Understanding Diverse-Stakeholder Preferences for Ecosystem Services in Southern California Montane Forests: Informing Forest Management Practices via Inclusion

UNDERSTANDING DIVERSE-STAKEHOLDER PREFERENCES FOR ECOSYSTEM SERVICES IN SOUTHERN CALIFORNIA MONTANE FORESTS: INFORMING FOREST MANAGEMENT PRACTICES VIA INCLUSION

By

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TABLE OF CONTENTS

LIST OF TABLES

TABLE OF FIGURES

ABSTRACT

Understanding forest management preferences from a diverse set of stakeholders is critical for public land managers, particularly in landscapes undergoing disturbances such as fire, invasives species, climate change, urbanization and increasing visitor use. The aim of this research is to inform forest management by co-developing an "intuitive" survey instrument suited for a diverse set of stakeholders, including marginalized communities (e.g., those who typically do not participate in public input mechanisms of the US Forest Service), frequent participants, as well as environmental groups. This survey elicited preferences for several specific ecosystem services (e.g., recreational benefits from rivers and lakes), non-ecosystem services (e.g., amenities such as public restrooms and grills), along with silvicultural forest management practices (e.g., forest thinning). Data for this thesis was collected from participants who reside near the San Bernardino National Forest in California, using a best-worst choice survey method – a hybrid approach that enable estimation of- both preferences (e.g., willingness-to-pay [WTP]) and importance rankings (e.g., Dawes et al., 2018). Results indicate that mechanical thinning (i.e., cutting down/removing unwanted trees with mechanical equipment) is ranked more important than prescribed/controlled fires, while overall, paying an additional price of $1 ranked as lowest. Public restrooms ranked highest in terms of amenities. The above were not statistically significant when assessing preferences – except for paying an additional price for parking.

1. INTRODUCTION

In 1910, roughly five years following the creation of the U.S. Forest Service (USFS), 3 million acres of forest land spreading across Montana, Idaho, and Washington burned down in just two days, in what became known as the "Big Blow Up". It was this and many other large fires during the early 1900's that caused a big push for fire suppression and prevention policies at a federal and state level (Smith R. K., 2007). In efforts to educate the public, the famous "Smokey the Bear" character became the symbol for forest fire prevention across the U.S. Although there were contemporary advocates for the benefits forest fires (Cohen J. , 2008), it was not until the 1970's that forest fires were recognized as a key ecological process to forest health and growth (Forest History Society, 2023).

Wildfires are an important part of the ecological process in forests. When wildfires burn large trees and underbrush, it allows for sunlight to reach smaller, growing trees/plants and the ashes serve as nutrients for these new plants (Verma et al., 2012). However, as fires become more intense and burn for longer, the damages begin to outweigh the benefits (Verma et al., 2012). Due to earlier policies of fire suppression and prevention, there has been an accumulation of fuel in forests leading to larger, more intense forest fires. Additionally, the effects of climate change and human development in forests have intensified the potential for intense fires (Keane et al., 2010). Suppression methods can be costly; federal costs of suppressing forest fires in 2021 reached a total of $4.4 billion by the Forest Service and other DOI agencies (National Interagency Fire Center, 2022). Adding to the difficulty of managing a forest's health, while maintaining the safety of nearby residents, there are organizations that lobby for their management of forests on behalf of their own interest group. Whether these interests represent the needs of the general public, the current understandings of forest ecology, or their own pursuits, is generally unknown (Smith et al., 2021).

Located in southern California, near the San Bernardino National Forest, the San Bernardino valley is a good intersection for forest policy management and a diverse community engagement. As of 2021, over 64% of the population is Hispanic or Latino (U.S. Census Bureau, 2021) in the San Bernardino Valley. At a national level, the Hispanic/Latino community is estimated to cover 28% of the U.S. population by 2050 (Thomas et al., 2022). When we consider that this group represents the majority of the people in this valley, it would be sensible that policies and establishments would reflect the values of the Hispanic/Latino population. However, this specific group is often left out of the policy-making process due to socio-economic barriers to participation (Thomas et al., 2022). The majority of the population in this valley falls under the category of “disadvantaged community”, or an area throughout California where most suffer from a combination of economic, health, and environmental burdens. These burdens include high unemployment, poverty, presence of hazardous wastes, air and water pollution, as well as high rates of asthma and heart disease (California Environmental Protection Agency, 2023; California Public Utilities Commission, 2021).

Outdoor recreation in National Forests is subject to the impact of forest fires, whether they are prescribed or not. Forest fires also impact the health and well-being of those living near the montane forests. Nearby residents have the best opportunity to participate in forest recreation (in terms of geographical distance) and would similarly be impacted by forest fire management policies when considering aspects of health. Given all the above, it is therefore critical to identify and understand potential differences – in preferences and importance - between those who reside nearby (and who have participated in forest management policy stakeholder mechanisms, either in surveys or direct involvement in policy development), and those who have never engaged in such public input opportunities. Such insight could evidence the re-examine results from previous public input efforts as well as the exploration of potential barriers to participate.

This research contributes to the above by exploring possible stakeholder heterogeneity of preferences and opinions on ecosystem services derived from Montane Forests in Southern California, in particular, the San Bernardino National Forest. Stakeholders from diverse backgrounds were surveyed to examine the following specific research questions: 1) do stakeholders who typically participate in USFS public input mechanisms exhibit differences in preferences and importance - when compared to other residents/stakeholders from historically underrepresented communities?; and 2) what are the tradeoffs between various ecosystem services (ES), as these relate to specific alternative forest management options? The focus on ES to examine the latter is appropriate given that these are a subset of ecosystem conditions and processes that not only result in useful or valuable services to humans (Sekercioglu, 2010), but also sustain and fulfill human life (Costanza et al., 2017). The above is explored using a best-worst choice (BWC) survey approach (following Dillman et al. (2014) method) to develop ES and Non-ES rankings. The overall goal of this work is to generate timely knowledge which informs efforts towards the development of more holistic forest management practices that comprehensively benefit all stakeholders and ecosystems, alike.

2. LITERATURE REVIEW

2.1 BWS Method

Best Worst Scaling (BWS) was introduced first by Louviere and Woodworth (1991) and is an extension of the paired comparison method (Thurstone, 1927; Finn & Louviere, 1992). It has subsequently used in healthcare and marketing research as a new method of measuring utility, overcoming some of the limitations of traditional DCE's (McIntosh & Louviere, 2002; Cohen E. , 2009; Louviere & Flynn, 2010; Louviere, et al., 2013). BWS models can be exhaustive, but Street et al. (2005) describes the quantitative principles to organize BWC surveys through orthogonality. Orthogonal arrays in survey methods are used to compare survey attributes while avoiding confusion and bias (Street et al., 2005). Using orthogonal arrays is a common practice in BWC survey designs (Cheng, 2021; Soto et al., 2016; Flynn et al., 2007; Flynn et al., 2008) and is it implemented in this survey.

Escobedo et al. (2011) state that ecosystem services are valued by information and perceived importance of particular ecosystem services and pollutants to people and suggest an analysis of ecosystem preferences should focus on the services, rather than the functions, that inform discrete management practices. Soto et al. (2018) implement the BWS method to reduce the likelihood of survey bias while producing estimates of utility for ecosystem services and disservices. This research takes a similar approach, by using a BWC survey to estimate a ranking of importance of ES and non-ES. By using management practices related to these services (thinning, amenities, access to water features), I seek to reduce the confusion that may arise among groups that are unfamiliar with ES terminology (density, diversity, understory, etc.).

Lusk & Briggeman (2009) used the BWS method to find preferences for new food values/attributes (Naturalness, taste, price, safety, convenience, nutrition, tradition, origin, fairness in production, appearance, and environmental impact) and preference for organic food. Their econometric analysis included both the random parameter logit (RPL) and the multinomial logit model (MNL) in measuring the relative importance of each attribute. To produce a natural interpretation of the results, they provide a share of the preferences as a percentage. They revealed that safety is the most important attribute on average, while the origin of the food was the least important attribute. Those who selected price as the most important attribute held a lower preference to purchasing organic food. This provides support for using income as a distinguishing variable for preference in purchasing a good. In our case, the respondent's income should be controlled to see whether they would pay to park at a national forest.

Dawes et al. (2018) follows a mixed method approach to analyzing the effectiveness of a tree distribution program. They utilized a BWS mean score (standard score) to rank the preference of each attribute and level of the tree distribution program and a logit regression model to analyze the binary task of accepting the program. Instead of the WTP, Dawes et al. (2018) implements a willingness-to-accept (WTA). The standard score showed results that aligned with the logit regression model. The use of BWS mean score is a useful statistic for measuring preferences/importance between different attributes without running a regression. Even though the WTA is different from the WTP, the estimation of the WTA using a dichotomous choice logit provides a suitable framework for estimating the WTP for ES and non-ES attributes in this study.

2.2 Choice of Attributes

Thomas et al. (2022) reviewed literature covering the preferences, behavior, and participation of Hispanic/Latino communities on public lands. Though intragroup differences exist, most Latinos tend to visit public lands in large groups, mainly with family and friends. Picnicking is a popular activity, but cooking is often done on-site. Water-based activities such as swimming and playing in streams appear to be more popular than walking or hiking. Latinos were shown to prefer more developed sites with better facilities and amenities (grills, water faucets, etc.). As water features and amenities are important to this group, the survey includes these two attributes. Furthermore, residents of southern California may value having water features in the forest for esthetic appeal rather than the market value of a water resource.

Kalies et al. (2016) suggest that mechanical thinning and prescribed fires reduce the intensity of future fires. They reviewed 56 published papers on treating forest fire fuel, some of which contained examples of results for treated and untreated forests. Measuring treatment effectiveness is a challenge due to the unpredictable timing of wildfires. However, they found substantial literature on the effectiveness of fuel treatment throughout the western U.S. in reducing fire severity, crown and bole scorch, and tree mortality. Likewise, Kalies et al. (2016) state that dense forests may provide more carbon sequestration and provide refuge for small animals. Additionally, open spaces allow for more recreational activity. Some people may prefer a dense forest or a spacious forest for the esthetics, (De Meo et al. 2020). The two methods for thinning, mechanical and controlled burning, are related to the density of a forest as it reduces the number of trees or plants within a specified area. In this survey, mechanical thinning and prescribed fires are levels to the thinning attribute.

3. METHODOLOGY

3.1 Non-Econometric Framework

Following Dawes et al. (2018), a BWS means score was used as a non-econometric measure of importance. A BWS score is calculated using the following formula:

$$BWS\ SCORE = \frac{(Count_b - Count_w)}{f * n}$$

[EQ. 1]

Where the numerator is the difference between the number of times a level is selected as the best and worst in all sets. *f* is the number of times a level is presented as an option in a set and *n* is the number of respondents. To see the frequency of each level, refer to **Appendix *A***: Orthogonal Array.

3.2 BWS Econometric Framework

BWS choice modeling is a useful tool in market research for informing new product development, health, business, and forest management practices (Louviere et al., 2015). This reduces the middle ranking ambiguity typically found in simple ranking structures. By limiting the number of options to only extremes, respondents are forced to make trade-offs while minimizing bias. Understanding the utility respondents may have for each specific attribute and level can be interpreted as the trade-off for other attributes. In the BWS model, we associate the least preferred choice, or worst choice, as the value that respondents are willing to trade for assuring that at least their preferred, or best, choice remains. By this logic, we can infer a maximum difference (or MaxDiff) between the best and worst value in terms of importance. Marley et al. (2007), states that most of the models for MaxDiff use a multinomial logit (MNL) assumes some maximum utility u. The MNL determines the combination of attributes and levels with the biggest difference in importance:

$$B_C(x) = \frac{e^{u(x)}}{\sum_{z \in C} e^{u(z)}}$$

[Eq. 2]

Where $B_C(x)$ is the probability that attribute *y* is chosen as the best in C, *u(x)* is the utility for x, and *u(z)* is the overall utility for all the other elements in *C*. Likewise, there is a probability $W_C(y)$ for *y* to be chosen as the worst attribute in C (Marley et al., 2005):

$$W_C(y) = \frac{e^{-u(y)}}{\sum_{z \in C} e^{-u(z)}}$$

[Eq. 3]

The MaxDiff model assumes that the probability of a choice for the worst option in C is the negative valence of the best option in C. This makes the probability of *x* and *y* picked as *best* and *worst*:

$$BW_C(x, y) = \frac{e^{[u(x)-u(y)]}}{\sum_{\{p,q\} \in C} e^{[u(p)-u(q)]}} \ , x \neq y, p \neq q \in C.$$

[Eq. 4]

The denominator represents the sum of all BWS combinations $\{p, q\}$ where $p \neq q$. The utility difference equation for x_{tj}^i as the most important and x_{tk}^i as the least important attribute level in choice set *C,* of BWS profile *t*, for respondent *i,* can be measured following Soto et. al (2018):

$$U_{mnt}^i = \beta_m x_{tm}^i - \beta_n x_{tn}^i + \varepsilon_{tm}^i - \varepsilon_{tn}^i \, , \qquad m \neq n$$

[Eq. 5]

Where β_m and β_n are parameters for estimation and the ε's are the error terms. This can be applied to the earlier equation for calculating the probability of each choice set by replacing *x* and *y* in eq. 3 for *m* and *n,* respectively:

$$BW_C(m,n) = \frac{e^{[\beta_m x_{tm} - \beta_n x_{tn}]}}{\sum_{\{p,q\}\in C} e^{[\beta_p x_{tp} - \beta_q x_{tq}]}}$$

[Eq. 6]

Using maximum likelihood estimation, we can calculate the β parameters. We can modify the BWS pairs to estimate the level scale impact (LSV) from the BWS. The LSV estimates the effect on importance from each level. This survey has 4 attributes and 11 levels. The estimation is done for only 10 levels, selecting a level as a base of reference to avoid the "dummy variable trap" (Soto et al., 2018). The following is the utility function expressing importance through the LSV:

$$U_{mnt}^{i} = \beta_{a2}^{i}\delta_{a2}^{i} + \cdots + \beta_{d3}^{i}\delta_{d3}^{i} + \varepsilon^{i}$$

[Eq. 7]

Here, β attached to the $\delta_{a2\ldots d3}^{i}$, shows us the attribute impact when δ^{i} takes on the value of 1 if selected as the best level in a choice set, -1 if selected as the worst level, and 0 otherwise. To estimate the difference in importance between groups, I used the interaction of FP and Hispanic/Latino respondents with each attribute level:

$$U_{mnt}^{i} = \beta_{a1}^{i}\delta_{a1}^{i} + \beta_{a1}^{i}\delta_{a1}^{i}H + \beta_{a1}^{i}\delta_{a1}^{i}F + \cdots + \varepsilon^{i}$$

[Eq. 8]

Where H is a dummy variable representing Hispanic/Latino respondents and F are the FP. These interactions can be estimated using the conditional logit model (CLM) following Soto et al. (2016). The CLM is used to estimate the utility (or rather importance) of an attribute level in the presence of alternate attribute levels. There is a specific number of possible combinations for *J* attributes in each comparison (choice set), *J(1-J)*. For this experiment, I used 4 attributes, therefore

J(J-1) = 12. The variable representing the chosen outcome was expanded 12 times per choice set, a 1 indicating the selected BWS combination. This means there were 12 alternatives to each choice. There were 9 choice sets (or questions) in the BWS, resulting in 108 possible outcomes per respondent.

To avoid confusion with the coefficients, we will scale them to a shared value of importance, referred to as a "share of preference" (Lusk & Briggeman, 2009). This will provide a proportionate coefficient for importance, meaning that if a share is 2.00 for one variable, it can be interpreted as twice as important as the base (or omitted) variable. [**Eq**. 9 shows the formula for calculating the value for each share of preference. Where β_i represents the coefficient of the LSV *i,* limited to 10 coefficients (11 levels minus the base level). Covariates can have their own shares, as long as they have the same base level.

$$Share\ of\ preference = \frac{e^{\beta_i}}{\sum_{i=1}^{10} e^{\beta_i}}$$

[Eq. 9]

WTP Econometric Framework

For every choice set, there is a binary choice where respondents will either agree or disagree to increasing the price of parking by $1, $3, or $5, considering the choice set C. We can define the probability of agreeing to pay as *P(yes)* and model it in the following equation:

$$P(yes) = P(U_y > U_n)$$

[EQ. 10]

Where $P(U_y > U_n)$ is the probability of the utility for yes (U_y) being greater than the utility for no (U_n). To simplify this, we can normalize U_n to equal zero without compromising the significance of this model by subtracting it from U_y:

$$P(yes) = P(U_y - U_n > 0)$$

[EQ. 11]

Now, we can redefine $U_y - U_n$ as U_i, and the probability of choosing *yes* based on utility of individual *i* becomes:

$$P(yes) = P(U_i > 0)$$

[EQ. 12]

Integrating this identity with this survey model, we will use a random effects logit (REL) to represent the utility equation for an individual *i*, and the binary choice *t*:

$$U_{it} = \beta' x_{it} + \alpha_i + \varepsilon_{it}$$

[EQ. 13]

$$Y_{it} = (U_{it} > 0)$$

[EQ. 14]

Where the individual specific error α_i, and the overall error term ε_{it}, are added to the attribute that was selected x_{it}. β represents the vector for the estimated parameters, and Y_{it} is the outcome of the choice, taking the value of 1 if selected and 0 otherwise. We can assume the error terms are independent random variables that are uncorrelated with x_{it}. Additionally, we want to identify the differences in WTP among groups of interest. We can represent this model with the following equation:

$$P(Y=1|x_{it}) = \frac{exp(\beta' x_{it} + \beta' F_i + \beta' H_i + \beta' N_i + \beta' I_i + \beta' P_i + \alpha_i)}{1 + exp(exp(\beta' x_{it} + \beta' F_i + \beta' H_i + \beta' N_i + \beta' I_i + \beta' P_i + \alpha_i))}$$

EQ. 15

The first portion, $P(Y = 1|x_{it})$, denotes the probability that a respondent answered yes (or Y=1), given the individual choosing from choice set *t*. The second portion is the logistic distribution for the estimated parameters β for the selected attribute x_{it}, FP respondents F, Hispanics/Latinos H, respondents that never go to montane forests N, and income I. P_i is the price respondent *i* is willing to pay, the additional cost of \$1, \$3, or \$5 to park at the National Forest to fund the other attributes (e.g., thinning; amenities; access to water features). For the non-attribute estimates, the coefficient can be interpreted as the change in probability that the respondent would say "Yes" or "No" to paying for any attribute.

The respondents' WTP can be calculated in a dollar value using the negative ratio of the coefficient of a non-price attribute over the coefficient for price (Salm, Bockarjova, Botzen, & Runhaar, 2023). Eq. 16 below uses β_i as the resulting coefficient from the REL model for attribute i, while β_p represents the price coefficient. This helps interpret the estimates' proportional importance, i.e., if a share of preference is twice as big for one attribute level in comparison to another, it can be considered twice as important.

$$WTP = -\frac{\beta_i}{\beta_p}$$

EQ. 16

4. SURVEY AND DATA

4.1 Survey Description

The survey was launched in May of 2023, hosted by Qualtrics, signaling the process of collecting data. Qualtrics survey administrators sampled individuals older than 18 years of age from the San Bernardino area (East of Los Angeles, CA). Qualtrics stratifies their frame by census regions, income levels, gender, and age. The collaborating community partners (San Bernardino National Forest, Angeles National Forest, San Gabriel National Monument, Los Angeles Urban Center, Amigos de Los Rios, Nature for all, Southern California Forest Montane Alliance, Tree People, The Nature Conservancy, US Forest Service Pacific Southwest Research Station, Cal Fire) hosted the left part of the survey through their contacts and networks.

Respondents had the opportunity to complete surveys at a time that is most convenient for them and through preferred platforms: tablets, cell phones, or a computer. As mentioned above, this research followed the Dillman Method (Dillman et al., 2014), which offers a guideline for online surveys and received the approval of The University of Arizona's Institutional Review Board (STUDY00002586).

The survey began with a participant consent question, followed by a filter question to remove respondents that do not live in or near the San Bernardino Valley (This includes the cities of San Bernardino, Fontana, and Highland).

In the section that followed, respondents answered a series of background questions relating to forest management – for the purpose of assessing their knowledge on the subject matter (i.e., forest fires.)

The following attributes were used to develop the hypothetical forest ecosystem management (see Figure 1 for example question): a) thinning (2 levels; controlled fire and mechanical thinning); b) amenities (3 levels; public grills, garbage bins, and public restrooms); c) water (3 levels; rivers/streams, waterfalls, and lakes); and d) parking (3 levels; $1, $3, and $5) (Table 1). The additional parking fees were determined from the local forest experts' comments. Table 1 details these attributes.

Table 1: A list of National Forest attributes and their respective levels of service.

Attribute	Definition	Levels
Thinning	Removing fallen branches, twigs, and dry shrubs with controlled fire or removing dead/unwanted trees by cutting them down mechanically to reduce the risk of fire and decrease forest density.	Controlled Fire Mechanical Thinning
Amenities	Facilities and services provided by the U.S. Forest Service that allow for more comfort to visitors.	Public Grills Garbage Bins Public Restrooms
Water	Providing access to water features (rivers, streams, lakes, etc.) within the National Forest.	Rivers/Streams Waterfalls Lakes
Parking	Paying an additional dollar amount to pay for parking in order to fund services above.	$1 $3 $5

Given that a choice experiment that accounts for all combinations (i.e., full factorial) would include $2 \times 3 \times 3 \times 3 = 54$ management hypothetical scenarios (perhaps too long a survey for practical purposes). This study instead made use of the statistical software SAS's macro %mktex in order to generate a balanced fractional factorial orthogonal design (SAS, 9.4). The D-optimal efficiency was 99 percent (Appendix A), with 9 choice tasks per respondent. Figure 1 illustrates the choice tasks.

Figure 1: Example of the BW and Binary WTP question from the survey

Please indicate which service is the **most important** and which is the **least important** to you.

Most important to you		Least important to you
○	**Thinning**: Removing fallen branches, twigs, and dry shrubs with **controlled fire.**	○
○	**Amenities**: Providing garbage bins.	○
○	**Water:** Providing access to rivers/streams.	○
○	**Parking:** Paying an additional $3 to park.	○

Would you pay an additional $3 ($8 total) to park at a forest with all these services above?

- Yes
- No

4.2 Demographics

The last section of the survey solicits demographic information. **Table 2** details the characteristics for our respondents in comparison to the demographics of the San Bernardino Valley (U.S. Census Bureau, 2021), as well as the proportion of frequent participants (FP) and non-FP respondents. As is common with online data collection, the yielded sample did not perfectly align with the demographic profile of the U.S. Census data. There is mainly overrepresentation for non-Hispanic white respondents and Hispanic/Latino respondents of any race (respondents do represent over a third of the combined respondents and almost half of the FPs). The Qualtrics panel could not guarantee or commit completely to the quotas for each characteristic from the 2021 U.S. Census due to the small geographic region and the short time for data collection; the Qualtrics panel distributed the survey for a period of one month. Expanding the distribution period could result in reaching the percentage quotas.

Table 2: The Demographics For Frequent Participants (FP) And Non-FP Compared To The U.S. Census Results From 2021 By Percentage.

Characteristic	FP (n = 48)	Non-FP (n = 338)	Survey Total (n = 386)	2021 U.S. Census
Age				
18 to 29	41.7%	20.4%	23.1%	17.1%
30 to 44	41.7%	27.5%	29.3%	21.3%
45 to 64	6.3%	36.7%	32.9%	23.5%
65 and Up	10.4%	15.1%	14.5%	10.9%
Gender				
Female	52.1%	47.6%	48.2%	50.0%
Male	45.8%	51.2%	50.5%	50.0%
Other Gender	2.1%	1.2%	1.3%	–
Education				
Some High School	2.1%	2.7%	2.6%	22.3%
High School	33.3%	29.3%	29.8%	31.8%
Some College	16.7%	24.9%	23.8%	19.8%
Associate	6.3%	7.4%	7.3%	7.4%
Bachelor	22.9%	21.3%	21.5%	12.1%
Graduate	18.8%	14.5%	15.0%	6.6%
Race/Ethnicity				
Asian alone	0.0%	6.2%	5.4%	5.8%
Black alone	8.3%	10.9%	10.6%	8.8%
Hawaiian Pacific alone	0.0%	1.2%	1.0%	0.2%
Middle Eastern alone	0.0%	0.3%	0.3%	–
Indigenous alone	0.0%	2.4%	2.1%	0.2 %
White	62.5%	64.5%	64.2%	42.0%
Hispanic/Latino (of any race)	45.8%	29.0%	31.1%	66.6%
White (non-Hispanic)	45.8%	50.6%	50.0%	15.2%
Other	20.8%	9.8%	11.1%	51%
Multiple race/ethnicity	8.3%	4.7%	5.2%	2.9%
Income				
< $35,000	20.8%	24.9%	24.4%	22.1%
$35,000 to $49,999	12.5%	13.0%	13.0%	10.0%
$50,000 to $74,999	27.1%	17.8%	18.9%	17.9%

$75,000 to and over	39.6%	44.4%	43.8%	50.0%

Note: The 2021 U.S. Census does not include data on non-binary genders or respondents who only consider themselves Middle Eastern. Most Hispanic respondents consider themselves White. The survey total is based only on the single-bound respondents. Percentages are based on each column, i.e., 41.7% of FP respondents are in the 18-29 age range. The percentages in the 2021 U.S. Census are an aggregated value from the cities of San Bernardino, Fontana, and Highland, CA.

To verify that respondents were paying attention to the survey questions, this study made use of "attention-check" questions. These questions tell the respondent to choose a specific answer from the choices below. Figure 2 shows an example of an "attention-check" question. The response time was also recorded to distinguish between those who took reasonable time to respond (details below) and those who sped through the survey. Responses from surveys that were complete in a time greater than 6 minutes (half of the median response time) were retained for this analysis, this, as well as the inclusion criterion of those who lived near or have lived near the San Bernardino Valley (including Highland and Fontana), and who correctly answered the "attention-check" questions. There were 2587 participants, of which 782 were retained (an approximate 30% retention rate), but only 338 were involved in this specific portion of the study. Additionally, out of the 2587 original responses, 53 were provided by the U.S. Forest Service. Only 33 of the U.S. Forest Service responses were retained. Most of the unretained responses were incomplete surveys. Respondents had the opportunity to opt out of the survey at any time if they did not feel comfortable with a question or if they simply did not want to finish the survey.

Background questions offer a deeper perspective from respondents and assist in modeling their responses. It is important to know the San Bernardino valley residents' sentiments towards the National Forest to comprehensively analyze what they deem important and their WTP. **Table 3** shows the responses in percentages for questions regarding how frequently respondents visit the National Forest, exposure to smoke, their general knowledge over prescribed fires, and their support towards prescribed fires. Using the term "controlled" fires over “prescribed” fires was a strategic decision to reach a broad audience with limited understanding over the subject. The biggest difference between FPs and non-FPs is in their participation, or the number of times they visit a montane forest in a year. Non-FPs are less likely to visit, perhaps due to barriers such as time, transportation, or lack of knowledge of forests. These barriers are highlighted in

Appendix B.

Table 3: Responses to background questions by percentage for Frequent Participants (FP) and non-FPs.

How many times a year do you visit any montane forest in southern California?			
	Non-FP (N = 338)	FP (N = 48)	Total (N = 386)
At least 5 times a year	10.36%	14.58%	10.88%
At least 3 times a year	15.09%	33.33%	17.36%
At least once a year	14.50%	27.08%	16.06%
Irregularly but I have visited	29.88%	22.92%	29.02%
Never	30.18%	2.08%	26.68%
How often have you been exposed to smoke from wildfires or controlled fires in the last 5 years since living in southern California?			
Every Month	4.1%	16.7%	5.7%
Every 6 months	16.3%	33.3%	18.4%
Once a year	39.6%	29.2%	38.3%
Once in the last 3 years	22.5%	14.6%	21.5%
Never	17.5%	6.3%	16.1%
Do you know the difference between a wildfire and a controlled fire?			
Yes	91.7%	97.9%	92.5%
No	8.3%	2.1%	7.5%
Would you support the use of controlled fires in the national forests of southern California?			
Yes	*84.3%*	*87.5%*	*84.7%*
No	*15.7%*	*12.5%*	*15.3%*

Figure 2: Example of an attention check question

What is the color of the sky? (Please select “Red”, we are making sure folks are reading the questions and following instructions)

- Blue
- Red
- Yellow
- Gray
- Turquoise

5. RESULTS

5.1 BWS Mean Score

The BWS scoring indicates importance in a direct comparison of least and most important attribute levels using a mean value for importance. Using the means is a useful way to analyze the importance without using econometric measures. The importance of forest density, as it relates directly to thinning, is particularly high. Mechanical thinning is on average, more important to respondents than prescribed fires. The price variables continue to be the lowest ranking in general, as expected by economic theory. However, the estimate for the additional $1 is ranked the lowest in relative importance. This is surprising, because higher prices would typically signal less importance. The influence of FP respondents is notable, as their shared importance is significantly higher than the other two groups for controlled fires, mechanical thinning, garbage bins, rivers/streams, and waterfalls.

Water features and amenities (particularly public grills) were attributes recognized as highly important to Hispanic/Latino communities during the pre-testing period. However, we see that thinning is, on average, esteemed as a the more important attribute than water features and amenities. Additionally, respondents considered public grills to be the least important attribute level more times than most important. This is the only non-price attribute to have a negative BWS Score. Respondents may be connecting public grills to the possibility of more wildfires, bringing down importance.

Table 4: Best-Worst (BWS) Scores for each attribute level.

Attribute/Level Name	Best Count	Worst Count	BWS Difference	BWS Score
Thinning				
Controlled Fire Thinning	892	377	515	2.86
Mechanical Thinning	478	190	288	3.20
Amenities				
Public Grills	122	374	-252	-2.80
Garbage Bins	227	167	60	0.67
Public Restrooms	364	130	234	2.60
Water				
Access to Rivers/Streams	402	126	276	3.07
Access to Waterfalls	361	161	200	2.22
Access to Lakes	407	127	280	3.11
WTP				
Additional $1	65	625	-560	-6.22
Additional $3	86	616	-530	-5.89
Additional $5	70	581	-511	-5.68

Using this score, we can expect the biggest difference in importance to lie between mechanical thinning and the additional cost of one dollar. Confusion remains over the scale of importance, i.e., whether it is important to their community, the environment, or to only themselves, but I allow the respondents to make that decision on their own for this portion of the survey. Some of the reasons why an FP would choose mechanical thinning could be to avoid the use of controlled burns. Other respondents commented that the price for parking should not increase, as it creates an even bigger barrier to low-income households participating in outdoor recreation. We can expect the price attribute and levels to have the lowest relative importance to those in the lower-income brackets as well.

5.2 CLM Model

The CLM model was regressed using STATA 17. The results from the CLM model are shown in ***Table 5.*** The importance rankings of attribute-levels relative to the omitted level (or reference case), “additional $5”, which serves as the “zero”. To understand how different groups value attributes of ecosystem and non-ecosystem services, we calculate the interaction of these attributes and levels to the Hispanic/Latino population and FP respondents. ***Table 6*** also depicts the relative importance in terms of shares, or a proportion, to standardize the units of importance among all levels as explained in Lusk et al., 2009.

Table 5: Conditional logit model results for relative importance of each level.

Attribute Levels	Estimate (Std. Error)		Covariates			
			Frequent Participant		Hispanic/Latino	
Controlled Fire Thinning	1.166	***	-0.115		-0.154	
	(0.069)		(0.161)		(0.117)	
Mechanical Thinning	1.2	***	-0.188		-0.0511	
	(0.079)		(0.187)		(0.136)	
Public grills	0.179	**	-0.274		0.163	
	(0.077)		(0.184)		(0.133)	
Garbage bins	0.856	***	-0.161		-0.0343	
	(0.078)		(0.184)		(0.134)	
Public restrooms	1.359	***	-0.591	***	-0.323	**
	(0.080)		(0.185)		(0.136)	
Rivers/streams	1.222	***	-0.327	*	-0.0983	
	(0.079)		(0.186)		(0.136)	
Waterfalls	1.031	***	-0.188		-0.047	
	(0.079)		(0.185)		(0.135)	
Lakes	1.257	***	-0.26		-0.209	

	(0.080)		(0.188)		(0.137)
Additional $1	-0.179	**	0.331	*	0.0533
	(0.086)		(0.195)		(0.145)
Additional $3	-0.0628		-0.0414		0.0833
	(0.085)		(0.198)		(0.144)
Additional $5	Omitted		Omitted		Omitted
Individuals	386				
Number of Choices	41,688				

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Covariates and attribute levels variables were regressed in the same model.

Table 6: The share of preference for the conditional logit model

Attribute Levels	Estimate	Frequent participant	Hispanic
Controlled Fire Thinning	0.126	0.104	0.090
Mechanical Thinning	0.130	0.097	0.100
Public grills	0.047	0.089	0.124
garbage bins	0.092	0.099	0.102
public restrooms	0.153	0.065	0.076
Rivers/streams	0.133	0.084	0.096
waterfalls	0.110	0.097	0.101
lakes	0.138	0.090	0.086
additional 1	0.033	0.163	0.111
additional 3	0.037	0.112	0.115
Additional $5	Base	Base	Base

The attribute levels on their own are almost all statistically significant. The only attribute level that does not display statistical significance are the last price level (additional $3). All of the non-price attribute levels display a positive coefficient for importance. The covariates (FP and Hispanic/Latino), differ in sign but are mostly statistically insignificant. More public restrooms is the only attribute level significant across all covariates. FP respondents differ from non-FP respondents in importance for public restrooms, access to rivers/streams, and the additional $1 change to parking.

5.3 Willingness to Pay (Binary Model)

The REL was calculated using STATA 17. ***Table 7*** depicts the results of the binary logit model for WTP. Every non-price level is grouped by each price level in the choice sets where these appear as the WTP. The outcome for the estimate is the probability in selecting "yes" to paying an additional dollar amount when the level is one of the characteristics of forest services available. The WTP calculation uses the price variable as a base to compare the differences in dollar value, as seen in Eq. 16. The first five variables are attribute levels. The next four variables are the choice characteristics to identify the differences among groups. The last variable is the price variable, used to measure the WTP. According to the results, mechanical thinning exhibits a lower WTP than controlled fires (the omitted level). Public grills are the only amenities with a positive WTP. Similarly, lakes resulted in a positive WTP among the water features and showcases the highest WTP overall. However, there is no statistical significance for the non-price attributes, and therefore, these results cannot be used to strongly suggest that respondents are more willing to pay for public grills than any other attribute. Likewise, there is no significant difference between FP and non-FP respondents. Lastly, the respondents who never visit a montane forest showed a negative association with paying a higher price for parking.

Table 7: Binary Random Effects Logit estimates and willingness to pay (WTP) for attribute levels.

Levels/Variables	Estimate (Std. Error)	WTP
Mechanical Thinning	-0.108	-$0.14
	(0.143)	
Garbage bins	-0.0293	-$0.04
	(0.165)	
Public grills	0.00173	$0.002
	(0.164)	
Waterfalls	-0.122	-$0.16
	(0.164)	

Lakes	0.102		$0.13
	(0.166)		
FP	-0.544		
	(0.680)		
Hispanic/Latino	0.492		
	(0.491)		
Never	-1.482	***	
	(0.523)		
Income	4.42E-05	***	
	(0.000)		
Additional Price	-0.767	***	
	(0.051)		
Number of choices	3,474		3,474
Number of PID	386		386

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
The attribute level coefficients are estimated omitting the first level for each non-price attribute.

6. DISCUSSION

The CLM provides a way to identify the differences among different groups through covariates in the regression model. Public restrooms remain a significant attribute level that changes in importance between FP and non-FP, although the relative importance is not different between FP and Hispanics/Latinos. With exception of the $3 price attribute level, the price attribute is relatively more important to FP than non-FP, given that all the significant non-price attributes relative to the $5 increase are negative and an increase in $1 for parking is the most important attribute level for FP respondents. This holds true for Hispanics/Latinos, except for public grills. This attribute level is the holds the highest share of importance, contrasting the BWS means score from Table 4. During the pre-testing period, public grills were identified as a popular attribute among Hispanics/Latinos and the model, though statistically insignificant, shows that distinct interest for Hispanic/Latino respondents.

Despite the overwhelming change of going from positive to negative values for importance between the FP and non-FP respondents, the statistical significance to suggest a strong difference between the two groups is lacking. This can be attributed to the small number of FP and Hispanic respondents in the data in comparison to other groups. Putting statistical significance aside, a difference does exist for a few variables between FP and non-FP respondents.

The REL model offers another comparison between levels in each attribute that highlights the difference between importance and preference. Although the CLM puts public restrooms as the most important attribute level, the REL shows a higher WTP for public grills. If something is considered important, then it would be expected to hold a high value. Interestingly, the BWSS score places public grills as the least important of non-price attribute levels and the only one with a negative score. However, REL does not hold statistical significance for the WTP and making such an inference would be an overreach of the current results. This statistical insignificance may also be the reason as to why the WTP does not align with importance.

7. CONCLUSION

The primary objectives were to identify the trade-offs between ecosystem and non-ecosystem services through importance rankings, understand a respondent's willingness to pay for these services, and examine possible differences between frequent participants (FP) and non-FP. The results from the best-worst scaling model tell us that providing more public restrooms, a direct service, has the highest relative importance than any other attribute. Forest fire management is still important to the respondents, as thinning (as it relates to forest density), exhibits high shares of importance in the conditional logit model when compared to the base level of an additional \$5 to park. This changes for FP's, as they consider the additional cost of \$1 to park as the most important attribute level. When analyzing the willingness-to-pay results, we see a disconnect between importance and preference. This is likely due to a lack of statistical significance in the non-price attributes.

Repeating this study in other parts of the U.S. may have an impact on the way the USDA conducts survey for importance of attributes. The Northwest may not have the same demographics but there can be similar differences among FP and non-FP's there. The Northeast is currently experiencing the effects of wildfires. Understanding how their frame of importance has shifted during this period may prove useful to informing USDA forest management policy.

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APPENDIX

Appendix A: Orthogonal Array

Choice Set	Att. 1	Att. 2	Att. 3	Att. 4
1	1	1	1	1
2	1	1	3	3
3	1	2	1	2
4	1	2	2	3
5	1	3	2	1
6	1	3	3	2
7	2	1	2	2
8	2	2	3	1
9	2	3	1	3
Count lev. 1	6	3	3	3
Count lev. 2	3	3	3	3
Count lev. 3	0	3	3	3
D-efficiency	98.5			

Appendix B: Respondents' general feelings towards montane forests in southern California and the reasons for not participating.

Do you agree (or disagree) with the following statements about montane forests in southern California?			
	Agree	Neutral	Disagree
I want to visit montane forests, but I lack transportation.	34.5%	27.7%	37.8%
I don't have enough time to visit montane forests.	26.7%	37.3%	36.0%
It costs too much to go to the forest (gas, parking, preparing food, etc.).	29.3%	36.0%	34.7%
Would rather go to the beach or a nearby park	30.6%	33.9%	35.5%
I don't know very much about montane forests	55.2%	24.1%	20.7%