The economic value of forest campsite closures in Hawai‘i

Abstract

Hawai‘i's unique ecosystems face escalating anthropogenic pressures, including climate change-related extreme events such as fire, intense rains, and flooding. A related repercussion is the heightened risk of closure of available camping sites, diminishing Hawaiian residents' access to recreational services for overnight or longer stays. These are critical services for residents, offering affordable vacation opportunities, and particularly for Native Hawaiians, opportunities to connect with their cultural heritage. Deriving reliable nonmarket use values estimates of campsite closure is thus crucial for developing effective management strategies delivering the highest benefits at least cost. Relatedly, our key contribution is to conduct the first analysis of the economic value associated with campsite closures across the Hawaiian Islands, utilizing administrative forest reservation data. The reservation data is from 2018 to 2023, encompassing 11,696 reservations made by 6,136 Hawaiian residents across all 22 campsites regulated by the Division of Forestry and Wildlife. As a novelty, we account for inter-island travelling expenses and time across campsites in the travel cost calculations. To analyze the data, we, as one of the few papers in environmental economics, employ the multiple discrete-continuous extreme value model. Our results show significant welfare loss among Hawaiian residents of campsite closure, varying between USD 332 000 to USD 530 000 aggregated across all campsites.

Keywords: Cultural ecosystem services; Recreation; Nonmarket valuation; Revealed preferences; Travel cost model; Forest campsites; MDCEV

JEL codes: Q26; Q51; Q57

1 Introduction

The economic value of nature-based recreation reflects a critical component of the total economic value of natural environments. However, quantifying and integrating this value in economic appraisal poses a challenge, as the value of recreational benefits eludes direct market transactions. As a result, recreational benefits from natural environments tend to be underestimated in policymaking (Hanley & Barbier, 2009), leading to sub-optimal decisions (Bateman et al., 2013; Iversen et al., 2024).

Hence, developing and applying methods to derive the economic value of nature-based recreation has been a focal point of research among environmental economists for decades (e.g., Burt & Brewer, 1971; Bockstael et al., 1987; Smith & Kaoru, 1990; Phaneuf et al., 2000; English et al., 2018; Lupi et al., 2020; Lloyd-Smith & Becker, 2020; Börger et al., 2023). Understanding the economic value derived from engaging in recreational activities in these settings is vital for developing effective environmental conservation strategies (Goldstein et al., 2012). These strategies aim to maximize benefits while minimizing costs, ensuring that efforts to preserve and maintain high-value recreational infrastructure are both economically efficient and environmentally sustainable (Bateman et al., 2013; Bateman & Mace, 2020).

In an era increasingly defined by the escalating environmental impacts of climate change and a pressing nature crisis, exacerbated by extensive land use changes and environmental degradation, the importance of understanding the economic value of recreation becomes even more crucial (Chan & Wichman, 2020). Climate change and environmental degradation are diminishing available ecosystem services (Foley et al., 2005; Balvanera et al., 2006), including those related to recreation (Hasan et al., 2020; Dundas & von Hafen, 2020; Chan & Wichman, 2020; Dundas & von Hafen, 2021), with potentially profound implications for human welfare through changed quality and availability of recreational spaces (Kosanic & Petzold, 2020).

In assessing the economic value of nature-based recreation, travel cost (TC) models, a revealed preference approach, have been a cornerstone (Parson, 2017). This approach posits that the economic value of these areas is reflected in visitors' willingness to travel and the opportunity cost of their time, as entry typically incurs minimal expenses. The traditional TC method approach primarily relies on survey data to estimate the demand of recreational sites, extracting information about travel expenses and behavior, see e.g., Xie and Adamowicz (2023) for a recent application.[1] However, use of the traditional survey-based TC method is associated with substantial challenges. Generally, these surveys are prone to recall bias (Lupi et al., 2020) while on-site TC surveys are subject to oversampling of frequent visitors (Shaw, 1988), leading to endogenous stratification (Englin & Shonkwiler, 1995).

As suggested by Lloyd-Smith and Becker (2020), the use of non-survey data, as an alternative, can mitigate these biases. Non-survey datasets in recreational research often rely on entry fees or purchased permits but such records have historically been not widely available (Lupi et al., 2020). Over the past few decades, however, many management agencies have embraced the adoption of online reservation systems to effectively handle recreational demand (Wells et al., 2018; Rice et al., 2022). The widespread use of online reservations has expanded access to non-survey recreational datasets, significantly improving spatial insights into the economic value of outdoor recreation (Lloyd-Smith & Becker, 2020). This enhanced data resolution provides a valuable opportunity to analyze the decisions made by numerous individuals over time regarding their engagement in nature-based recreation. Additionally, it allows us to establish connections between site-specific conditions and the associated economic value (Loomis et al., 2009; Gellman et al., 2023; Lowe Mackenzie, 2023).

[1] Stated preference (SP) methods, often combined with the travel cost method, has also been used, particularly to estimate welfare effects of changes in environmental quality/quantity, see e.g., Zhang and Sohngen (2018). A well-known limitation of limitation of SP methods is hypothetical bias, i.e., that the estimated welfare effects are based on hypothetical payments/required compensation and thus inflated (Penn & Hu, 2018). However, recent research suggest that more advanced survey instruments can reduce hypothetical bias (Fang et al., 2021).

In this study, we explore a novel approach to evaluating the economic impact of campsite closures in Hawai‘i, underscoring the intricate connection between the environment and human well-being, as campsite closure directly impacts individuals by reducing access to essential cultural ecosystem services. The ongoing management of these resources is essential, as they offer a diverse range of ecosystem services crucial to both Hawaiian residents and tourists. Utilizing a comprehensive administrative dataset, we analyze over 11,696 camping trips by 6,136 Hawaiian residents across 22 niche campsites managed by the Department of Land and Natural Resources Division of Forestry and Wildlife (DOFAW). Most campsites are located in areas designated for hunting. This dataset, spanning from 2018 to 2023, provides a unique insight into the camping behaviors of residents across ecologically sensitive regions in O‘ahu, Kaua‘i, Molokai‘i, and the Island of Hawai‘i. Unlike traditional applications that often rely on intercept surveys, our approach leverages actual administrative reservation data, thus avoiding the highlighted biases of endogenous stratification and recall bias (Jaung & Carrasco, 2020).

Our methodology involves estimating the travel costs for each camper to each campsite, factoring in both intra- and inter-island travel expenses and time. This novel approach allows for a more nuanced understanding of the value campers place on available reservation campsites. Given that the data has multiple campsites that are imperfect substitutes for one another, we employ the multiple discrete-continuous extreme value (MDCEV) model (Bhat, 2008). This model accounts for choices among campers in terms of which campsite to visit and the number of trips in utility maximizing framework. Based on the estimated parameters of the MDCEV approach, we use simulations to provide non-market use values associated with closing each of the 22 campsites. From the simulation exercise, we further undertake spatial mapping of aggregated welfare loss of campsite closure across islands and zip codes, offering environmental managers valuable insights into the geographic distribution of these losses.

This paper has two key contributions. First, we contribute to the small but growing body of research utilizing non-survey data for recreation demand analysis, being one of the few papers in environmental economics applying the MDCEV model (Xie & Adamowicz, 2023). Existing research utilizing non-survey data to estimate recreational demand includes the use of data from social media (Keeler et al., 2015; Sinclair et al., 2022), crowdsourcing (Kolstoe & Cameron, 2017; Jayalath et al., 2023; Guilfoos et al., 2023), camping reservations (Lloyd-Smith & Becker, 2020; Gellman et al., 2023), and mobile signal data (Dai et al., 2023). Gellman et al. (2023) use an online reservation camping dataset to examine the welfare loss of wildfire smoke by applying a zonal TC approach which concentrates on the participation level. Kolstoe and Cameron (2017) and Guilfoos et al. (2023) estimate the recreational value of birding sites from a random utility model using ebird data. Lloyd-Smith and Becker (2020) use administrative data from an online camping reservation system in Alberta, Canada to employ the MDCEV model to simulate the welfare impacts of campsite closure.

Our second contribution relates to providing insights into the economic value of outdoor recreational services in Hawai‘i, addressing a topic that has hitherto been largely unexplored in economics. A notable exception is Fezzi et al. (2023) who use a survey among residents on the island of Maui to develop a random utility TC model to value recreational services provided by outdoor sites across the island. This gap is noteworthy, especially considering that Hawai‘i has the highest outdoor recreation value relative to state GDP in the United States, accounting for 5.6 percent in 2022 (BEA, 2023). Camping in Hawaiian forests offers access to remaining native forests, which are habitat for countless rare, threatened, and endangered species of conservation value (Duffy & Kraus, 2006; Sakai et al., 2002), plants important for traditional medicine and ceremonies (Kamelamela, 2019), and subsistence hunting grounds (Lohr et al., 2014; Lepczyk et al., 2019). Climate change could diminish access to and quality of nature-based recreational services as habitats shift, non-native species increasingly invade, and fire and flooding risks escalate (Fortini et al., 2015; Trauernicht, 2019; Frazier et al., 2023). Access to campsites for over-night or longer stays is important for residents who are typically priced out of the tourism market, and particularly Native Hawaiians, who, due to the legacy of colonialism, continue to be dispossessed of their lands (Trask, 1999). Campsites offer an affordable means to sustain connection with the natural environment, which is an essential aspect of Native Hawaiian cultural heritage and identity (Kana‘iaupuni & Malone, 2006; McCubbin & Marsella, 2009). This study is the first to use a non-market valuation method to determine the recreational value of forest campsite closures in Hawai‘i among its residents.

2. Data and methods

2.1 Reservation Data

The spatial scope of the analysis lies in the Hawai‘i Forest Reserve (HFR), whose aim is to preserve and enhance the significant upland forested lands for a multitude of public benefits and values. The Department of Land and Natural Resources Division of Forestry and Wildlife (DOFAW) oversees public HFR lands today, which cover 683,964 acres (2768 km^2) of state-managed land. HFR campsites are often remote, mountainous locations, providing a wilderness experience with high privacy. Campsites are accessed by hiking, 4WD vehicles, and have few or no amenities.

Hawai‘i adopted an online reservation system for a multitude of campsites managed by both Hawai‘i State Parks (HSP) and HFR. Online reservation systems assist land managers in efficiently managing visitor flow, ensuring adequate staffing and resources for the expected number of visitors. The web-based services interface features an interactive map where potential campers can browse all campsites across the islands. Each campsite has specific information about the current conditions, location, amenities and activities available at the campsite. Campers can make reservations up to one month in advance. There are 22 HRF sites to choose from, distributed across 4 of the 6 Main Hawaiian Islands (MHI), see Figure 1. Oʻahu provides a total of 10 campsites scattered throughout the Na Ala Hele Trail System. The majority of these campsites promote dispersed camping along the trail system including Kamananui, Kaunala, Kuaokalā, Kulanaʻahane, Kuliʻouʻou, Waimano, and Wiliwilinui Ridge Trail. Two specific campsites, Peacock Flats A and B, are accessible by 4WD vehicles and are located in close proximity to each other. For this analysis Peacock Flats A and B are considered as one campsite. The island of Kauaʻi has 8 HFR campsites all within the Na Pali-Kona Forest Reserve. The Big Island features 3 campsites, including 2 with cabin facilities and one exclusive campsite accessible only to Hawaiʻi residents located along the north coast. Lastly, Molokaʻi hosts a single campsite in the Molokaʻi Forest Reserve. For summary statistics of the attributes of the 22 campsites, see Table A.1 in the Appendix. As can be seen in the Figure 1 and Table A.1, a majority of the campsites are located in areas designated for hunting.

When a camper is ready to make a reservation, they are required to create an account within the online reservation system. The process includes creating a unique account where individuals are asked to enter their contact information which includes the user's postal zip code. The zip code provides a location origin. Using anonymized User IDs, we can follow each person's decisions for undertaking recreational trips over time. From 2018 to 2023, 19,299 reservations were made at the 22 campsites within HFR. Residents of Hawaiʻi account for a majority of these reservations with 11,696 usable reservations[2]. Each reservation provides information on the days, the specific campsite chosen, and the number of people in the party. Table A.2 in the Appendix presents data on the proportion of participants relative to the number of reservations or trips made to the campsites, whereas Table A.3 illustrates the distribution of participants according to the number of different campsites they visited. Table A.4 shows the number of visits to each campsite across the data collection period.

[2] With usable, we refer to reservations were a valid HI zip-code was provided with the reservation.

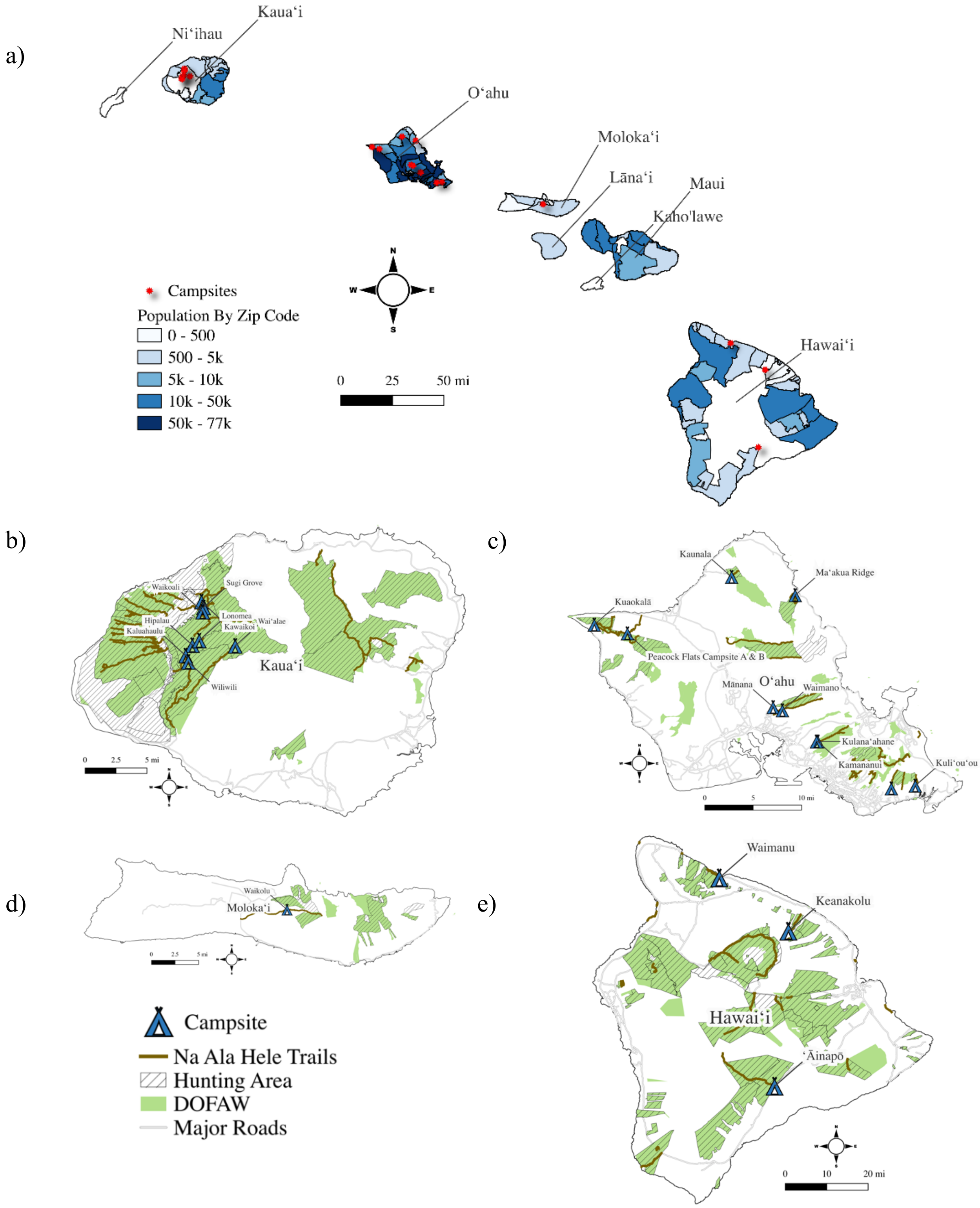

Figure 1. Locations of Division of Forestry and Wildlife (DOFAW) campsites across the Main Hawaiian Islands (MHI). a) MHI formation with population by zip code; b) 8 campsites in Kaua'i are concentrated in the Na Pali-Kona Forest Reserve; c) 10 campsites across the island of O'ahu; d) Single Moloka'i campsite located within Molokai'i Forest Reserve; e) 3 campsites across the island of Hawai'i. Figures b) to e) defines green areas as forest reserves regulated by DOFAW, diagonal lines as hunting areas, brown lines as the Na Hele trail system, and outlined areas as major road systems on each island.

2.2 Travel Cost

The computation of distance and travel time for each unique zip code across the island was carried out using the Open Source Routing Machine (OSRM) (Huber & Rust, 2016). OSRM is an open-source software project that provides a high-performance routing engine for various applications, particularly in the field of routing and navigation. It is designed to calculate the shortest or fastest route between two points on a map, taking into consideration various factors such as road networks, traffic conditions, and transportation modes. Leveraging OSRM's advanced routing algorithms, our methodology ensures a cost-effective, accurate, and efficient solution for estimating travel times comparable to more costly options such as Google Distance Matrix API and ArcGIS Network Analysis (Fu et al., 2023). For this analysis, OSRM is operational on a local server configuring the OSRM backend.[3]

The comprehensive analysis encompasses both intra-island and inter-island travel reservations. Intra-island travel estimates are composed of a calculation of the distance and time it takes from each centroid for each zip code and the roundtrip to each campsite on the island. The inter-island reservations require additional assumptions to calculate the TC function. Each inter-island reservation requires a flight as well as a mode of transportation from the from the destination airport to the campsite. This introduces complexity to the traditional TC calculation method, which has historically been computed as the average driving distance from the origin to the destination, a methodology proposed by Hotelling (1947) to the National Parks Service. However, Hawai'i presents a unique scenario where inter-island travel within the state is a necessity.

To address this distinctive aspect of Hawai'i, we incorporate the required costs for inter-island travel for residents. Drawing from the work of English et al. (2018), which stands as, to the best of the authors' knowledge, the initial recreational TC analysis attempting to encompass

[3] https://github.com/Project-OSRM/osrm-backend

round-trip expenses for those necessitating air travel for recreational activities. The comprehensive approach involves considerations such as:

1. The round-trip distance and time from the zip code's centroid to the main airport on the island of origin.
2. The round-trip distance and time from the destination island's airport to each respective campsite.
3. The round-trip average flight cost and time between each island.
4. The average cost of renting a vehicle.
5. Parking fees

By incorporating these additional factors, the aim is to provide a more accurate and nuanced assessment of the travel costs associated with recreational activities, particularly for residents of Hawai‘i who rely on inter-island travel to engage in such activities. Hotel nights are not included in this analysis given the recreactional trip is for an overnight trip in the backcountry.

The TC function is assumed to be:

$$TC_{it} = \frac{\left[C_{ij}^{D} * D_{it} + d_{ij} \cdot f_{ij}\right]}{n} + C_{ij}^{F} + VTT_{it} * T_{ijt}\,, \tag{1}$$

where the first part defines the round-trip driving distance D_{ij} for individual, i, from the centroid of the reported zip code to the campsite, j, multplied by the sum of the per mile operational cost of the automobile[4], which includes per-mile gasoline, maintenance, and per-mile depreciation, defined by C_{ij}^{D}. The first part also includes the reservation fee times the number of nights at the campsite, $d_{ij} \cdot f_{ij}$. The first part is divided by the average number of people in the reservation party, n, which is equal to 3.78. The second part (C_{ijf}^{F}) defines inter-island TC, including the average cost of a flight between the island of origin and the destination

[4] The average operating cost per mile in 2023 for a medium sedan was USD 0.74, see https://newsroom.aaa.com/wp-content/uploads/2023/08/YDC-Fact-Sheet-FINAL-8.30.23-1.pdf.

island for campsites requiring inter-island flights. Consistent with English et al. (2018), C_{ijf}^{F} also includes the average car rental cost at the destination island for campsites requiring inter-island flights, and the daily parking fee at the island where the individual lives. The average car rental cost is multiplied by the number of days the individual reserved, divided by the average number people in the reservation party. The parking fee is multiplied by the number of days the individual reserved. The last part defines the value of time (VTT_i) for the individual who reserved the campsite multiplied by the time spent traveling to the location, T_{ij}, which includes air travel time. The air travel time includes the recommended 90 minutes on the airport of origin before an inter-island flight, plus the actual flight time. The value of time was calculated based on the 3/4 of the median income in the zip code where the participant lives (Fezzi et al., 2014), assuming 2000 work hours per year (Haab & McConnell, 2002). All cost are reported in 2023 US dollars. Considering the inter-island expenses, the average TC is USD 385.39. Over 16 percent of the sample visited another island for camping.

2.3 Kuhn-Tucker model

To analyze the reservation data, we employ the Kuhn-Tucker (KT) with the MDCEV specification, which is typically favored to the traditional KT with linear expenditure system specification[5] (Bhat, 2008). In our context, the KT framework assumes that individual i maximizes their utility function $U(x_j, \boldsymbol{Q}_j, z)$, a function defined by deciding on the number of trips x_j to take to each campsite j, how much to spend on the numeraire good z that represents all other expenditures, and vectors of campsite attributes $\boldsymbol{Q}_j$, subject to a budget constraint, which gives us the following maximization problem:

$$\max_{x_{j,z}} U(x_j, \boldsymbol{Q}_j, z) \quad \text{s.t} \quad y \geq \sum_{k=1}^{K} p_j x_j + z, \quad j = 1, \dots, J. \tag{2}$$

[5] See e.g., Phaneuf and Siderelis (2003) and Whitehead et al. (2010) for applications of the traditional KT recreation demand model, i.e., without the MDCEV specification.

In the budget constraint, p_j is the round-trip TC to campsite j, y is the disposable annual income, while the price for z is normalized to 1. The maximization problem provides us with the following first order KT conditions to derive the optimal number of trips x_j to take to each campsite j:

$$\frac{\partial U/\partial x_j}{\partial U/\partial z} \leq p_j, \qquad j = 1, \dots, J, \tag{3}$$

$$x_j \left[\frac{\partial U/\partial x_j}{\partial U/\partial z} - p_j\right] = 0, \qquad j = 1, \dots, J. \tag{4}$$

For our empirical model, we use, as introduced by Bhat (2008), a translated generalized constant elasticity of substitution utility specification, defined as follows:

$$U\left(x_j, \boldsymbol{Q}_j, z\right) = \sum_j \frac{\gamma_j}{\alpha} \Psi_j \left[\left(\frac{x_j}{\gamma_j} + 1\right)^{\alpha} - 1\right] + \frac{\Psi_1 z^{\alpha}}{\alpha}, \tag{5}$$

where the Ψ_j parameters define the marginal utility of a trip to campsite j when no trips are undertaken. Likewise, Ψ_1 is the marginal utility of the numeraire good when not consumed, while γ_j are translation parameters that allow for satiation effects and corner solutions (when 0 trips are undertaken) and α measures the diminishing marginal utility of additional campsite trips or consumption of the numeraire good (Bhat, 2008). We define the utility function parameters using the following specification: $\Psi_j = \exp\left(\beta_q \boldsymbol{Q}_j + \varepsilon_j\right)$, $\gamma_j = \exp\left(\gamma_j\right)$, and $\alpha = 1 - \exp(\alpha)$, where $\boldsymbol{Q}_j$ consists of site-specific constants for each campsite to account for any distinct and unobserved preferences associated with specific campsites. The error term ε_j is assumed to follow an extreme value distribution, independently distributed across alternatives and individuals with the associated scale parameter σ. Our dataset exhibits truncation, as it only includes participants who took at least one trip. To account for truncation, we follow Lloyd-Smith and Becker (2020) and von Haefen and Phaneuf (2005). The model is estimated using maximum likelihood with 100 multivariate normal draws for computation of standard errors. The “rmdcev” package in R was used to estimate the model (Lloyd-Smith, 2021).

Notably, in comparison with previous KT applications, e.g., Whitehead et al. (2010), our model excludes campsite attributes for several reasons. First, observed and unobserved attributes are captured by the alternative specific constants for each campsite, avoiding potential endogeneity bias compared to an approach controlling solely for observed attributes (Murdock, 2006). Second, we are interested in the economic value of campsite closure, as explained in the next section, which require only to control for alternative specific campsite constants, see e.g., Lopes and Whitehead (2023). At last, the campsites share most observable attributes. Thus, controlling for attributes would lead to multicollinearity issues, a common problem in random utility models of recreation demand (Lopes & Whitehead, 2023).

2.4 Welfare analysis

To conduct welfare analysis, we follow the approach outlined in Lloyd-Smith (2018; 2020), using a Monte Carlo simulation approach applying the estimated parameters of the KT model, trip data, and TC to estimate the Hicksian demand for each campsite and the corresponding Hicksian compensating surplus CS^H. The Hicksian CS^H for a change in the price from the baseline price p^0 to a given new price level p^1 is defined by the following expenditure function, $e(\cdot)$:

$$CS^H = y - e(p^1, U^0, \boldsymbol{\theta}, \varepsilon), \tag{6}$$

Where y is income, p^1 is the new price level, U^0 is the baseline utility level equal to the following indirect utility function $U^0 = V(p^0, y, \boldsymbol{\theta}, \varepsilon)$, $\boldsymbol{\theta}$ is a vector defining all utility parameters $(\gamma_j, \Psi_j, \alpha)$, and ε defines the error term that is unknown to the researcher. In the simulation exercise, the new price p^1 is set to a very high level, effectively mirroring campsite closures, see e.g., Lloyd-Smith (2021). We follow Lloyd-Smith and Becker (2020) and Xie and Adamowicz (2023) and simulate the closure of one campsite at a time using 100 conditional errors per individual using the modified Latin hypercube sampling algorithm (Hess, et al., 2006). As we have 22 campsites, we simulate 22 policy scenarios, providing us with the expected welfare loss $E(CS^H)$ per individual per policy scenario. In other words, we use the conditional approach to get individual-specific welfare estimates (von Haefen & Phaneuf, 2005).

Using these estimates, we compute two key metrics: first, the average welfare value per trip, which is derived by averaging the individual welfare estimates across all campers; and second, the welfare value per trip specifically for campers who have made at least one trip to a specific campsite, averaged over individual welfare estimates of campers visiting that specific campsite. In line with Lloyd-Smith (2021), we refer to the first metric as welfare estimates per person and the latter metric as welfare estimates per participant. While the per participant estimates only reflect welfare effect of campsite closure among actual visitors, the per person estimates are based on the assumption that every campsite holds value for the entire sample of campers, even for non-visitors (Lloyd-Smith, 2021; Xi & Adamowicz, 2023).

3 Results

3.1 Kuhn-Tucker results

The estimated KT model with the MDCEV specification is displayed in Table 1, presenting in total 45 parameters defining the campsite-specific translation parameters γ_j and marginal utility parameters Ψ_j, along with the satiation α and the scale parameter σ. We present two versions of the KT model, which we from now refer to as Model 1 and Model 2. The two models have the same utility specification, but Model 1 use low travel costs, while Model 2 use high travel costs. Low travel costs are calculated excluding the expenses for car rentals and inter-island plane tickets. As all participants in the data took at least one trip to one campsite, both models account for truncation of trips, following Lloyd-Smith and Becker (2020). We include year-specific dummy variables to assess to evaluate the extent of variation in recreational demand over different years.[6]

First and foremost, we can see that Model 2 performs better than Model 1 through having lower AIC and BIC values, and a lower log-likelihood, which indicates that the specification with the high TC variable fits the data better. The parameters are similar across models. However, as Model 2 fits the data better, we will focus on this for interpretation of the results. Nonlinearities in the utility function make interpretation of estimated parameters challenging (Lloyd-Smith & Becker, 2020).

Almost all campsite-specific marginal utility parameters (β_q) are statistically significant, with each parameter reflecting the preference direction for a campsite relative to the baseline campsite when consumption starts at zero. In simpler terms, a positive value for a campsite-specific marginal utility parameter indicates a higher preference for that campsite compared to the baseline campsite; and the larger this parameter, the greater the likelihood of a camper selecting that particular campsite over the baseline campsite. The baseline is defined as ʻĀinapō, situated on the Island of Hawaiʻi. Campsites associated with a more positive preference than our baseline campsite when consumption starts at zero are Kawaikoi, Keanakolu, Peacock Flats, Sugi Grove, Waikoali, and Waimanu, where most campsites are located in the island of Kauaʻi. The three campsites of Peacock Flats and Waimanu are particularly associated with more positive utility parameters.

The coefficients for the year-specific dummy variables exhibit statistical significance, with 2018 designated as the reference year and therefore set to zero. The data reveal a statistically significant negative difference between 2018 and 2019. However, starting from 2020 through to 2022, more trips are likely to be taken compared to 2018, holding travel costs

[6] Both models were estimated excluding the year-specific dummy variables. Results remained stable, however, model fit was reduced through higher AIC, BIC and log-likelihood value, both for Model 1 and Model 2.

constant. Contrarily, the coefficient for 2023 is negative and statistically significant, suggesting a decrease in the number of trips occurring in 2023 relative to 2018 (and 2020-2022). This finding supports existing research examining the impacts of COVID-19 on recreation, highlighting the crucial role recreational spaces played during the global pandemic when other substitutable activities were extremely limited (Landry et al., 2021; Volenec et al., 2021; Shartaj et al., 2022; Lowe Mackenzie, 2023).

The α parameter measures satiation and is statistically significantly less than 1 and different from zero. The translation parameters γ_j measures the satiation effect and a corner solution for a specific campsite, where a greater value indicates a more gradual decline in marginal utility from each subsequent trip to the specific campsite. We can see that all translation parameters are statistically significant.

Table 1. Kuhn-Tucker model with multiple discrete-continuous extreme value specification.

	Model 1		Model 2	
Campsite	Mean β_q	Mean γ_j	Mean β_q	Mean γ_j
‘Āinapō	0.000	3.604***	0.000	2.488***
	(fixed)	(0.367)	(fixed)	(0.266)
Hipalau	-0.281***	2.973***	-0.210***	2.166***
	(0.045)	(0.302)	(0.069)	(0.228)
Kaluahaulu	-0.313***	2.920***	-0.255***	2.081***
	(0.041)	(0.324)	(0.065)	(0.208)
Kamananui	-1.945***	3.154***	-2.563***	2.215***
	(0.060)	(0.617)	(0.090)	(0.355)
Kaunala	-0.926***	3.031***	-1.356***	2.181***
	(0.046)	(0.341)	(0.082)	(0.262)
Kawaikoi	0.379***	3.802***	0.645***	2.524***
	(0.034)	(0.225)	(0.056)	(0.143)
Keanakolu	0.406***	3.339***	0.487***	2.322***
	(0.033)	(0.225)	(0.052)	(0.147)
Kuaokalā	0.260***	3.716***	0.072	2.567***
	(0.032)	(0.181)	(0.052)	(0.118)
Kulana‘ahane	-2.040***	3.862***	-2.676***	2.723***
	(0.068)	(0.765)	(0.100)	(0.619)
Kuli‘ou‘ou	-1.366***	3.156***	-1.735***	2.262***
	(0.039)	(0.295)	(0.057)	(0.204)
Lonomea	-0.015	3.717***	0.201***	2.517***
	(0.039)	(0.262)	(0.055)	(0.182)
Ma‘akua	-1.410***	3.039***	-1.920***	2.037***
	(0.064)	(0.503)	(0.092)	(0.366)
Mānana	-1.203***	3.223***	-1.615***	2.267***
	(0.040)	(0.316)	(0.059)	(0.197)
Peacock Flats	0.815***	3.706***	0.782***	2.536***
	(0.031)	(0.111)	(0.050)	(0.086)
Sugi Grove	0.260***	3.370***	0.520***	2.290***
	(0.032)	(0.197)	(0.057)	(0.124)
Wai‘alae	-0.787***	3.175***	-0.800***	2.203***
	(0.056)	(0.453)	(0.077)	(0.322)
Waikoali	0.127***	3.630***	0.315***	2.550***
	(0.035)	(0.269)	(0.060)	(0.213)
Waikolu	-1.277***	3.017***	-0.297***	2.139***
	(0.055)	(0.465)	(0.079)	(0.343)
Waimano	-1.447***	3.284***	-1.995***	2.349***
	(0.054)	(0.426)	(0.076)	(0.347)
Waimanu	0.706***	3.363***	0.973***	2.261***
	(0.031)	(0.128)	(0.050)	(0.093)
Wiliwili	-0.268***	3.032***	-0.126***	2.120***
	(0.041)	(0.266)	(0.061)	(0.206)
Wiliwilinui	-1.888***	3.110***	-2.465***	2.179***
	(0.059)	(0.513)	(0.082)	(0.373)
Year 2019	-0.079*		-0.117*	
	(0.048)		(0.064)	
Year 2020	0.181***		0.216***	
	(0.046)		(0.064)	
Year 2021	0.134***		0.189***	
	(0.038)		(0.051)	
Year 2022	0.093***		0.121**	
	(0.040)		(0.061)	
Year 2023	-0.064		-0.082	
	(0.044)		(0.066)	
Satiation parameter (α)	0.724***		0.746***	
	(0.004)		(0.006)	

Scale parameter (σ)	0.356***	0.499***
	(0.005)	(0.006)
Log-likelihood	-28352.110	-26910.470
AIC	56804.230	53920.930
BIC	57140.320	54257.030
Observations	134992	134992
Individuals	6136	6136

Note: *p<0.1, **p<0.05, ***p<0.01. Confidence intervals in brackets ().

3.2 Welfare simulations

Table 2 displays the results of the simulation exercise of welfare effects of campsite closure. As described in Section 3.3, we present two welfare estimates per campsite, i) per person, and ii) per participant. We present welfare estimates simulated both from Model 1 and Model 2. The welfare estimates reflect the average compensation needed to offset the closure of a specific campsite, ensuring that individuals maintain the same level of utility as if the campsite remained open (Lloyd-Smith & Becker, 2020). The per person estimates, which represent the mean welfare effect of campsite closure considering the whole sample, vary across models between USD 0.05 to USD 33. Peacock Flats, located on the Northern-Western part of O‘ahu, is the campsite with the highest welfare loss of closure, equivalent to 32 USD considering the high-cost model. This campsite is also the most visited, see Table A.4 in the Appendix, thus providing the overall largest aggregated welfare loss of campsite closure. Remining campsites with relatively high welfare losses are Waimanu (in the Island of Hawai‘i) and Kuaokalā (in O‘ahu), equal to 17 USD and 10 USD, respectively considering the high-cost model. Selected campsites in Kaua‘i also generate relatively high welfare loss (Kawaikoi, Lonomea), ranging from USD 5-6.

Table 2. Simulation exercise of welfare estimates of site closure.

Campsite	Model 1 Mean CS^H	Model 1 Lower bound	Model 1 Upper bound	Model 2 Mean CS^H	Model 2 Lower bound	Model 2 Upper bound
Per person						
‘Āinapō	-1.23	-1.42	-1.05	-2.01	-2.31	- 1.72
Hipalau	-0.64	-0.74	0.51	-1.47	-1.73	-1.23
Kaluahaulu	-0.49	-0.59	-0.41	-1.42	-1.65	-1.25
Kamananui	-0.05	-0.07	-0.03	-0.07	-0.09	-0.06
Kaunala	-0.31	-0.37	-0.26	-0.41	-0.48	-0.32
Kawaikoi	-3.39	-3.64	-3.14	-5.60	-5.99	-5.21
Keanakolu	-2.21	-2.42	-2.03	-3.14	-3.55	-2.87
Kuaokalā	-7.19	-7.70	-6.79	-9.64	-10.3	-9.11
Kulana‘ahane	-0.09	-0.11	-0.06	-0.11	-0.14	-0.08
Kuli‘ou‘ou	-0.38	-0.43	-0.32	-0.58	-0.66	-0.50
Lonomea	-2.29	-2.50	-2.07	-4.61	-5.20	-4.23
Ma‘akua	-0.10	-0.13	-0.07	-0.15	-0.22	-0.11
Mānana	-0.31	-0.35	-0.27	-0.47	-0.53	-0.40
Peacock Flats	-24.00	-24.90	-22.90	-32.20	-33.50	-30.40
Sugi Grove	-2.66	-2.89	-2.45	-4.49	-4.77	-4.15
Wai‘alae	-0.33	-0.41	-0.27	-0.92	-1.07	-0.76
Waikoali	-2.01	-2.16	-1.82	-3.07	-3.47	-2.74
Waikolu	-0.13	-0.17	-0.09	-0.95	-1.23	-0.74
Waimano	-0.14	-0.16	-0.10	-0.22	-0.28	-0.18
Waimanu	-7.44	-7.93	-6.96	-16.10	-16.90	-15.00
Wiliwili	-0.74	-0.83	-0.65	-2.00	-2.23	-1.72
Wiliwilinui	-0.07	-0.09	-0.06	-0.12	-0.15	-0.09
Per participant						
‘Āinapō	-49.84	-51.34	-48.33	-81.59	-84.18	-79.01
Hipalau	-28.41	-29.40	-27.43	-65.21	-67.56	-62.86
Kaluahaulu	-23.19	-24.08	-22.29	-67.48	-69.58	-65.39
Kamananui	-6.56	-6.97	-6.14	-9.85	-10.28	-9.42
Kaunala	-18.92	-19.66	-18.18	-24.93	-25.95	-23.91
Kawaikoi	-47.47	-48.26	-46.68	-78.41	-79.64	-77.17
Keanakolu	-38.38	-39.13	-37.64	-54.40	-55.46	-53.34
Kuaokalā	-55.09	-55.82	-54.37	-73.81	-74.74	-72.89
Kulana‘ahane	-14.09	-14.96	-13.22	-18.75	-19.74	-17.76
Kuli‘ou‘ou	-12.15	-12.48	-11.83	-18.38	-18.88	-17.87
Lonomea	-46.84	-47.78	-45.89	-94.31	-96.40	-92.22
Ma‘akua	-13.81	-14.50	-13.12	-20.29	-21.70	-18.88
Mānana	-11.33	-11.64	-11.02	-16.87	-17.32	-16.41
Peacock Flats	-66.56	-67.13	-65.99	-89.20	-90.12	-88.29
Sugi Grove	-40.57	-41.32	-39.82	-68.31	-69.33	-67.30
Wai‘alae	-29.30	-30.53	-28.07	-81.43	-84.51	-78.35
Waikoali	-46.73	-47.58	-45.88	-71.40	-73.10	-69.71
Waikolu	-14.85	-15.71	-13.99	-111.77	-117.58	-105.96
Waimano	-11.98	-12.51	-11.45	-19.79	-20.64	-18.93
Waimanu	-42.95	-43.46	-42.44	-92.96	-94.07	-91.84
Wiliwili	-26.97	-27.66	-26.27	-72.44	-74.46	-70.43
Wiliwilinui	-8.39	-8.76	-8.03	-13.85	-14.59	-13.10

Note: Mean estimates and 95 percent confidence intervals were calculated with 30 simulations and 100 conditional draws using the modified Latin hypercube sampling algorithm.

The seemingly low per person estimates are explained by the fact that we include non-visitors in the welfare effect calculation. Turning to the per participant estimates, these reflect the welfare loss exclusively among individuals who actually visited the various campsites during the study period. As illustrated in Table 2, these estimates, ranging from USD 7 to USD 112 considering simulations from both models, are significantly higher than the per person estimates, underscoring the more substantial impact of campsite closure on visitors as opposed to the general sample. For instance, Peacock Flats, the most visited campsite, has a welfare loss per participant of approximately 89 USD from the high-cost model, which is almost three times higher compared to its per person estimate. Similarly, other campsites like Waimanu and Lonomea exhibit pronounced increases in welfare loss per participant, with values reaching up to almost USD 100, considering the high-cost model. Interestingly, Waikolu emerges as the campsite with the highest welfare loss per participant if we consider the high-cost model, amounting to USD 112. The result, including the significant discrepancies between the per person and per participant estimates, underscore the importance of considering visitor frequency and engagement when evaluating the impact of campsite closures. We discuss this further in the discussion section.

4 Discussion and conclusion

In this study, we contributed to the growing body of economic literature on estimating recreational demand using non-survey travel data, marking the first application of this approach in Hawai‘i. The data applied included over 11,696 reservations made by 6,136 Hawaiian residents across all 22 campsites managed by the Division of Forestry and Wildlife. Using the KT recreational demand model with MDCEV specification (Bhat, 2008), we estimated Hawaiian residents' marginal utility of visiting the 22 niche campsites and then simulated their welfare loss from closing one campsite at a time.

Our application of analyzing reservation data is unique because the campsites are distributed across different islands of Hawaii and a significant share of campers engaged in inter-island camping. This required us to account for residents' travel costs, including both airport transportation and inter-island expenses related to flights and car rentals for campsites located on different islands from their residences. Inter-island expenditure considerations have rarely been addressed in the recreational demand literature. A related exception is English et al. (2018) who estimate a survey-based recreational demand model to quantify the economic losses of the general population of the U.S linked to the reduction in shoreline recreation days resulting from the 2010 Deepwater Horizon oil spill in the Gulf of Mexico. They calculate flying costs for respondents choosing flying as transportation mode to visit affected shoreline sites, recognizing the importance of accounting for flying as a transportation mode (and related cost).

To address inter-island expenditures, we employed two approaches of calculating the TC and estimate the KT model. Initially, we calculated travel costs to campsites on different islands from residents' homes without including inter-island expenditures. Subsequently, we refined the model by fully integrating these expenditures into the TC estimations. Our results remained stable across estimation procedures, with expected discrepancies in the simulated welfare estimates of campsite closure (lower when not accounting for inter-island travel expenses). However, the latter approach fit the data better, suggesting that inter-island expenditures should be accounted for. Further research is required to determine the extent to which such travel expenditures are directly related to the decision to visit specific campsites, thereby enhancing our understanding of the economic factors influencing recreational choices in multi-island settings.

Our results suggest significant welfare loss of campsite closure. The simulated welfare loss differs not only across various campsites but also depends on whether it is calculated for the entire sample of campers (on a per person basis) or for campers who actually visited a campsite that is being closed (on a per participant basis). The highest per person welfare loss of campsite closure was found to be in Peacock Flats situated on O‘ahu, equal to USD 32 considering the high-cost model with inter-island travel expenditures. The per participant welfare estimate of closure of Peacock Flats was also found to be one of the highest, equivalent to USD 89. Peacock Flats was also the most visited campsite (Table A.4), resulting in the highest aggregated welfare loss of campsite closure, between USD 142-190 000 over the time period of the data collection if we consider the entire sample of campers.

Interestingly, Waikolu emerged as the campsite with the highest welfare loss per participant if we consider the high-cost model, amounting to USD 112. Waikolu is situated in the island of Molokaʻi, an island that is less accessible and deeply entrenched in traditional Hawaiian culture. The island is home to a Native Hawaiian community that is dedicated to preserving a rural lifestyle that is closely tied to their heritage. Waikolu was one of the least visited campsites (Table A.4 in the Appendix), however, as Molokaʻi is more inaccessible than other islands, inter-island travel costs are higher and a significant share of the visits to Waikolu is conducted by participants residing on other islands, explaining the high welfare loss of campsite closure among participants with the high-cost model. With the low-cost model, where inter-island expenditures were ignored, the welfare loss of closing down Waikolu was significantly lower, amounting to USD 15 per participant. The result, including the significant disparity between the per person and per participant estimates, underscore the necessity of tailoring conservation efforts to not only consider the broader population but also to address the specific needs and values of regular campsite users, particularly among Native Hawaiians. The per participant data, therefore, offer crucial insights into the depth of impact that campsite closures have on the core group of campsite users.

In line with Lloyd-Smith and Becker (2020), by summing all per person estimates in Table 2, we are able to calculate the aggregated welfare loss per person across all campsites from closure, which we find to vary between USD 56 to USD 90 (depending on inter-island cost assumption) over the data collection period. Multiplying each campsite-specific per person welfare loss with the number of campers in our sample for then to sum each estimate, we are further able to calculate the total aggregated welfare loss across all campsites from site closure, ranging from USD 332 000-530 000. Peacock Flats account for 36 percent of the total welfare loss. It is crucial to emphasize that these estimates exclusively represent the recreational values as perceived by campers who are residents of Hawaiʻi, thus being significant underestimates of the total recreational value, and the total economic value of these campsites. The total recreational value accounts for all users, such as tourists and day visitors, with the latter group typically not requiring reservations for most campsites. The total economic value of these campsites would be even higher, as the sites provide other valuable ecosystem services and biodiversity, including potential non-use values.

Our results have important management implications. The economic values we provide are informative for resource and land managers in facilitating effective recreational services. Typically constrained by limited resources and budgets, these managers face challenges in allocating funds and prioritizing conservation and recreational facilitation efforts. The economic values provided can guide these decisions, enabling a more efficient allocation of scarce resources toward campsites with higher recreational value. As Hawaiʻi is a globally popular destination dependent on tourism with high tourism-related costs due to international demand, local residents often face exclusion from the mainstream tourism market. This reality makes camping (also across islands) an essential, affordable alternative, emphasizing the importance of efficiently managed recreational sites that meet the specific needs and preferences of the local residents.

Furthermore, in the context of climate change, our analysis gains additional relevance. As climate change increases the likelihood of altering site conditions, and potentially lead to campsite closures due to extreme weather events or fires, our welfare loss estimates offer valuable economic insights into the potential consequences of such disruptions for campers.

This information is vital for planning and preparedness in the face of environmental changes (Chan & Wichman, 2020).

Moreover, Hawai‘i’s colonial legacy lends greater weight to the repercussions of closure of these campsites. The colonialization of Hawai‘i led to the dispossession of Indigenous Hawaiians from their lands. Hence, the availability of affordable camping sites is more than a recreational space; it represents a vital link for native Hawaiians to reconnect with their ancestral environment. This aspect elevates the management of these campsites from a question of resource efficiency to one of restorative justice, ensuring that local and Indigenous populations have equitable access to their natural heritage. While our data did not allow for analysis by ethnicity, our per participant estimates, particularly from areas like Moloka‘i, highlight the deep cultural connection of native communities to these campsites.

An interesting aspect for resource managers is to get an understanding of how the welfare loss varies spatially (Fezzi et al., 2023; Iversen & Dugstad, 2024), which is important for understanding the extent of the market (Glenk et al., 2020). To better illustrate the spatial distribution of the aggregated welfare loss per person across all campsites from site closure, we created a map showing the mean welfare loss across Hawaiian zip codes (using the high-cost model), see Figure 2. The welfare loss specific to each zip code was calculated as the average of aggregated individual-specific welfare estimates among campers residing in that respective zip code. For Hawaiian zip codes excluded from the reservation data, the welfare loss was assigned a value of zero.[7]

[7] Because some zip codes were not associated with any camping reservation, individuals residing in those zip codes per definition have zero use-values of camping. Thus, we set the value equal to zero.

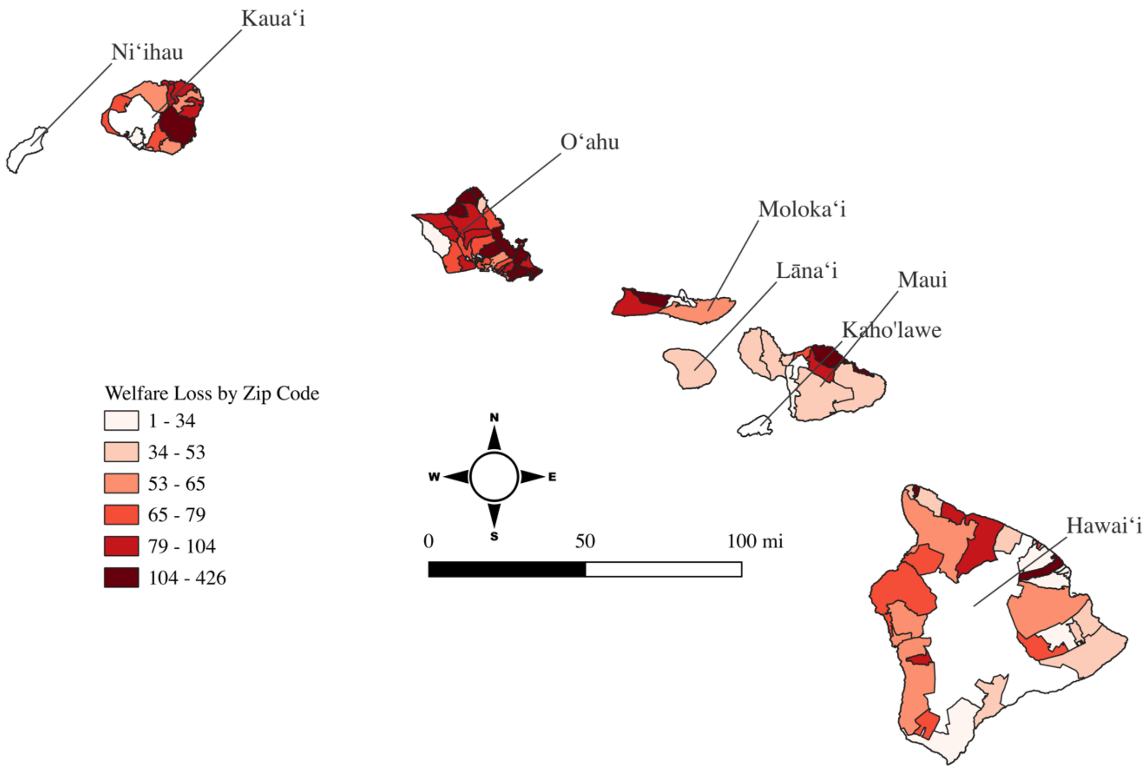

Figure 2. Aggregated Welfare Loss by Zip Code

As can be seen, we observe welfare loss across all MHI. The overall pattern is driven by travel costs (where campers live, distance to the campsites, zip-code income) and number of visits. Areas where the welfare loss is low can be explained by low participation in camping from these regions. In Oʻahu, we observe that all areas with the highest median income level (see Figure A.1 for a map of median income across zip-code areas for all MHI) experience the highest welfare loss level. These wealthy areas are located in the South-Eastern part of Oahu (Kāhala, Hawaiʻi Kai, Koʻolaupoko, Waikāne, Kāneʻohe). However, there is no general pattern across all MHI indicating that wealthier areas experience higher welfare loss. For example, as can be seen in Figure 2, the eastern part of Molokaʻi also has the highest welfare loss level, but residents there have a relatively low-income level (Figure A.1). While few residents of Molokaʻi went camping overall, the majority of those who did traveled to other Hawaiian Islands, explaining the high aggregated welfare loss. Interestingly, significant welfare loss is also observed in the north-eastern area of Maui. This result is most likely driven by the fact that Maui does not have any HRF campsites, forcing the residents to fly to other islands to participate in camping in HRF campsites. Additionally, our visitation data show that campers from the north-eastern area of Maui, on average, make the most trips, which underscore our finding. Preferences for these niche campsites across Hawaiian residents is strongest among residents in the north-eastern part of Maui. Notably, these areas in Maui also have the highest density of Native Hawaiians in the island.

In conclusion, our study has contributed significantly to the nonmarket valuation literature using non-survey data to estimate demand for recreational services, quantifying the welfare loss among residents in Hawai‘i from campsite closures in ecologically rich areas. Our results deliver key insights for ecosystem management, increasingly relevant in planning for challenges posed by climate change. They also highlight distributional welfare effects of campsite closures in Hawai‘i, information of high importance for equity considerations and restorative justice initiatives among Native Hawaiians in management decisions. Our findings open avenues for further research, particularly in expanding our understanding to include tourist demand to get a more comprehensive view of the economic value of campsites. A rather large share of our sample (16 percent) engaged in inter-island traveling for camping. As noted, an important area of further research in contexts like ours would be a better understanding of how much inter-island travel expenditures account for visiting specific campsites.

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Appendix

Table A.1

Attributes	Share of campsite, n=22
Campsite facilities	
Pavilion	72%
Cabin	9%
Restrooms	59%
Picnic tables	86%
Recreational activities	
Hunting	54%
Fishing	4%
Hiking	95%
Sightseeing	45%
Wildlife	31%
Swimming	13%
Biking	27%
4WD	13%
Beach	4%
Average Miles on Na Hele Trail System to Site	4.5

Table A.2

Trips	Share of persons
1	68.30%
2	17.60%
3	6.05%
4	2.95%
5	1.68%
6	1.04%
7	0.73%
8	0.44%
9	0.33%

Table A.3

Number of campsite visited	Share of persons
1	86.16%
2	10.69%
3	2.12%
4+	1.03%

Table A.4

Campsite	Number of visits
‘Āinapō	211
Hipalau	157
Kaluahaulu	136
Kamananui	51
Kaunala	111
Kawaikoi	657
Keanakolu	456
Kuaokalā	1265
Kulanaahane	57
Kuliouou	235
Lonomea	467
Maakua	48
Manana	211
Peacock Flats	3649
Sugi Grove	550
Wai‘alae	84
Waikoali	396
Waikolu	57
Waimano	84
Waimanu	1414
Wiliwili	190
Wiliwilinui	60

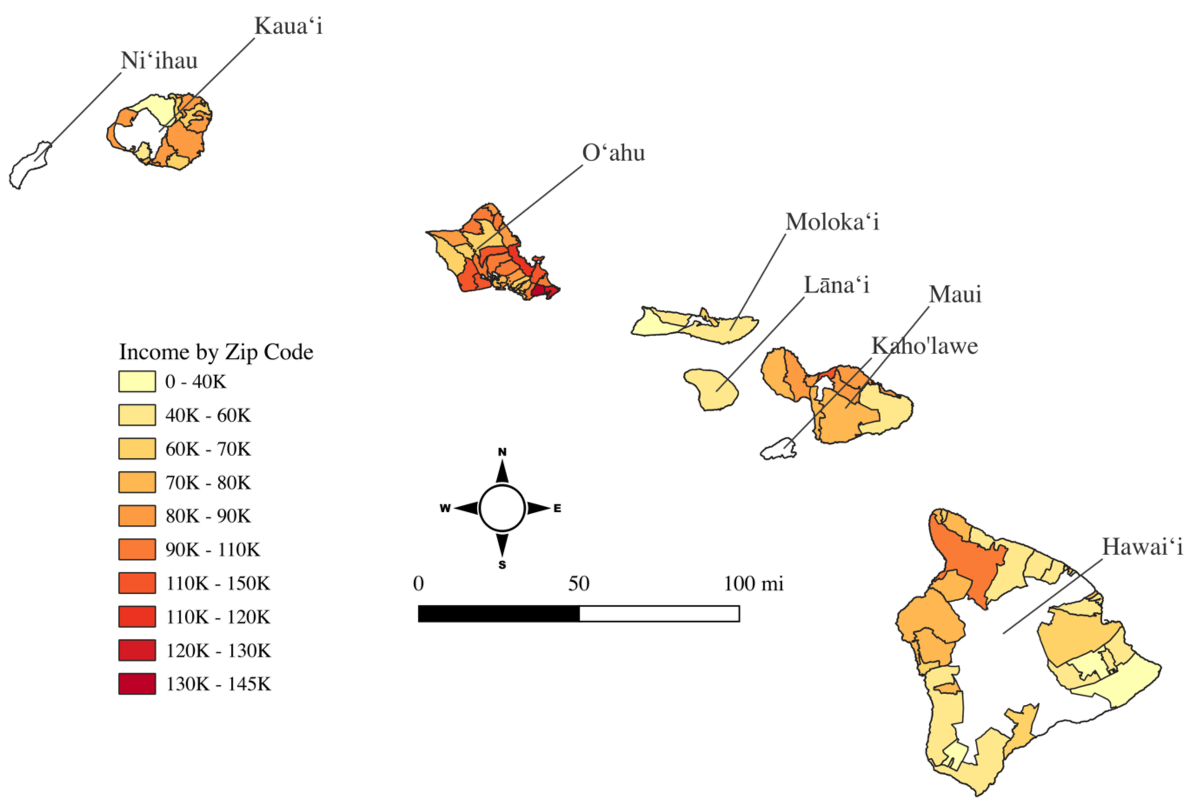

Figure A.1. Map of median household income groups at zip-code level.