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Economics of Forest Fire Management: Spatial Accounting of Costs and Benefits

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by

José Julio Sánchez

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Dissertation Committee:
Dr. Kenneth Baerenklau, Chairperson
Dr. Armando González-Cabán
Dr. Kurt Schwabe

The Dissertation of José Julio Sánchez is approved:

Committee Chairperson

University of California, Riverside

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To my parents, Vicente and Rosalba, my wife, Cecilia and my children, Jacqueline and Julio.

ABSTRACT OF THE DISSERTATION

Economics of Forest Fire Management: Spatial Accounting of Costs and Benefits

by

José Julio Sánchez

Doctor of Philosophy, Graduate Program in Environmental Sciences
University of California, Riverside, June 2014
Dr. Kenneth Baerenklau, Chairperson

This study uses a non-market valuation method to investigate the recreation values of the San Jacinto Wilderness in southern California. The analysis utilizes survey data from a stated-choice experiment involving backcountry visitors who responded to questions about hypothetical wildfire burn scenarios. Benefits of landscape preservation are derived using a Kuhn-Tucker (KT) demand system. Model results suggest that recreationists are more attracted to sites with recent wildfires that can be viewed up-close. For example, recreational welfare estimates increased for sites that were partially affected by different types of wildfires, with the greatest gains being observed for the most recent wildfires. However, wildfires that cause trail closures create welfare losses. Seasonal losses for complete closure of particular sites range from $19 to $169.

Additionally, a latent class modification of the standard KT model is proposed as a method for incorporating unobserved heterogeneity in preferences, and for controlling

for endogenous spatial sorting. Using the standard maximization likelihood technique, the latent class KT model suggests that two groups exist in the sample. The groups consist of "hiking enthusiasts" and "casual users." The hiking enthusiasts take twice as many trips as casual users, but their estimated per-trip welfare is smaller. These results are consistent with Parsons (1991) argument that individuals with stronger preferences for recreation ("enthusiasts") might choose to live closer to recreation sites they frequently visit to reduce their travel costs.

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1. Introduction

Wildland fires affect millions of people worldwide. Globally it is estimated that 350 million hectares of wildland burn annually (A. González-Cabán, 2008). In the United States, from 2000 to 2013 the Forest Service alone has incurred suppression costs of $18.83 billion and 37.3 million ha of wildlands burned (table 1.1). This translates to an annual average of 2.66 million ha of wildlands burned at an annual average suppression cost of $1.34 billion (National Interagency Fire Center Wildland Fire Statistics, 2014). Considering that the figures reported in table 1.1 only include the Forest Service, the values would be considerably larger when taking account other federal and state agencies with wildland fire protection responsibilities.

Table 1.1. US Department of Agriculture Forest Service area burned and associated suppression costs for the period 2000-2013 (Current Dollars). Source: National Interagency Fire Center Wildland Fire Statistics.

Year	**Area Burned (million ha)**	**Suppression Cost ($US Billions)**
2013	1.37	1.34
2012	2.95	1.44
2011	3.53	1.41
2010	1.39	0.90
2009	2.41	1.02
2008	2.21	1.98
2007	3.78	1.80
2006	4.00	1.90
2005	3.52	0.88
2004	2.75	0.89
2003	1.99	1.33
2002	2.81	1.66
2001	1.45	0.92
2000	3.41	1.36
Total	37.30	18.83
Average	**2.68**	**1.34**

The loss of natural resources, property, and life from wildfires is also a major concern. Forested areas are particularly valuable because of their multiple uses (e.g., residential, recreation, and carbon sequestration among others). The forest also offers other amenities that are not directly useable but that people enjoy in some other way (e.g., knowledge that unique ecosystems exist, preservation for future generations or future use). To promote efficient land management strategies, it is necessary to determine both the use and nonuse values of those areas. Some use values can be directly identified from market transactions (e.g., the price of residential land, entrance fees). For other nonmarket uses and nonuse values, resource economists use techniques such as the Contingent Valuation Method (CVM) (Loomis et al., 2002), Travel Cost Method (TCM) (Hesseln et al., 2003), Hedonic Price Method (HPM) (Mueller et al., 2009), and Stated Choice Experiment Method (CE) (Louviere et al., 2000) to determine the economic values. However, traditional nonmarket valuation analyses do not attempt to determine the specific values of each piece of the landscape or how welfare is affected if only part of the forest area is impacted by fire, rather the entire landscape. Such information would enable resource managers, stakeholders and policy makers to make better-informed decisions on how to use resources more efficiently.

A recent change that will benefit forest management due a better representation is the use of spatial analysis software. The use of this software is now possible given recent increases in computing power have given researchers the ability to make greater use of geographic information systems (GIS). As use of this tool has become more popular, researchers have begun combining GIS software with nonmarket valuation methods to assist land and forest managers (Baerenklau et al., 2010; González-Cabán et al., 2003). This combination has allowed researchers to derive spatially-explicit representations of landscape values; however, such studies are uncommon and little is known about how the aggregate value of a forest area should be allocated to the landscape.

This study examines how recreation activity and fire conditions co-determine landscape values at the parcel level. I develop an approach for determining spatially explicit values associated with outdoor recreation (i.e., hiking), and apply it to the San Jacinto Wilderness in southern California (figure 1.1).

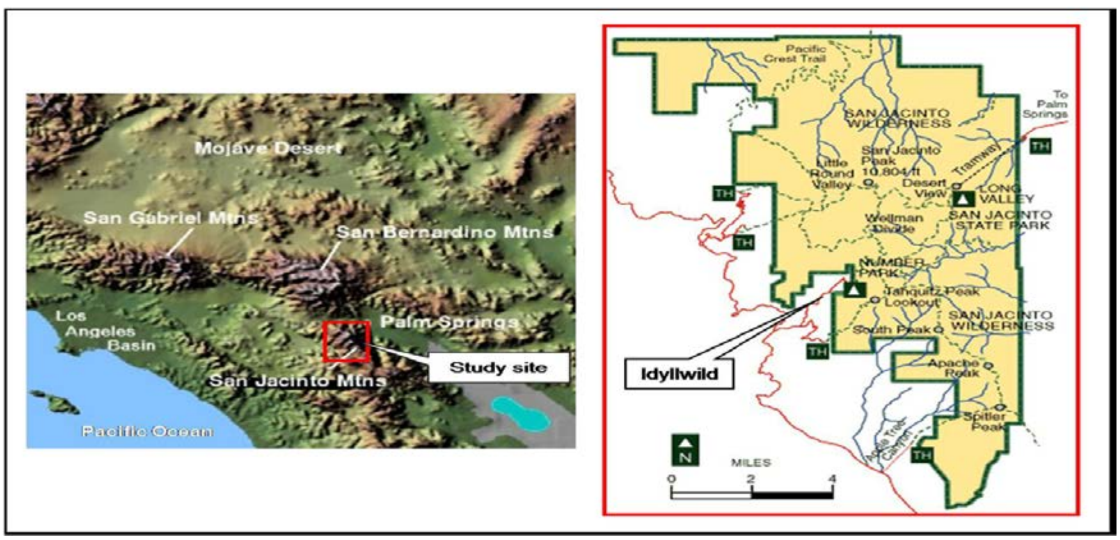

Figure 1.1— Site location-San Jacinto wilderness area. Map provided by Baerenklau et al. (2010).

The San Jacinto Wilderness serves as an excellent case study because it is a popular recreation area, accessible to millions of people throughout southern California, and at the time of the study it had not experienced a fire in several decades[1]. The approach utilizes a web-based survey to collect both revealed and stated choice data from backcountry visitors who responded to questions about past trip-taking behavior and

[1] A wildfire occurred recently (July 2013) affecting a part of the area, but not during the study period.

hypothetical wildfire burn scenarios. Benefits of landscape preservation are derived from both the revealed and stated choice data using a Kuhn-Tucker (KT) demand system (Phaneuf et al., 2000; von Haefen et al., 2004). The results can help researchers understand better the economic effects of wildfires and fire managers to plan more efficient fire management strategies and reduce potential losses from wildfires.

1.1 Fire management

Wildfire has been a constant threat to western United States (US) ecosystems, but it has become a more serious problem in part due to increasingly dry conditions and forest management practices that have promoted ladder fuel accumulation. In a recent assessment, the U.S. Department of Agriculture Forest Service (USDAFS) reported that annually, on average, 1.7 million acres burned in the US while it suppressed more than 6,600 wildfires and expended $1.4 billion for firefighting (USDA, 2012)[2]. Recently fire suppression costs have increased dramatically while congressional funding levels have remained flat (USDA, 2009). Land and forest managers need tools to understand which management strategies are more efficient. However, current tools used by USDAFS only consider cost of fire prevention or suppression, not the economic benefits a forest provides. Therefore, managers are limited information in their efforts to evaluate investments in and trade-offs associated with fire management strategies.

1.2 Forest Benefits

A forest provides several benefits to society ranging from conservation of ecosystems to recreation use. Resource economists have different nonmarket valuation methods that

[2] There is a difference from table 1.1 because data reported is based on calendar year data while the USDA report is based on fiscal year data (October 1, 2010 to September 30, 2011).

can be implemented to estimate the economic benefits of use and nonuse values of natural resources. Loomis and González-Cabán (1998) used a CVM survey to estimate the economic benefits of reducing fires in an old growth forest. Fix and Loomis (1997) examined the economic benefits of mountain biking on trails that offer scenic views, in Moab, Utah, using a TCM, while Powe et al. (1997) used an HPM to estimate the benefits residents received from woodland access. Hanley et al. (1998) used CE to estimate the values of environmental assets (forests, rivers). Knowledge of the benefits and values produced from forests can help managers prioritize decisions to protect the most valuable lands potentially affected from fires and implement appropriate management strategies to reduce fire impacts.

1.3 Fire impacts

There are many types of natural and human-made disasters that damage or affect natural resources. Although fire is a natural part of many landscapes, catastrophic fires--often produced by a combination of both natural and human factors--are particularly damaging to forests. The impact of fire on natural resources and the associated economic consequences are difficult to estimate (González-Cabán et al., 2003). The difficulty arises because there is limited information about the effects of fire on nonmarket values provided by forests. Early studies (Flowers et al. 1985 and Vaux et al., 1984) found that intense fires are likely to have negative impacts on recreation. Recent studies have explored these negative effects. Loomis et al. (2001) surveyed visitors of National Forests in Colorado to study the effects of fire on hiking and mountain biking visits and benefits. Using TCM, authors found that crown fires indirectly affected recreation benefits for mountain bikers, while having no significant effect on hiking trips. The present study follows a similar line of investigation but also utilizes stated preference methods to further investigate impacts on hiking.

Also using TCM, Hesseln et al. (2003) found that both hikers and mountain bikers in New Mexico reacted similarly to recovering prescribed fires and crown fires, with each group decreasing its visitation rate. Hesseln et al. (2004) also found similar results when surveying hikers and mountain bikers in four national forests in western Montana. Differences in results between Loomis et al. (2001) and Hesseln et al. (2003, 2004) suggest that geographic variations may help to determine how recreation users react to fire. Another possible explanation could be socio-economic differences between the two samples.

In studying two hiking trails in the Cascade Mountains affected by a large scale forest fire (40,000 acres), Hilger and Englin (2009) found that, in the short term, the forest ecosystem affected by fire had an increase in visitation but trip values were largely unaffected. Englin et al. (2001) examined the long term dynamic path of recreation value following a forest fire in three different states: Colorado, Wyoming, and Idaho. Using the TCM the authors found that visitation increased for recent fire, followed by a 17 years decrease, and then rebounded for the remaining 8 years of their observation period. In a similar study by Boxall and Englin (2008) for canoeing in the Canadian Shield boreal forest, damages associated with a fire occurred immediately following a fire, but after 35 years of regrowth, the forest amenity values returned to pre-fire levels. The present study also considers how time since fire impacts visitation and values in a hiking context, while also controlling for other fire characteristics such as intensity and spatial characteristics of the burn.

1.4 Geographic Information Systems

Increased computing power has made GIS more accessible and useable in conjunction with nonmarket valuation methods to derive spatially explicit landscape values. For example, Eade and Moran (1996) developed an “economic value map” for the Rio Bravo Conservation Area in Belize using the benefit transfer method and GIS to spatially allocate ecosystem service values. Troy and Wilson (2006) used a similar approach to produce a map of ecosystem service flow values based on land cover types for three case studies. González-Cabán et al. (2003) estimate the effect of prescribed burning on deer harvest by using time-series data and GIS approaches with TCM and CVM. Additionally, Cavailhès et al. (2009) evaluated the landscape values and found land cover around houses has an effect on housing prices using GIS and HPM.

A highly relevant study for this dissertation is the GIS-based landscape valuation application by Baerenklau et al. (2010). The authors use recreation permit data and a zonal TCM to estimate the aggregate recreation values and spatially allocate that value to the landscape using GIS-based “viewshed” analysis. However, this technique used untested assumptions about perceptions of scenic quality that recreation permit data alone cannot validate. The web-based survey used in the present study is designed to provide the missing information that is needed to more rigorously allocate the wilderness recreation value across the landscape.

1.5 Study Objectives and Methods

The present study uses GIS tools and nonmarket valuation methods to obtain a spatial representation of recreation value for the entire San Jacinto Wilderness, San Bernardino National Forest, California. The research has three main objectives:

1.5.1 Objective 1-Estimate trailhead access values

Using TCM, the economic use values (trailhead access) are estimated and used to determine how changes in viewshed characteristics (due to fire intensity, percentage of area burn, and viewing distance) affect trip behavior. Data to estimate these values is collected through a web-based survey that was administered to participants visiting the San Jacinto Wilderness between June 2012 and September 2012.

1.5.2 Objective 2-Derive spatially explicit landscape values

The study by Baerenklau et al. (2010) used TCM and readily available data from recreation permits and census demographics to estimate wilderness access values. The authors also used a viewshed analysis technique to derive spatially explicit landscape values. However, this technique used untested assumptions about perceptions of scenic quality that recreation permit data alone cannot validate. The web-based survey used here provides the necessary information to spatially allocate the wilderness recreation value using a similar approach to Baerenklau et al. (2010). The estimated landscape values are compared to Baerenklau et al. (2010) to determine if using their simpler and less data-intensive (permit data) method yields appropriate welfare estimates.

1.5.3 Objective 3-Account for spatial sorting of visitors

Most recreation demand models neglect to account for the expected tendency of individuals to choose to live closer to things that they enjoy using, such as wilderness areas. As noted by Parsons (1991), this oversight can bias welfare estimates. Baerenklau (2010) implements a control for spatial sorting but finds a counter-intuitive result: the more enthusiastic backcountry hikers tend to live further from the wilderness, suggesting that wilderness proximity is valued for the other (non-recreation) benefits that it provides. The present study reexamines this question with a latent class KT demand model, estimated with the web-based survey data. The model is implemented to test the hypothesis that proximity to natural resources for purpose of recreation is not an important determinant of residential location in southern California.

1.6 Summary

This section discusses several studies on forest benefits and the impact fire has on recreation trips and benefits. In addition, there is a literature review of recent methods for combining GIS approaches and nonmarket valuation techniques to derive spatially explicit landscape values. The section concludes by discussing the study's objectives and explains how the research questions will be addressed.

The dissertation is organized as follow. Chapter 2 has a detailed description of the study site, design and implementation of the web-based survey (i.e., focus groups, pre-test survey, and sampling), survey instrument, and a summary of the dataset used in the recreation demand models. Chapter 3 describe the KT demand system model to estimate the factors that affect trip-taking decisions in the study area, introduce a procedure for forecasting demand, discuss empirical results, and provide a description on how the econometric modeling will inform the spatial allocation of recreation value. In chapter 4, I present an application of the Latent Class Kuhn Tucker (LCKT) model methodology (Kuriyama et al., 2010) used to account for the spatial sorting of individuals (Baerenklau, 2010). This chapter has a summary of the parameter and welfare estimates, test the hypothesis that individual who live closer to natural resources enjoy other amenities besides recreation activities (Baerenklau, 2010) and provide a discussion on policy implications. The final chapter summarizes the results, presents my conclusions, and provides recommendations for future research.

2. Survey Design

This section discusses the study site, the development of the survey instrument (i.e., focus groups and pre-tests), data collection, and summarizes the dataset. The focus group section addresses participants' reactions to questions regarding hypothetical burn scenarios, payment mechanisms, and attributes that make the San Jacinto Wilderness a desirable place to recreate. This section also discusses the fractional factorial design for the hypothetical burn scenario and data collection procedures (i.e., recruitment, participation incentives, and survey reminders). The chapter concludes by providing descriptive statistics on the variables used in the econometric models.

2.1 Study Site

This study focuses on backcountry hikers who visit the San Jacinto Wilderness Area, San Bernardino National Forest in southern California (figure 1.1)[3]. The wilderness covers 13,350 hectares and is located within a 2.5 hour drive from the highly urbanized Los Angeles, Orange, Riverside, San Bernardino, and San Diego counties. Elevations range from 1,800 to 3,300 meters. The wilderness area receives approximately 60,000 visitors annually; an additional 350,000 people visit Mt. San Jacinto State Park via the Palm Springs Aerial Tramway, but do not enter the backcountry (Baerenklau et al., 2010). In 2011, the number of people visiting the wilderness areas was 54,286, while the approximate annual number of visitors to Mt. San Jacinto State Park via the Palm Springs Aerial Tramway was 491,472 (Andrew Smith and Bart Grant, personal communication, USDA Forest Service and Mt. San Jacinto State Park Ranger, October 2013).

[3] Description is adapted from Baerenklau et al. (2010).

The wilderness area is regulated by both USDAFS and State Park. The most popular activity is day hiking. Recreationists enter the wilderness area via the tramway or by driving to the trailheads located in Long Valley and Idyllwild (figure 1.1). Recreationists entering the wilderness area must acquire a wilderness permit. The permits are free and are obtained at either the Idyllwild or Long Valley Ranger Station. Recreationists can also mail or fax the wilderness application to the Idyllwild Ranger Station. According to Forest Service estimates, the compliance rate is approximately 75% (Andrew Smith, personal communication, USDA Forest Service, October 2013). Thus barring any selection effects associated with those that submit permits versus that do not, we assume that sampling administered on recreationists that obtain a wilderness permit fairly represents the population of wilderness visitors.

2.2 Focus Group

To help develop and refine the survey instrument, three focus groups were conducted from October 2011 to March 2012. Focus groups participants were recruited from University of California, Riverside (UCR) Outdoor Excursions Club, Idyllwild residents, and residents from Riverside and San Bernardino counties. For the first focus group, UCR Outdoor Excursion Club, an e-mail invitation to participate in the focus group was sent to all members. For the Idyllwild residents focus group, recruitment flyers (figure 2.1) were left at Idyllwild Ranger Station, local grocery store, town hall, and other facilities frequently visited by residents. For Riverside and San Bernardino residents, recruitment flyers (figure 2.1) were left at several local sporting goods stores where you can purchase National Forest Adventure Pass.

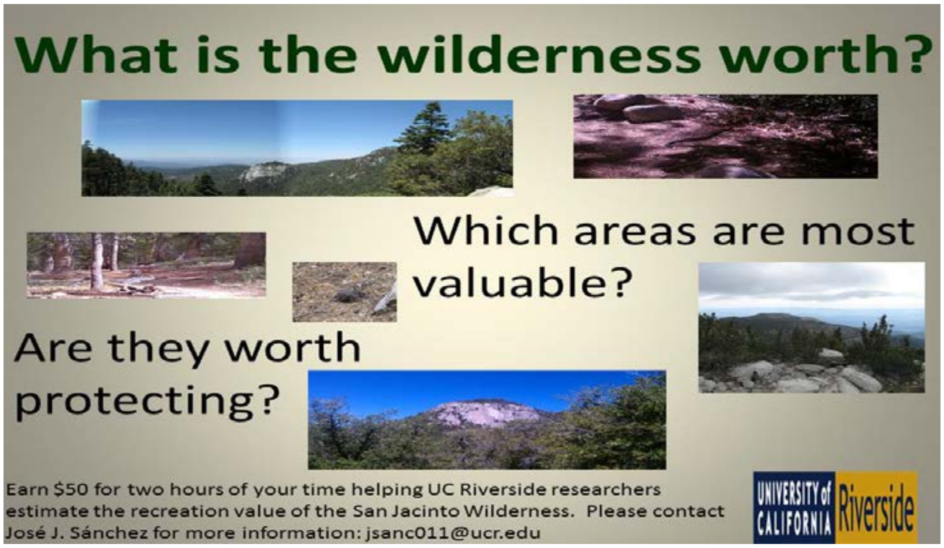

Figure 2.1— Focus group recruitment flyer

Two of the focus groups were conducted at the UCR campus and one at the Idyllwild Ranger Station. The focus groups addressed the following survey objectives:

1) Identify the most important features of the San Jacinto Wilderness
2) Determine the most effective way to visually and objectively depict burn scenarios
    a. Are digitized burn photos suitable for making decisions about the number of site visits?
    b. Compare digitized burn photos against actual burn photos with landscape characteristics similar to those of the San Jacinto Wilderness.
3) Determine the appropriate payment range for a hypothetical wilderness permit fee.
4) Develop survey questions

5) Refine the wording of the questions to remove ambiguity and misunderstanding (last focus group)

Focus group discussions were structured and conducted in a series of steps in order to elicit information regarding the objectives. For example, each focus group session was video recorded (responses were transcribed) and had 5 parts: 1) general knowledge of the wilderness (i.e., vegetation, wildlife, and trails), 2) recreation behavior (i.e., number of visits, trails/sites visited, and activities engage during visit), 3) protecting the wilderness (i.e., threats and cost), 4) implementation of a wilderness permit fee and 5) hypothetical scenarios. The focus groups lasted approximately 2 hours and had between four and seven participants with mixed characteristics in gender, age, and recreational experience. All focus groups participants had some knowledge of the San Jacinto Wilderness and were regular forest visitors. They emphasized the importance of protecting the wilderness for current and future use. Participants identified four important features of the wilderness for recreation: beautiful scenic views, variety of animal and plant species (biodiversity), isolation (serenity), and proximity to the city (being able to escape the city).

The information gathered from the initial two focus groups (UCR Outdoor Excursion group and Idyllwild residents) showed that participants preferred to view actual burn pictures rather than a digitized burn pictures. Participants mentioned that the colors of the digitized pictures made them look “cartoon like” and unrealistic. They also objected to the idea of implementing a payment mechanism (i.e., permit fee) for a wilderness permit. This was particularly true for the second focus group, Idyllwild residents. The participants mentioned that Idyllwild residents are already taxed too much to preserve the wilderness and non-residents should be responsible for the extra protection.

The information collected from the UCR Outdoor Excursion and Idyllwild resident focus groups served as a pilot study for the development of the survey instrument. The last focus group (Southern California residents) was given a survey draft to evaluate study design, clarity of wording, use of graphics (actual burn photos), range of values used for an increase in cost to visit the San Jacinto Wilderness, and completion time. They were also asked to consider if important issues were omitted or obscured in the survey instrument. Survey completion time was less than 20 minutes. The focus group did mention a few minor issues with the language in some of the questions and description of the burn pictures. For example, in the introduction to the survey, participants suggested to include the approximate time to complete the survey. For the activities question, participants believed bird watching must be added as an activity and bicycling must be removed because it is not allowed in the wilderness. For the trip expense question, participants felt that too much information was included and should be simplified by removing vehicle and equipment depreciation (e.g., vehicle depreciation and equipment rental fee or depreciation for taking the trip). Participants assisted in categorizing the burn photos into the middle ground and background viewing distance because they did not agree with the initial categorization. The changes were made before the pre-test survey was conducted.

2.3 Pre-test Survey

Revised versions of the survey were pre-tested (May and June 2012) on San Jacinto Wilderness visitors to evaluate whether or not respondents were answering questions in a sensible manner, verify that the web-based survey was working properly (i.e., survey link is active, pictures are loading correctly, responses were being stored correctly, etc.), and verify the time required to complete the survey (approximately 20 minutes). In the first pre-test, we were able to determine issues when selecting "other" as an option in the multiple choice questions. For example, in questions where "other" was selected by respondents, they were still required to select another multiple choice option. This was corrected before the second pre-test was administered. The average completion time was less than 15 minutes. There were no technical or survey issues in the second pre-test survey, but the participation rate were lower (20 participated in the first pre-test and 7 in the second pre-test). Therefore, to increase participation rate, the sampling procedure was modified to include an individual recruiter at each of the ranger stations to explain the research purpose, answer questions, and collect e-mail addresses of potential survey participants.

2.4 Sampling Design

Recreationists were recruited into the survey while obtaining their wilderness permits at the USDAFS Ranger Station in Idyllwild and the Mt. San Jacinto State Park Ranger Station in Long Valley during the summer months of June 2012 to September 2012. The recruitment flyer (figure 2.2) included the study objective, incentive information for participants who complete the survey, and the researcher's contact information. To decrease self-selection bias and increase response rate, a UCR undergraduate student was stationed at the Idyllwild Ranger Station on the weekends and once during the weekday during regular office hours (8am to 4pm).

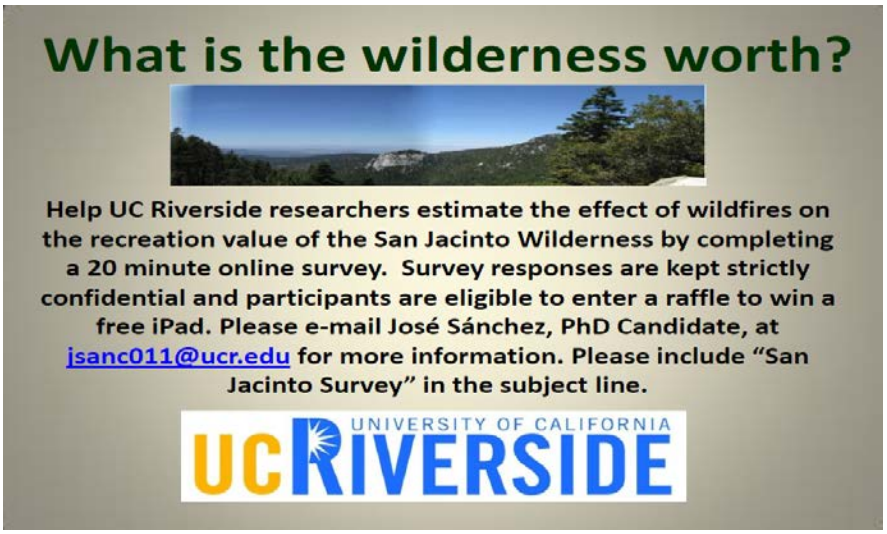

Figure 2.2— Recruitment flyer

The student approached the recreationists on their way into the Idyllwild Ranger Station. The student then introduced him or herself and provided a brief study description and incentives for participating in the study (see Appendix I for recruitment script). They collected e-mail addresses of recreationists that were interested in participating in the study and kept a count of the number of people that declined to participate. Collecting e-mail addresses allowed the researcher to send the survey link and friendly weekly e-mail reminders for those who had not completed the survey. The number of declined participant provided information necessary to compute the overall participation rate. A similar protocol was followed at the Long Valley Ranger Station, but a student was there only on the two highest visitation days, Friday and Saturday.

Across both ranger stations, a total of 37 days were sampled from the sampling frame: students recruited participants for 25 days at the Idyllwild Ranger Station and for 12 days at the Long Valley Ranger Station. As mentioned before, recruitment flyers were given every day to recreationists at both sites. For Long Valley, there also was a sign-up sheet inside the ranger station, but no additional participants signed-up.

The web-based survey was implemented using a modified Dillman (2007) approach. The researcher initially notified potential participants (those who provided an e-mail address when obtaining a wilderness permit, including both those intercepted by the students and those that were not) via e-mail that a survey link would be sent within a day by SurveyMonkey©[4], a web-based survey software and questionnaire tool. The e-mail sent by SurveyMonkey© included a unique link to the online survey and an opt-out option. Approximately one week after receiving the survey link, non-responders received a friendly e-mail reminder to complete the survey. The reminder included the link to the survey and incentive information for completing the survey. A final e-mail reminder was sent to non-responders approximately 3 weeks after the initial contact. The complete e-mail scripts can be seen in Appendix II. Non-responders were removed from the participation list one week after sending the second e-mail reminder.

Interested participants who did not provide their e-mail address when obtaining the wilderness permit received a flyer (figure 2.2) with the researcher's contact information. These recreationists e-mailed the researcher directly requesting the survey link (the number of participants who contacted the researcher was less than five percent). Within

[4] https://www.surveymonkey.com/

one day of receiving a participant's e-mail address, the researcher sent an e-mail thanking them for agreeing to participate. A survey from SurveyMonkey© followed shortly thereafter and e-mail reminders were sent following the same protocol described above.

All participants who completed the survey were entered into the iPad raffle. The raffle was conducted by generating a random uniform (0, 1) number for each survey participant. The person with the highest randomly generated number was selected as the winner. The lucky winner was contacted by e-mail; congratulating him and requesting his mailing address to mail the iPad (see Appendix III). The iPad was mailed within a week of receiving the mailing address.

2.5 Survey Instrument

The web-based survey mode has become popular for its advantages over other conventional survey modes. Two of its most visible advantages are its faster and lower-cost delivery and its ability to provide multimedia and/or interactive graphics (Berrens et al., 2003; Couper, 2000; Fricker and Schonlau, 2002). However, other potential methodological advantages (e.g., sampling, response rates, and data quality) remain unclear.

Web-based surveys present a problem in conducting random sample surveys. This increases the probability of having coverage or sampling error, because everyone in the target population (e.g., recreationists) might not be in the sampling frame, due to lack of internet access. Another problem is that currently there is no way to accurately obtain a random sample similar to telephone surveys (e.g., random digital dialing). This presents a major problem when results of web-based surveys are used to generalize about the target population; if the sample population does not represent the target population, results may be biased.

Given the advantage of faster delivery, lower cost, and superior graphics, the web-based survey was selected as the survey method. The web-based survey is divided into three sections (see Appendix IV for complete survey instrument)[5]. The first section elicits the recreation trip behavior, preferred forest characteristics, and cost-related information for the past 12 months. The second section elicits trip taking behavior for hypothetical burn scenarios[6] that contain five attributes of interest: percent of viewshed burned (25%, 50%, and 75%), intensity of fire (low, medium, and high), time since burn (0-5 years, 6-15 years, and more than 15 years), viewing distance (foreground, middle ground, and background), and trail affected by fire. In Idyllwild the four trails selected in the study are: Deer Springs, Devil's Slide, Marion Mountain, and South Ridge; in Long Valley there is one trail: Long Valley. The five trails were selected because they have the highest visitation rates based on 2005 data[7]. The final section of the survey collects demographics and personal information, including gender, ethnicity, age, education level, employment status and income. The income information was used to derive the travel cost variable and test the income effect in the econometric model.

There are a total of 405 (3^4x5) possible treatment combinations for the burn scenarios. A full factorial design was not implemented because higher order interactions

[5] There are nine different survey versions. Version 1 is shown here.
[6] Source of photos: S. Haase, Forest Service, http://www.azfirescape.org/catalina/photo_point_full_index?page=10, http://www.natgeocreative.com/ngs/, https://www.flickr.com/, and http://www.google.com/imghp
[7] Out of a total of 34,218 permitted visitors to the San Jacinto Wilderness, 33,194 visited the 5 trails (Baerenklau et al. 2010). Similar results were found using 2011 wilderness permit data.

are considered negligible and would require either a very large sample size or a large respondent burden to estimate. Instead, a fractional factorial design (Montgomery, 2005) was implemented. A D-efficient design of 100%, which contained 45 treatment combinations was selected for the fractional factorial design using the %*mktruns, %mktex*, and %*mkteval* programs in SAS statistical software (SAS Institute, 2010)[8].

Survey participants received a set of five burn pictures (one for each trail in the study) that represent the landscape of the San Jacinto Wilderness if a fire were to occur. For example, a hypothetical burn scenario would be represented by a picture of a recent low-intensity burn in the foreground that burned 50% of the viewable area along the Deer Springs trail (figure 2.3). Participants were asked to report how many trips would they have taken in the past 12 months to each of the 5 trails if the trail conditions changed as described in the survey. The fire conditions and trail affected changed from picture to picture. The question order for the five burn pictures was assigned randomly in each survey to elimate or reduce order effect (Dillman, 2007). The collection of responses to these hypothetical scenarios, along with cost information, forms the basis for demand and welfare analysis under different wildfire burn scenarios.

These data also is used for the spatial sorting of individuals and test the hypothesis that individual who live closer to natural resources enjoy other amenities besides recreation activities.

[8] 90 treatment combinations were also 100% D-efficient, but selected 45 due to the lower burden to respondents.

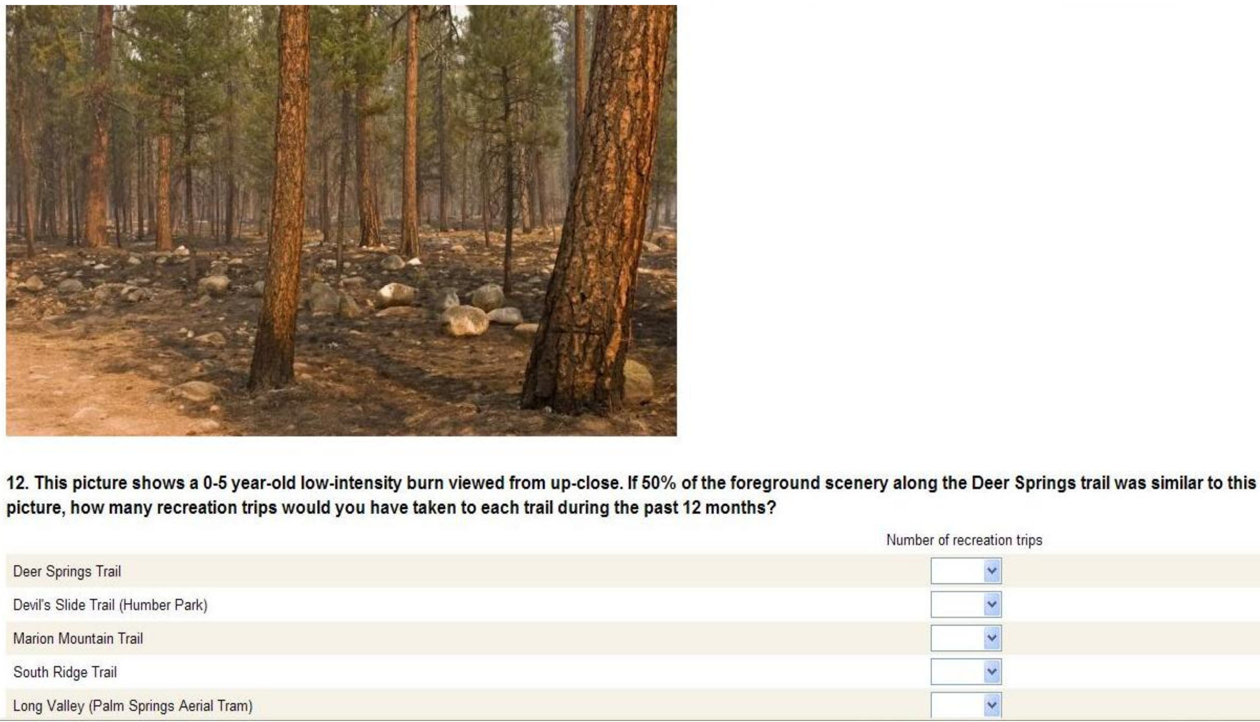

Figure 2.3— Web-based survey hypothetical burn scenario example

2.6 Data

The number of recreationists that were contacted to participate in the survey was 2,201. Of all the visitors that were contacted, 1,573 agreed to participate and provide an e-mail address. The final survey participants with valid e-mail addresses were 1,527. The overall participation rate, individuals that agreed to participate out of the total number contacted, was 71.5%. A total of 768 completed surveys were received, representing a response rate of 50.3%[9]. Observations with travel times greater than 3 hours or travel costs over $1000 were removed from the database, producing 698 surveys for analysis. After deleting the additional participants, the effective response rate is 46% (698/1527).

[9] Response rate is based on the total number of completed survey and the total number of valid e-mail addresses.

Descriptive statistics for respondent characteristics used in the empirical model are shown in table 2.1. All the sites have similar travel costs ($57 to $69 cost per trip) as expected. The travel costs are a function of distance (estimated from Google Maps) and the average per-mile cost of operating a typical car ($0.585/mile; AAA, 2012). Time costs are a function of travel time (estimated from Google maps) and the opportunity cost of time, which is assumed to be one-third of the respondent's average hourly income (Hagerty and Moeltner, 2005). Perhaps the most interesting statistics are the income, age and education variables (table 2.1). Visitors to the wilderness are high income earners ($87,235), relatively older (44)[10], and highly educated individuals (71% have at least a Bachelor's degree). Furthermore they take relatively few trips each year. Data on individual characteristics of wilderness visitors is not available. Therefore, the sample descriptive statistics can be compared to southern California residents, which consists of five counties (Los Angeles, Orange, Riverside, San Bernardino, and San Diego). Their median annual household income is $61,405, median age is 34, 37.7% are white, and 28% of the population has at least a bachelor's degree (U.S. Census Bureau, 2010).

[10] Median age is 45.

Table 2.1*—Descriptive statistics of survey responses for variables included in the econometric model specifications*

Variable	Description	Mean (std. dev.)
Trips_Dr	Trips to Deer Springs site	.61 (1.73)
Trips_Dv	Trips to Devil's Slide site	1.22 (3.53)
Trips_MM	Trips to Marion Mtn site	.24 (.62)
Trips_SR	Trips to South Ridge site	.37 (1.49)
Trips_LV	Trips to Long Valley site	2.42 (5.91)
TC_Dr	Per trip travel cost to Deer Springs	$57.28 (26.90)
TC_Dv	Per trip travel cost to Devil's Slide	$59.55 (27.29)
TC_MM	Per trip travel cost to Marion Mtn	$59.90 (26.89)
TC_SR	Per trip travel cost to South Ridge	$59.87 (27.36)
TC_LV	Per trip travel cost to Long Valley	$69.84 (23.76)
Age	Respondent's age	43.82 (12.59)
Degree (dummy variable)	Having at least a Bachelor's degree; if Yes = 1; else = 0	.71 (.45)
Employed (dummy variable)	Being employed in the past year; if Yes = 1; else = 0	.65(.48)
EnvGrp (dummy variable)	Belonging to an environmental group; if Yes = 1; else = 0	.21 (.41)
Gender (dummy variable)	Respondent's gender; Male =1 Female = 0	.58 (.49)
Minority (dummy variable)	*Being in a minority group if Yes=1; else=0*	*.10(.30)*
Income	Household annual income	$87,235 (46,930)
n = 698		

2.7 Summary

This research focuses on hikers that visit the San Jacinto Wilderness during the summer months. Focus groups and pre-tests were administered to develop and refine the web-based survey. The survey elicits the recreation trip behavior and cost-related information for the past 12 months, introduces hypothetical burn scenarios that change the current wilderness conditions, and collects demographic and personal information. When compared to the southern California residents, visitors to the wilderness are high income earners ($87,235), relatively older (45), and highly educated individuals (71% have at least a Bachelor's degree). The hypothetical burn scenario combinations were selected using an efficient fractional factorial design. The information collected from participant on past trips and hypothetical burn scenarios forms the basis for demand and welfare analysis.

3. Econometric Model

3.1 Introduction to the Kuhn-Tucker Model

The web-based survey produces individual consumption data for multiple trailheads located in the San Jacinto Wilderness under current and varying hypothetical fire conditions (refer to Section 2.5 for conditions). Trail-specific demand often equal to zero, a common feature of recreation demand data with multiple sites as many recreationists visit only a subset of sites. A Kuhn-Tucker (KT) model provides a theoretically consistent framework for estimating demand functions and welfare effects in a situation like this with multiple goods and corner solutions (i.e., zero consumption or no visits to a particular site). The KT model was initially developed by Hanemann (1978) and Wales and Woodland (1983). It can model simultaneous decisions on which sites to visit and how many trips to make to each site over the course of a season. The key feature of the KT model is that the corner solution for recreation data is handled in a theoretical consistent way (von Haefen et al. 2004).

In the past, KT models were not extensively used because of the computational difficulties associated with nonlinearity in the model. Closed-form solutions typically do not exist, requiring the use of Monte Carlo integration techniques (Phaneuf et al., 2000). Recent advancement in computing power has made it much more efficient to estimate the KT models. Phaneuf et al. (2000) and von Haefen et al. (2004) developed a method for estimating the expected welfare effects by compensating variation associated with hypothetical policy changes. This study uses the web-based survey data to implement a

KT model for a system of trailhead demands and compares the welfare results with traditional count data travel cost models.

3.2 Modeling Framework

In a KT demand model, the individual's direct utility function is $u(x, z; q, \varepsilon, \Gamma)$, where x is a vector of trips taken to each trailhead j, z (numeraire good) is spending on all other goods with price normalized to one, q is a vector of site characteristics, ε is random error term unknown to the researcher, but known to the individual, and Γ represents parameters of the utility function that are to be estimated. Individuals maximize utility over a season subject to their budget constraint (von Haefen and Phaneuf, 2005):

$$(3.1) \quad \max_{x,z} u(x, z; q, \varepsilon, \Gamma), \qquad s.t. \;\; y = z + xp, \qquad x_j \geq 0, j = 1, \ldots, M$$

where y is the annual income and p is the price (travel cost) of visiting each trailhead access point. If we assume that for equation 3.1, u is a quasi-concave, increasing, and continuously differentiable function of (x, z), the first-order KT conditions that implicitly define the solution to the optimal consumption bundle (x^*, z^*) are

$$(3.2) \quad \frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} \leq p_j, j = 1, \ldots, M,$$

$$(3.3) \quad x_j \times \left[\frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} - p_j \right] = 0, j = 1, \ldots, M.$$

von Haefen et al. (2005) explains these equations and shows that for each visited site, the marginal rate of substitution between trips and the numeraire is equal to the travel cost, while for an unvisited site, the marginal rate of substitution between trips and numeraire falls below the travel cost.

In general the Hicksian compensating surplus (CS^H) for a change in price and quality from baseline conditions p^0 and q^0 to new levels p^1 and q^1 can be defined implicitly using indirect utility functions:

(3.4) $V(p^0, y; q^0, \gamma, \varepsilon) = V(p^1, y - CS^H; q^1, \gamma, \varepsilon)$,

or explicitly using expenditure functions:

(3.5) $\mathrm{CS}^H = y - e(p^1, q^1, U^0, \gamma, \varepsilon)$,

where $U^0 = V(p^0, y; q^0, \gamma, \varepsilon)$.

The ε's in CS^H (equation 3.5) are unknown to the researcher, implying CS^H is a random variable. The ε's are drawn such that the model predicts the individual's revealed behavior perfectly under baseline conditions (von Haefen et al. 2004). The CS^H cannot be calculated precisely, but it can be estimated by the expected value, $E(CS^H)$. However, no close-form solution for $E(CS^H)$ exists. Therefore, computation of the welfare estimates must be done using Monte Carlo simulation techniques. In recent years, computational improvements have enabled researchers to estimate welfare measures as seen in Phaneuf et al. (2000) and von Haefen et al. (2004).

3.2.1 Empirical Specification

The KT modeling approach relies on the assumption that consumer preferences are additively separable $\left(i.e., U = \sum_j^M u_j\left(x_j\right) + u_z(z)\right)$. Therefore, the specific parameterization of the utility function employed is the following[11]:

$$(3.6) \quad U = \sum_{j=1}^{M} \Psi_j \, ln\left(\phi_j x_j + \theta\right) + \frac{1}{\rho} z^{\rho},$$

$$\Psi_j = exp\left(\delta' s + \varepsilon_j\right) \qquad j = 1, \ldots, M$$

$$\phi_j = exp\left(\gamma' q_j\right)$$

$$\rho = 1 - exp(\rho^*)$$

$$\mu = exp(\mu^*)$$

$$\theta = exp(\theta^*)$$

$$z = y - p'x$$

$$\varepsilon_j \sim EV(\mu)$$

where s is a vector of individual characteristics, $\delta, \gamma, \theta^*, \rho^*, and\ \mu^*$ are parameters that may vary randomly across individuals in the population to capture unobserved heterogeneity. The $\varepsilon_1, \ldots, \varepsilon_M$ represent additional unobserved heterogeneity that varies randomly across individuals and sites and it is assume each error term is an independent draw from the normalized type I extreme value distribution.

The additive separability assumption preference structure rules out a priori inferior goods and implies that all goods are Hicksian substitutes (von Haefen et al.,

[11] First suggested by Bockstael et al. (1986) and later modified by von Haefen et al. (2004).

2005). The authors further explain that for a cross section of outdoor recreationists the additive separability implies that on average, wealthier recreationists will take more trips to more sites. This assumption can be troubling for other applications, but for our study, it is plausible: wealthier individuals have more disposable income; therefore they can afford to take more trips. Also, additive separability implies that the marginal utility for each good is independent of all other goods. von Haefen et al. (2004) argue that the assumption does not allow marginal utility to decrease (or increase) with the increase in consumption of other goods.

In addition, equation 3.6 introduces quality through ϕ (repackaging parameter) and weak complementarity is satisfied for all parameter values $\left(\frac{\partial U}{\partial q_j} = 0, if\ x_j = 0, \forall j\right)$. This means that all value derived from the quality attributes arises exclusively from its use (von Haefen et al., 2004 and von Haefen, 2007).

3.2.2 Fixed Parameter Classical Estimation

Following Phaneuf et al. (2000), the advantage of using the utility function in equation 3.6 is that the implicit equation for ε can be solved using the KT conditions, yielding the following first-order conditions:

(3.7) $\varepsilon_j \leq g_j(x, y, p; q, \gamma),$

$x_j \geq 0, \qquad x_j\left[\varepsilon_j - g_j(x, y, p; q, \gamma)\right] = 0$

where $g_j(x, y, p; q, \gamma)$ is the solution to $\left[\frac{\frac{\partial U}{\partial x_j}}{\frac{\partial U}{\partial z}} - p_j\right] = 0$. If we assume the ε_j are independent and follows a type I extreme value distribution, then we can use equation 3.7 to derive the probability of observing an individual's trip-taking outcomes. Phaneuf and

Siderelis (2003) discuss that the probability that no trips are taken is $prob(x_j = 0) = prob(\varepsilon_j < g_j)$. The probability that x trips is taken is $prob(x_j = x) = prob(\varepsilon_j = g_j)$. Therefore, the likelihood of observing an individual's outcome x conditional on the structural parameters, $(\delta, \gamma, \theta^*, \rho^*, \mu^*)$, is (von Haefen et al., 2004):

$$(3.8) \quad L(x|\delta, \gamma, \theta^*, \rho^*, \mu^*) = |\mathbf{J}| \prod_j \left[exp\left(-g_j(\cdot)/\mu\right)/\mu\right]^{1_{x_j>0}} \times \ exp\left[-exp\left(-g_j(\cdot)/\mu\right)\right],$$

where $|\mathbf{J}|$ is the determinant of the Jacobian for the transformation from ε to (x_j, ε_j) and $1_{x_j>0}$ is an indicator function equal to one if x_j is strictly positive and zero otherwise.

3.2.3 Calculating Hicksian Consumer Surplus

As discuss previously, the ε's in CS^H are unknown to the researcher. Hence, we can only compute the expected value of CS^H. The ε's are drawn such that the model predicts the individual's revealed behavior perfectly under baseline conditions. Monte Carlo integration techniques are used to simulate the errors (unobserved heterogeneity) and CS^H is calculated conditional on each simulated value (von Haefen et al., 2004).

Phaneuf et al. (2000) developed the first method to solve for CS^H using the simulated unobserved heterogeneity. This has since been refined by von Haefen et al. (2004) to significantly reduce the computational burden. The iterative algorithm of von Haefen et al. (2004) numerically solves the consumer's constrained optimization problem using the numerical bisection routine. This method is a more efficient numerical algorithm because the approach requires that the analyst solves only one constrained minimization problem while other methods requires the analyst to solve a larger number of constrained maximization problems (von Haefen et al., 2005).

Following von Haefen et al. (2004), the KT conditions take the general form:

$$(3.9) \quad \frac{\partial u_j(x_j)}{\partial x_j} \leq \frac{\partial u_z(z)}{\partial z} p_j \quad \forall j,$$

$$(3.10) \quad x_j \left[\frac{\partial u_j(x_j)}{\partial x_j} - \frac{\partial u_z(z)}{\partial z} p_j \right] = 0 \quad \forall j,$$

$$(3.11) \quad x_j \geq 0 \quad \forall j,$$

$$(3.12) \quad z = y - \sum_j p_j x_j.$$

To solve the consumer's problem conditional on values for the exogenous variables and the simulated unobserved heterogeneity, von Haefen et al. (2004) develop the following numerical bisection algorithm:

1. At iteration i, set $z_a^i = \left(z_l^{i-1} + z_u^{i-1}\right)/2$. To initialize the algorithm, set $z_l^0 = 0$ and $z_u^0 = y$.
2. Conditional on z_a^i, solve for x_i using equations 3.9 to 3.11.
3. Use equation 3.12 and x_i to construct $\tilde{z}^i$.
4. If $\tilde{z}^i > z_a^i$ set $z_l^i = z_a^i$ and $z_u^i = z_u^{i-1}$. Otherwise, set $z_l^i = z_l^{i-1}$ and $z_u^i = z_a^i$.
5. Iterate until $abs\left(z_l^i - z_u^i \leq c\right)$, where c is arbitrarily small.

Figure 3.1 shows how the algorithm procedure works graphically.

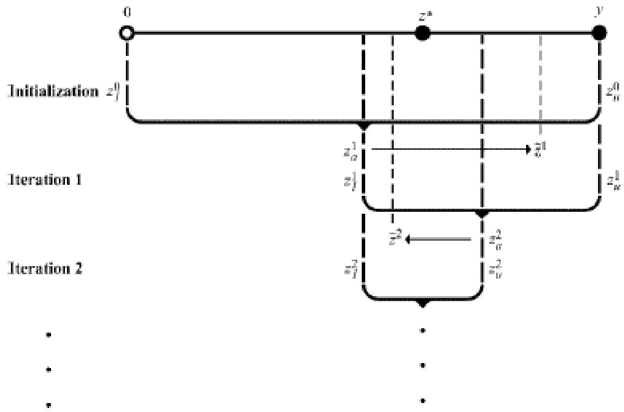

Figure 3.1— Solving the consumer's problem (von Haefen et al., 2004)

von Haefen et al. (2004) show that to solve for the unique solution on the consumer's problem, the algorithm relies on the strict concavity of the utility function. Substituting the optimal solution into equation 3.6 allows the researcher to evaluate the consumer's utility condition on (p, Q, y, ε).

3.3 Forecasting Procedure

3.3.1 Introduction

The algorithm of von Haefen et al. (2004) permits construction of welfare measures conditional on a set of unobserved heterogeneity values. Their approach simulate ε, the error terms such that at baseline conditions the model perfectly predicts the observed choices in the data. This differs from traditional methods that use the structure of the model, but not the error terms, to predict what individuals do at baseline conditions; such prediction is inherently imperfect. Therefore, a goodness of fit procedure was implemented to test and compared how well the KT model fits the observed data using both a traditional prediction method (simulating the entire distribution of unobserved heterogeneity) and conditional approach as suggested by von Haefen et al. (2004). A simple and efficient forecasting algorithm for a Multiple Discrete-Continuous Extreme Value model proposed by Pinjari and Bhat (2011) was modified for the KT model. The algorithm is non-iterative in nature and results in analytically expressible consumption quantities for the utility function form.

3.3.2 Model Structure

KT demand systems are based on resource allocation. The individual operates with a fixed amount of resources (i.e., time and money), and is assumed to allocate resources to consume various goods to maximize their utility.

Following closely the same derivations and procedure as Pinjari and Bhat (2011), consider the additively separable utility function mentioned previously (equation 3.6). The consumption-based utility function can be expressed in terms of expenditures (e_j) and prices (p_j) as[12]:

$$(3.13) \quad U(e) = \sum_{j=2}^{6} \Psi_j ln\left[\phi_j \frac{e_j}{p_j} + \theta\right] + \frac{1}{\rho}\left(\frac{e_1}{p_1}\right)^{\rho}, where\ \frac{e_1}{p_1} = z\ and\ \frac{e_j}{p_j} = x_j$$

The individual maximizes the random utility given above (by equation 3.6) subject to a linear budget constraint and non-negativity constraints on x_j:

$$y = z + \sum_{j=2}^{M} x_j p_j\ \ (where\ y\ is\ total\ budget)\ and\ x_j \geq 0\ \forall\ \mathrm{j}\ (j = 1,2, \ldots, M)$$

By forming the Lagrangian and applying the KT conditions, the optimal consumption levels can be derived. The following is the Lagrangian function:

[12] For the first alternative, $p_1 = 1$, since it is the "numeraire" good.

$$(3.14)\quad \mathcal{L} = \frac{1}{\rho}\left(\frac{e_1}{p_1}\right)^{\rho} + \sum_{j=2}^{M} \Psi_j ln\left(\phi_j \frac{e_j}{p_j} + \theta\right) - \lambda\left(\frac{e_1}{p_1} + \sum_{j=2}^{M} e_j - y\right),$$

where λ is the Lagrangian multiplier associated with the budget constraint. The KT first-order conditions for the optimal allocations $\left(e_j^*; j = 1,2, \dots, M\right)$ are given by:

$$(3.15)\quad \frac{\partial L}{\partial e_1} = \frac{1}{p_1}\left(\frac{e_1}{p_1}\right)^{\rho-1} - \frac{\lambda}{p_1} = 0, \quad e_1^* > 0.$$

$$(3.16)\quad \frac{\partial L}{\partial e_j} = \frac{\Psi_j}{\left(\phi_j \frac{e_j}{p_j} + \theta\right)}\left(\frac{\phi_j}{p_j}\right) - \lambda = 0, e_j^* > 0.$$

$$(3.17)\quad \frac{\partial L}{\partial e_j} = \frac{\Psi_j}{\left(\phi_j \frac{e_j}{p_j} + \theta\right)}\left(\frac{\phi_j}{p_j}\right) - \lambda < 0, \quad e_j^* = 0.$$

The KT conditions derived (equations 3.15-3.17) are used to derive the properties of the KT model that can be utilized to develop a highly efficient forecasting algorithm.

3.3.3 Model Properties

The properties and corollaries in this section are the same as Pinjari and Bhat (2011), but the proof of the properties differ to account for the additional parameters (i.e., repackaging ϕ and θ parameters) in the utility function (equation 3.6) used in this study. The ϕ parameter accounts for the site quality characteristics and θ parameter accounts for weak complementarity $\left(i.e., \frac{\partial U}{\partial q_j} = 0 \; if \; x_j = 0, \forall j, von\ Haefen\ et\ al., 2004\right)$.

Property 1: *The price-marginalized marginal utility*[13] *of a chosen good is always greater than that of a good that is not chosen.*

[13] Price-marginalized marginal utility is defined to be the marginal utility at zero consumption of a good.

$\frac{\Psi_i \phi_i}{\theta p_i} > \frac{\Psi_j \phi_j}{\theta p_j}$, if ‘i’ is a chosen good and ‘j’ is not a chosen good.

Proof: The KT conditions in equations 3.15 – 3.17 can be written as:

$$(3.18) \quad \lambda = \left(\frac{e_1^*}{p_1}\right)^{\rho-1}, e_1^* > 0.$$

$$(3.19) \quad \lambda = \frac{\Psi_j}{\left(\phi_j \frac{e_j^*}{p_j} + \theta\right)} \left(\frac{\phi_j}{p_j}\right), e_j^* > 0,$$

$$(j = 2, \ldots J)\ (i.e., for\ all\ chosen\ goods)$$

$$(3.20) \quad \lambda \geq \frac{1}{\theta}\left(\frac{\Psi_j \phi_j}{p_j}\right), \quad e_j^* = 0,$$

$$(j = 2, \ldots J)(i.e., for\ all\ goods\ that\ are\ not\ chosen)$$

The above KT conditions (equation 3.18 and 3.19) can further be rewritten as:

$$\left(\frac{e_1^*}{p_1}\right)^{\rho-1} = \frac{\Psi_j}{\left(\phi_j \frac{e_j^*}{p_j} + \theta\right)} \left(\frac{\phi_j}{p_j}\right)$$

$$\left(\frac{e_1^*}{p_1}\right)^{\rho-1} \left(\phi_j \frac{e_j^*}{p_j} + \theta\right) = \frac{\Psi_j \phi_j}{p_j}$$

$$\phi_j \frac{e_j^*}{p_j} \left(\frac{e_1^*}{p_1}\right)^{\rho-1} + \theta \left(\frac{e_1^*}{p_1}\right)^{\rho-1} = \frac{\Psi_j \phi_j}{p_j}$$

$$\frac{\phi_j}{\theta} \frac{e_j^*}{p_j} \left(\frac{e_1^*}{p_1}\right)^{\rho-1} + \left(\frac{e_1^*}{p_1}\right)^{\rho-1} = \frac{\Psi_j \phi_j}{p_j \theta}$$

$$(3.21) \quad \frac{\Psi_j \phi_j}{p_j \theta} = \left(\frac{e_1^*}{p_1}\right)^{\rho-1} \left(\frac{\phi_j}{\theta} \frac{e_j^*}{p_j} + 1\right), e_j^* > 0, (j = 2, \ldots J)$$

$$(3.22) \quad \frac{\Psi_j \phi_j}{p_j \theta} < \left(\frac{e_1^*}{p_1}\right)^{\rho-1}, e_j^* = 0, (j = 2, \ldots J)$$

Following Pinjari and Bhat (2011), consider two alternatives 'i' and 'j', where 'i' represents the chosen good and 'j' is not the chosen good by an individual. Therefore for that individual, the KT conditions for alternative 'i' and 'j' can be written as:

$$(3.23)\qquad \frac{\Psi_i \phi_i}{p_i \theta} = \left(\frac{e_1^*}{p_1}\right)^{\rho-1} \left(\frac{\phi_i}{\theta}\frac{e_i^*}{p_i} + 1\right), and$$

$$(3.24)\qquad \frac{\Psi_j \phi_j}{p_j \theta} < \left(\frac{e_1^*}{p_1}\right)^{\rho-1}$$

Further, since $\left(\frac{\phi_j}{\theta}\frac{e_j^*}{p_j} + 1\right)$ is always greater than 1, one can write the following inequality:

$$(3.25)\qquad \frac{\Psi_j \phi_j}{p_j \theta} < \left(\frac{e_1^*}{p_1}\right)^{\rho-1} < \left(\frac{\phi_i}{\theta}\frac{e_i^*}{p_i} + 1\right)\left(\frac{e_1^*}{p_1}\right)^{\rho-1}$$

The second term is λ and the third term is $\frac{\Psi_i \phi_i}{p_i \theta}$. We can rewrite the inequality in equation 3.25 as:

$$(3.26)\qquad \frac{\Psi_j \phi_j}{p_j \theta} < \lambda < \frac{\Psi_i \phi_i}{p_i \theta}$$

By the transitive property of inequality of real numbers, the above inequality implies that $\frac{\Psi_i \phi_i}{p_i \theta} > \frac{\Psi_j \phi_j}{p_j \theta}$. Therefore, the price-marginalized marginal utility of a chosen good is always greater than that of a good that is not chosen.

Corollary 1.1: *It naturally follows from the property above that when all the J alternatives/goods available to a consumer are arranged in a descending order of their price-marginalized marginal utility at zero consumption (with the outside good being the first in the order), and if it is known that the number of chosen alternatives is M, then one can easily identify the chosen alternatives as the first M alternatives in the arrangement.*

Corollary 1.2: *The Lagrange multiplier of the consumer's utility maximization problem (i.e., the marginal utility at optimal consumption) is always greater than the price-marginalized marginal utility of any not-chosen good, but less than that of any chosen good. It naturally follows from this property that λ is greater than the highest price-marginalized marginal baseline utility among the not-chosen goods, but less than the lowest price-marginalized marginal baseline utility among the chosen goods.*

Property 2: *The minimum consumption of the outside good is* $\left(max_{\forall j=(2,3,\ldots J)} \frac{\Psi_j \phi_j}{p_j \theta}\right)^{\frac{1}{\rho-1}}$

Proof: Using KT conditions, equations 3.15 and 3.17, and considering market baskets that involve only the consumption of the outside good $\left(i.e., e_j^* = 0, \forall j > 1\right)$. One can write the following:

$$(3.27) \qquad \frac{\Psi_j \phi_j}{p_j \theta} < \left(\frac{e_1^*}{p_1}\right)^{\rho-1}, \forall j = (2,3, \ldots J),$$

$$or \;\; max_{\forall j=(2,3,\ldots J)} \left(\frac{\Psi_j \phi_j}{p_j \theta}\right) < \left(\frac{e_1^*}{p_1}\right)^{\rho-1}.$$

Hence, $\frac{e_1^*}{p_1} > \left(max_{\forall j=(2,3,\ldots J)} \frac{\Psi_j \phi_j}{p_j \theta}\right)^{\frac{1}{\rho-1}}$

The right side of the above equation represents the "minimum" amount of consumption of the outside good. This means that after the "minimum" amount of outside good is consumed, all other goods (and the outside good) start competing for the remaining amount of the budget. Therefore, if the budget amount is less than that corresponding to the minimum consumption of the outside good in equation 3.27, no other good will be consumed.

Property 3: *When all the satiation parameters[14] are equal, and if the corner solutions (or discrete choices) are known (i.e., if the chosen and non-chosen alternatives are known), the continuous optimal consumption choices of the chosen goods can be expressed in an analytic form.*

Proof[15]: Using the 1st and 2nd KT conditions in equations 3.15 to 3.17 and assuming without loss of generality that the first M goods are chosen, the optimal consumptions can be express as follows:

$$(3.28) \qquad \frac{e_1^*}{p_1} = (p_1\lambda)^{\frac{1}{\rho-1}}, and$$

$$(3.29) \qquad \frac{e_j^*}{p_j} = \frac{\Psi_j}{\lambda p_j} - \frac{\theta}{\phi_j}; \forall \mathrm{j} = (2,3,\ldots,M)$$

Using these expressions, the budget constraint can be written as follows:

$$(3.30) \qquad E = \frac{e_1}{p_1} + \sum_{j=2}^{6} p_j \left(\frac{\Psi_j}{\lambda p_j} - \frac{\theta}{\phi_j}\right)$$

These properties and corollaries help develop an efficient forecasting procedure that is explained in the next section.

3.3.4 Forecasting Algorithm

The KT parameter estimates must be assessed to determine how well they fit the data. To accomplish this, the non-iterative forecasting algorithm developed by Pinjari and Bhat (2011) was modified using the utility function (equation 3.6) described above. Following closely Pinjari and Bhat (2011), let $\hat{\lambda}$ and $\hat{E}$ be estimates of λ (the Lagrange multiplier)

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[14] The utility function (equation 3.6) used in this study assumes satiation parameter = 1.
[15] This is a known property of KT demand model systems (Pinjari and Bhat, 2010). Proof is provided for completeness.

and E (the budget), respectively, and let $\delta_\lambda$and $\delta_E$be the tolerance values (for estimating lambda and E, respectively), which can be as small as desired[16]. Let $\hat{\lambda}_L$ and $\hat{\lambda}_U$ be the lower and upper bounds of λ. Based on the budget constraint, define $\hat{E}$ (the estimate of E) as a function of $\hat{\lambda}$ (estimate of λ) as below (as shown above, equation 3.30):

$$\hat{E} = \frac{e_1}{p_1} + \sum_{j=2}^{M} p_j \left(\frac{\Psi_j}{\hat{\lambda} p_j} - \frac{\theta}{\phi_j}\right).$$

The algorithm procedure (Pinjari and Bhat 2011) is:

Step 0: Assume that only the outside good is chosen and let the number of chosen goods M=1.

Step 1: Compute the price-marginalized marginal utility values for all j alternatives:

$$MU_j = \frac{\Psi_j \phi_j}{\theta p_j}$$

Outside good[17]= $\left(\frac{e_1}{p_1}\right)^{\rho - 1}$

Arrange all the j alternatives available to the consumer in a descending order of their price-marginalized marginal utility values (with the outside good in the first place).

Step 2: Let $\hat{\lambda} = MU_{M+1} = \frac{\Psi_{M+1}\phi_{M+1}}{p_{M+1}\theta}$, the price-marginalized marginal utility of the alternative in position M+1.

Substitute $\hat{\lambda}$ into the estimated budget amount $\hat{E}$:

$$\hat{E} = \frac{e_1}{p_1} + \sum_{j=2}^{M} p_j \left(\frac{\Psi_j}{\hat{\lambda} p_j} - \frac{\theta}{\phi_j}\right)$$

[16] The tolerance value must be small to allow for convergence to a solution.
[17] This is based on the KT condition for the outside good being consumed (see equation 3.18).

Step 3: If $\hat{E} < E$:

Go to step 4.

Else, if $\hat{E} > E$

$\lambda_L = MU_{M+1}$ and $\lambda_U = MU_M$ (because $MU_{M+1} < \lambda < MU_M$)

Go to step 5 to estimate λ via numerical bisection.

Step 4: M = M +1.

If M < j

Go to step 2.

Else, if M = j

$\lambda_L = 0$ and $\lambda_U = MU_j$ (because $0 < \lambda < MU_j$)

Go to step 5 to estimate λ via numerical bisection.

Step 5: Step 5.1: Let $\hat{\lambda} = \frac{(\lambda_L + \lambda_U)}{2}$ and estimate $\hat{E}$ of E.

Step 5.2: If $(|\lambda_L - \lambda_U| \leq \delta_\lambda)$

Go to step 6.

Else, if $\hat{E} < E$

Update the upper bound of λ as $\lambda_U = \frac{(\lambda_L + \lambda_U)}{2}$, and go to Step 5.1

Else, if $\hat{E} > E$

Update the lower bound of λ as $\lambda_L = \frac{(\lambda_L + \lambda_U)}{2}$, and go to Step 5.1

Step 6: Compute the optimal consumption of the first M alternatives in the above descending order using

$$x_j^* = \frac{e_j}{p_j} = \frac{\Psi_j}{\lambda p_j} - \frac{\theta}{\phi_j}$$

Set the consumptions of other alternatives to zero and stop.

This forecasting algorithm forecasts the number of trips taken to each destination conditional on the parameter estimates derived from the maximum likelihood routine described in Section 3.2. A comparison of observed and forecasted values can then be conducted to measure the goodness of fit of the model.

3.3.5 Empirical Illustration-Results

In this section I present the KT model parameters estimates described in Section 3.2. In the first section I present parameter estimates for three different data sets: (1) revealed preference estimates using trailheads as sites; (2) revealed preference estimates using trailhead/destination combinations as sites; and (3) combined revealed/stated preference data (i.e., hypothetical burn scenarios) using trailheads as sites. In the second section the welfare estimates are presented using the same modeling approach for the 3 different data sets. All the data sets are based on day-use recreation. Lastly, I present maps that represent the spatial allocation of value for the landscape using each of the first two approaches.

3.3.5.1 Parameter Estimates

The three data sets have the same information on individual characteristics, but differ in the number of sites in the model. In the first analysis, revealed preference estimates using trailheads as sites, the data set has information on the number of trips taken in the past 12 months to each of the 5 sites selected in the survey. There are more trailheads in the San Jacinto Wilderness, but only 5 sites were selected because they have the highest visitation rates (97% of all visits are taken to the 5 trailheads selected). In the second analysis, revealed preference estimates using trailhead/destination combinations as sites, the data included the number of trips taken in the past 12 months to each of the 20 trailhead/destinations combinations. To specify the hiking routes in this model, I assume that the average recreationist can hike for 8 miles in a day (limited the destination choices to 8 miles from trailhead) and that the entry and exit trailheads are the same. I also exclude certain hiking routes based on information obtained from the Idyllwild Ranger[18] station. A total of 20 allowable hiking routes were established out of more than 40 possible hiking routes. The final analysis, combined revealed/stated preference data, included information on the number of trips taken in the past 12 months to each site based on current conditions (revealed preference data) and the number of trips they would have taken if the trail conditions changed due to a hypothetical fire (stated preference data). Hypothetical fire descriptions are found in Section 2.5.

Table 3.1 contains estimates for the fixed parameter model using revealed preference data on trips taken to each trailhead in the past 12 months. In the Ψ matrix (individual characteristics), being male and belonging to an environmental group increases trips to each trailhead, while trips decrease as age increases. The signs of the statistically significant estimates are intuitive: environmental friendly individuals visit the wilderness more often than non-environmental friendly individuals and relatively older individuals take fewer trips. The remaining estimates, including minority status,

[18] The Idyllwild District Ranger provided a list of highly unlikely hiking routes for an average recreationist, given the difficulty, trail distance, and better alternative trail that leads to the same destination.

having at least a bachelor's degree and being employed full-time, are not statistically significant.

Table 3.1— *Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead (trailhead only).*

Parameter	**Model**		
	Estimate	**Std. Err.**	**t-statistics**
Ψ Index parameters			
Constant	-1.2323*	.6574	-1.8745
Gender	0.4180***	.0818	5.1126
Age	-0.0125***	.0035	-3.5565
EnvGrp	0.2387***	.0898	2.6574
Minority	0.0672	.1393	0.4827
Degree	0.0035	.0953	0.0366
Employed	0.0294	.0904	0.3252
Translating parameter			
Θ	0.2727	90.5099	0.0030
Φ *parameters*			
Constant	-0.2727	90.5099	-0.0030
Devil's Slide Dummy	0.3385***	.0765	4.4269
Marion Mtn Dummy	-0.3688***	.0884	-4.1743
S. Ridge Dummy	-0.2801***	.0866	-3.2334
Long Valley Dummy	0.8404***	.0756	11.1093
Rho parameter			
ρ	-0.9044***	.1538	-5.8806
Type I extreme value scale parameter			
μ	-0.0224	.0264	-0.8489
Log-likelihood	-4524.0583		

Note: * indicates significance difference from zero at the 0.10 level, *** indicates significance difference from zero at the 0.01 level.

In the web-based survey, no site characteristics variables were collected. To implement the model and capture individual preferences for site characteristics, we need both individual (Ψ matrix) and site characteristics (Φ matrix) information. Having no site characteristics data, the site-specific (trailhead) dummy variables were used in the Φ matrix instead of the Ψ matrix (except for revealed and stated preference analysis)[19]. Using the dummy variables in the Φ matrix is appropriate because these variables account for the distinct features of each site: elevation gain, vegetation (chaparral at

[19] In the revealed and stated preference analysis, site characteristics data is available. Therefore, the site-specific dummy variables are located in the ψ matrix as suggested by von Haefen et al. (2004).

lower elevations and Yellow and Ponderosa pine at higher elevations), panoramic views, trail distance and hiking difficulty. The Φ parameter estimates effectively demonstrate the popularity of the trails and have magnitudes that are consistent with the visitation data shown in table 3.2.

Table 3.2—*Total San Jacinto wilderness visitors (2011)*

Trailhead	**Visitors**
Deer Springs	6,271
Devil's Slide	12,362
Marion Mtn	2,325
South Ridge	2,118
Long Valley	32,163
Total	55,239

Table 3.3 contains estimates for the fixed parameter model using revealed preference data and trailhead/destination route combinations. The results show that the Ψ parameters, being male, belonging to an environmental group, and having at least a bachelor's degree increases visitation to each hiking route. The results are consistent with Baerenklau et al. (2010) who find that males and college graduates exhibit greater demand for hiking trips in this same study area.

Table 3.3— *Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead (trailhead/destination route combinations).*

Parameter	**Model**		
	Estimate	**Std. Err.**	**t-statistics**
Ψ Index parameters			
Constant	-2.2533***	.4948	-4.5539
Gender	0.5069***	.0581	8.7251
Age	-0.0019	.0026	-0.7359
EnvGrp	0.3065***	.0594	5.1624
Minority	0.1031	.0994	1.0381
Degree	0.1464**	.0678	2.1604
Employed	0.0777	.0634	1.2264
Translating parameter			
Θ	.8331	73.9048	0.0112
Φ *parameters*			
Constant	-0.8311	73.9059	-0.0112
Deer to Saddle	-0.6869***	.1945	-3.5323
Devil's to Peak	-0.1503	.1770	-0.8491
Devil's to Saddle	1.5630***	.1232	12.6876
Devil's to Tahquitz Valley	0.6801***	.1375	4.9450
Devil's to Skunk	1.0513***	.1305	8.0534
Devil's to Fire Lookout	0.7931***	.1336	5.9346
Devil's to Round Valley	-0.2336	.1835	-1.2728
Devil's to Hidden Valley	-1.2328***	.2900	-4.2505
Marion Mtn to Peak	0.7009***	.1389	5.0457
Marion Mtn to Little RV	0.6629***	.1420	4.4289
S. Ridge to Saddle	0.1499	.1605	0.9337
S. Ridge to Tahquitz Valley	0.4117***	.1490	2.7640
S. Ridge to Skunk	0.1221	.1620	0.7535
S. Ridge to Fire Lookout	0.8695***	.1337	6.5032
Long Valley to Peak	1.8351***	.1225	14.9801
Long Valley to Little RV	1.3241***	.1313	10.0878
Long Valley to Tamarack	1.1046***	.1363	8.1023
Long Valley to Hidden Valley	1.0824***	.1374	7.8760
Long Valley to Round Valley	1.8884***	.1235	15.2962
Rho parameter			
ρ	-.9243***	.1158	-7.9791
Type I extreme value scale parameter			
μ	-0.1414***	.0219	-6.4523
Log-likelihood	-26597.82		

Note: ** indicates significance difference from zero at the 0.05 level, *** indicates significance difference from zero at the 0.01 level.

In the Φ parameters, recreationists prefer all of the Long Valley and Marion Mountain hiking routes, four of the Devil's Slide routes, and two of the S. Ridge routes. The signs of the results are expected: Long Valley and Devil's Slide trails are the most popular, while hiking from Deer Spring to Saddle and Deer Spring or Devil's Slide to Peak is extremely difficult for the average recreationist (approximately 9.2, 8.2, and 8.0 miles, respectively). The results are consistent with 2011 California State Park data, where San Jacinto Peak and Round Valley are the most popular destinations. See table 3.4 for number of visitors to each destination[20].

Table 3.4*—Total San Jacinto wilderness destination visitors (2011)*

Destination	**Visitors**
San Jacinto Peak	9,297
Round Valley	6,862
Round Valley Loop	6,346
Hidden Valley	280
Tamarack	257

Table 3.5 contains estimates for the fixed parameter model using revealed and stated preference data. The individual characteristics that increases visitation to each site are being male, belonging to an environmental group, being a minority, and being employed. As age increases, the number of visits decreases. The popular sites are Devil’s Slide and Long Valley, while Deer Springs, Marion Mountain, and South Ridge are the least popular sites. The fire characteristics (Φ parameters) that are preferred by visitors are recent, foreground fires, while fire intensity and percent of viewshed burn has no statistical influence in preference. This means that recreationists will prefer visiting sites with a recent foreground fire. Considering the time since fire variable, the effect of a burn on visitation remains positive, but decreases through time. One possible reason for this is the curiosity factor: the San Jacinto Wilderness has not burned in over 30 years, and recreationists may want to experience burned trails surroundings immediately

[20] Information on destination for Idyllwild sites is not available. Forest Service does not collect information on destination, only entry and exit trailhead.

following a fire. This effect seems to be the result of the novelty of experiencing a fire-effected ecosystem. The recent burn ecosystem is more different from baseline conditions than older burn and recreationists value such novel experience.

Table 3.5— *Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead (revealed and stated preference data).*

Parameter	**Model**		
	Estimate	**Std. Err.**	**t-statistics**
Ψ Index parameters			
Constant	-0.4626**	.2347	-1.9712
Gender	0.4114***	.0306	13.4510
Age	-0.0179***	.0013	-14.0810
EnvGrp	0.0980***	.0358	2.7334
Minority	0.3664***	.0450	8.1436
Degree	-0.0133	.0344	-0.3871
Employed	0.1272***	.0346	3.6807
Deer Springs Dummy	-0.1333*	.0740	-1.8016
Devil’s Slide Dummy	0.2233***	.0724	3.0832
Marion Mtn Dummy	-0.6358***	.0900	-7.0641
S. Ridge Dummy	-0.5103***	.0869	-5.8728
Long Valley Dummy	0.9970***	.0673	14.8191
Translating parameter			
Θ	-0.0338	.0220	-1.5343
Φ parameters			
Time	-0.0095***	.0011	-8.4151
% Burn	-0.0003	.1314	-0.0023
Foreground	0.2506***	.0949	2.6397
Middle ground	0.0703	.0982	0.7153
Background	0.1386	.0972	1.4263
Fire Intensity	-0.0026	.0107	-0.2392
Rho parameter			
ρ	-1.0857***	.0672	-16.1484
Type I extreme value scale parameter			
μ	0.0985***	.0098	10.0004
Log-likelihood	-31382.70		

Note: * indicates significance difference from zero at the 0.10 level, ** indicates significance difference from zero at the 0.05 level, *** indicates significance difference from zero at the 0.01 level.

We expected the visitation rates to decrease following a fire due to a degradation of site quality and a slow increase as attributes returned to pre-fire conditions. Even though these results were not expected, the results are consisted with previous studies (Englin et al., 2001 and Hilger and Englin, 2009) who find an increase in visitation after recent fires. Furthermore, our results suggest positive but declining visitation rate over time, are consistent with Englin et al. (2001) where they find that visitation rates start to increase one to two years following a fire, then a slow decrease for the next 17 years.

In the three analyses, the popularity of the sites are consistent and agree with the visitation data: Devil's Slide and Long Valley are the most popular sites to visit. The individual characteristics that influence the number of trips in all the analyses are being male and belonging to an environmental group, which have a positive effect on the number of trips while age has a negative effect.

3.3.5.2 Forecasting: Goodness of Fit

The forecasting analysis was implemented to test and compare the goodness of fit of the KT model for the traditional and conditional approaches using the KT parameter estimates (table 3.1). Comparisons between actual and predicted trips were done using the average number of trips to each trailhead (tables 3.6 and 3.7) and simple regression analyses (figures 3.2 and 3.3)[21].

Table 3.6*—Predicted (using conditional approach) and observed trips to San Jacinto wilderness.*

	Predicted		Observed	
Trail	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Deer Springs	0.5899	1.7171	0.6132	1.7323
Devil's Slide	1.2139	3.5353	1.2206	3.5342
Marion Mtn	0.2279	0.6024	0.2378	0.6207
South Ridge	0.3853	1.4981	0.3725	1.4860
Long Valley	2.4433	5.8207	2.4226	5.8128

Table 3.7*—Predicted (using unconditional approach) and observed trips to San Jacinto wilderness.*

	Predicted		Observed	
Trail	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Deer Springs	1.0207	3.1094	0.6132	1.7323
Devil's Slide	1.2827	2.7599	1.2206	3.5342
Marion Mtn	0.2725	0.9744	0.2378	0.6207
South Ridge	0.5535	2.5342	0.3725	1.4860
Long Valley	2.0444	4.6733	2.4226	5.8128

[21] Similar results were found for the different modeling structures.

The results demonstrate that using the conditional approach in the forecasting procedure produces predicted trips that are very similar to the observed trips. Using the unconditional approach also produces acceptable results overall (table 3.7) but also exhibits much more variability than does the unconditional approach (figure 3.3). Regardless the unconditional approach performs better than von Haefen et al. (2003), who examine recreation data and find persistent overprediction of predicted trips when using continuous and count data models.

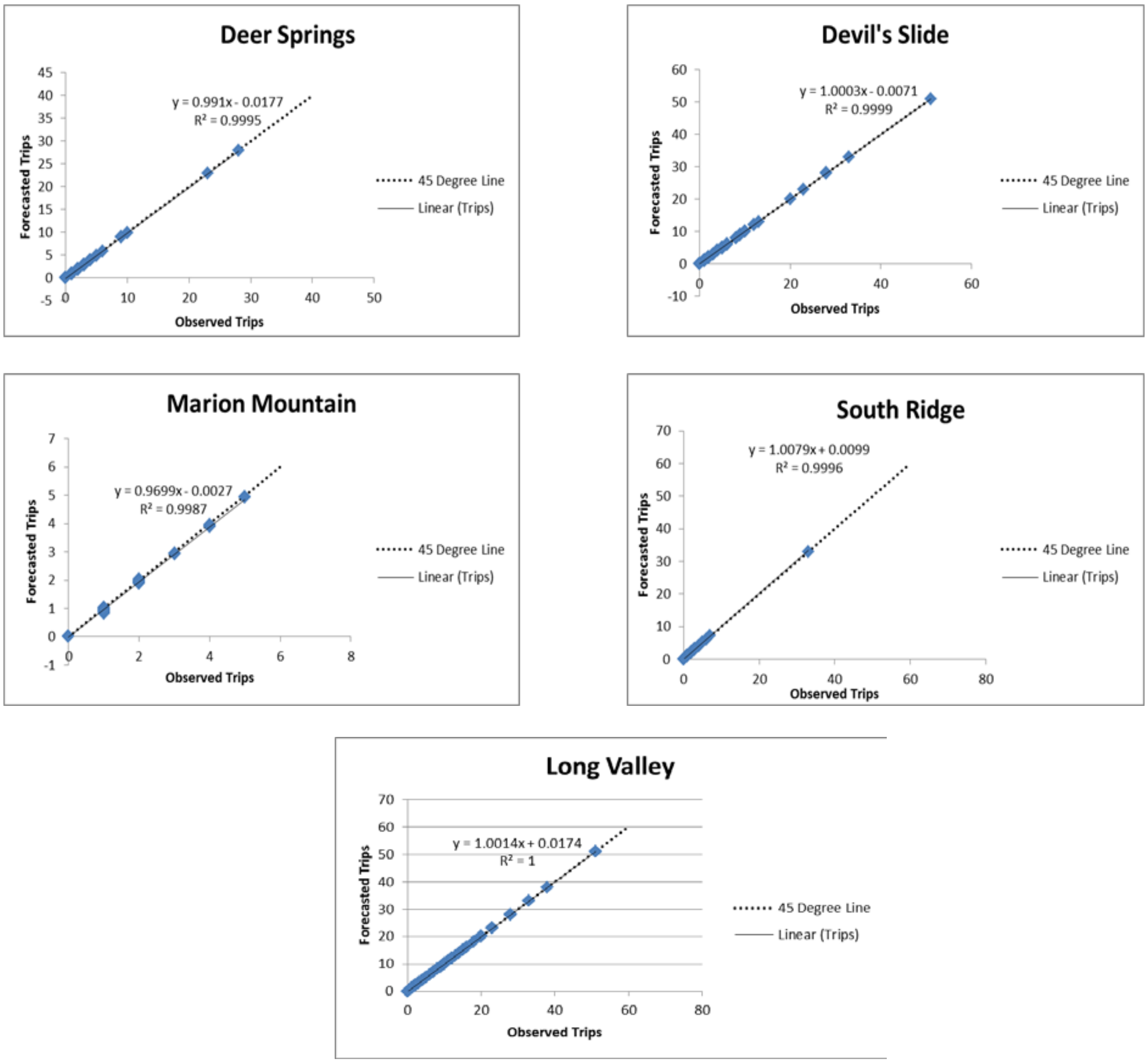

Figure 3.2—Regression using conditional approach

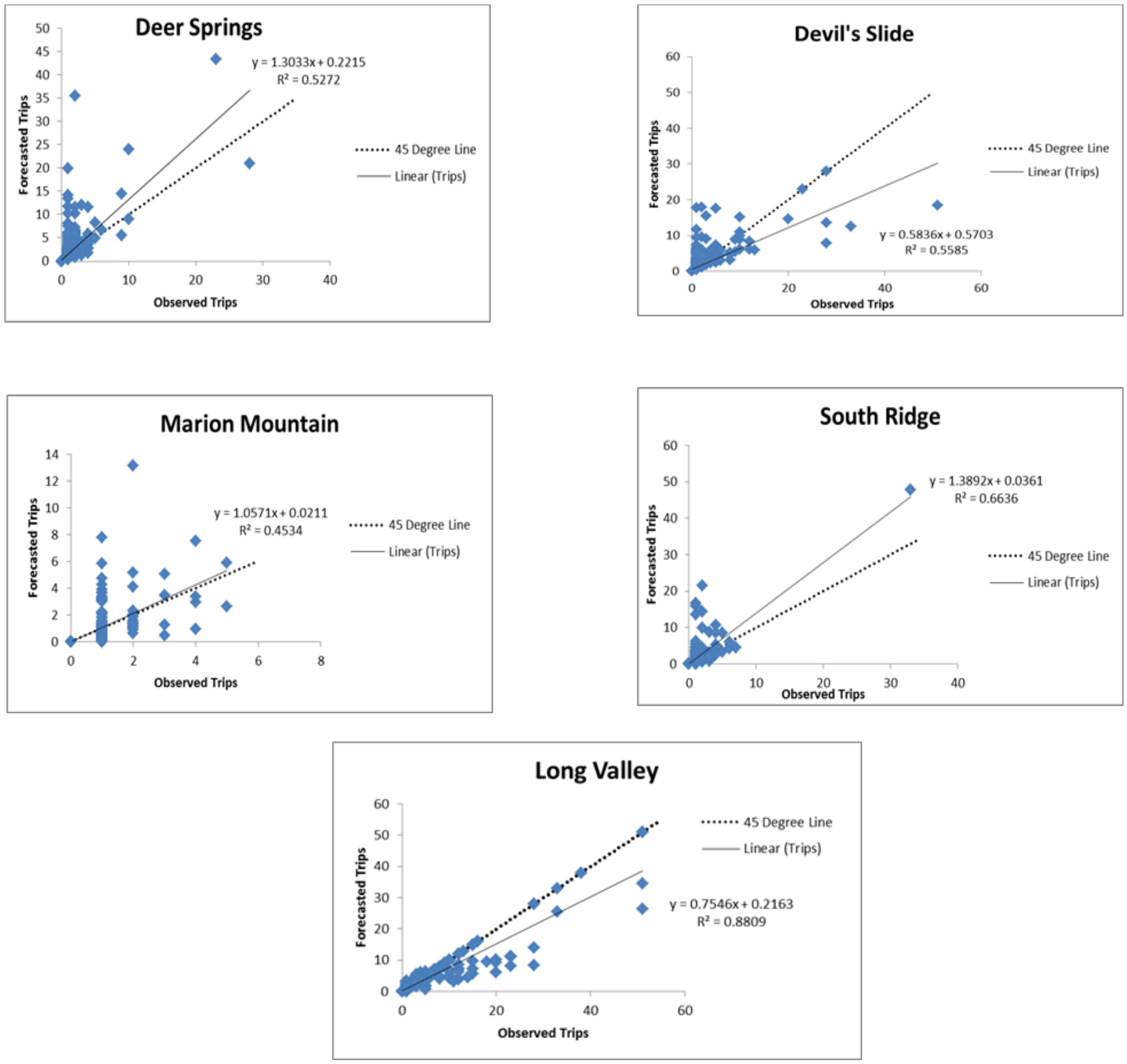

Figure 3.3— Regression using unconditional approach

3.3.5.3 Welfare Analysis

One of the drawbacks of using the conditional approach is that the estimated models cannot be applied to data outside the estimation sample (e.g. hypothetical conditions) since it is impossible to derive the appropriate conditional distributions for such data without also observing trip taking behavior. The welfare effects of site closures can be treated as either in-sample our out-of-sample forecasting problems. In-sample forecasting involves assuming that all conditions facing recreationists were the same—including the unobserved shocks that appear in the error terms—aside from the site closure. This is a reasonable assumption for purposes of welfare estimation and is consistent with the approach taken by von Haefen et al. (2004), so I adopt it here.

The first analysis uses the parameter estimates from table 3.1 (revealed preference data) to simulate the welfare loss that might be associated with a high intensity fire that will result in closure of each trailhead and the entire wilderness[22]. Table 3.8 shows that the individual mean welfare loss is the greatest for Long Valley and Devil's Slide, with Marion Mountain being the site with the lowest welfare loss.

Table 3.8— *Mean individual seasonal welfare estimate for trailhead (2012 dollars).*

Scenario	**Mean**	**Std. Err.**
Loss of Deer Springs site	-$13.43	0.8602
Loss of Devil's Slide site	-$57.87	2.2807
Loss of Marion Mtn site	-$3.06	0.2438
Loss of South Ridge site	-$8.02	0.5407
Loss of Long Valley site	-$221.49	6.4917
Loss of All sites	-$305.22	9.1015

The second analysis uses the parameter estimates from table 3.2, which contains specific hiking routes. As shown in table 3.9, the highest welfare loss is seen for the Long Valley and Devil's Slide routes.

[22] Closure of one trail at a time and keeping everything else constant.

***Table 3.9** — Mean seasonal individual welfare estimate for trailhead/destination (2012 dollars).*

Scenario	Mean	Std. Err.
Loss of Deer Springs & Peak route	-$0.47	0.0336
Loss of Deer Springs & Saddle route	-$0.08	0.0117
Loss of Devil's & Peak route	-$0.41	0.0418
Loss of Devil's & Saddle route	-$39.90	1.4228
Loss of Devil's & Tahquitz route	-$3.87	0.2711
Loss of Devil's & Skunk route	-$12.02	0.4355
Loss of Devil's & Lookout route	-$3.86	0.2415
Loss of Devil's & RV route	-$0.53	0.0712
Loss of Devil's & Hidden route	-$0.33	0.0507
Loss of Marion Mtn & Peak route	-$1.75	0.0710
Loss of Marion Mtn & Little RV route	-$1.18	0.1012
Loss of S. Ridge & Saddle route	-$0.46	0.0614
Loss of S. Ridge & Tahquitz route	-$0.73	0.0755
Loss of S. Ridge & Skunk route	-$0.37	0.0553
Loss of S. Ridge & Lookout route	-$2.39	0.1569
Loss of Long Valley & Peak route	-$31.45	0.7150
Loss of Long Valley & Little RV route	-$31.63	0.9796
Loss of Long Valley & Tamarack route	-$13.91	0.7649
Loss of Long Valley & Hidden route	-$14.25	0.7860
Loss of Long Valley & Round V route	-$94.12	2.1102
Loss of All routes	-$260.72	4.4037

The final two welfare analyses (tables 3.10 and 3.11) use the parameter estimates from table 3.3, which has both revealed and stated preference data. Table 3.10 represents the welfare loss of entire site closure, while table 3.11 represents the welfare effects due to a specific change in site quality (hypothetical burn scenario).

***Table 3.10** — Mean seasonal individual welfare estimate using revealed and stated preference data (2012 dollars).*

Scenario	Mean	Std. Err.
Loss of Deer Springs site	-$25.10	0.1617
Loss of Devil's Slide site	-$56.67	0.3118
Loss of Marion Mtn site	-$19.28	0.1245
Loss of South Ridge site	-$20.23	0.1240
Loss of Long Valley site	-$169.50	0.8418
Loss of All sites	-$292.11	1.5421

Table 3.10 has a similar trend as the first welfare analysis: Long Valley and Devil's Slide have the highest welfare losses due to trail closure, but the estimates are lower, while there is an increase in welfare loss for the remaining trails. The increase is

partly due to individuals demanding more recreational trips to the wilderness for the different site conditions (burn scenarios).

Table 3.11 shows the welfare estimates for a change in quality, from current trail conditions to a hypothetical burn: specifically, a recent, low intensity fire that burns 25% of a trail's viewshed. The analysis demonstrates that there is a welfare gain when the conditions change due to a fire[23]. The greatest aggregate welfare gain is seen at the begin years after the fire and decreases as trails return to pre-fire conditions (figure 3.4), but unlike Englin et al. (2003), the number of years it take to return to pre-fire condition was not examined. The most popular trails (Devil's Slide and Long Valley) obtain the greatest gain, but least popular trails still have significant welfare gains. Part of the welfare gain is due to increased wilderness visitation. The increase in visitation is due in part to the novelty experience of a fire-effected ecosystem. As Englin et al. (2001) suggest that visitation increase in the early years of a fire because recreationists find recent burns a desirable situation. For example, burn scenario (recent, low intensity foreground fire that burns 25% of Deer Springs trail) reported average trips to Deer Springs that are higher compared to current conditions average trips to Deer Springs (.88 vs .53)[24].

[23] Similar welfare gains, but not as high, were found for all hypothetical burns combinations.
[24] Similar results were found for different burn scenarios.

__Table 3.11__— Mean seasonal individual welfare estimate for hypothetical burn scenario (2012 dollars).

Scenario	**Mean**	**Std. Err.**
Recent, low intensity foreground fire that burns 25% of trail		
Deer Springs	$2.65	0.4638
Devils Slide	$5.09	0.8470
Marion Mtn	$1.32	0.2432
South Ridge	$1.62	0.2889
Long Valley	$10.96	2.4217
All Sites	$22.17	3.7066

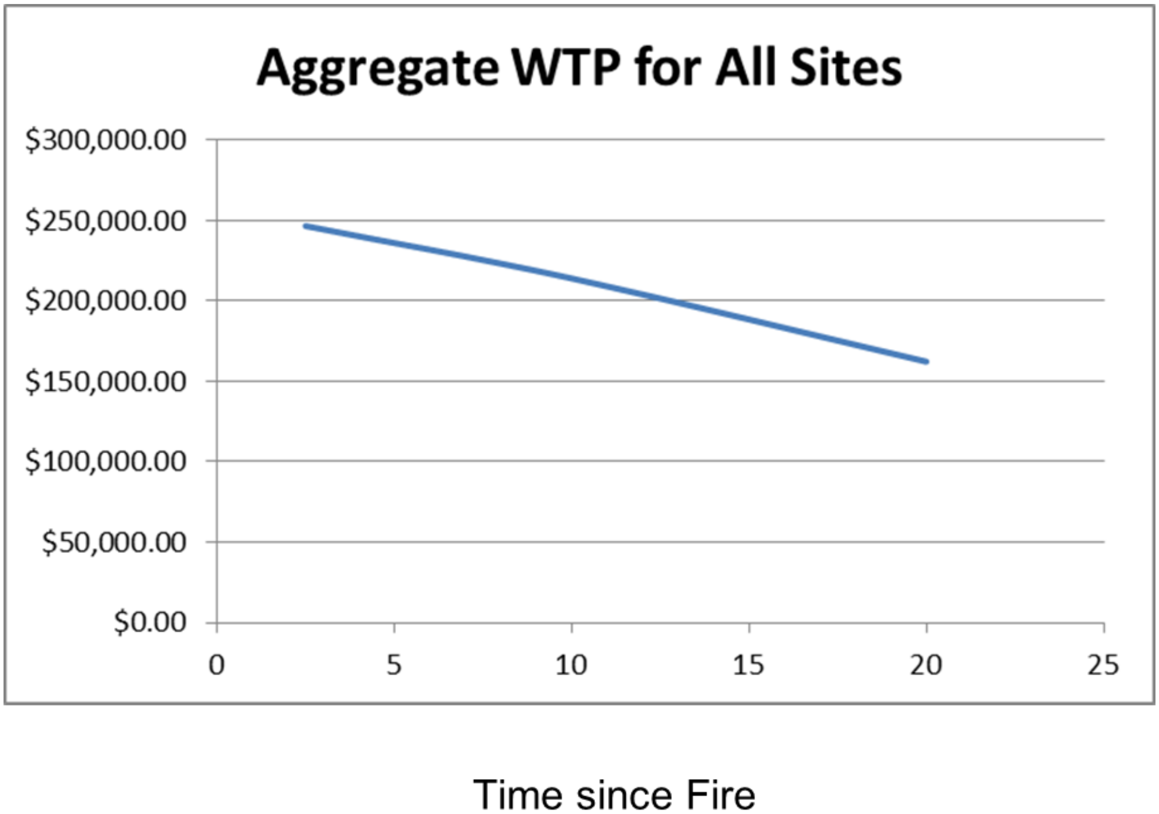

Figure 3.4— Aggregate WTP for hypothetical burn scenario (low intensity foreground fire that burn 25% of trails)

3.3.6 Conclusion

A KT model was used with the web-based survey data for estimating seasonal recreation demand and calculating welfare measures for hiking trails in the San Jacinto wilderness.

An advantage over tradition travel cost models is that the KT model can handle corner solutions for recreation data in a theoretically consistent way and can estimate simultaneous decisions on which sites to visit and how many trips to make to each site over the course of a season (von Haefen et al. 2004).

The estimated model facilitates two important steps toward more efficient management of wildfire prevention and suppression efforts. First, the model allows us to determine the current recreation value of each trailhead and hiking routes. This information allows forest managers to prioritize the use of limited resources to maintain and protect high value hiking areas. The welfare results show that Devil's Slide and Long Valley trailheads are the most valuable (average welfare loss \$58 and \$221 per individual, respectively) and strategically would be more important for forest manager to spent existing resources in conserving and preventing complete trail closures to all trails.

Second, the modeling approach allow us to derive, for each trail, the recreation-related welfare effects of wildfire-induced changes in scenic quality associated with mature forests. This includes not only trailhead closures but also the residual impacts of prior burns of varying intensities. Our study found that there is a welfare gain immediately following a fire and as time passes, the welfare gain decreases, but still remains positive. But if there is a complete closure or no access to the trailhead, as shown above, there is a substantial welfare loss. The survey did not ask recreationists perception of wildfire and how it affects the ecosystem. Perhaps the welfare gains are due to the "curiosity" effect of individuals who have never seen a burned wilderness wanting to see how a burned site looks after a fire. In a recent fire, the ecosystem is unique and more people may visit to view this phenomenon. As time passes, the ecosystem recovers and fewer people visit the burn area as the curiosity effect wears off. Additionally, these results consider only recreation values, thus the welfare impact could potentially change when other non-use (i.e., option, bequest, and existence) values are included in the analysis.

One of the drawbacks of the KT model is that the additive separability assumption implies weak substitution effects for the goods which have small income effects, as is the case here. As Kuriyama et al. (2006) argue, this assumption means that KT models may overestimate welfare losses due to individual site closures because of artificially weak substitution effects. Using a different modeling structure such as a dynamic KT model approach or a non-additively separable utility function can help reduce the estimated bias (Kuriyama et al. 2006).

3.4 Spatial Allocation of Value

In this section, the approach implemented by Baerenklau et al. (2010) is used to spatially allocate forest access value to the landscape. The approach uses GIS, visitation data, and the assumption that landscape values for backcountry hikers are closely related to scenic quality. I present the procedure to spatially allocate the access values (obtained from the KT model) throughout the landscape. I provide a description of the GIS viewshed analysis tool, GIS data and the landscape value maps. The section concludes by explaining how the information from the spatial landscape values can be used by forest and land managers.

3.4.1 Introduction

The access or trip values estimated with the KT model (see Section 3.2.1) can be allocated to the individual parcels that together represent the landscape of our study to derive a recreation value map. I develop three such maps using: (1) trailheads as sites; (2) trailhead/destination route combinations as sites; and (3) the difference between map 1 and 2. The trailhead approach follows the same method as Baerenklau et al. (2010). I expand the procedure to include individual recreation data, trailhead/destination route combinations and allocate the route value to the landscape. Comparisons are made with the different maps to determine if there is a benefit from using individual data and including destination in the welfare analysis.

3.4.2 Spatial Allocation Procedure

To determine the monetary values for each trail segment and consequently for the entire landscape, the first step is to establish how the use of a trail generates value in the surrounding landscape. The allocation of trail values throughout the surrounding landscape is based on scenic quality. The recreation value of the parcel is a function of how frequently that parcel is viewed by visitors and from what distance it is viewed. The visual experience of an individual hiker is simulated with a visibility analysis that was performed using the viewshed tool in GIS. The viewshed tool identifies and calculates the number of times a location in a Digital Elevation Model (DEM) is visible by scanning the surrounding areas of one or more observations points. Locating areas of varying visual significance within the study site allows for a redistribution of the aggregate trip value across the heterogeneous landscape to allocate recreation values to individual pixels (30x30 meter cells). The values calculated in each cell are added to the map layer. The scan angles were set at 180 degrees vertical and 360 degrees horizontal. The offset value was set to 1.7m, which corresponds to the average American height. In addition, the maximum search radius is 30km, which is the maximum distance between points along the hiking trail and boundaries of the study area.

The web-based survey focused on 5 entry points: Long Valley and the 4 most popular entry points in Idyllwild. The web-based survey data includes the entry point, sites and destinations visited, but the actual routes taken through the wilderness are unknown. Using GIS maps from the USDA FS with over 35 miles of trails, a total of 20 possible hiking routes were identified[25]. These trails consisted of continuous segments that extend between two trail junctions or a junction and a destination. With the limited web-based survey data on trailhead/destination route combinations, assumptions were made to determine the possible hiking paths for visitors during one-day hiking trips. These assumptions were: a maximum of 8 miles one-way, entry and exit points were the same, and exclusion of certain hiking routes based on information obtained from the Idyllwild Ranger.

Using only trailhead data, hiking paths can be predicted by calculating the probability that a trail will be used during a one-day hiking trip. These calculations start at one of the 5 main entry points by assigning each entry trail an initial probability of 100%. Trail junctions are then assigned equal probabilities. This means that if there is a two-way junction, the probability of both trails leading away from this junction is 50%

[25] There are more hiking routes, but this study only focuses on the most popular ones.

(of initial probability); the probability of all trails at a three-way junction is 33%, and so forth (see figure 3.5).

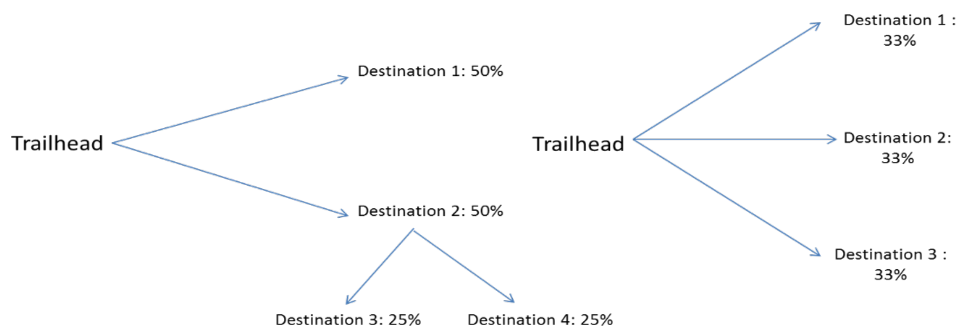

Figure 3.5- Probability tree

3.4.3 Estimated Landscape Values

Using the approach of Baerenklau et al. (2010) along with the GIS viewshed tool and the web-based survey data, three spatial landscape maps (trailhead only, trailhead/destination route combination, and the difference between trailhead only and trailhead/destination route combination) are derived from the different data sets. The welfare estimates in table 3.8 are used to derive the landscape value map (trailhead only). As shown in figure 3.6, the annual values range from .01 cents to $13,040.50/ha throughout the wilderness, with a mean of $204.24/ha. The high parcel values are concentrated in areas with high elevations (San Jacinto Peak) and popular sites (Long Valley). Because our spatial allocation method is based on visibility, these parcels received higher visibility weights and thus contribute more to the value of a trip. Therefore, parcels that are both highly visible and frequently viewed receive the highest values. In contrast, parcels located in relatively remote areas and away from trails in our study have lower and sometimes no recreation value because of their limited visibility and/or low visitation rates (or having no data on the particular trailhead[26]). However, this does not mean that those areas do not have economic values; rather we did not have any information to calculate the recreation values.

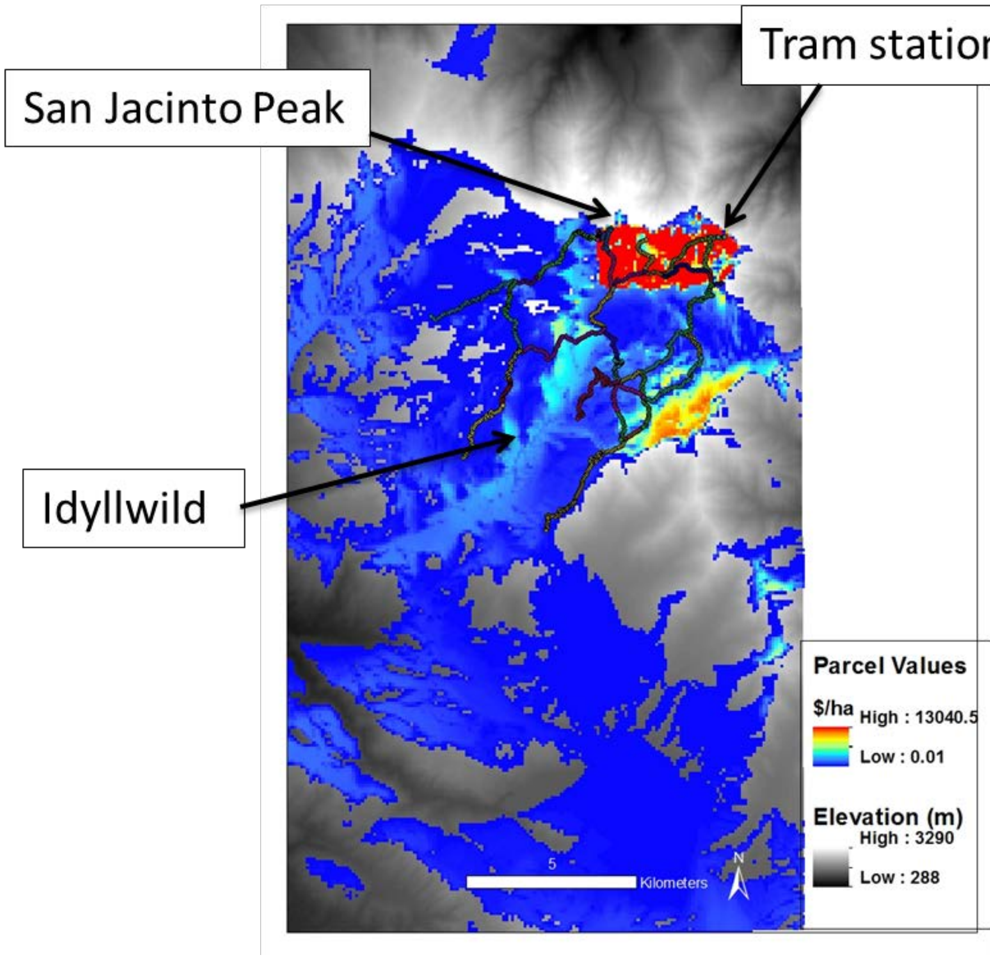

Figure 3.6 —Landscape values for trailhead

Parcel values are different when more information is added to the analysis, e.g., using the welfare estimates in table 3.9, which contains information about specific hiking routes. Figure 3.7 shows the trailhead/destination route combination landscape value map. The

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[26] The San Jacinto wilderness has more than 10 trailheads. The web-based survey only collected data on 5 trailheads.

annual values range from .01 cents to $4,224.25/ha throughout the wilderness, with a mean of $123.86/ha.

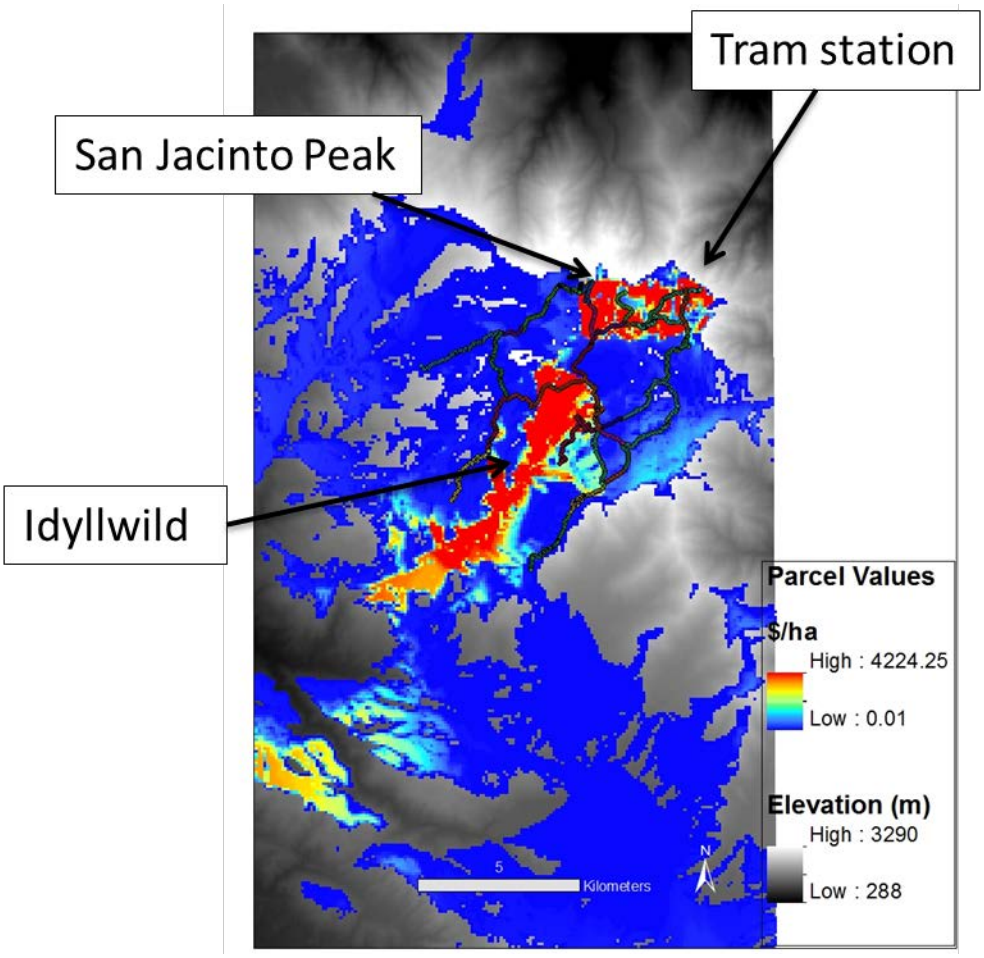

Figure 3.7— Landscape values for trailhead/destination route

These annual values differ in magnitude compared to the previous map. This can be explained, in part, by the different welfare estimates (tables 3.8 and 3.9). In general, the trailhead only welfare estimates have higher welfare losses than trailhead/destination route combination estimates. Part of the reason is that not all the trailhead/destination route combinations are included in the analysis. As in the previous case, high parcel values are concentrated in high elevation (San Jacinto Peak and Tahquitz Peak) and popular hiking routes. A similar explanation as in the previous map can be used when discussing the parcel values.

Comparing the results with Baerenklau et al. (2010), the trailhead only map is more comparable. A possibility for the difference in landscape values can attribute to the model and data used by Baerenklau et al. (2010) to derive the welfare values, a zonal travel cost model with permit data, while my analysis used a KT model with individual web-based survey data. The landscape values derived by Baerenklau et al. (2010) are similar, ranging from \$41 to \$10,369/ha with a mean of \$378/ha. The maps also have similar trends: there is a concentration of high values in a relatively small area of the wilderness (i.e., areas being accessed by Long Valley and Devil's Slide) and low values across most of the landscape. Therefore, it appears that the preservation of recreation opportunities is limited to small area of the wilderness.

The difference between landscape values map (figure 3.8) was created by combining both spatial landscape value maps (figures 3.6 and 3.7) and subtracting the trailhead/destination route combinations map (figure 3.7) from the trailhead only map (figure 3.6). As shown in figure 3.8, the annual differences range from -\$1,509.22 to \$8,816.24/ha throughout the wilderness, with a mean of \$76.91/ha. The negative values in this map show that the trailhead only data underestimate the values that are located near the Idyllwild entrance, Deer Springs, Devil's Slide and South Ridge trailheads. The positive values represent an overestimation of landscape values, which are mostly concentrated in the Long Valley area. However, the additional information provided by the trailhead/destination route combination data is more reliable for estimating the landscape values because it does not require the equal probability assumption (figure 3.5) when facing a trail junction. This is because there are destinations in the San Jacinto wilderness that recreationists enjoy more than others. For example, recreationists entering the Marion Mountain trailhead have a much higher probability of taking the hiking trail (north) leading to the peak, rather than going towards Deer Springs (south).

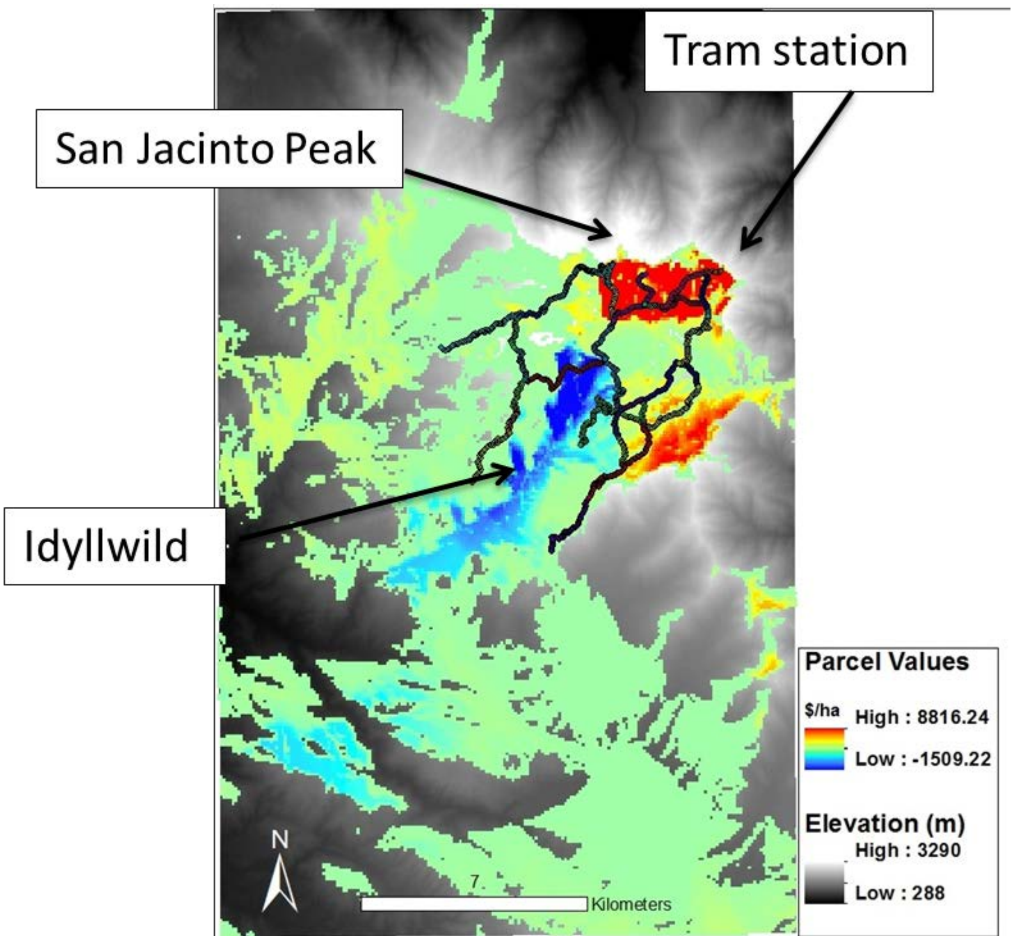

Figure 3.8—Difference between trailhead and trailhead/destination route landscape values

3.4.4 Conclusion

To better evaluate the potential impacts of wildland fire in the San Bernardino National Forest, I developed a GIS data layer containing non-market values derived from a KT recreation demand model using visitation data and data collected from backcountry hikers entering the San Jacinto Wilderness during the summer of 2012. Each pixel in the data layer contains an estimate of the recreation values at that location.

The spatial elements in the regression (trailhead only and trailhead/destination route combination) allow us to estimate how the aggregate trailhead values and welfare effects are derived from the different parcels that comprise a trail's viewshed. Together, these two steps enable estimation of the value of recreation benefits derived from the scenic quality of different parts of the landscape. The trailhead only map estimates high values for Long Valley (i.e., San Jacinto and Tahquitz Peak) and relatively low values for Idyllwild. Including additional information on which destinations individuals visited, a hiking route was created to estimate alternative landscape values. The trailhead/destination route combination map shows that the highest values are located in Devil's Slide and Long Valley trailheads and at higher elevations. These trailheads are the most popular and have access to desirable destinations (i.e., Saddle Junction and San Jacinto Peak). Comparing the maps by taking the difference, the trailhead only data underestimates the Idyllwild sites and overestimate the Long Valley trail. The trailhead/destination route combination map provides more accurate landscape values than trailhead only data because it includes more information about the choices actually made my visitors.

However, it appears from this and other studies that scenic quality may not be degraded by certain types of fires. The hypothetical burn scenario analysis suggests that recreationists derive a positive welfare effect from experiencing burned landscapes.

Although the welfare impact becomes negative when fires cause complete trail closures, it appears that there is no direct connection between scenic quality degradation and fire. This suggests that fire managers should focus on protecting portions of the landscape that, if burned, would lead to trailhead closures. However the derived value maps may not be appropriate to use as a decision aid tool for fire risk assessment that supports forest management strategies. Nonetheless, the value maps might be used to manage risks to scenic quality from other threats such as bark beetle, invasive species, development, etc., provided recreationists perceive these threats to the landscape as potentially degrading scenic quality.

4. Latent Class Approach to Kuhn-Tucker Model

4.1 Introduction

Most recreation demand models neglect to account for the expected tendency of individuals to choose to live closer to things that they enjoy using, such as wilderness areas. As noted by Parsons (1991), this oversight can bias (underestimate) welfare estimates. Baerenklau (2010) implements a control for spatial sorting but finds a counter-intuitive result: the more enthusiastic backcountry hikers tend to live further from the wilderness, suggesting that wilderness proximity is valued for some other non-measured (non-recreation) benefits that it provides. The present study reexamines this question with a latent class KT demand model, estimated with the web-based survey data. The model is implemented using standard maximum likelihood techniques to test the hypothesis that proximity to natural resources for purpose of recreation is not an important determinant of residential location choice in southern California.

4.2 Model Specification

A latent class approach to the KT model (von Haefen et al. 2004) is proposed as a method for incorporating unobserved heterogeneity in preferences for recreation behavior using a utility theoretical framework and used to control for endogenous spatial sorting. Using standard maximum likelihood techniques and following Kuriyama et al. (2010), this section describes the latent class approach to the KT demand model. The model assumes the existence of G groups in a population with individual n belonging to group g (g = 1,…, G). The individuals within a group are assumed to have homogeneous preferences.

The maximization problem for nth individual in group g is given by (Kuriyama et al., 2010):

$$(4.1) \quad Max\ U(x_n, q_m, z_n, \beta_g, \varepsilon_n) \quad s.t. p'x_n + z_n \leq y_n, z_n > 0,\ x_n \geq 0,$$

where $x_n = (x_{n1}, \dots, x_{nm})'$ is a vector of M sites to be analyzed, $q_m = (q_1, \dots, q_M)'$ is an M x K matrix of K quality attributes for the M sites, z_n is the Hicksian composite good, β_g is a vector of group-specific parameters for group g, $p = (p_1, \dots, p_M)$ is a vector of prices (travel cost, access fees, etc.), y_n is the annual income and $\varepsilon_n = (\varepsilon_{n1}, \dots, \varepsilon_{nM})'$ is a vector of random components, which are assumed to be known to the individual, but unknown to the researcher. Assuming U is a quasi-concave, increasing, and continuously differentiable function of (x_n, z_n), and using the following notation, $U_j = \frac{\partial U}{\partial x_{nj}}$ and $U_z = \frac{\partial U}{\partial z_n}$, the first-order Kuhn-Tucker conditions for the utility maximization problem are

$$(4.2) \quad \frac{U_j(x_n^*, q_m, y_n - p'x_n^*, \beta_g, \varepsilon_n)}{U_z(x_n^*, q_m, y_n - p'x_n^*, \beta_g, \varepsilon_n)} \leq p_j,$$

$$x_{nj}^* \geq 0,$$

$$x_{nj}^* \times \left[\frac{U_j}{U_z} - p_j\right] = 0,$$

for each site j = 1,…, M. and x_n^* is the optimal solution to the maximization problem in equation 4.1. Assumptions must be made to the utility function to allow first-order condition to be restated in a convenient and particular form. Following Phaneuf et al. (2000) and Kuriyama et al. (2010), if we make the subsequent assumptions:

$$U_{z\varepsilon} = 0,$$

$$\frac{\partial U_j}{\partial \varepsilon_{nk}} = 0 \quad (\forall\, k \neq j),$$

$$\frac{\partial U_j}{\partial \varepsilon_{nj}} > 0 \quad (\forall\, j),$$

then the first-order conditions for site j can be rewritten as

$$(4.3) \quad \varepsilon_{nj} \leq g_{nj}\left(x_n^*, p, y_n, q_m, \beta_g\right),$$

$$x_{nj}^* \geq 0,$$

$$x_{nj}^* \times g_{nj}\left(x_n^*, p, y_n, q_m, \beta_g\right) = 0,$$

where $g_{nj}$is the solution to $\frac{U_j\left(x_n^*, q_m, y_n - p' x_n^*, \beta_g, g_{nj}\right)}{U_z\left(x_n^*, q_m, y_n - p' x_n^*, \beta_g, g_{nj}\right)} = p_j$. If ε_{nj} is assumed to be an independent and identically distributed draw from type I extreme value distribution with inverse scale parameter μ_g for all j, the likelihood function of observing x_{nj}^* conditional on the individual n belonging to group g is (Kuriyama et al., 2010):

$$(4.4) \quad L\left(x_n^* | \beta_g\right) = |J| \prod_j \left(\left[\frac{1}{\mu_g} exp\left(\frac{-g_{nj}}{\mu_g} \right) \right]^{1\left[x_{nj}^* > 0\right]} exp\left[-exp\left(\frac{-g_{nj}}{\mu_g} \right) \right] \right),$$

where |J| is the determinant of the Jacobian for transformation and $1\left[x_{nj}^* > 0\right]$ is an indicator function equal to one if x_{nj}^* is strictly positive and zero otherwise.

The probability that an individual n belongs to group g (g = 1, …, G) often is assumed to be logistic:

$$(4.5) \quad \pi_{ng} = \frac{\exp\left(\lambda_g a_n\right)}{\sum_{g=1}^{G} \exp\left(\lambda_g a_n\right)}$$

where each λ_g is an estimable parameter vector ($\lambda_1 \equiv 0$ for identification), and a_n are individual characteristics thought to influence group membership. The unconditional probability of observing x_n^* is (Kuriyama et al., 2010):

$$(4.6) \quad P_n(\beta_g, \lambda_g) = \pi_{ng} L_n(x_n^* | \beta_g)$$

The preference specification of the model follows von Haefen et al. (2004), later modified by Kuriyama et al. (2010) to account for the latent class approach:

$$(4.7) \quad U(\cdot) = \sum_{j=1}^{M} \Psi_j \, ln(\phi_j x_j + \theta_g) + \frac{1}{\rho_g} z^{\rho_g},$$

$$\Psi_j = exp(\delta_g' s + \varepsilon_j) \qquad j = 1, \ldots, M$$

$$\phi_j = exp(\gamma_g' q_j)$$

$$\rho_g = 1 - exp(\rho_g^*)$$

$$\theta_g = exp(\theta_g^*)$$

$$\mu_g = exp(\mu_g^*)$$

$$\varepsilon_j \sim EV(\mu_g)$$

where s is a vector of individual characteristics, and $\delta_g, \gamma_g, \theta_g^*, \rho_g^*, and \mu_g^*$ are parameters. The $\varepsilon_1, \ldots, \varepsilon_M$ represent additional unobserved heterogeneity that varies randomly across individuals and sites and it is assumed each error term is an independent draw from the normalized type I extreme value distribution with inverse scale parameter μ_g for all j.

Using the indirect utility function, $V(p^0, y; q^0, \beta_g, \varepsilon)$, the compensating variation (CV) for a change in price and quality from baseline conditions p^0 and q^0 to a new levels p^1 and q^1 can be defined implicitly as

(4.8) $V(p^0, y; q^0, \beta_g, \varepsilon) = V(p^1, y - CV_g; q^1, \beta_g, \varepsilon)$.

The estimation of CV is calculated using an iterative algorithm developed by von Haefen et al. (2004). Using the same approach, the algorithm finds compensating variation $CV_{g,}$ given group-specific parameters for group g and random components

1. At iteration i, set $z_a^i = (z_l^{i-1} + z_u^{i-1})/2$. To initialize the algorithm, set $z_l^0 = 0$ and $z_u^0 = y$.
2. Conditional on z_a^i, solve for x_i using equation 4.2
3. Use equation $z = y - \sum_j p_j x_j$ and x_i to construct $\tilde{z}^i$.
4. If $\tilde{z}^i > z_a^i$ set $z_l^i = z_a^i$ and $z_u^i = z_u^{i-1}$. Otherwise, set $z_l^i = z_l^{i-1}$ and $z_u^i = z_a^i$.
5. Iterate until $abs(z_l^i - z_u^i \leq c)$, where c is arbitrarily small[27].
6. Calculate $CV_g = y - (\boldsymbol{p}\boldsymbol{x}^i + z_a^i)$.

As mentioned previously (Chapter 3), CV is unknown to the researcher. The CV_g cannot be calculated precisely, but it can be estimated by the expected value, $E(CV_g)$. However, no close-form solution for $E(CV_g)$ exists (von Haefen et al. 2004). Therefore, computation of the welfare estimates for each group can be estimated using first-order conditions and the Monte Carlo simulation techniques developed by von Haefen et al. (2004).

4.3 Application

To illustrate the latent class KT approach, this model was applied to the backcountry hiking data presented in Chapter 2. This approach assumes the endogenous spatial

[27] It is recommended to have the tolerance level to be 1.0 x e^{-6}

sorting of individuals is relative to recreation sites. Therefore, the demand equation includes seven individual characteristic variables: *age, degree, employed, gender, envgrp, minority*; five forest attitudes variables: *Escape, Winter Rec, Summer Rec, Water Source, and Preservation* (see table 4.1 for description on each variable), along with a constant and a binary variable for ID (*dummyID).* The forest attitudes variables are constructed from the survey question that asked, "What characteristics of San Jacinto Wilderness are important to you?" The responses are based on a Likert scale where 5 = very important, 4 = important, 3 = slightly important, 2 = not important, and 1 = no opinion. The group membership equation includes the same demographic variables as well as three additional variables thought to explain differing location choice, assuming some type of sorting behavior is taking place in the population (Baerenklau 2010). These variables are the same as those in Baerenklau (2010): *miles_ID*, *miles_SIM*, and *popdens*; however they have been rescaled to fit the model more appropriately. The variable *miles_ID* measures the proximity of the recreationist's home to Idyllwild, a mountain community that provides residents with non-recreation amenity benefits, as well as the entry point for the San Jacinto Wilderness; *miles_SIM* measures the proximity of the recreationist's home to the nearest similar mountain community, Forest Falls or Lytle Creek, that provides comparable recreation opportunities and amenity benefits. Following the same explanation as Baerenklau (2010), negative coefficients on these variables would indicate that the corresponding groups tend to live closer to these communities, while positive coefficients would indicate that the corresponding groups tends to live further away. Furthermore, Baerenklau (2010) explains that the variable *popdens* is included to help further identify whether there exists an amenity value-seeking group in the population. A negative coefficient indicates that the corresponding group tends to live in less densely populated areas, while a positive coefficient means the opposite. As Baerenklau (2010) further explains, the recreational preferences (group-specific demand and welfare estimates) can be matched with the corresponding locational preferences to inform the question of spatial sorting.

Table 4.1*—Definitions and summary statistics of survey responses for variables included in the latent class KT model*

Variable Name	**Variable Description**	**Mean (std. dev.)**
Trips_ID	Trips to Idyllwild sites	2.26 (5.07)
Trips_LV	Trips to Long Valley sites	3.00 (7.07)
TC_ID	Per trip travel cost to Idyllwild sites (2012 dollars)	$57.28 (26.90)
TC_LV	Per trip travel cost to Long Valley sites (2012 dollars)	$69.84 (23.76)
Miles_ID	Distance in miles from Idyllwild (Miles_ID/100)	0.784 (0.34)
Miles_SIM	Distance in miles from nearest site that is similar to Idyllwild (Miles_SIM/100)	0.649 (0.298)
popdens	Population density (persons per square mile/1,000)	3.79 (4.17)
Age	Respondent's age (Age/100)	43.82 (12.59)
Degree (dummy variable)	Having at least a Bachelor's degree; if Yes = 1; else = 0	0.71 (0.45)
Employed (dummy variable)	Being employed in the past year; if Yes = 1; else = 0	0.65(0.48)
EnvGrp (dummy variable)	Belonging to an environmental group; if Yes = 1; else = 0	0.21 (0.41)
Gender (dummy variable)	Respondent's gender; Male =1 Female = 0	0.58 (0.49)
Minority (dummy variable)	*Being in a minority group if Yes=1; else=0*	0.10 (0.30)
Income	Household annual income	$87,235 (46,930)
Escape	Escape the city (Liker scale) (5=Very Important, 2= Not Important)	4.64(0.64)
Winter Rec	Winter Recreation (Liker scale) (5=Very Important, 2= Not Important)	3.30(1.18)
Summer Rec	Summer Recreation (Liker scale) (5=Very Important, 2= Not Important)	4.73(0.55)
Water Source	Forest is a source of water (Liker scale) (5=Very Important, 2= Not Important)	3.79(1.19)
Preservation	Preserve forest for future use or future generations (Liker scale) (5=Very Important, 2= Not Important)	4.73(0.62)
n = 698		

4.4 Results and Discussion

Results are summarized in tables 4.1, 4.2, 4.3, and 4.4.[28] Table 4.1 summarizes the descriptive statistics. Both sites have similar (and not statistically different) travel costs ($57 to $69 per-trip; see Chapter 2 for description on travel cost derivation). *Escape, Summer Rec and Preservation* have on average the highest importance, while *Winter Rec* and *Water Source* have on average the lowest importance. These results were expected, especially for *Winter Rec* and *Summer Rec* variables because the San Jacinto Wilderness visitation is highest during the summer months. The descriptive statistics for the other variables are the same as for the previous analysis (see Chapters 2 and 3), e.g., visitors are high income earners (average household income is $87,000) and highly educated (71% have at least a bachelor's degree). Tables 4.2 and 4.3 provide the estimation results for the one and two group versions of the model;[29] table 4.4 provides measures of fit and welfare calculations. Model 1 assumes there is only one group in the population and estimates a standard KT model using the standard maximum likelihood algorithm mentioned in Chapter 3. Table 4.2 shows that 9 of the 16 estimates for this model are significant at the 10% level and below. The model also numerically estimates the income effect[30] (ρ) and it is negative and highly significant. This means that if the household income increases, the relative utility will decrease given that the new income level will cause a reduction in trips. In the Ψ matrix (individual characteristics), being male and

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[28] Everyone in the sample took at least one trip to the wilderness, thus parameter and welfare estimates are based on the truncated likelihood function.
[29] Numerical errors (i.e., Hessian matrix not positive semi-definite) were encountered when estimating a three group latent class KT model, an outcome likely due to the large number of parameters (76); therefore, this option was not explored any further.
[30] The income effect is part of the utility function and must be numerically estimated because there is no closed-form solution.

having a college degree increases trips to each trailhead, while trips decrease as age increases. The signs of the statistically significant estimates are similar to Baerenklau (2010) and intuitive; for example, generally relatively older individuals take fewer trips. All of the forest attitude variables, except for winter recreation variable are significant. *Escape* and *Water source* coefficients are negative, meaning that demand is lower among individuals who want to escape the city or believe that the forest is a source of water, implying that frequent visitors don't view this recreation as an escape or important source of water, rather for other reasons (e.g., exercise). *Summer Rec* and *Preservation* coefficients are positive, meaning that the demand is higher among individuals who visit the wilderness for summer recreation activities or believe that the forest should be protected for future use or generations. In the Φ matrix, the proxies for site characteristics (constant and dummy variables) are not significant but have the anticipated sign, with Long Valley being the more popular site to visit.

Table 4.2— *Standard Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead.*

Parameter	**Model 1**	
	Estimate	**Std. Err.**
Group 1 demand		
Ψ Index parameters		
Gender	0.2820***	0.1016
Age	-0.0108***	0.0043
EnvGrp	0.0067	0.1181
Minority	-0.1426	0.1785
Degree	0.2301*	0.1194
Employed	-0.0657	0.1095
Escape	-0.1886***	0.0799
Winter Rec	0.0501	0.0423
Summer Rec	0.4534***	0.0935
Water source	-0.0939**	0.0436
Preservation	0.1449*	0.0830
Translating parameter		
Θ	0.2997	50.2778
Φ parameters		
Constant	0.0466	50.2791
Dummy_ID	-0.3462	50.2791
Rho parameter		
ρ	-1.5234***	0.2193
Type I extreme value scale parameter		
μ	-0.1212***	0.0321

Note: * indicates significance difference from zero at the 0.10 level, ** indicates significance difference from zero at the 0.05 level *** indicates significance difference from zero at the 0.01 level.

Table 4.4 shows for Model 1 that the estimated per-trip CV is $32 for the Idyllwild trails and $74 for the Long Valley trails. Based on 2011 visitation data, the aggregate CV for each site is estimated by multiplying the per-trip CV of each site by the number of site visitors. The estimated CV for the entire wilderness is above $3.2 million. These estimates are 2.5 to 8 times more than the results obtained by Baerenklau (2010). This discrepancy could be due to differences in the average number of trips to each site across samples (5.28 vs 2.5) and differences in model structures: Baerenklau (2010) used a zonal travel cost model (discrete) with permit data, while the present study implements a Kuhn-Tucker demand model (continuous) with individual web-based survey data.

Table 4.3— *Latent class Kuhn-Tucker model estimates. The dependent variable is the number of trips taken in the past 12 months to each trailhead.*

Parameter	**Group 1**		**Group 2**	
	Estimate	**Std. Err.**	**Estimate**	**Std. Err**
Group 1 demand				
Ψ Index parameters				
Gender	0.2029***	0.0544	0.4052*	0.2712
Age	-0.0066***	0.0024	-0.0349***	0.0120
EnvGrp	0.2223***	0.0593	-0.3762	0.3347
Minority	0.0486	0.0835	-0.8812*	0.6279
Degree	0.0037	0.0589	0.3634	0.3659
Employed	-0.0319	0.0571	-0.2510	0.3107
Escape	0.0116	0.0489	0.0789	0.2651
Winter Rec	-0.0133	0.0230	0.1381	0.1125
Summer Rec	0.3016***	0.0631	0.3942*	0.2379
Water source	-0.0039	0.0243	-0.0075	0.1409
Preservation	0.1465***	0.0612	-0.0385	0.2104
Translating parameter				
Θ	0.6742	26.5560	0.5754	48.4062
Φ *parameters*				
Constant	-0.4014	26.5443	-0.0052	48.4043
Dummy_ID	-0.6736	26.5455	-0.5824	48.4047
Rho parameter				
ρ	-1.2371	0.1127	-1.5488***	0.6259
Type I extreme value scale parameter				
μ	-0.8696	0.0513	-0.1052	0.0873
Group 2 membership				
Gender			1.3386*	0.7530
Age			-0.1166***	0.0423
EnvGrp			0.4580	0.6428
Minority			-0.7680	1.0435
Degree			0.2527	0.7163
Employed			0.0842	0.6367
Escape			0.6136	0.5338
Winter Rec			0.0913	0.2571
Summer Rec			1.4917***	0.6366
Water source			-0.3832*	0.2641
Preservation			0.0588	0.5219
Miles_ID			-15.0758***	3.5241
Miles_Sim			3.2830*	1.9570
Pop_Den			0.1731*	0.1314

Note: * indicates significance difference from zero at the 0.10 level, *** indicates significance difference from zero at the 0.01 level.

Model 2 introduces two latent classes into the analysis. Comparing the goodness of fit tests (log-likelihood, Akaike Information Criterion, and Bayesian Information Criterion) this model is a noticeable improvement upon Model 1 as shown in table 4.4.

Seventeen of the 46 parameter estimates in table 4.3 are significant at the 10% level and below, including all the coefficients on the group membership that are thought to explain different location choice. Further analyzing the results (i.e., group specific mean trips) displayed in both tables, Model 2 suggests that there exists a group of “hiking enthusiasts” (Group 2) and a different group of “casual users” (Group 1). Table 4.4 shows that the hiking enthusiasts make up a relatively small portion of the total population (19.9%), but tend to hike twice as much as the casual users. These results are similar to Baerenklau (2010), who finds that the hiking enthusiasts group is only 24% of the total population tend to hike roughly 10 to 15 times more than casual users.

However casual users value each trip to both Long Valley and Idyllwild sites more highly than hiking enthusiasts. This result is different from Baerenklau (2010) which finds that hiking enthusiasts have a higher per-trip value to both sites. The reader may wonder whether it is appropriate to label this group “enthusiasts” when the other group has higher per-trip welfare. However because the hiking enthusiasts have on average a higher mean trips and live closer to Idyllwild, the label of the group seems appropriate. As Parsons (1991) argues, individuals with stronger preferences for recreation (“enthusiasts”) might choose to live closer to recreation sites they frequently visit to reduce their travel costs.

The significant group membership coefficients in table 4.3 show that the hiking enthusiasts tend to be relatively older white males who live closer to Idyllwild. They also believe summer recreation activities are important, but don’t think the forest is a source of water. Table 4.3 elucidates how demand varies within each group according to demographic characteristics. The significant parameter estimates in the group-specific demand show that, among the casual users group, being male and belonging to an environmental group increase trips to each trailhead. Additionally, the *Summer Rec* and *Preservation* coefficients are positive, meaning that the demand is higher among individuals who visit the wilderness for summer recreation activities or believe that the forest should be protected for future use or generations. Among hiking enthusiasts, trips are affected positively for being a white male who believes that summer recreation activities are important. Age affects negative trips to both sites, but casual users group has a higher magnitude. Comparing the one-group and two-group model welfare estimates (tables 4.2 and 4.3), the aggregate value of the wilderness is slightly higher when estimated using Model 1 instead of Model 2. The results are consistent, but of smaller magnitude, with Baerenklau (2010) who finds that the one-group model overestimates the two-group model by 40%.

Regarding the hypothesis that wilderness proximity is valued for the other (non-recreation) benefits, the model finds mixed results: hiking enthusiasts live closer to Idyllwild but further from similar places, whereas the opposite implicitly holds for the casual users. Therefore, the possible sorting outcome is that recreationists live closer to recreation sites for recreation opportunities rather than amenity values. The result is different from Baerenklau (2010), who finds the more enthusiastic backcountry hikers tend to live further from the wilderness, suggesting that wilderness proximity is valued for the other (non-recreation) benefits that it provides.

Table 4.4*—Goodness-of-fit measures and welfare calculations.*

Estimated Sample Statistics	**Model 1**	**Model 2**
Log Likelihood at convergence (LL)	-2917.23	-2778.58
Number of parameters (P)	16	46
Akaike information criterion[31]	5866.45	5649.16
Bayesian information criterion[32]	5939.22	5858.38
Group 1		
Per trip CV, Idyllwild ($/trip)	$32.46	$29.37
Per trip CV, Long Valley ($/trip)	$74.29	$90.38
Proportion of total population	100%	80.1%
Aggregate CV, Idyllwild ($/yr)	$718,124	$520,452
Aggregate CV, Long Valley ($/yr)	$2,389,389	$2,328,420
Mean Trips to Idyllwild	2.28	1.77
Mean Trips to Long Valley	3.00	2.13
Mean Trips to wilderness	5.28	3.9
Group 2		
Per trip CV, Idyllwild ($/trip)		$11.71
Per trip CV, Long Valley ($/trip)		$36.94
Proportion of total population		19.9%
Aggregate CV, Idyllwild ($/yr)		$51,553
Aggregate CV, Long Valley ($/yr)		$236,432
Mean Trips to Idyllwild		4.26
Mean Trips to Long Valley		4.19
Mean Trips to wilderness		8.45
Population[33]		
Idyllwild annual visitors	22,123	22,123
Long Valley annual visitors	32,163	32,163
Aggregate CV, Idyllwild ($/yr)	$718,124	$572,005
Aggregate CV, Long Valley ($/yr)	$2,389,389	$2,564,853
Aggregate CV, wilderness ($/yr)	$3,207,513	$3,136,858

4.4 Conclusions

This study demonstrates how a latent class framework can be applied to the KT model, in particular to address endogenous spatial sorting resulting from unobserved heterogeneity that may impact welfare estimates from KT models. The approach allows the researcher to simultaneously model recreational participation and site selection decisions, while allowing for corner solutions, in the presence of latent unobserved heterogeneity. The

[31] Calculated as -2 x LL + 2 x P
[32] Calculated as -2 x LL + ln(N) x P, where N = 698 is the number of observations.
[33] Annual visitors for Idyllwild and Long Valley is based on 2011 San Jacinto wilderness visitor data.

estimation algorithm works well for a relatively small number of groups, which is the case in our situation where a model with only two groups appears to fit the data well.

The significant variables in the latent class KT model that influence demand are age, gender, and belonging to an environmental group. The forest attitudes variables that are significant at the 10% level or below are summer recreation activities and preservation of forest for future use or generations. In the group membership equation, the results show that the hiking enthusiasts tend to be people who are older males living near Idyllwild, while casual users tend to be younger females who live further from Idyllwild. The mean per-trip CV estimated using the two group latent class KT model ranges from $12 to $90 and the aggregate value of the wilderness is over $3.1 million.

Model 2 suggests that there exist two groups that are distinctly different in terms of average trips taken to the wilderness and per-trip welfare. Hiking enthusiasts recreate more compare to casual user, but have a lower welfare estimate. The results suggest that the hypothesis by Baerenklau (2010) that wilderness proximity is valued for some other non-measured (non-recreation) benefits that it provides is inconsistent with these results. However, these results are consistent with Parsons (1991) argument that individuals live closer to recreation sites for recreation opportunities and to reduce cost.

A concern is that the welfare estimates differ substantially compared to Baerenklau (2010). Therefore, additional research is recommended to test how well the standard and latent class KT models compares to other latent class models. One possible solution is to re-run the analysis using the web-based survey data with the latent class approach used by Baerenklau (2010) to compare the welfare estimates. Applying this procedure would reveal both the robustness of the latent class KT method and to what extent the sorting behavior described here appears to exist. Another, possibility is to implement or develop a more flexible preference structure than the additive separability assumption. As explain in chapter 3, the assumption might overestimate the welfare losses due to individual site closures because of artificially weak substitution effects. Using a non-additively separable utility function can help reduce the possible estimation bias. Lastly, using standard maximum likelihood estimation resulted in numerical problems when estimating a three group model. Thus, other estimation techniques such as the Expectation-Maximization (EM) algorithm might be used to determine if the same or larger number of broadly relevant groups can be identified.

5. Conclusions

This thesis focuses on backcountry visitors who responded to questions about past trip-taking behavior and hypothetical wildfire burn scenarios. Using a KT demand model with the web-based survey data, recreation demand and welfare measures were derived for hiking trails in the San Jacinto wilderness. Estimates suggest that recreationists derive welfare gains from experiencing wildfire scars up-close but welfare losses from wildfire induced trail closures. The derived value maps thus may be most useful for guiding scenic quality preservation efforts against threats other than wildfire, such as bark beetle infestation, invasive species, or development. A latent class version of the KT model further suggests that individuals choose to live closer to wilderness areas due to the recreation opportunities provided by those areas.

The focus groups and pre-tests provided useful information for developing implementing the survey instrument. Focus group participants emphasized that actual burn photos convey a better representation of site quality changes than digitized photos. Digitized photos were too “cartoon like” and did not represent real wilderness settings. During the pre-tests phase of the web-based survey, the initial sampling procedure (providing a recruitment flyer to everyone who obtained a wilderness permit) produced low response rates. Therefore, the sampling scheme was modified to have undergraduate students located at the Idyllwild and Long Valley Ranger Stations providing study information and collecting e-mail addresses of potential survey participants. An interesting finding from our study demonstrates that survey participants exhibit notable differences from typical southern California residents. Visitors are mostly white (90%), have a median household income of $85,000, are relatively older (median age of 45), and are highly educated (71% have at least a Bachelor's degree). Using most recent US Census data, southern California residents are compose of 37.7% white individuals, with a median household income of $61,405, are relatively younger (median age of 34), and only 28% have at least a Bachelor's degree.

The first analysis conducted herein facilitates two important steps toward the management of wildfire prevention and conservation of scenic quality. First, the estimated model allows us to determine the current recreation value of each trailhead and hiking route. This information allows forest managers to prioritize the use of limited resources to maintain and protect high value hiking areas from trail closures. The welfare results show that Devil's Slide and Long Valley trailheads are the most valuable with average seasonal welfare loss due to site closure of $58 and $221 per individual, respectively. Second, the modeling approach allows us to derive, for each trail, the recreation-related welfare effects of wildfire-induced changes in scenic quality associated with mature forests. This includes not only trailhead closures but also the residual impacts of hypothetical burns of varying intensities. An important finding of this work, which is consistent with previous studies, is that there is a welfare gain immediately following a fire and as time passes, the welfare gain decreases, but still remains positive. These results are based solely on recreation values, and thus might change if non-use values (i.e., existence, option, and bequest) are included. Also, fires can cause complete closure, which have negative welfare impacts and are substantially greater than the welfare gain from a burn scenario. Future work in this area should further explore the hypothetical burn scenarios to better understand the causes of increased visitation, and whether this might be due to a curiosity effect that goes away after the first visit or if it is more persistent. This also would help to shed more light on the connection between burned landscapes and perceptions of scenic quality.

The GIS maps provide information on the landscape values throughout the wilderness. The highest values are located in the highest elevations and most frequently visited sites. Taking the difference between the trailhead only and the trail/destination routes shows that the trailhead only map estimates lower welfare values in Idyllwild. Because the trail/destination routes map utilizes more information about visitation, this suggests a downward bias in the true values when this information is omitted. Although this study does not establish a link between wildfire and degradation of scenic quality, the value map nonetheless can be used by forest managers to help reduce risk and damage to scenic quality as a result of other threats to the landscape.

The welfare estimates and GIS maps derived herein differ significantly from Baerenklau et al. (2010). The difference can be partly explained by the modeling structure and the type of data. Baerenklau et al. (2010) implemented a travel cost model with permit data, while the present study used a KT demand model with individual data. Additionally, when deriving the GIS maps, the current study did not account for all the trailheads in the wilderness as in Baerenklau et al. (2010). Instead, this dissertation focuses on trailheads that account for 95% of the all wilderness visitors, while Baerenklau et al. (2010) considered all the trailheads. As a consequence, these GIS maps have large areas with very low or zero recreation value, where there is no visitation information or the land cannot be seen from the study trails. One possible solution to account for the low values would be to collect additional individual data on all the trailheads in the wilderness and re-develop the GIS maps. Finally, the additive separability assumption in the KT model might be a source of bias in the welfare estimates. The derived welfare estimates may overestimate the welfare losses due to individual site closures because of artificially weak substitution effects. Using a non-additive separable utility function or a different modeling structure such as a dynamic KT could help reduce the bias.

Finally, this study demonstrates how a latent class framework can be applied to the KT demand model, in particular to address endogenous spatial sorting resulting from unobserved heterogeneity that may impact welfare estimates from KT models. The estimation algorithm works well for a relatively small number of groups, with a model with only two groups appearing to fit the data well. A comparison of the one-group and two-group model welfare estimates shows that the aggregate value of the wilderness is slightly higher when estimated using a standard KT model instead of a latent class KT model. The two-group model suggests there is a group of hiking enthusiasts and a different group of casual users. The hiking enthusiasts take, on average, twice as many trips as casual users, but have lower per-trip CV estimates. The hiking enthusiasts group is characterized by white males who believe summer recreation is important and live closer to Idyllwild; while the casual user group is characterized by younger females who live further from Idyllwild. Demand is negatively affected by age for both groups, but the impact is larger for the hiking enthusiasts group.

Regarding the hypothesis that the more enthusiastic backcountry hikers tend to live further from the wilderness, the model finds mixed results: hiking enthusiasts live closer to Idyllwild but further from similar places, whereas the opposite implicitly holds for the casual user group. This suggests that recreationists do live closer to recreation sites for recreation opportunities.

This study could be extended in several ways to test how the standard and latent class KT models compare to other models. A possible approach is to re-run the analysis using the web-based survey data with both the standard and latent class approach used by Baerenklau (2010) to compare the welfare measures. Applying this procedure would reveal both the robustness of the latent class KT model and to what extent the sorting behavior described here appears to exist. Another possibility to help reduce the potential welfare bias in the KT model is to use a non-additively separable utility function or modeling structure such as a dynamic KT model. Lastly, other estimation techniques such as the EM algorithm can be used to determine if perhaps the same group membership variables are found and if a larger number of broadly relevant groups can be identified.

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Appendix

Appendix I

Recruitment Script:

You will be approaching recreationists obtaining hiking permits at the Idyllwild Ranger Station and asking if they are interested in participating in an online survey. They must be 18 years old or older to participate in the study.

<u>Instructions for employee</u>

1. Be cordial and respectful

2. Approach recreationists obtaining hiking permits at the Idyllwild Ranger Station.

3. Ask them their ages; if less than 18, don't ask for their e-mail address.

4. If a recreationist becomes upset, please desist immediately and back away. Remember: Safety above all!

5. Keep a tally of all recreationists approached that refused to participate.

6. At the end of the day, please forward all e-mail addresses to José Sánchez at: jsanc011@ucr.edu.

Hi my name is **___________**, an undergraduate student at the University of California, Riverside. We are doing a study on the effect of wildfires on the recreation value of the San Jacinto Wilderness and would like your help by completing a 20 minute online survey. Participation is completely voluntary. Survey responses are kept strictly confidential and your e-mail information will NOT be provided to any other groups. All participants completing the survey are eligible to enter a raffle to win a free iPad. If you are interested, please provide us your e-mail address. A survey link will be sent to your e-mail address within 24 hours.
Thank you for your participation.

Purpose of Study:
Determine the value of trailhead access, derive spatially explicit landscape values, and analyze how forest recreation values recovers after a wildfire for the San Jacinto Wilderness Area, which is located in the San Bernardino National Forest.

Previous Study:
Baerenklau et al., 2010. Spatial allocation of forest recreation value. Journal of Forest Economics 16, 113-126.

Recreationists who want further information should contact José Sánchez at jsanc011@ucr.edu

Appendix II

San Jacinto Wilderness Survey and e-mail reminders

E-mail-Survey information:

Subject: San Jacinto Wilderness Study Participation

Dear Study Participant,

Thank you for your interest in participating in the San Jacinto Wilderness Survey. In the online survey we ask you to recall your visits to the San Jacinto Wilderness Area over the past year and answer questions on recreation trips and about possible future fires in the wilderness. The survey questions should take no more than 20 minutes of your time. All the answers to our questions will be completely anonymous, kept confidential, and will be used for the purpose of this study. As a token of our appreciation, you will be entered in a raffle to win a free iPad.

You will be receiving an e-mail (from SurveyMonkey©) with a link to the survey within a day. If you don't receive the e-mail by tomorrow afternoon, please reply to this e-mail so we can send you the survey link. If you have questions, please feel free to contact me by e-mail, jsanc011@ucr.edu.

Again, thank you for your participation.

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

Survey Link:
Dear Survey Participant,

Thank you for your interest in participating in the San Jacinto Wilderness study.
Here is a link to the survey:

[SurveyLink]

This link is uniquely tied to this survey and your email address. Please do not forward this message.

Thanks for your participation!

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

1st Reminder E-mail:

Dear Survey Participant,

Last week an e-mail was sent to you with a link to the survey. The survey has not been completed. You still have time to complete the survey and be eligible to enter a raffle to win a free iPad.

Please complete the survey as soon as possible.

Here is a link to the survey:

[SurveyLink]

This link is uniquely tied to this survey and your email address. Please do not forward this message.

Thanks for your participation!

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

2nd Reminder E-mail:

Dear Survey Participant,

Approximately two weeks ago an e-mail was sent to you with a link to the survey. The survey has not been completed. You still have time to complete the survey and be eligible to enter a raffle to win a free iPad.

Please complete the survey as soon as possible.

Here is a link to the survey:

[SurveyLink]

This link is uniquely tied to this survey and your email address. Please do not forward this message.

Thanks for your participation!

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

Final E-mail contact:

San Jacinto Wilderness Survey-Final Reminder

Dear Survey Participant,

Approximately three weeks ago you agreed to participate in the San Jacinto Wilderness survey. We sent you an e-mail with a link to the survey. The survey has not yet been completed. We appreciate if you could complete the survey. You still have one week to complete the survey and be eligible to enter a raffle to win a free iPad.

After this time, the survey link will be removed from the system. Please complete the survey as soon as possible.

Here is a link to the survey:

[SurveyLink]
This link is uniquely tied to this survey and your email address. Please do not forward this message.

Thank you for your participation!

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

Appendix III

E-mail to iPad winner:

Dear Survey Participant,

Congratulations! You are the San Jacinto Wilderness study participant who has been randomly selected to receive the free iPad. Please send me your complete name and mailing address so the UCR Bookstore can mail it to you. If you have any questions, please feel free to contact me at jsanc011@ucr.edu.

Again, congratulations and thank you for your participation!

Sincerely,

Jose Sanchez
PhD Candidate
University of California, Riverside
jsanc011@ucr.edu

Appendix IV

Survey Instrument:

Survey1

Consent

You are being asked to participate in this survey because you have recently visited the San Jacinto Wilderness. Participation is completely voluntary. All responses will be kept confidential and will be used for the purpose of this study. Your responses will be combined with others and used in such a way that individual responses cannot be identified. If you have any questions, please feel free to contact Jose Sanchez (jsanc011@ucr.edu), PhD Candidate in the Department of Environmental Sciences at the University of California, Riverside.

If you have questions about your rights as a research subject, please contact the UCR Office of Research Integrity at (951) 827-4810, or to contact them by email, please use IRB@ucr.edu.

1. Do you agree to the consent information listed above?

- ◯ Yes, I am at least 18 years old, understand that participation is voluntary and agree to participate in the online survey
- ◯ No, I am not at least 18 years old or don't agree to the above consent.

Survey1

Introduction

Wildfire is a natural part of many ecosystems. Wildfires also can threaten and destroy valuable property such as private homes and public infrastructure. This survey is meant to provide information that will help promote appropriate wildfire management strategies in and around the San Jacinto Wilderness Area. This wilderness area is located in the San Bernardino National Forest in Southern California and covers approximately 51 square miles.

In this survey we ask you to recall your visits to the San Jacinto Wilderness Area over the past year and answer questions about possible future fires in the wilderness. These fires have not taken place, but suggest possible fire-induced conditions that visitors to the wilderness area might encounter in the future. By completing the survey, you can help provide better information to decision-makers for forest management strategies.

The survey questions should take no more than 20 minutes of your time. You will not be able to return to the survey, so please complete the entire survey once you begin. As a token of our appreciation, you are eligible to enter a raffle to win a free iPad. You will be able to enter the raffle by providing your email address at the end of the survey. The winner of the raffle will be notified by November 2012.

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Recreation

2. How many times have you accessed the San Jacinto Wilderness from the east side (i.e., Palm Springs Aerial Tramway, Long Valley Ranger Station) in the past 12 months, including your most recent trip?

- ◯ None
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ Other (please specify)

3. How many times have you accessed the San Jacinto Wilderness from the west side (i.e., Idyllwild Ranger Station and nearby trailheads) in the past 12 months, including your most recent trip?

- ◯ None
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ Other (please specify)

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4. Which activities have you engaged in when visiting the San Jacinto Wilderness during the past 12 months, including your most recent trip? (Select all that apply)

- [ ] Bird Watching
- [ ] Camping
- [ ] Day Hiking
- [ ] Horse Riding
- [ ] Jogging/Running
- [ ] Outdoor Learning
- [ ] Overnight Backpacking
- [ ] Picnicking
- [ ] Rock Climbing
- [ ] Sightseeing
- [ ] Winter Sports (i.e., Sledding/Tubing, Snowshoeing, Skiing, etc.)
- [ ] Other (please specify)

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5. Think about the characteristics of the San Jacinto Wilderness that are important to you. Below are some characteristics that you might feel are important. How important is each characteristic to you?

	Very Important	Important	Slightly Important	Not Important	No Opinion
Habitat for wildlife populations	○	○	○	○	○
A quiet place to seek solitude or escape city life	○	○	○	○	○
Opportunity for recreation such as snowshoeing, skiing, sledding, or tubing	○	○	○	○	○
Opportunity for recreation such as hiking, backpacking, or rock climbing	○	○	○	○	○
Opportunity for viewing natural scenery, the changing seasons, or a flowing creek	○	○	○	○	○
Opportunity for environmental education	○	○	○	○	○
A source of water supply	○	○	○	○	○
A source of inspiration	○	○	○	○	○
A preserved natural area for future generations to enjoy	○	○	○	○	○

Other: Please list below

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Trip Information

6. Please report the number of recreation trips taken to each trail in the past 12 months, including your most recent trip (e.g., 0, 1, 2, 3, etc.).

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

7. Please report the number of times you visited the following destinations in the past 12 months, including your most recent trip (e.g., 0, 1, 2, 3, etc.).

	Number of recreation trips
Hidden Divide Natural Preserve	
Little Round Valley	
Mt. San Jacinto Peak	
Round Valley	
Saddle Junction	
Skunk Cabbage Meadow	
Tahquitz Peak (Fire Lookout)	
Tahquitz Valley	
Tamarack Valley	

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Trip Expense

Think about how much it typically costs you to visit the San Jacinto Wilderness. These costs could include your share of gas, food, access fees, equipment rental fees, and other costs. Do not include the cost of your time.

8. How much does it typically cost you to visit the San Jacinto Wilderness?

Typical cost per visit ($)

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Trip Expense

9. If the typical cost had been $10 higher, how many recreation trips would you have taken to each trail during the past 12 months (e.g., 0, 1, 2, 3, etc.)?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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Scenarios

In this section you will see several post-fire pictures of forests that have landscapes similar to the San Jacinto Wilderness. The pictures are intended to represent the appearance of the San Jacinto Wilderness after different types of fires. In reality, a fire can affect several trails. For the purpose of this study, assume that only the specified trail will be affected by fire. When answering questions about these pictures, keep in mind your recreation trips to the San Jacinto Wilderness over the past year.

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0-5 year-old low-intensity burn, foreground

10. This picture shows a 0-5 year-old low-intensity burn viewed from up-close. If 25% of the foreground scenery along the Deer Springs trail was similar to this picture, how many recreation trips would you have taken to each trail during the past 12 months?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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6-15 year-old high-intensity burn, background

11. This picture shows a 6-15 year-old high-intensity burn viewed from a far distance. If 25% of the background scenery along the Marion Mountain trail was similar to this picture, how many recreation trips would you have taken to each trail during the past 12 months?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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6-15 year-old medium-intensity burn, background

12. This picture shows a 6-15 year-old medium-intensity burn viewed from a far distance. If 25% of the background scenery along the Devil's Slide trail was similar to this picture, how many recreation trips would you have taken to each trail during the past 12 months?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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Greater than 15 year-old medium-intensity burn, middle ground

13. This picture shows a 15+ year-old medium-intensity burn viewed from a moderate distance. If 75% of the middle ground scenery along the Long Valley trail was similar to this picture, how many recreation trips would you have taken to each trail during the past 12 months?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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Greater than 15 year-old medium-intensity burn, background

14. This picture shows a 15+ year-old medium-intensity burn viewed from a far distance. If 50% of the background scenery along the South Ridge trail was similar to this picture, how many recreation trips would you have taken to each trail during the past 12 months?

	Number of recreation trips
Deer Springs Trail	
Devil's Slide Trail (Humber Park)	
Marion Mountain Trail	
South Ridge Trail	
Long Valley (Palm Springs Aerial Tram)	

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Household Information

15. In which ZIP code is your home located? (enter 5-digit ZIP code; for example, 94305)

16. Are you male or female?

- Male
- Female

17. Which category below includes your age?

- 18-20
- 21-29
- 30-39
- 40-49
- 50-59
- 60 or older

18. Are you currently a member of a conservation or environmental organization?

- Yes
- No

19. How would you describe your racial or ethnic background? (Check the best answer)

- Asian or Pacific Islander
- Black or African-American
- Hispanic or Latino
- Native American Indian
- White or Caucasian
- Other (please specify)

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20. What is the highest level of education you have completed?

- ◯ Less than high school degree
- ◯ High school degree or equivalent (e.g., GED)
- ◯ Some college but no degree
- ◯ Associate degree
- ◯ Bachelor degree
- ◯ Graduate degree

21. Which of the following best describes your employment status during the past 12 months? (Check the best answer)

- ◯ Employed Full Time
- ◯ Employed Part Time
- ◯ Unemployed
- ◯ Retired
- ◯ Student
- ◯ Other (please specify)

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22. What was your total household income during the past 12 months before taxes and other deductions? (Check the best answer)

- ◯ under $9,999
- ◯ $10,000 - 19,999
- ◯ $20,000 - 29,999
- ◯ $30,000 - 39,999
- ◯ $40,000 - 49,999
- ◯ $50,000 - 59,999
- ◯ $60,000 - 69,999
- ◯ $70,000 - 79,999
- ◯ $80,000 - 89,999
- ◯ $90,000 - 99,999
- ◯ $100,000 - 109,999
- ◯ $110,000 - 119,999
- ◯ $120,000 - 129,999
- ◯ $130,000 - 139,999
- ◯ $140,000 - 149,999
- ◯ $150,000 and over

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Additional Comments

23. Do you have any additional comments for us?

24. If you would like to be included in the drawing for a free iPad, please provide your email address.