0661	0.0037	<0.01
PCinc	γ	Average per-capita income for the ZIP code ($2005)	−1.611e-6	2.613e-6	0.27

$\lambda_j \equiv E(x_j) \equiv \exp(a_j(\mathbf{q}) + \beta p_j + \gamma y), \forall j$. Thus we interpret the framework presented in (1)–(6) as a system of *expected* demands. Finally, because we are using aggregate demand by ZIP code rather than individual demand, we take advantage of the property that the sum of N independent Poisson distributions is also Poisson with parameter $\Sigma_N \lambda_n$. Assuming homogeneity of individual demands within each ZIP code gives:[7]

$$Pr(x_{ij} = x^*_{ij}) = \frac{\exp(-n_i\lambda_{ij})(n_i\lambda_{ij})^{x^*_{ij}}}{x^*_{ij}!} \tag{8}$$

where n_i is the population of ZIP code i, and x^*_{ij} is the observed aggregate demand by ZIP code i for site j. Substituting our simplified version of (3) into (8), taking logs, dropping constant terms, and summing across I=586 ZIP codes and J=10 trailheads gives the log-likelihood function for the estimation:

$$L = \sum_{i=1}^{I}\sum_{j=1}^{J}(x^*_{ij}\ln\lambda_{ij} - n_i\lambda_{ij}) \tag{9}$$

with $\lambda_{ij} \equiv \exp(\delta'\mathbf{q}_{ij} + \beta p_{ij} + \gamma y_i), \forall j$. Estimation is conducted in Gauss (Aptech Systems, 2003).

Table 3 summarizes the estimation results. The log-likelihood value at convergence is 266,298.30. Significance levels are high overall. Most parameter estimates, including the coefficients on *travcost*, *white*, *urban*, and *college*, are significant at the 1% level. Two more are significant at the 5% level.

[7] This assumption, although standard in count data models, potentially leads to aggregation bias if individuals exhibit significant heterogeneity (Stoker, 1993). But in an application similar to this one, Moeltner (2003) found that this bias was only around 5% in the welfare calculations.

Table 4
Access values.

Trailhead name	Total number of users[a]	Mean travel cost to trailhead ($2005/trip)	Mean equivalent variation ($2005/trip)	Mean total value ($2005/trip)[b]	Aggregate travel cost ($2005/yr)[c]	Aggregate equivalent variation ($2005/yr)[c]	Aggregate total value ($2005/yr)[c]
Fuller ridge	586	64.67	18.89	83.56	37,897	11,070	48,966
Seven pines	348	60.85	18.89	79.74	21,176	6574	27,750
Marion mountain	2546	58.83	18.89	77.72	149,781	48,094	197,875
Deer springs	8656	54.72	18.89	73.61	473,656	163,512	637,168
Devil's slide	15,138	56.45	18.89	75.34	854,540	285,957	1,140,497
Ernie maxwell	478	55.40	18.89	74.29	26,481	9029	35,511
Spitler peak	316	61.21	18.89	80.10	19,342	5969	25,312
Fobes trail	82	65.22	18.89	84.11	5348	1549	6,897
South ridge	3827	56.67	18.89	75.56	216,876	72,292	289,168
Long valley	28,678	73.25	18.89	92.14	2,100,664	541,727	2,642,391
Total wilderness	60,655	–	–	–	3,905,761	1,145,773	5,051,534

[a] Includes all documented day hikers; adjusted upward to account for 75% permit compliance rate.
[b] Total value=travel cost+equivalent variation.
[c] Aggregate measures=total number of users × individual measures.

The remaining estimates, including those for *prop12* and *PCinc*, are somewhat less significant (levels range from 17–27%). Trip cost has a strong negative effect on demand, as anticipated. ZIP codes voting in favor of Proposition 12 ("Safe Neighborhood Parks, Clean Water, Clean Air, and Coastal Protection Bond Act"), those with more white residents, more male residents of any age, and more residents with college degrees tend to exhibit greater demand for hiking trips. ZIP codes that are more urban and those with more female residents aged 18–39 and over 60 tend to exhibit less demand. Interestingly, income has a relatively small but negative effect on demand in our sample. Economists refer to goods exhibiting negative income effects as "inferior" goods: wealthier people tend to demand less of them, as appears to be the case here. This is not entirely surprising: hiking in a remote area requires a relatively small cash expenditure but a large amount of time. Therefore it may appeal more to lower income earners who tend to have relatively less cash and lower opportunity costs of time, versus higher income earners who tend to have more cash but higher time costs.

Table 4 provides statistics on the derived access values for each trailhead.[8] The mean equivalent variation per trip (i.e., $\Sigma_i v_i n_i / \Sigma_i x_{ij}$, where i indexes each ZIP code) is $19. By construction this estimate does not vary across trailheads in this model; but it could if, for example, the travel cost parameter varied across trailheads. This per-trip value is reasonable in magnitude and similar to values reported by previous studies.[9] Intuitively, it means that $19 would be adequate compensation for the average person who had to cancel a hiking trip in the San Jacinto Wilderness. This may seem like a relatively small amount, and for some hikers it certainly would not be sufficient compensation; but note that a cancelled trip also saves the user his/her travel cost and affords the opportunity to participate in an alternative activity (on which the $19 could be spent).

Aggregate access values vary by trailhead because travel costs and visitation rates vary. Table 4 presents two such aggregate measures: aggregate equivalent variation and aggregate total value. The former represents the economic loss due to foregone recreational enjoyment that would be

[8] Predicted demand for each trailhead is not reported because the Poisson model, by construction, exactly predicts aggregate demand within the sample.
[9] Our negative binomial specification produced an equivalent variation of $31 per trip, which is very close to Moeltner's (2003) welfare estimates of $31–33 from a negative binomial model of day hiking.

suffered by day hikers if one or more trailheads were closed to hiking for a year. The latter is the sum of this amount plus travel cost and thus represents the "gross benefit" derived from day hiking. As stated above, most valuation studies conclude with welfare measures like these. However the purpose of this article is to demonstrate a method for spatially allocating these values to the landscape to better inform public land management decisions.

Spatial allocation of value

A spatial representation of forest access value requires it to be allocated to the landscape according to some rational methodology. Of course it would be possible to infer from a travel cost analysis – or some other non-market valuation method – with more detailed data the value of specific features in the landscape. This approach may be desirable when very unique features (e.g., Half Dome) exist. But generally it will not be possible to use this approach to value each separate piece of an arbitrarily large landscape. At best, such an analysis would be costly and time consuming; furthermore, analysts often must work only with the type of permit and census data we have for this study. From permit data we can infer both the value of a backcountry trip and how many people enter the wilderness at each trailhead. With some additional permit-derived information about destinations and some assumptions about hiking speeds, we can infer the likelihoods of various paths taken through the wilderness. Thus it is straightforward to allocate the trailhead access value to various trail segments, but the problem of allocating it to the surrounding landscape still remains.

To proceed, we make the reasonable assumption that landscape values for backcountry hikers are closely related to scenic quality. Obviously certain unique landscape features may have particularly high values, but in a relatively homogenous wilderness such as the San Jacinto, we posit the value of any specific location in the landscape may be well approximated by its visibility to backcountry users. For example, land traversed by a popular trail is viewed up-close by many users; therefore it would have higher value than land which is viewed only at a distance and by a few users. Land, which cannot be seen from any trails would have no recreation value.[10]

A normalized weighting function can be calculated for each point in the landscape that indicates its relative scenic value for forest users. Consider a forest consisting of J points and K trail segments, with each segment traversed by n_k users during a recreation season.[11] Each segment can be represented by a path in three-dimensional space from its starting point $t_k{}^s$ to its end point $t_k{}^e$. At any point t on trail segment k, let $S_k(t)$ be the set of visible landscape points, and let $I_j(t)$=1 if $j \in S_k(t)$ and 0 otherwise. Let $x_j(t)$ be the distance between points j and t, and let $w(x)$ be a weighting function such that $w>0$ and $\mathrm{d}w/\mathrm{d}x<0$. For each trail segment k, we can then define the "absolute visual weight" of point j as:

$$\nu_{jk} = \int_{t_k^s}^{t_k^e} I_j(t) w(x_j(t)) \mathrm{d}t \tag{10}$$

and the "normalized visual weight" of point j as:

$$V_{jk} = \nu_{jk} / \Sigma_J \nu_{jk} \tag{11}$$

such that $\Sigma_J V_{jk} = 1$. If the value of a trip on trail segment k is p_k, then $\Sigma_k n_k p_k V_{jk}$ gives an estimate of the scenic value of point j.

To implement this spatial valuation framework, we utilize standard tools available in ArcGIS (ESRI, 2006). Our study area is divided into 30-by-30 meter grid cells within a Digital Elevation Model (DEM). Trails are divided into 42 unique trail segments, each connecting two trail junctions or a junction and a dead end. Each trail segment is divided into observation points that are located at

[10] Eade and Moran (1996) use a similar approach to map the "strength of tourism assets." Note that, to the extent unique features are viewed up-close and by many people, this method will reflect their relatively higher values.

[11] The notation used in this section is unrelated to the notation used in the previous section.

intervals of 60 m along the trail. The visual experience of an individual hiker at each point is then simulated with the Viewshed Analysis tool. This tool identifies and calculates the number of times each parcel in the DEM is visible from the set of observation points by scanning the area surrounding each point. We set the scan angles to obtain a 180° vertical and a 360° horizontal scan. The offset value is set at 1.7 m, which corresponds to the average height of adult Americans. We limit the maximum search radius to 30 km as this is the maximum distance between any point along any of our trail segments and the boundary of our study area. As in previous viewshed studies (e.g., Llobera, 2003), our analysis does not account for effects of varying atmospheric conditions or the presence of vegetation that could render the landscape less visible than implied by the viewshed results. If spatially explicit data on vegetation height and density were readily available, the analysis could be further refined to achieve a more precise depiction of the viewshed from any observation point.[12]

To define the weighting function, we rely on previous empirical work by Higuchi (1983) that establishes a method for measuring the quality of visual landscape characteristics based on their appearance from a given observation point. Using trees as the standard object of analysis, Higuchi creates distance indices that help identify at what point qualitative differences are discernible. He divides the landscape into the foreground, middle ground, and background. Trees are discernible as separate units at short-distance, but are only visible as outlines and more recognizable as a forest unit at middle distance. At long-distance, one can only observe major topographical features, such as mountains and valleys and colors differ only by shade contrasts.

In our study we modify the indices suggested by Higuchi and increase the short and middle distances to account for bigger trees in our study area (i.e., Yellow and Ponderosa pines). In addition, we divide the far-distance band into two separate bands where the "far background" begins at 15 km, instead of having one far-distance band that extends past 5 km as described by Higuchi. This gives us four distance bands around each observation point: 0–0.2, 0.2–5, 5–15, and 15–30 km. To reduce our computational burden, each point in each band is assigned the average radius of the band from the observation point. We then calculate the weight of each parcel as

$$w(x_j) = e^{-\bar{x}_j/10} \tag{12}$$

where $\bar{x}_j$ is the average band radius in km. This gives us band weights of 0.99, 0.72, 0.34, and 0.10, from nearest to farthest.

Finally we must specify the number of people hiking each trail segment and the value of a trip on each segment. As is often the case with permit data, we do not have complete information about the specific routes taken through the forest by each hiker; but we do know entry and exit points for each trip, we know destinations for some trips, and we know all trips are day trips. To proceed, we assume an average hiking speed of 3.3 km/h and a maximum round-trip hiking time of 8 h, and – when lacking destination data – we assume that when a trail junction is encountered there is an equal probability of taking each trail segment from that junction. This produces a relative trip frequency for each trail segment which, when combined with the number of entries at each trailhead, gives an estimate of the number of hikers on each segment, n_k. To calculate the value of a trip on each segment, p_k, we allocate the total value (i.e., the "gross benefit") of a trip taken from each trailhead to the associated trail segments based on the relative magnitude of $\Sigma_J v_{jk}$ for each segment.[13] This is because, all else equal, longer trail segments and segments with more expansive viewsheds tend to have larger $\Sigma_J v_{jk}$, and thus should contribute relatively more to the value of a trip.

As shown in Fig. 2, we obtain annual values ranging from \$41 to \$10,369/ha throughout the wilderness, with a mean of \$378/ha and a median of \$173/ha. Ninety percent of these values are less than \$750/ha. The skewness of this distribution is due to a relatively small number of high-value

[12] This would be similar to the approach taken by Englin and Mendelsohn (1991) who used linear distance to characterize travel through dense forest and acreage to characterize travel above the treeline in a hedonic travel cost model of forest recreation.

[13] Alternatively we could use equivalent variation rather than gross benefit as the basis for valuing the landscape. Equivalent variation measures the net benefit of hiking and thus the economic loss experienced by a user when access is denied; this is less than the total benefit obtained from hiking due to unavoidable travel costs. We think the concept of gross benefit is a more appropriate representation of forest value in this context.

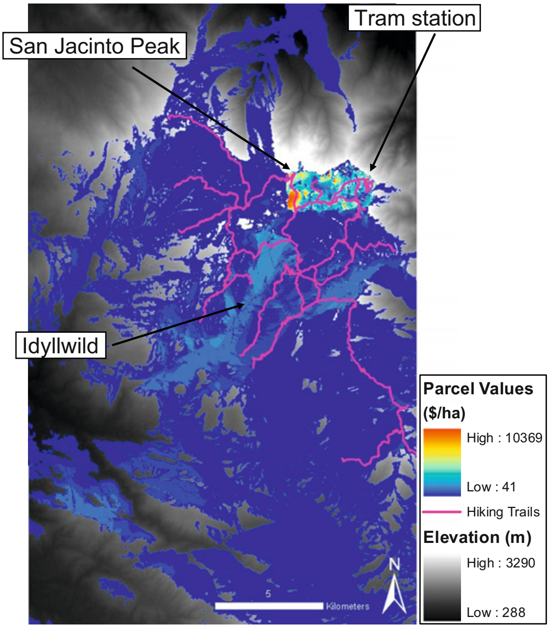

Fig. 2. Estimated landscape values.

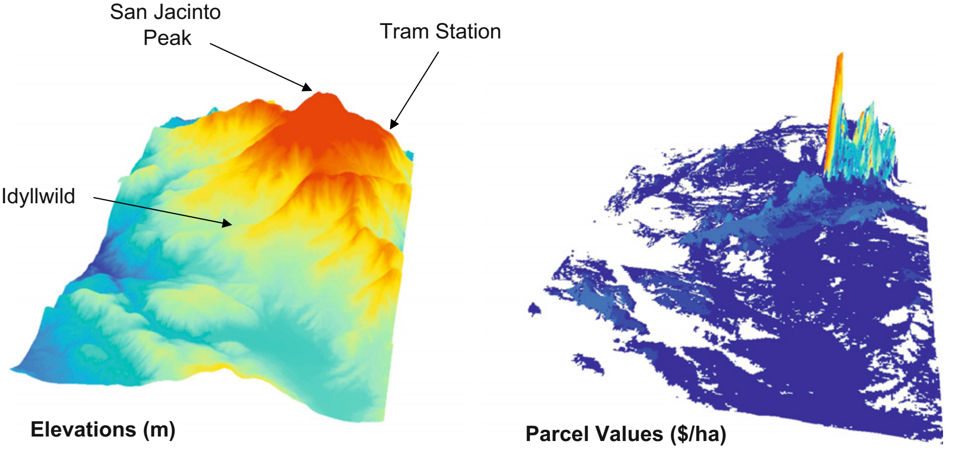

Fig. 3. Three-dimensional wilderness elevations and landscape values.

parcels. Fig. 3 shows these parcels are concentrated in areas with the highest elevations, in particular around the high peaks in the northeast. These include San Jacinto and Jean Peaks with elevations of 3302 and 3252 m. Because the high mountain peaks have the best visibility from most points along the trails, these parcels receive higher visibility weights and thus contribute more to the value of a trip. However, these values can only partially be explained by the visibility and elevation of these parcels because parcel value also depends on viewing distance and trail use frequency: therefore it is parcels that are both highly visible and frequently viewed that receive the highest values. In contrast, parcels located in relatively remote areas and on steep slopes descending away from trails generally have lower and sometimes zero values because of their limited visibility. By comparison, the annualized market value of one hectare of private real estate (including structures) in the nearby communities ranges from $1177 to $300,148 with an average of $32,381.[14] Although the average forest recreation value is only around 1% of this average value, the aggregate wilderness value is 15% of the aggregate real estate market value due to the significantly larger wilderness area.

Discussion and conclusion

As mentioned previously, this work was motivated by the USDA Stewardship and Fireshed Assessment process which is designed to enable the Forest Service to more effectively allocate fuels treatment efforts throughout a varied landscape. Currently the SFA process cannot estimate the benefits of those efforts making it difficult to evaluate investments in and trade-offs associated with fire management strategies. In cases where fire poses an imminent threat to life, crucial public infrastructure, or valuable private property, it is unlikely that decision-makers would undertake a formal cost-benefit analysis before taking action. But consider, for example, a fire in a remote location used exclusively for backcountry recreation. Should resources be allocated to this fire at all? If so, which resources and where should they be located? Or consider the option to undertake fire prevention activities in a mixed use landscape. Where should brush be cleared? Where should trees be thinned? Which areas should be protected given limited fire prevention resources? Without the capability to assess the benefits of fire prevention and suppression activities (i.e., the value of assets at risk) in a spatial context, efficient resource utilization is difficult to achieve.

Given the concentration of high values in a relatively small area in Fig. 2, and the broad expanse of low values across most of the landscape, it appears that the benefit of preserving recreation opportunities is significant only in a limited area of this wilderness. However, Fig. 2 should be interpreted carefully. If a fire in a low value area is expected to spread to a high value area, then resource allocation decisions clearly should incorporate this risk. Similarly, if a small fire is expected to spread to a large area of even low value landscape, this risk also should be incorporated. In both cases, prevention and suppression activities could be justified in any area regardless of its value to preserve nearby recreation opportunities. Furthermore, in addition to space, the dimension of time also must be considered because economic losses from fire are realized across multiple time periods. Other studies (e.g., Boxall and Englin, 2008; Hilger and Englin, in press) have investigated the dynamic intertemporal effect of fire on recreation, and have shown that activity levels and welfare measures tend to rebound as a forest recovers from a fire. Therefore a spatial and dynamic cost-benefit analysis framework that explicitly incorporates these findings is needed to properly evaluate management decisions. The information in Fig. 2 is most appropriately interpreted as an input to this framework.[15]

Furthermore, the value surface in Fig. 2 is determined in part by our assumptions about how values are derived from the landscape. Therefore an obvious next step would be to collect additional data on actual routes traversed and times/distances traveled, as well as on the effects of hypothetical fire damage and trail closures on recreation behavior, in order to verify and calibrate the methodology. A trailhead-intercept survey asking hikers if they would have taken their trip if they knew that certain areas of the forest had recently burned would be an effective and straightforward test of the approach described in Section 4, and likely would yield useful information about recreation preferences, as well.

This article demonstrates how commonly available data on forest use, demographics, and landscape characteristics can be combined using standard methods and tools to produce a spatially-explicit representation of recreation value. To our knowledge this is the first such explicit representation to appear in the published literature on recreation valuation. We expect there should

[14] Derived from inflation-adjusted Riverside County Assessor sale price data.

[15] In this case, EV should be used as the basis for valuing the landscape because it represents users' "willingness to pay" for preserving recreation opportunities, over and above the unavoidable travel costs they must incur. If this net recreation benefit exceeds the preservation cost, then preservation activities have economic justification.

be numerous extensions to other applications besides wildfire planning, including: trail network design, campground development, zoning and building regulations for rural and urban-fringe communities, locating scenic byways and overlooks, shoreline development regulations, design of location-specific development impact fees, and generally more precise identification of the sources of non-market values that motivate and justify landscape preservation efforts.

Acknowledgements

Generous research funding was provided by Cooperative Agreement No. 05-JV-11272165-094 between the United States Forest Service Pacific Southwest Research Station and the University of California at Riverside. The views expressed in this article are solely those of the authors and not of the Forest Service. Able research assistance was provided by Yeneochia Nsor, Sunil Patel, and Victoria Voss. The authors also thank Daniel Hellerstein of the USDA ERS, Melinda Lyon, Jerry Frates, and Roman Rodriguez of the US Forest Service's Idyllwild and Long Valley Ranger Stations, and Eddie Guaracha of the Mt. San Jacinto State Park Office in Idyllwild for their assistance.

References

American Automobile Association (AAA), 2005. Despite Higher Gas Prices, 2005 Driving Costs Nearly Unchanged From 2004, AAA Says. Available at: 〈http://www.aaanewsroom.net/main/Default.asp?CategoryID=4&ArticleID=361〉. Accessed March 2007.
Aptech Systems, 2003. Gauss for Windows v.5.0.
Bishop, R.C., Boyle, K., Welsh, K., 1987. Glen Canyon Dam Releases and Downstream Recreation: an Analysis of User Preferences and Economic values. Glen Canyon Environmental Studies Report No. 27/87. Bureau of Reclamation. Washington DC.
Boxall, P., Englin, J., 2008. Fire and recreation values in fire-prone forests: exploring an intertemporal amenity function using pooled RP-SP data. Journal of Agricultural and Resource Economics 33, 19–33.
California Secretary of State, 2000. Statement of Vote 2000 Primary Election. Available at: 〈http://www.sos.ca.gov/elections/sov/2000_primary/contents.htm〉. Accessed March 2007.
Cameron, A., Trivedi, P., 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. Journal of Applied Econometrics 1, 29–54.
Duffield, J., 1982. The Value of Recreational Use of Kootenai Falls. Kootenai Falls Hydroelectric Project Final EIS. Montana Department of Natural Resources and Conservation, Helena, MT.
Eade, J.D.O., Moran, D., 1996. Spatial economic valuation: benefits transfer using geographical information systems. Journal of Environmental Management 48, 97–110.
Englin, J., Holmes, T., Neill, R., 2006. Alternative models of recreational off-highway vehicle site demand. Environmental & Resource Economics 35, 327–338.
Englin, J., Boxall, P., Watson, D., 1998. Modeling recreation demand in a poisson system of equations: an analysis of the impact of international exchange rates. American Journal of Agricultural Economics 80 (2), 255–263.
Englin, J., Mendelsohn, R., 1991. A hedonic travel cost analysis for valuation of multiple components of site quality: the recreation value of forest management. Journal of Environmental Economics and Management 21, 275–290.
ESRI, 2006. ArcMap 9.2. Using ArcGIS Spatial Analyst. Environmental Systems Research Institute, Redlands, CA.
González-Cabán, A., Loomis, J., Griffin, D., Wu, E., McCollum, D., McKeever, J., Freeman, D., 2003. Economic value of big game habitat production from natural and prescribed fire. US Forest Service Pacific Southwest Research Station Research Paper #249. Available at: 〈http://www.fs.fed.us/psw/publications/documents/psw_rp249/〉. Accessed April 2008.
Hagen, D., Vincent, J.W., Welle, P.G., 1992. Benefits of preserving old-growth forests and the spotted owl. Contemporary Economic Policy X (2), 13–26.
Hagerty, D., Moeltner, K., 2005. Specification of driving costs in models of recreation demand. Land Economics 81 (1), 127–143.
Hellerstein, D., 1995. Welfare estimation using aggregate and individual-observation models: a comparison using Monte Carlo techniques. American Journal of Agricultural Economics 77 (3), 620–630.
Higuchi, T., 1983. The Visual and Spatial Structure of Landscapes. MIT Press, Cambridge.
Hilger, J., Englin, J., in press. Utility theoretic semi-logarithmic incomplete demand systems in a natural experiment: forest fire impacts on recreational values and use. Resource and Energy Economics.
Imber, D., Stevenson, G., Wilks, L., 1991. A Contingent Valuation Survey of the Kakadu Conservation Zone. Research Paper No. 3. Resource Assessment Commission, AGPS, Canberra, Australia.
Krutilla, J., Fischer, A., 1975. The Economics of Natural Environments: Studies in Valuation of Commodities and Amenity Resources. The Johns Hopkins University Press for Resources for the Future, Baltimore.
LaFrance, J.T., 1990. Incomplete demand systems and semilogarithmic demand models. Australian Journal of Agricultural Economics 34 (2), 118–131.
LaFrance, J.T., Hanemann, W.M., 1989. The dual structure of incomplete demand systems. American Journal of Agricultural Economics 71 (2), 262–274.
Llobera, M., 2003. Extending GIS-based visual analysis: the concept of visualscapes. International Journal of Geographical Information Science 17 (1), 25–48.

Loomis, J., 1987. Balancing public trust resources of Mono Lake and Los Angeles' water right: an economic approach. Water Resources Research 23 (8), 1449–1456.

Moeltner, K., 2003. Addressing aggregation bias in zonal recreation models. Journal of Environmental Economics and Management 45 (1), 128–144.

Shonkwiler, J.S., Englin, J., 2005. Welfare losses due to grazing on public lands: a count data system wide treatment. American Journal of Agricultural Economics 87, 302–313.

Shonkwiler, J.S., 1999. Recreation demand systems for multiple site count data travel cost models. In: Herriges, J.A., Kling, C.L. (Eds.), Valuing Recreation and the Environment. Edward Elgar, Northampton, MA, pp. 253–269.

Shonkwiler, J.S., 1995. Systems of travel cost models of recreation demand. In: Larson, D. (Ed.), Benefits and Costs Transfer in Natural Resource Planning: Eighth Interim Report W-133. Western Regional Research Publication, pp. 3–20.

Signorello, G., Englin, J., Longhorn, A., De Salvo, M., in press. Modeling the demand for sicilian regional parks: a compound poisson approach. Environmental and Resource Economics.

Stoker, T.M., 1993. Empirical approaches to the problem of aggregation over individuals. Journal of Economic Literature 31, 1827–1874.

Troy, A., Wilson, M.A., 2006. Mapping ecosystem services: practical challenges and opportunities in linking GIS and value transfer. Ecological Economics 60 (2), 435–449.

United States Department of Agriculture (USDA), 2005. Updated Outdoor Recreation Use values on National Forests and Other Public Lands. Prepared by J. Loomis. Pacific Northwest Research Station General Technical Report PNW-GTR-658. October.

United States Department of Agriculture (USDA), 2006. CECW-CP USACE Economics Guidance Memorandum, 06-03, Unit Day Values for Recreation, FY2006. Available at: ⟨http://www.economics.nrcs.usda.gov/technical/recreate/⟩. Accessed March 2008.

United States Department of Commerce, 2000. United States Census 2000. Available at: ⟨http://www.census.gov/main/www/cen2000.html⟩. Accessed March 2007.

Van der Horst, D., 2005. Spatial cost-benefit thinking in multi-functional forestry; towards a framework for spatial targeting of policy interventions. Ecological Economics 59, 171–180.

Varian, H.R., 1992. Microeconomic Analysis, third edition Norton, New York.

Von Haefen, R., 2002. A complete characterization of the linear, log-linear, and semi-log incomplete demand system models. Journal of Agricultural and Resource Economics 27 (2), 281–319.

Von Haefen, R.H., Phaneuf, D.J., 2003a. Estimating preferences for outdoor recreation: a comparison of continuous and count data demand system frameworks. Journal of Environmental Economics and Management 45, 612–630.

Von Haefen, R.H., Phaneuf, D.J., 2003b. A note on estimating nested constant elasticity of substitution preferences for outdoor recreation. American Journal of Agricultural Economics 85 (2), 406–413.

Weber, M., Berrens, R., 2006. Value of instream recreation in the Sonoran Desert. Journal of Water Resource Planning and Management 132 (1), 53–60.