Ecosystem Services 69 (2024) 101648

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

Full Length Article

Comparing individual and collective valuation of ecosystem service tradeoffs: A case study from montane forests in southern California, USA

Haotian Cheng [a,*], Francisco J. Escobedo [b], Alyssa S. Thomas [b], Jesus Felix De Los Reyes [c], José R. Soto [a]

[a] School of Natural Resources and the Environment, The University of Arizona, Tucson, AZ 85721, USA
[b] Pacific Southwest Research Station, USDA Forest Services, Riverside, CA 92507, USA
[c] Department of Applied Economics, Utah State University, Logan, UT 84322, USA

ARTICLE INFO

Keywords:
Hispanics
Cultural ecosystem services
Regulating ecosystem services
Trade-offs
Wildland-Urban Interface
Peri-urban forests

ABSTRACT

Accounting for the tradeoffs and importance urban, disadvantaged communities place on ecosystem services has implications for the management of nearby forests. Although stated preference valuation approaches are often used, they are based on an individual's perspective and rarely account for collective or societal values. Thus, alternative methods are needed to capture this dichotomy from urban communities who may not even be aware of these benefits to themselves or society at-large. We explored individual and collective importance of, and tradeoffs for, ecosystem services (ES) and ecosystem disservices (ED) by urban residents living near montane forests in greater Los Angeles, California, USA. Using an online panel survey, individual (*I*-rationality) versus collective (*We*-rationality) scenarios, best-worst scaling (BWS) choice experiments, and latent class analyses, we ranked the importance and tradeoffs among ES-ED attributes to nearby residents based on the frequency of visits to montane forests as well as Hispanic ethnicity. Results show statistically significant tradeoffs and differences in importance rankings between individual versus collective valuation scenarios. Under the individual valuation scenario, non-Hispanics highly ranked the high forest density indicator, which has implications for wildfire EDs to montane forests and communities. Gender and income were more influential sociodemographic factors affecting importance for water and recreation-related ES than was education. Our BWS and econometric methods, attributes, and importance rankings can facilitate participatory processes with diverse urban communities and designing more effective policies and management guidelines. This approach can also more inclusively, and equitably, account for the tradeoffs and values that nearby urban communities place on ES/ED from Wildland-Urban Interface forests.

1. Introduction

Forests near cities provide a suite of key ecosystem services and other market and non-market amenities (Friggens et al., 2014; Sloggy et al., 2022). However, their management and conservation are affected by changes such as: growing populations, wildfire, climate change, invasive species, and other socio-political factors (Jenerette et al., 2022). More specifically, these drivers can also affect the ecosystem structure, function, and subsequent provision of ecosystem services (Aznar-Sanchez et al., 2018); particularly in *peri*-urban or Wildland-Urban Interface (WUI) forests located near highly populated and diverse communities (Sloggy et al., 2022; Yadav et al., 2023). Although such forest ecosystem service valuation issues have been documented, less is known about how different urban community and socio-demographic groups living near these forests (e.g., disadvantaged communities, minority groups, low-income households, infrequent users) place importance on such ecosystem services either individually or collectively (Vatn, 2009).

Ecosystem services (ES) are the benefits that humans obtain from ecosystems and are generally categorized into four main types: provisioning (e.g., food and water), regulating (e.g., climate regulation and flood control), cultural (e.g., spiritual and aesthetic benefits), and supporting (e.g., nutrient cycling and soil formation; De Groot et al., 2002). Of these, cultural ESs include non-material co-benefits such as: spiritual enrichment, cognitive development, education opportunities, aesthetic values, and other direct uses such as recreation and increased property values (Bullock et al., 2018). Monetary valuation of ES is as a common

* Corresponding author.
E-mail address: haotiancheng1991@gmail.com (H. Cheng).

https://doi.org/10.1016/j.ecoser.2024.101648
Received 15 March 2024; Received in revised form 9 July 2024; Accepted 21 July 2024
Available online 30 July 2024

metric for estimating welfare and for placing ecosystem functions "on par with other economic interest" (Lienhoop et al., 2018). However, methods can be polemic because of uncertainty in their ability capture the multiple and inherent value dimensions of nature (Vatn, 2009) as well as the inability – or unwillingness- to capture inequities in the distribution of ESs across all societal groups (Wilson and Howarth, 2009); thus other more inclusive metrics for assessing the importance of ESs and their tradeoffs are warranted.

Therefore, effective management of WUI forests and wildfire near population centers necessitates the integration of ESs with socio-economic factors and policy instruments to address the complexities of these *peri*-urban ecosystems (Plieninger et al., 2015; Wilkerson et al., 2018). Socio-economic factors include demographic trends, economic activities, and social behaviors, while policy instruments encompass governance structures, land use regulations, market instruments, and environmental policies (Sloggy et al., 2022). Integrating these factors ensures a more inclusive and socio-ecologically based approach to planning and management that enhances ecosystem resilience and sustains the delivery of ES to nearby communities (Bullock et al., 2018; Yadav et al., 2023).

Forests and other ecosystems in Mediterranean climates located near major population centers such as those of southern California in the United States (US) are important as they provide climate regulation (Plieninger et al., 2012; Underwood et al., 2019) and cultural ESs (Tanner et al., 2022). For example, recreation on US national forests in 2016 alone provided approximately $49 billion in benefits and 826,000 jobs (Cline and Crowley, 2018). Other recreation-related ESs include hiking, picnicking, viewing scenery, and visiting heritage sites (Plieninger et al., 2012). Forests in southern California have some of the highest numbers of recreation visits in the US and are frequently affected by frequent and severe wildfires, urbanization, and other extreme climatic events (Underwood et al., 2019; Yadav et al., 2023). Demand-based valuation studies in these forests are typically based on secondary data or elicited values where specific user groups such as highly educated, well informed, and frequent users predominate (Plieninger et al., 2012; Tanner et al., 2022). But to our knowledge, urban residents, Hispanics, or infrequent visitors are not often a focus of such studies.

Several studies from southern California, USA- have assessed the use and perception of these WUI forests from different socio-demographic groups, particularly regarding recreation (Flores and Sanchez, 2020; Thomas et al., 2022) and water-related ESs (Tanner et al., 2022). However, such studies often assess these values from individuals, not collectively, nor do these studies account for the tradeoffs that socio-demographically diverse communities make when valuing different ecosystem services. Indeed, the importance of different ES can change according to individual versus societal values as well as spatially and temporally (Darvill and Lindo 2016; Soto et al., 2018). Studying community-level ES values therefore, provides for a more comprehensive understanding of how different groups prioritize and make tradeoffs among various ESs since individual-based studies might not capture the collective preferences and synergies that emerge at the community level (e.g., shared priorities, areas of consensus and conflict, identification of community-specific needs; Wilson and Howarth, 2002). As such, identifying these collective values can also demonstrate the complexity and variability of values within diverse community; thereby better addressing issues of environmental justice and more inclusive governance of these ecosystems (Yadav et al., 2023).

Ecosystem service valuation methods can better inform forest management, planning, and conservation decisions (Sánchez et al. 2021). Stated preference valuation is one such method that estimates the value and potential demand for ESs (Lienhoop et al, 2018; Cheng et al., 2023a) and consists of asking respondents to base responses on their individual needs, rather than those of society (Lienhoop et al., 2015). However, ESs affect not only individuals, but also society at large and future generations (Wilson and Howarth, 2002). Thus, considering only individual needs when making ESs- related management and policy decisions is insufficient for understanding society's needs (Dietz et al., 2005). As such, there is often a mismatch between personal preference and long-term societal values (Niemeyer and Spash, 2001; Groot and Steg, 2008; Vatn, 2009).

This dichotomy in individual versus collective valuation is particularly important given the ecological and socioeconomic complexity of US national forests located near cities. Accordingly, there is growing interest in social preferences and values, as well as in eliciting people's interest in collective or broad distributional considerations by asking individuals to consider their own opinions or preferences, in addition to others, for ESs (Dolan et al., 2003). Vatn (2009) proposed the 'I-rationality' and 'We-rationality' scenarios to describe this mismatch between personal and societal needs, each respectively signaling which logic pertains to specific scenarios. In the 'I-rationality' scenario, an individual only counts self-interest, and costs and benefits. In the 'We-rationality' scenario, individuals are supposed to develop sound arguments and solutions concerning how best to comply with the common interest of society (Rommetvedt, 2005).

The role of environmental governance and individual versus collective rationalism has been addressed by Soma et al. (2016) and Horodecka and Vozna (2021), respectively. Alvarez-Farizo et al. (2007), for example, used choice experiments to understand individual versus collective interest in environmental valuation, while Lienhoop et al. (2015) discussed the role of institutions and deliberative valuation of biodiversity policies. Dolan et al. (2003) documented the importance of considering a range of perspectives because a person's preferences may depend on the perspective that the person is asked to adopt. Additionally, Soto et al. (2018) used a choice experiment method called Best-Worst Choice (BWC) to estimate homeowners' preferences for urban forest ESs from their properties versus their surrounding neighborhood.

Although effective forest management and governance requires input from a diversity of people, Reed et al. (2018) note there are few incentives for the public to participate in planning processes often due to time constraints, perception their input will not be considered by decision makers, and other factors. Conversely, the public that does participate is often over-represented by older, higher income, highly educated, white males (Davis et al., 2017). As such, the values of participants in planning processes do not always correspond to those held by nearby "minority" populations (Rasch, 2019) or consider the adaptive social capacity of adjacent communities (Sánchez et al. 2021). Thus, more collective, and inclusive ES valuation approaches are needed to account for diverse urban communities living near forests.

Therefore, the aim of this study was to better understand the importance and tradeoffs in how – individually and collectively – urban communities living near montane forests value cultural and regulating ESs. The specific objectives were to 1) assess how nearby residents' frequent and infrequent visitation to montane forests influences individual and collective importance and tradeoffs for different ES attributes, 2) identify the differences between individual and collective valuation of montane forests among Hispanic and non-Hispanic residents, and 3) better understand how the socio-economic characteristics of respondents influence Objectives 1 and 2.

2. Methods

2.1. Study area

The study area was the northern and eastern Greater Los Angeles area comprised of the urbanized portions of Los Angeles, Riverside, and San Bernardino Counties in California, USA (Appendix A). The study area is approximately 12,561 km^2 and has a population of approximately 18.5 million. As of 2020, the Greater Los Angeles area's population was 49.1 % Hispanic, making it the largest majority-Hispanic metropolitan area nationally (U.S. Census Bureau, 2020).

The study area has a Mediterranean-type climate and is part of the South Coast bioregion that encompasses urban, grassland, shrubland,

Table 1
Ecosystem Service (ES)/Disservice (DS) attributes and levels used to create choice experiments.

Attribute (Sources, references)	Definition (ES or ED)	Levels
Forest density (Minnich et al., 1995)	The number of tree stems per unit area (Wildfire risk/ED)	Low (less than 200 stems/ hectare), High (more than 200 stems/ hectare)
Forest understory (Minnich, 2007)	Understory plant cover consisting of small shrubs, forbs, and grasses under 1 m tall. A *covered* understory has visible plant understory. A *bare* understory is mostly bare soil or litter with little to no plant cover. (Cultural ES)	Bare (~less than 25 % plant cover), Covered (~greater than 25 % plant cover)
Water (Hammitt et al., 1994; Tanner et al., 2022)	Presence of water feature (s) within the national forest. (Regulating ES)	No water, Streams (including rivers), Waterfalls, Lakes
Forest diversity (Minnich, 2007; Soliño et al., 2018)	The number of visible trees, tall shrubs, and understory plant types. (Cultural ES)	Low (less than 5 plant types), High (more than 5 plant types)

woodland, and forest ecosystems that range from sea level to over 3000 m in elevation (Keeley and Syphard, 2018). Located within the study area at elevations greater than approximately 1500 m are high elevation montane forests. Montane forests are dominated by various *Pinus spp*., *Abies concolor*, and *Calocedrus decurrens* trees as well as other *Quercus spp* trees, shrubs and other understory grasses and forbs (Keeley and Syphard, 2018). These montane forests are key components in southern California's water supply and provide various recreation opportunities but are very disturbed due to highly populated nearby communities, high recreational use, invasive species, and frequent and severe wildfires (Jenerette et al., 2022). These various disturbances within the montane forests have resulted in different forest structural and compositional attributes that subsequently affect ES supply (Underwood et al., 2019).

2.2. Best worst Scaling

Empirical studies using Best-Worst Scaling (BWS) have increased as an alternative method for determining respondents' stated preferences (Cheng et al., 2023b) since it is a probabilistic data collection method (Finn and Louviere, 1992). Specifically, rather than exclusively selecting the 'best' option, respondents are asked to select both the 'best' and the 'worst' options among the alternatives, forcing them to make tradeoffs (Bruzzese et al., 2022). Unlike conjoint analysis, which is an alternative method to determine stated preferences, BWS can help researchers better understand respondents' preferences for all options rather than the most preferred option (Cheng et al., 2023b). For example, Tyner and Boyer (2020) used BWS to estimate the preferred reason for restoration and conservation and found that human health and protection of native species were the most preferred reasons. Soto et al. (2018) estimated homeowner's consumer demand for key urban forest ES and disservice attributes and found that property value and tree condition were the most important attributes for Florida, USA residents.

2.3. Survey design

The survey instrument was developed based on an online workshop in January 2023 and a subsequent focus group with experts in February 2023. During the initial online workshop, 66 transdisciplinary participants were asked to rank the importance of different uses, values, and management activities related to the conservation of montane forests. The top five values selected were: biodiversity, watershed, community protection, recreation, and scenic values. Afterwards a focus group consisting of 10 interdisciplinary experts used the broadly defined values from the online workshops to deliberatively develop a series of ecosystem structure–function-ES indicators and attributes for montane forests. The focus group identified three montane forest attributes that were then used as attributes of forest-based ES supply and attribute levels and that could be identified and applied by both experts and non-experts. Given the importance of watersheds and waterbodies to regulating and cultural ESs in the study area (Tanner et al., 2022; Underwood 2019), we also included an additional water-based ES attribute (Table 1). The four-ecosystem structure–function states and attributes are regularly used indicators for subsequent regulating and cultural ESs (Underwood et al., 2019).

The above approach was then used to develop a survey instrument that consisted of four sections: 1) introduction, consent, and participant screening, 2) awareness of and visitation frequency to montane forests, 3) choice experiments, and 4) socio-demographics. The second section contained a series of questions that assessed respondents' familiarity with (i.e., Do you agree or disagree with the statement 'I do not know very much about montane forest') and frequency of visits to (i.e., how many times a year do you visit any montane forest in southern California) nearby montane forests. A check question was included to detect whether respondents paid attention when responding to survey items (Cheng et al., 2021; Cheng et al., 2024). Instructions directed respondents to select 'none of the above' in response to a question unrelated to montane forests.

In the third section of the survey, a split design approach was used to randomly assign respondents to one of two versions of the choice experiments. The first version ('Individual') asked respondents to select the most and least important attribute levels to *them* (i.e. the most important to you) for each policy scenario. Respondents to the second version ('Collective') were asked to select the most and least important attribute levels to *their community* for each policy scenario. Respondents were presented with eight hypothetical ecosystem structure-service states with different attribute levels (Table 1). Four attributes and respective levels were tested: 1) forest density (low or high); 2) forest understory (bare or covered); 3) water (no water, streams, waterfalls, and lakes); and 4) forest diversity (low or high).

A fractional, orthogonal main effect design was used to minimize correlation between policy scenarios and to structure the choice tasks (Lentner and Bishop, 1986). Specifically, there were $4 \times 2^3 = 32$ possible combinations in the choice experiment's design space. A 100 percent D-efficiency balanced design resulted in 8 BWS questions per respondent (Appendix D). In these questions respondents were instructed to select the most and least important levels, thereby making tradeoffs between the four ES attributes and their respective levels. The survey was pilot tested with 20 experts, community members, and graduate students in March 2023 for cultural and technical relevance.

Table 2
Respondent socio-demographic characteristics for the survey and study area (Los Angeles, Riverside, and San Bernardino Counties).

Characteristic	Individual ($n = 377$)	Collective ($n = 390$)	Survey Total ($n = 767$)	Study area ˆ
Age				
18 to 29	26.3 %	25.5 %	25.7 %	ˆˆ
30 to 44	28.2 %	31.5 %	29.7 %	28.9 %
45 to 64	34.1 %	27.6 %	32.6 %	32.7 %
65 and over	11.2 %	14.3 %	13.8 %	19.6 %
Gender				
Female	49.2 %	49.3 %	49.2 %	49.8 %
Male	48.7 %	49.1 %	48.9 %	50.2 %
Other	1.9 %	0.7 %	1.2 %	N/A
Educational Attainment				
Some High School	3.1 %	2.8 %	3.0 %	18.8 %
High School	29.6 %	29.4 %	29.5 %	22.6 %
Some College	34.4 %	33.4 %	34.0 %	26.5 %
Bachelor's degree	22.0 %	18.5 %	19.6 %	20.4 %
Graduate Degree	10.7 %	15.0 %	13.1 %	11.7 %
Ethnicity				
Hispanic/Latino (of any race)	34.6 %	34.6 %	34.6 %	49.1 %
Race				
Asian (non-Hispanic)	9.4 %	9.9 %	9.7 %	24.4 %
Black/African American (non-Hispanic)	13.9 %	12.4 %	13.0 %	14.5 %
White (non-Hispanic)	72.5 %	74.4 %	73.7 %	52.7 %
Other(non-Hispanic)	4.2 %	3.3 %	3.7 %	8.4 %
Annual Household Income				
< $35,000	23.2 %	24.3 %	23.8 %	21.7 %
$35,000 to $49,999	16.2 %	14.0 %	15.3 %	9.3 %
$50,000 to $74,999	21.2 %	22.0 %	21.7 %	14.9 %
$75,000 to and $99,000	18.4 %	16.4 %	17.2 %	12.8 %
$100,000 or more	20.8 %	22.4 %	21.3 %	41.5 %
Political Ideology				
Conservative	26.5 %	31.1 %	29.1 %	N/A
Moderate	40.8 %	41.1 %	40.9 %	N/A
Liberal	32.5 %	26.9 %	28.2 %	N/A
Frequecy of Visiting the Montane Forest				
At least once per year	45.0 %	47.1 %	46.0 %	N/A

ˆ The 2020 U.S. Census Riverside-San Bernardino-Los Angeles County Statistical Area reports.
ˆˆ The U.S. Census reports the metro area residents' age group from 20 to 29 years old category, which includes 14.4 % of the greater LA area.

2.4. Survey implementation

To address our objectives, we focused on the socio-demographic characteristics of urban communities located near montane forests (i.e., less than approximately 25 km or a 1.5-hour drive in distance). We used the US Census defined populations of San Bernardino-Fontana-Highlands communities that are within 1 h drive from the montane forests of the San Bernardino National Forest – to define Qualtrics survey panel population quotas and filter out respondents living in distant areas. Specifically, the data were collected from an online Qualtrics survey launched in May 2023 for respondents 18 years or older via e-mails using a computer, cellphone, or tablet. The Qualtrics panel population was identified using a screening question: “Do you live, or have you lived, in or near the cities of San Bernardino, Fontana, or Highland (San Bernardino County, California)?” To proceed with the survey, the respondent needed to respond ‘yes’ to this question. The sample frame was then stratified by US Census income level, gender, and age.

2.5. Econometric analysis

For research objectives 1 and 2, we used a paired method which considers each best-worst pair to derive choice frequencies, which is then used to estimate the importance of attribute/indicator levels (Flynn et al., 2008). This method assumes that individuals can evaluate all pairs and levels before selecting the most important choice as a tradeoff among all pairs (Flynn et al., 2008). If one profile contains J levels, then the number of possible best and worst pair levels for the profile is $J \times (J-1)$. Following Al-Janabi et al. (2011) we extended the paired model method by including dummy variables to code our attribute levels. When an attribute was selected as the most important it was coded as one, otherwise as negative one (Al-Janabi et al., 2011). Following Soto et al. (2018), the paired method results were analyzed using multinomial logit regression (MNL).

Additionally, based on McFadden (1973)'s random utility model, the indirect utility was assumed linear in arguments with systematic and random components:

$$v_{ijt} = \mathbf{x}_{ijt}\beta + \epsilon_{ijt} \quad (1)$$

where v_{ijt} is the indirect utility individual i receives from selecting alternative j on profile t, $\mathbf{x}_{ijt}$ and which is a vector of attributes for alternative $j = 1,\ldots J$, β is a J by 1 vector of attribute coefficients, and ϵ_{ijt} is an unobserved random disturbance term from the extreme value distribution with an expected value of zero and variance σ^2_ϵ. Appendix B provides a description of how choice probability can be generated from these data using a typical MNL model. For our third objective, we used a latent class logistic (LCL) regression to model the number of available latent classes for the respondents in the ‘individual’ scenario and estimate preference parameters for each latent class. Appendix C provides a description of how choice probability can be generated from these data using a typical LCL model. Both the MNL and the LCL models were estimated with Stata 15 using the Gauss – Hermite quadrature routine and simulated maximum likelihood.

3. Results

3.1. Sample population and frequency of visits

The initial sample population was 869 but 102 were filtered (fail to

Table 3
Best-Worst Scaling of residents' 'Individual' and 'Collective' Scenarios for visiting southern California Montane Forest at least once a year and less than once a year groups.

	Visit Montane Forests At Least Once a Year								Visit Montane Forest Less Than Once a Year							
	Individual				Collective				Individual				Collective			
Attribute	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking
Low density	0.3547	0.0735	***	7	0.3793	0.0707	***	7	0.3744	0.0675	***	7	0.3221	0.0691	***	7
High density	0.5952	0.0742	***	4	0.5336	0.0713	***	4	0.6091	0.0682	***	4	0.5646	0.0700	***	4
Bare	0.2955	0.0734	***	9	0.1663	0.0706	**	9	0.1653	0.0672	**	9	0.1364	0.0688	*	9
Covered	0.4053	0.0736	***	6	0.3867	0.0707	***	6	0.3295	0.0673	***	8	0.2817	0.0690	***	8
No water	0.3518	0.0914	***	8	0.2282	0.0876	**	8	0.5418	0.0835	***	5	0.3989	0.0839	***	6
Streams	0.8219	0.0939	***	1	0.8986	0.0910	***	1	1.1505	0.0888	***	1	1.4803	0.0952	***	1
Waterfalls	0.6663	0.0928	***	2	0.6834	0.0892	***	3	0.8257	0.0854	***	3	1.2111	0.0909	***	3
Lakes	0.6425	0.0927	***	3	0.8228	0.0903	***	2	1.0514	0.0877	***	2	1.2714	0.0918	***	2
High diversity	0.4219	0.0785	***	5	0.4272	0.0756	***	5	0.4483	0.0721	***	6	0.5272	0.0740	***	5
Low diversity			***	10			***	10			***	10			***	10
N	169				184				208				206			
Log Likelihood	−3,290				−3,557				−3,941				−3,772			

* significant At 90%; ** significant at 95%; ***significant at 99% levels of statistical significance.

Table 4
Best-Worse Scaling' results for the 'Individual' and 'Collective' scenarios for Hispanic and Non-Hispanic groups.

	Hispanic								Non-Hispanic							
	Individual				Collective				Individual				Collective			
Attribute	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking	Estimate	Standard Error		Ranking
Low density	0.1216	0.0867		8	0.3625	0.0827	***	6	0.4824	0.0607	***	6	0.3403	0.0614	***	7
High density	0.3152	0.0870	***	6	0.5642	0.0835	***	4	0.7415	0.0616	***	3	0.5357	0.0620	***	5
Bare	0.1174	0.0866		8	0.2621	0.0825	***	9	0.2764	0.0605	***	9	0.0872	0.0613		9
Covered	0.1655	0.0867	*	7	0.2832	0.0825	***	8	0.4596	0.0607	***	8	0.3569	0.0614	***	6
No water	0.4003	0.1078	***	4	0.3638	0.1014	***	5	0.4838	0.0752	***	5	0.2903	0.0754	***	8
Streams	0.7704	0.1110	***	3	1.1447	0.1087	***	1	1.1109	0.0791	***	1	1.2113	0.0818	***	1
Waterfalls	0.7986	0.1115	***	1	0.9869	0.1065	***	3	0.7347	0.0762	***	4	0.9297	0.0788	***	3
Lakes	0.7895	0.1114	***	2	1.1289	0.1086	***	2	0.8997	0.0774	***	2	1.0060	0.0794	***	2
High diversity	0.3430	0.0927	***	5	0.3168	0.0886	***	7	0.4818	0.0648	***	7	0.5634	0.0658	***	4
Low diversity				8				10				10				9
N	122				139				255				251			
Log Likelihood	−2,348				−2,619				−4,885				−4,737			

* significant at 90%; ** significant at 95%; ***significant at 99%.

Table 5
Latent Class Best-Worst Scaling results for the 'Individual' Scenario.

Attribute	Class I Estimate	Standard Error		Ranking	Class II Estimate	Standard Error		Ranking	Class III Estimate	Standard Error		Ranking	Class IV Estimate	Standard Error		Ranking
Low density	0.0070	0.1087		7	0.1270	0.1339		6	0.4079	0.1289	***	8	1.1777	0.1478	***	2
High density	−0.3988	0.1337	***	8	1.5714	0.1925	***	1	0.5533	0.1351	***	7	1.6271	0.1704	***	1
Bare	0.2437	0.1172	**	5	−0.5820	0.1554	***	7	0.3702	0.1278	***	9	0.8740	0.1493	***	4
covered	0.1845	0.1060	*	6	0.0418	0.1335		6	0.6457	0.1268	***	6	0.9073	0.1346	***	3
No water	0.4907	0.1443	***	2	0.0515	0.1713		6	1.0670	0.1440	***	4	0.2864	0.1440	**	5
Streams	0.5562	0.1584	***	1	1.1249	0.2127	***	3	4.0911	0.3824	***	2	0.1044	0.1559		7
Waterfalls	0.3548	0.1529	**	4	0.9567	0.2065	**	4	2.6801	0.2291	***	3	−0.1322	0.1544		7
Lakes	0.3840	0.1523	***	3	0.7884	0.2154	***	5	4.6261	0.6939	***	1	0.0177	0.1582		7
High diversity	0.1553	0.1091		7	1.2236	0.1727	***	2	0.7243	0.1307	***	5	0.2607	0.1241	**	6
Low diversity				7				6				10				7
Class Share	28.0 %				20.2 %				26.9 %				24.9 %			
Log Likelihood	−6,624															
AIC	13,423															
BIC	13,764															

Individual Characteristics	Class I Estimate	Standard Error		Class II Estimate	Standard Error		Class III Estimate	Standard Error		Class IV Estimate	Standard Error
Age group 18 to 29	−1.5142	0.8612	*	−1.3330	0.8461		−2.5178	0.7417	***	–	–
Age group 30 to 44	−1.1483	0.8169		−0.8494	0.7698		−1.4844	0.6552	**	–	–
Age group 45 to 64	−1.7663	0.7824	**	−1.3807	0.7407	*	−1.4736	0.6237	**	–	–
Female	1.5898	0.4307	***	1.2825	0.4287	***	1.0391	0.3734	***	–	–
Hispanic	1.0913	0.4655	**	0.0758	0.5200		0.3744	0.4299		–	–
High school	0.0926	1.6906		−0.0721	2.0536		−0.6775	1.5735		–	–
Some college	−1.6332	1.6705		−0.2528	2.0229		−1.2244	1.5643		–	–
College	−1.1758	1.7606		0.9813	2.0883		−0.8128	1.6131		–	–
Graduate school	0.2536	1.8234		0.8242	2.1698		−1.0530	1.7199		–	–
$35,000 to $49,999	0.7893	0.7239		0.8323	0.7563		0.3054	0.6898		–	–
$50,000 to $74,999	−1.6819	0.6284	***	−1.6619	0.6613	**	−0.9629	0.4879	**	–	–
$75,000 to $99,000	−0.1399	0.6324		−0.1502	0.6465		−0.6124	0.5888		–	–
$100,000 or more	−0.1290	0.6697		−0.1176	0.6943		−0.0847	0.5723		–	–
Moderate	1.1005	0.5237	**	1.7496	0.5857	***	0.5791	0.4489		–	–
Liberal	1.1347	0.5163	**	1.0066	0.5559	***	−0.0381	0.4466		–	–
At least once per year	0.8983	0.4203	**	0.0509	0.4159		−0.5978	0.3817		–	–
Constant	0.0677	1.9016		−0.7418	2.2084		2.3384	1.6772		–	–
Class Share	28.0%			20.2%			26.9%			24.9%	
Log Likelihood	−6,624										
AIC	13,423										
BIC	13,764										

* significant at 90%; ** significant at 95%; ***significant at 99.

pass attention check and/or respondents' zip codes were outside of our study area) leaving $n = 767$ respondents with socio-demographics generally consistent with the study area (Table 2; Appendix A). Around 35 % of respondents were Hispanic and 46 % had visited a montane forest at least once per year. All indicator levels in each group and scenario were statistically significant at the 10 % level (Table 3). We found that estimated coefficient signs for the indicator levels in each group and scenario were positive suggesting that the base level, *low forest diversity*, was the least important level (rank 10). Thus, the *low diversity* level was omitted as the base and was accordingly the least important level for each group and scenario.

For frequent visitors, the importance rankings between the two scenarios were generally consistent in that they highly valued water over forest-related attributes, but the importance rankings for lakes and waterfall were different (Table 3). In the 'individual' scenario, *streams* was ranked as the most important level, followed by *waterfalls* and then *lakes*. In the 'collective' scenario, *streams* was again ranked as the most important level, followed by *lakes* and *waterfalls*. For the infrequent visitors, the top three most important levels in order were *streams*, *lakes*, and *waterfall*. In general, both frequent and infrequent visitors under both scenarios (i.e., 'individual' and 'collective') most valued water over forest-related attributes (Table 3).

3.2. Hispanics versus non-Hispanics

To avoid a "dummy variable trap", *low diversity* was omitted as the base as previously stated. All indicator levels in each group and scenario were statistically significant at the 10 % level, except *low density* and *bare* for Hispanic in the 'individual' scenario and *bare* for non-Hispanic in the 'collective' scenario (Table 4). The insignificant indicator levels suggest that these levels were not significantly different to the base level, *low diversity*. All estimated coefficient signs of attribute levels in each group and scenario were positive, suggesting that the base level, *low diversity*, was the least important level across all four groups as was the *bare* attribute.

For Hispanic respondents, in the 'individual' scenario, *waterfalls* was ranked as the most important level, followed by *lakes* and *streams*. In the 'collective' scenario, *streams* was ranked as the most important level, followed by *lakes* and *waterfalls*. Overall, Hispanics most valued water over forest-related ES attribute (Table 4). In contrast, in the non-Hispanic, 'individual' scenario, the three most important levels were *streams*, *lakes*, and a forest-based ES attribute and level *high forest density*. In the 'collective' scenario, *streams* was ranked as the most important level, followed by *lakes* and then *waterfalls* (Table 4).

3.3. Socioeconomic characteristics

Table 5 presents the maximum likelihood estimates results for the best fitting LCL model describing all Hispanic and non-Hispanic respondents in the 'individual' scenario. The indicator level *low diversity* was omitted and used as the base. Overall, respondents had a 28 % mean probability of belonging to Class I. Female respondents, respondents who indicated their political ideology as moderate and liberal, and those who visited montane forests at least once per year were more likely to belong Class I (Table 5). In general, Class I respondents ranked water-based attribute levels as the most important, followed by forest understory, while tree density and forest diversity were ranked as least important.

The mean probability of belonging to Class II was 20.2 %. Respondents whose political ideology was moderate and liberal as well as females were more likely to belong to this class, however respondents from 45 years to 64 years old with annual household incomes from \$50 k to \$74.999 k were less likely to belong to this class (Table 5). Respondents in Class II ranked high forest density as the most important attribute followed by high forest diversity. Water-based attributes were ranked as the third most important while forest understory indicators were regarded as least important.

Class III had a mean probability of membership of 26.9 %. Female respondents were more likely to be in this class. However, respondents 18 to 64 years old and those with annual household incomes from \$50 k to \$74.999 k were less likely to be in Class III (Table 5). Among the four classes, this was the only class where all attribute levels were statistically significant at the 10 % level, suggesting that respondents in this class could evaluate and distinguish each ecosystem level clearly. The water-based ES attribute was ranked as the most important by Class III respondents.

The mean probability of belonging to Class IV was 24.9 %. Respondents with annual household incomes from \$50 k to \$74.99 k and respondents from 45 years to 64 years old were more likely in Class IV while female respondents were less likely to be in Class IV, relative to the other 3 classes (Table 5). However, residents who indicated their political ideology as moderate and liberal were less likely to belong Class IV, relative to Classes I and II. Also, Hispanics were less likely to belong to Class IV, relative to Class I. The respondents in Class IV ranked *forest density* as the most important ES, followed by *forest understory* while the water-based ES attribute levels were ranked as least important.

4. Discussion

This study used a choice experiment and BWS approach to better understand the importance and tradeoffs that urban residents of the greater Los Angeles USA make – individually and collectively – from ES attributes from nearby montane forests. Findings show some statistically significant tradeoffs in the importance rankings of ES indicator levels when comparing the individual and collective scenarios (Tables 3 and 4). In the individual scenario, frequent visitors assigned a higher level of importance to waterfalls as compared to lakes, but this was reversed in the collective scenario (Table 3). Tanner et al. (2021) also found that sites with waterbodies and tree cover were highly desirable for visitors to national forests in the Los Angeles area. In terms of individual versus collective valuation of environmental amenities, there is often a mismatch between personal preferences and long-term societal values (Niemeyer and Spash, 2001; Vatn, 2009). However, our results provide limited evidence for Vatn (2009)'s conclusion that individual preferences are contradictory to environmental resource and ES demand (Lienhoop et al., 2015).

Similarly, for Hispanic and non-Hispanic respondents in both the individual and collective scenarios, most of the significant differences and mismatches were between the water-related ESs and the three levels that were all ranked as highly important (Table 4). Therefore, although there were statistically significant mismatches between frequent and infrequent visitors as well as Hispanic and Non-Hispanic respondents in both scenarios, results indicate that most respondent groups- except for non-Hispanics and high forest density which will be discussed later – generally prefer water-related regulating and cultural ESs.

Our findings are similar to Tanner et al. (2022) who found that visitors preferred southern California national forest recreation sites with waterbodies and tree cover and were willing to drive longer distances to the sites with water. Similarly, Hammitt et al. (1994) showed that forests with streams, rivers, and lakes were most preferred by respondents. Water was also one of the top three landscape features desired by respondents in the Netherlands (Van Berkel and Verburg, 2014). Although these studies took place in an agricultural rather than forest landscape, it suggests the strong importance attached to water may be independent of ecosystem type. Schmidt et al. (2019) also found that cultural ESs including experiencing, using, or learning about nature were most often located near water bodies.

Overall, when respondents had to assess the tradeoffs among the ESs in Table 1, they generally valued water over forest-based ESs. However, people's demand for water-related cultural ESs can motivate them to engage with forest ecosystems directly and indirectly (Plieninger et al., 2015). Therefore, although residents may be initially drawn to waterbodies, the hydrological cycle is largely regulated by montane forests (Plieninger et al., 2012; Underwood et al., 2019). As such, the preference for water can not only be used to communicate the importance of montane forests in providing and regulating water supply (Underwood et al., 2019), but also to communicate the importance of other ESs and their susceptibility to extreme climate change events that characterize southern California (e.g., drought, wildfires, floods; Manley and Egoh, 2022; Sánchez et al. 2021).

We found education levels were not a significant influence, but gender and income were, regarding the importance of ESs from montane forests (Tables 5). Generally, female respondents ranked *streams* and *lakes* as important while males, those with an annual household income from \$50 k to \$74.999 k, and 45 to 64 years olds ranked *density* and *understory* as most important (Table 5). These results provide further evidence of the heterogeneity of values for ESs as observed by Álvarez et al. (2021) and that socio-demographics can significantly affect the importance rankings of ESs (Table 5; Faehnle et al., 2014; Friggens et al., 2014). Martín-López et al. (2012) also found that people ascribed differing levels of importance to ESs depending on gender, age, and urban or rural residency.

The importance of the high forest density indicator for non-Hispanic respondents has important implications for forest health, as well as wildfire-related EDs to montane forests and communities in the WUI (Sánchez et al. 2021; Jenerette et al., 2022). Stephens et al. (2022) found that increased dead biomass and live tree densities were the two most influential factors in predicting fire severity and subsequent effects on forest structure and subsequent function and services as well as ecosystem disservices to nearby WUI and urban communities (Plieninger et al., 2012). Similarly, we found that two out of the four classes (i.e., Class II and IV) preferentially ranked high-density forests relative to the other attributes levels (Table 5). Respondents aged 18–29 were more likely to belong to these two classes. Plieninger et al. (2012) found that private landowners of "working" forests and rangelands (i.e., engaged in commercial livestock or timber activities) in California highly ranked the importance of fire prevention as well as wildlife habitat and recreation related ESs. Through visitor surveys and benefit transfer estimates Sánchez et al. 2021 did identify that reduced forest densities were effective in improving their resilience to changes in California's three Sierra Nevada national forests.

Our results found that Hispanics differentiate between their individual and collective valuation of ES and that they highly ranked water-based regulating and cultural ESs as important (Table 4). Flores and Sanchez (2020) and Thomas et al. (2022) indicate that Hispanics overwhelming support protecting public lands, but also found that discrimination was a substantial barrier to their use of public lands. Similarly, Yadav et al. (2023) found that urban communities as well as Hispanics and Asian-Americans were statistically and increasingly affected by wildfires during 2016–2020. Therefore, newer more inclusive and collective approaches are needed to account for urban, often overlooked, communities and how, why, and how much they value forest ESs. Similarly, results indicate the need to educate non-Hispanic groups of the increased risk of wildfire disservices associated with high forest density.

Stated preference studies are inherently subject to biases and limitations related to data collection methods and sampling approaches, so, we do note some limitations. First, we note that Hispanics and those with annual household income greater than \$100,000 were underrepresentative of the study area despite our panel quota requests; thus limiting our use of LCL analyses of the role of socio-demographic diversity within Hispanic respondents. Second, the BWS method used in this study could not calculate a respondent's willingness to pay, a common metric used to facilitate decision-making.

5. Conclusion

Tradeoffs occur when people place an importance on a suite of disparate, place-based ESs as well as EDs. Accordingly, this study explored how diverse urban residents living near socio-ecologically complex montane forests make these tradeoffs, both individually and collectively, and the influence of their frequency of visits, Hispanic ethnicity, and other socio-demographic characteristics. As such, our findings could be used to better inform different and diverse publics (i.e., Spanish speakers, culturally relevant education material) about the importance of conserving and managing montane forests. Similarly, the importance of water-related and forest density attributes, individually and collectively, has strong implications for the sustainable supply of ESs from montane forests. Specifically, their proximity to high population centers, unchecked recreation, and frequent, severe wildfires, increases their vulnerability to type conversion to shrublands or invasive species. Additionally, climate change can also decrease streamflow and baseflow thus threatening the provision of not just the recreation ESs we studied, but also for drinking water supply to nearby cities.

At the time of writing, policies such as the 2021 Bipartisan Infrastructure Law and the Wildfire Crisis Strategy, designated southern California montane forests as "firesheds" that will receive substantial funding for wildfire mitigation practices and management to conserve them. Thus, our attributes and importance rankings can also be used to establish restoration guidelines and decision-making priorities. Communities living near montane forest value them; therefore, informing the public about their critical role in water supply, air quality via wildfire smoke, and respite from increased urban heating can be used to promote their conservation and proper management. We hope that the findings as well as methods from this study contribute to this discourse and can be used to communicate the importance of forest ESs and EDs to underrepresented urban communities. We hope that science-based evidence provided by this study can lead to more equitable and inclusive participatory processes related to the management and conservation of Wildland-Urban Interface montane forests.

CRediT authorship contribution statement

Haotian Cheng: Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Francisco J. Escobedo:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization. **Alyssa S. Thomas:** Writing – review & editing, Writing – original draft. **Jesus Felix De Los Reyes:** Data curation. **José R. Soto:** Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

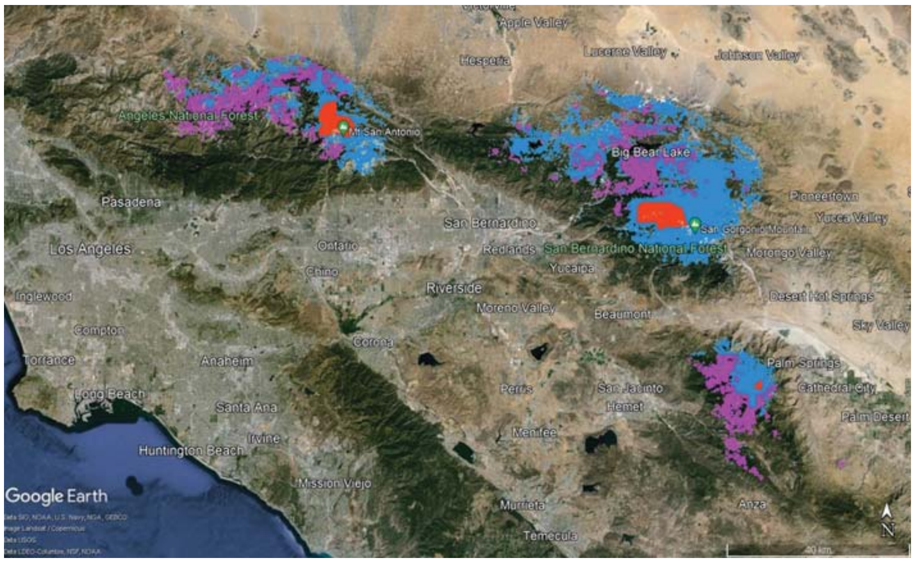
Data will be made available on request.

Acknowledgements

This research was funded by University of Arizona project # 3042210 and supported and funded in part by annual research appropriations from the Pacific Southwest Research Station, USDA Forest Service. We would like to thank the Climate Science Alliance, the Southern Montane Forest Project, and specifically Megan Jennigs, Nicole Molinari, and Sarah Hennessey, especially, for allowing us to participate and use the online workshop results as well as their help in designing our survey instrument. We also thank the Reviwers and Editors for their helpful comments.

Appendix A. Study area

The greater Los Angeles, California US study area using a Google Earth® image and location of the southern California montane forests characterized by the ponderosa pine (Pink), lodgepole pine (Red), and Douglas-fir / California mixed conifer (Blue) groups. The study area comprises the Riverside-San Bernardino-Ontario Metropolitan Statistical Area (MSA) and the Los Angeles-Long Beach-Glendale Metropolitan Division (MD) as defined by the US Census Bureau.



.

Appendix B. Probability methods

The probability of selecting the pair p takes an MNL of the form in the below equation:

$\Pr[p|\mathbf{x}_{it}] = \prod_{t=1}\prod_{i=1}\prod_{k=1}^{J-1}\frac{\exp(\mathbf{x}_{ijt}\beta)}{\sum_{k=1}^{J}\exp(\mathbf{x}_{ijt}\beta)}$ where $\mathbf{x}_{it}$ is the vector of attributes for all alternatives $j = 1,\dots J$. According to Aizaki and Fogarty (2019), the respondent's choice was coded as '1′ for the highest utility or '0′ otherwise. Then the paired-MNL model with dummy coding and utilities was computed based on the below equation:

$$U_{ijt} = \mathrm{Att1}_{1_{it}}\beta_{Att1_1} + \mathrm{Att1}_{2_{it}}\beta_{Att1_2} + \cdots + \mathrm{Att2}_{1_{it}}\beta_{Att2_1} + \mathrm{Att2}_{2_{it}}\beta_{Att2_2} + \cdots + \mathrm{Att4}_{1_{it}}\beta_{Att4_1} + \mathrm{Att4}_{2_{it}}\beta_{Att4_2} + \epsilon_{ijt}$$

where $\mathrm{Att}\#_{\#_{it}}$ is the dummy variable for attribute # level # individual i on profile t.

Appendix C. Latent Class methods

The LCL regression framework used for analyzing this random utility model specification, assumes that there are c classes of respondents, and each class c makes choices consistent with its own random effect logit model with utility coefficient vector β_c. The probability a respondent selects alternative j as the 'best' and m as the 'worst' is:

$$\Pr[j, m \mid \boldsymbol{x}_{it}]\prod_{t=1}\prod_{i=1}\prod_{k=1}^{J-1}\sum_{c=1}^{C}\frac{\exp(\boldsymbol{x}_{ijt}\boldsymbol{\beta}_c)}{\sum_{k=1}^{J}\exp(\boldsymbol{x}_{ijt}\boldsymbol{\beta}_c)}\frac{\exp(\boldsymbol{x}_{imt}\boldsymbol{\beta}_c)}{\sum_{k=1}^{J}\exp(\boldsymbol{x}_{imt}\boldsymbol{\beta}_c)}R_{ic}$$

where R_{ic} is the probability that individual i belongs to class c, which can be interpreted using the below equation as:

$$R_{ic} = \frac{\boldsymbol{exp}(\theta_c \boldsymbol{Z}_i)}{\sum_r \boldsymbol{exp}(\theta_r \boldsymbol{Z}_i)}$$

where Z_i is a set of respondent demographic that affect class membership, and θ_i is the parameter vector for respondents in class c. Following Alvarez et al. (2021), we used the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) to determine the optimal number of latent classes.

Appendix D. Example of the Best-Worst question used to make the tradeoffs in the survey instrument.

.

Select one item as *Most Important* & another as *Least Important to You*

Most Important to You		**Least Important to You**
☐	**Density**: Low; Few trees spread out.	☐
☐	**Understory:** Bare; clean surface with little to no plant cover and areas of bare soils.	☐
☐	**Water:** No water features in forest	☐
☐	**Diversity**: Low; one or two types of trees/shrubs	☐

References

Al-Janabi, H., Flynn, T.N., Coast, J., 2010. Estimation of a Preference-Based CARER Experience scale. Med. Decis. Making 31 (3), 458–468.

Álvarez, S., Soto, J.R., Escobedo, F.J., Lai, J., Kibria, A.S., Adams, D.C., 2021. Heterogeneous preferences and economic values for urban forest structural and functional attributes. Landsc. Urban Plan. 215, 104234 https://doi.org/10.1016/j.landurbplan.2021.104234.

Álvarez-Farizo, B., Hanley, N., Ortí, R.B., Lázaro, A., 2007. Choice modeling at the "market stall": Individual versus collective interest in environmental valuation. Ecol. Econ. 60 (4), 743–751. https://doi.org/10.1016/j.ecolecon.2006.01.009.

Aznar-Sánchez, J.A., Ureña, L.J.B., López-Serrano, M.J., Velasco-Muñoz, J.F., 2018. Forest Ecosystem Services: An analysis of Worldwide research. Forests 9 (8), 453. https://doi.org/10.3390/f9080453.

Bruzzese, S., Blanc, S., Melino, V.M., Massaglia, S., Brun, F., 2022. Civil society's perception of forest ecosystem services. A case study in the Western Alps. Front. Psychol. 13 https://doi.org/10.3389/fpsyg.2022.1000043.

Bullock, C., Joyce, D., Collier, M., 2018. An exploration of the relationships between cultural ecosystem services, socio-cultural values and well-being. Ecosyst. Serv. 31, 142–152. https://doi.org/10.1016/j.ecoser.2018.02.020.

U.S. Census Bureau. (2020). Census Bureau Tables. https://data.census.gov/table.

Cheng, H., Lambert, D.M., DeLong, K.L., Jensen, K.L., 2021. Inattention, availability bias, and attribute premium estimation for a biobased product. Agric. Econ. 53 (2), 274–288. https://doi.org/10.1111/agec.12679.

Cheng, H., Feuz, R., Lambert, D.M., 2023a. A comparison of best-worst scaling marginal and rank methods. Appl. Econ. Lett. 1–4 https://doi.org/10.1080/13504851.2023.2187019.

Cheng, H., Zhang, T., Lambert, D.M., Feuz, R., 2023b. An empirical comparison of conjoint and best-worst scaling case III methods. J. Behav. Exp. Econ. https://doi.org/10.1016/j.socec.2023.102049.

Cheng, H., Ng'ombe, J. N., & Lambert, D. M., 2024. A Bayesian generalized rank ordered Logit model. Journal of Choice Modelling 50, 100475. https://doi.org/10.1016/j.jocm.2024.100475.

Cline, S., Crowley, C., 2018. Economic Contributions of Outdoor Recreation on Federal Lands (2016). The U.S. Department of Interior, Office of Policy Analysis, Washington, DC. Retrieved from https://www.doi.gov/sites/doi.gov/files/uploads/recn_econ_brochure_fy_2016_2018-04-04.pdf.

Darvill, R., Lindo, Z., 2015. The inclusion of stakeholders and cultural ecosystem services in land management trade-off decisions using an ecosystem services approach. Landsc. Ecol. 31 (3), 533–545. https://doi.org/10.1007/s10980-015-0260-y.

Davis, E.J., White, E.M., Cerveny, L.K., Seesholtz, D.N., Nuss, M.L., Ulrich, D.R., 2017. Comparison of USDA Forest Service and stakeholder motivations and experiences in collaborative federal forest governance in the Western United States. Environ. Manag. 60 (5), 908–921. https://doi.org/10.1007/s00267-017-0913-5.

De Groot, R.S., Wilson, M.A., Boumans, R.M., 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. Ecol. Econ. 41 (3), 393–408. https://doi.org/10.1016/s0921-8009(02)00089-7.

Dietz, T., Fitzgerald, A., Shwom, R., 2005. Environmental values. Annu. Rev. Env. Resour. 30 (1), 335–372. https://doi.org/10.1146/annurev.energy.30.050504.144444.

Dolan, P., Olsen, J.A., Menzel, P.T., Richardson, J.R.J., 2003. An inquiry into the different perspectives that can be used when eliciting preferences in health. Health Econ. 12 (7), 545–551. https://doi.org/10.1002/hec.760.

Faehnle, M., Bäcklund, P., Tyrväinen, L., Niemelä, J., Yli-Pelkonen, V., 2014. How can residents' experiences inform planning of urban green infrastructure? Case Finland. Landsc. Urban Plan. 130, 171–183. https://doi.org/10.1016/j.landurbplan.2014.07.012.

Finn, A., Louviere, J.J., 1992. Determining the appropriate response to evidence of public concern: The case of food safety. J. Public Policy Mark. 11 (2), 12–25. https://doi.org/10.1177/074391569201100202.

Flores, D., Sánchez, J.J., 2020. The changing dynamic of Latinx outdoor recreation on national and state public lands. *J. Park. Recreat. Adm.* https://doi.org/10.18666/jpra-2020-9807.

Flynn, T.N., Louviere, J.J., Peters, T.J., Coast, J., 2008. Estimating preferences for a dermatology consultation using Best-Worst Scaling: Comparison of various methods of analysis. BMC Med. Res. Method. 8 (1) https://doi.org/10.1186/1471-2288-8-76.

Friggens, M.M., Raish, C., Finch, D.M., McSweeney, A.M., 2014. The influence of personal belief, agency mission and city size on open space decision making processes in three southwestern cities. Urban Ecosystems 18 (2), 577–598. https://doi.org/10.1007/s11252-014-0419-3.

Hammitt, W.E., Patterson, M.E., Noe, F.P., 1994. Identifying and predicting visual preference of southern Appalachian Forest recreation vistas. Landsc. Urban Plan. 29 (2–3), 171–183. https://doi.org/10.1016/0169-2046(94)90026-4.

Horodecka, A., Vozna, L., 2021. Between individual and collective rationality. In Words, Objects and Events in Economics: the Making of Economic Theory 139–158. https://doi.org/10.1007/978-3-030-52673-3_9.

Jenerette, G.D., Anderson, K.E., Cadenasso, M.L., Fenn, M., Franklin, J., Goulden, M.L., Larios, L., Pincetl, S., Regan, H.M., Rey, S.J., Santiago, L.S., 2022. An expanded framework for wildland–urban interfaces and their management. Front. Ecol. Environ. 20 (9), 516–523. https://doi.org/10.1002/fee.2533.

Keeley, J.E., Syphard, A.D., 2018. Historical patterns of wildfire ignition sources in California ecosystems. Int. J. Wildland Fire 27 (12), 781. https://doi.org/10.1071/wf18026.

Lentner, M., Bishop, T., 1984. Experimental design and analysis. Valley Book Company.

Lienhoop, N., Bartkowski, B., Hansjürgens, B., 2015. Informing biodiversity policy: The role of economic valuation, deliberative institutions and deliberative monetary valuation. Environ Sci Policy 54, 522–532. https://doi.org/10.1016/j.envsci.2015.01.007.

Lienhoop, N., Schröter-Schlaack, C., 2018. Involving multiple actors in ecosystem service governance: Exploring the role of stated preference valuation. Ecosyst. Serv. 34, 181–188. https://doi.org/10.1016/j.ecoser.2018.08.009.

Manley, K., Egoh, B.N., 2022. Mapping and modeling the impact of climate change on recreational ecosystem services using machine learning and big data. Environ. Res. Lett. 17 (5), 054025 https://doi.org/10.1088/1748-9326/ac65a3.

Martín-López, B., Iniesta-Arandia, I., García-Llorente, M., Palomo, I., Casado-Arzuaga, I., Amo, D.G.D., Gómez-Baggethun, E., Oteros-Rozas, E., Palacios-Agundez, I., Willaarts, B., González, J.A., 2012. Uncovering ecosystem service bundles through social preferences. PLoS One 7 (6), e38970.

McFadden, D., 1973. Conditional logit analysis of qualitative choice behavior. Frontiers in Econometrics 105–142. https://ci.nii.ac.jp/naid/10007461386.

Minnich, R.A., Barbour, M.G., Burk, J.H., Fernau, R.F., 1995. Sixty years of change in Californian conifer forests of the San Bernardino mountains. Conserv. Biol. 9 (4), 902–914. https://doi.org/10.1046/j.1523-1739.1995.09040902.x.

Minnich, R. A. (2007). Southern California conifer forests. In M.B. (Ed.), *Terrestrial Vegetation of California* (pp. 502–538). University of California Press.

Niemeyer, S., Spash, C.L., 2001. Environmental Valuation Analysis, Public Deliberation, and their Pragmatic Syntheses: A Critical Appraisal. Environment and Planning C-Government and Policy 19 (4), 567–585. https://doi.org/10.1068/c9s.

Plieninger, T., Ferranto, S., Huntsinger, L., Kelly, M., Getz, C., 2012. Appreciation, use, and management of biodiversity and ecosystem services in California's working landscapes. Environ. Manag. 50, 427–440. https://doi.org/10.1007/s00267-012-9900-z.

Plieninger, T., Bieling, C., Fagerholm, N., Byg, A., Hartel, T., Hurley, P.T., López-Santiago, C.A., Nagabhatla, N., Oteros-Rozas, E., Raymond, C.M., Van Der Horst, D., Huntsinger, L., 2015. The role of cultural ecosystem services in landscape management and planning. Curr. Opin. Environ. Sustain. 14, 28–33. https://doi.org/10.1016/j.cosust.2015.02.006.

Rasch, R., 2019. Are public meetings effective platforms for gathering environmental management preferences that most local stakeholders share? J. Environ. Manage. 245, 496–503. https://doi.org/10.1016/j.jenvman.2019.05.060.

Reed, M., Vella, S., Challies, E., De Vente, J., Frewer, L., Hohenwallner-Ries, D., Huber, T., Neumann, R.K., Oughton, E., Del Ceno, J.S., Van Delden, H., 2017. A theory of participation: What makes stakeholder and public engagement in environmental management work? Restor. Ecol. 26 (S1) https://doi.org/10.1111/rec.12541.

Rommetvedt, H., 2005. Norway: Resources count, but votes decide? from neo-corporatist representation to neo-pluralist parliamentarism. West Eur. Polit. 28 (4), 740–763. https://doi.org/10.1080/01402380500216674.

Sánchez, J.J., Marcos-Martinez, R., Srivastava, L., Soonsawad, N., 2021. Valuing the impacts of forest disturbances on ecosystem services: An examination of recreation and climate regulation services in US national forests. Trees, Forests and People 5, 100123.

Schmidt, K., Martín-López, B., Phillips, P.M., Julius, E., Makan, N., Walz, A., 2019. Key landscape features in the provision of ecosystem services: Insights for management. Land Use Policy 82, 353–366. https://doi.org/10.1016/j.landusepol.2018.12.022.
Sloggy, M.R., Escobedo, F.J., Sánchez, J.J., 2022. The role of spatial information in peri-urban ecosystem service valuation and policy investment preferences. Land 11 (8), 1267. https://doi.org/10.3390/land11081267.
Soliño, M., Yu, T., AlíA, R., Auñón, F., Bravo-Oviedo, A., Chambel, M. R., De Miguel, J. J., Del RíO, M., Justes, A., Martínez-Jauregui, M., Montero, G., Mutke, S., Ruiz-Peinado, R., & Barrio, J. M., 2018. Resin-tapped pine forests in Spain: Ecological diversity and economic valuation. Sci. Total Environ. 625, 1146–1155. https://doi.org/10.1016/j.scitotenv.2018.01.027.
Soma, K., Termeer, C., Opdam, P., 2016. Informational governance – A systematic literature review of governance for sustainability in the Information Age. Environ Sci Policy 56, 89–99. https://doi.org/10.1016/j.envsci.2015.11.006.
Soto, J.R., Escobedo, F.J., Khachatryan, H., Adams, D.C., 2018. Consumer demand for urban forest ecosystem services and disservices: Examining trade-offs using choice experiments and best-worst scaling. Ecosyst. Serv. 29, 31–39. https://doi.org/10.1016/j.ecoser.2017.11.009.
Stephens, S.L., Bernal, A.A., Collins, B.M., Finney, M.A., Lautenberger, C., Saah, D., 2022. Mass fire behavior created by extensive tree mortality and high tree density not predicted by operational fire behavior models in the southern Sierra Nevada. For. Ecol. Manage. 518, 120258 https://doi.org/10.1016/j.foreco.2022.120258.
Tanner, S., Lupi, F., Garnache, C., 2022. Estimating visitor preferences for recreation sites in wildfire prone areas. Int. J. Wildland Fire 31 (9), 871–885. https://doi.org/10.1071/wf21133.
Thomas, A.S., Sánchez, J.J., Flores, D., 2022. A review of trends and knowledge gaps in Latinx outdoor recreation on federal and state public lands. J. Park. Recreat. Adm. 40 (1).
Tyner, E.H., Boyer, T.A., 2020. Applying best-worst scaling to rank ecosystem and economic benefits of restoration and conservation in the Great Lakes. J. Environ. Manage. 255, 109888 https://doi.org/10.1016/j.jenvman.2019.109888.
Underwood, E.C., Hollander, A.D., Safford, H.D., Kim, J.B., Srivastava, L.S., Drapek, R.J., 2019. The impacts of climate change on ecosystem services in southern California. Ecosyst. Serv. 39, 101008 https://doi.org/10.1016/j.ecoser.2019.101008.
Van Berkel, D.B., Verburg, P.H., 2014. Spatial quantification and valuation of cultural ecosystem services in an agricultural landscape. Ecol. Ind. 37, 163–174. https://doi.org/10.1016/j.ecolind.2012.06.025.
Vatn, A., 2009. An institutional analysis of methods for environmental appraisal. Ecol. Econ. 68 (8–9), 2207–2215. https://doi.org/10.1016/j.ecolecon.2009.04.005.
Wilkerson, M.L., Mitchell, M.G., Shanahan, D., Wilson, K.A., Ives, C.D., Lovelock, C.E., Rhodes, J.R., 2018. The role of socio-economic factors in planning and managing urban ecosystem services. Ecosyst. Serv. 31, 102–110. https://doi.org/10.1016/j.ecoser.2018.02.017.
Wilson, M.A., Howarth, R.B., 2002. Discourse-based valuation of ecosystem services: establishing fair outcomes through group deliberation. Ecol. Econ. 41 (3), 431–443. https://doi.org/10.1016/s0921-8009(02)00092-7.
Yadav, K., Escobedo, F.J., Thomas, A.S., Johnson, N.G., 2023. Increasing wildfires and changing sociodemographics in communities across California, USA. Int. J. Disaster Risk Reduct. 104065 https://doi.org/10.1016/j.ijdrr.2023.104065.