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Mapping the Unseen: Integrating Hiking Activities Into Spatially Explicit Cultural Ecosystem Service Assessment Through Agent-Based Modeling

Moongi Choi[1] | Jang-Hwan Jo[2] | Hyeon Jung Kim[2] | Sanghoon Ji[3]

[1]Department of Geography, Florida State University, Tallahassee, Florida, USA | [2]Department of Forest Sciences and Landscape Architecture, Institute of Life Science and Natural Resources, Wonkwang University, Iksan, South Korea | [3]Division of Forest Human Service Research, National Institute of Forest Science, Seoul, South Korea

Correspondence: Jang-Hwan Jo (osmanthusfvam007@wku.ac.kr)

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ABSTRACT

This study introduces a trail-based framework for assessing spatially explicit cultural ecosystem services (ES) at a microscale, focusing on individual trail experiences within a mountain range. By integrating agent-based modeling with hiking data, we simulate and quantify the consumption of cultural ES by individuals on various trails, considering factors such as seasonal variations. Our approach contrasts with traditional map-based methods by emphasizing the dynamic, activity-based assessment of cultural ES supply and demand. The findings reveal significant spatial mismatches between the potential cultural ES provided by trails and their potential consumption by hiking, highlighting the importance of localized, trail-specific evaluations. The study's implications extend to environmental policy and management, where understanding these mismatches can guide targeted conservation and development efforts. While this study presents a contribution, we acknowledge limitations related to the geographic focus and dataset scope, suggesting that future research should incorporate more diverse data sources and expand the geographic range. This could enable more accurate simulations and assessments, particularly in data-scarce regions. Ultimately, this trail-based approach enhances the precision of cultural ES evaluation and offers valuable tools for policymakers and environmental managers to align conservation efforts with actual human activities.

1 | Introduction

Since the publication of the Millennium Ecosystem Assessment (MEA 2005), which analyzed the impact of human activities on ecosystem services (ES) over the past 50 years, worldwide efforts have been made to classify and evaluate ES for their integration into environmental improvement policies. The Economics of Ecosystems and Biodiversity assessed the economic impacts of natural capital loss (TEEB 2010), while the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services analyzed the global nature and ES, including their social values and the factors influencing ES changes (IPBES 2019). A 2011 study on the potential profitability of national ES assessments in the UK identified variations in sustainability across various types of ES (Watson et al. 2011). The IPBES (2019) also highlighted the decline in the supply of certain ES, including regulation and cultural services, while others experienced an increase.

In addition to the reports, many studies have been conducted to evaluate ES appropriately and quantitatively, considering its diverse characteristics (Christie et al. 2012; Logsdon and Chaubey 2013; Cheng et al. 2019; Jo et al. 2021, 2023). Previous research on the quantitative assessment of ES has primarily focused on evaluating either the supply or demand of ES or their mismatch (Shi et al. 2020; Wei et al. 2017; Wolff, Schulp, and Verburg 2015; Ala-Hulkko et al. 2019). Supply evaluations typically align with the four classifications defined by (MEA 2005). For example, provisioning services are primarily measured based on biological characteristics, such as edible plants and timber; regulating services by quantifying ecosystem processes, such as carbon absorption; cultural services by considering changes in societal demands and preferences, such as education and recreation; and supporting services by assessing biodiversity and interactions in various ecosystems (Maes, Egoh, et al. 2012; Seidl et al. 2019; Martínez-Harms and Balvanera 2012). Those supply assessments often quantify the total amount of natural assets providing ES to humans, regardless of actual human consumption (e.g., Sohel, Mukul, and Burkhard 2015; Vrebos et al. 2015; Jo et al. 2020; Arslan and Örücü 2021; Sieber et al. 2021).

In contrast, demand assessments for ES have utilized various approaches that consider human subjects consuming ES and the specific types of ES being consumed. Demand assessment has been measured to align with diverse aspects of individual and social activities, assuming that ES benefits humans and is consumed by them (Wolff, Schulp, and Verburg 2015; Ala-Hulkko et al. 2019). Such approaches have influenced the selection of ES types as the target ES types vary depending on the study area and target audience. For instance, in national parks, the demand for provisioning services, such as forest products, may be limited, whereas the demand for supporting services related to biodiversity improvement and cultural services associated with the landscape may be higher. Consequently, demand assessment and quantification have diversified more than supply evaluation, resulting in numerous studies exploring the comparison and mismatch between supply and demand to facilitate effective resource allocation from a forest policy and management perspective (e.g., Shi et al. 2020; Peña, Casado-Arzuaga, and Onaindia 2015; Herreros-Cantis and McPhearson 2021).

Among the ES types, particularly, methods for measuring cultural service demand have utilized a wider array of data and techniques, such as assessing individual behavioral experiences on a personal scale. This is because cultural services represent the intangible benefits derived from ecosystems, such as individual spiritual enrichment and landscape appreciation (Huynh et al. 2022; Pilarska et al. 2022; MEA 2005), and are intrinsically linked to direct human experiences with the natural environment, including the sensory and emotional experiences gained from activities such as hiking (Hall 2014; Price et al. 1999). Therefore, methods for measuring cultural services have often involved tools such as social media, questionnaires and individual hiking data, exploring how personal characteristics and external environmental factors are related to the potential demand for activities such as hiking (Balbi et al. 2013; Havel et al. 2022). However, these methods still fall short in adequately measuring the ES perceived by individuals on micro and local scales, such as mountain trails. From a policy perspective, particularly in areas such as recreation or landscape development, it is crucial to evaluate local demand for specific mountains and their trails, as well as to assess how demand changes due to external factors such as seasonal variations.

Therefore, this study aims to achieve the following objectives: First, we established a framework for measuring cultural ES scores at a trail-based microscale. The supply score was assessed at the trail level to allow for a comparison with demand scores, identifying mismatches. For demand, we applied agent-based modeling (ABM) to simulate individual hiking to evaluate hikers' potential cultural ES demand scores on each trail. Through these simulations, we aim to identify variations in scores under various scenarios, such as seasonal changes, to discover spatially explicit cultural ES scores. Second, we explored the advantages of this trail-based approach for calculating cultural ES scores compared to the traditional map-based approach.

2 | Methods

2.1 | Study Area

The study area of our research, Mireuksan in Iksan city, is a mountain located in the eastern part of the Noryeong mountain range, which extends north–south and is a branch of the Noryeong mountain range that connects to Daedunsan in the west (Figure 1). It is situated at 36°01′15″ N and 127°02′30″ E and spans across several administrative areas such as Geumma-myeon, Samgi-myeon, and Nangsan-myeon in Iksan City, Jeollabuk-do. The main peak in Mireuksan, Sajabong (430 m), is the highest summit in Iksan. Below the southern slope of Mireuksan lies Mireuksaji, a UNESCO World Cultural Heritage Site. Mireuksanseong, a fortress built with stone walls that stretch eastward and southward along the ridges and features pogok style stone fortifications across the eastern valley, is in the summit area. There are cultural heritage management zones such as Sajam-am and Gijunseong on the eastern slope (Schulp, Lautenbach, and Verburg 2014). Owing to the relatively cool summers and mild winters, hiking on Mireuksan is possible throughout all seasons. The mountain offers approximately 10 major hiking trails, most of which are approximately 3 km long and have moderate difficulty levels owing to gradual inclines.

2.2 | Data

In this study, three types of data were utilized to quantify the supply and demand scores of ES: a forest map, a land use and land cover map, and a national land and environment assessment map. The trail line data represent polyline vector data corresponding to the 10 trails of Mireuksan, drawn from each starting point to the peak point. A digital elevation model (DEM) and hiking data were used as parameters for the ABM to simulate mountain climbing by individual hikers. The number of hike visitors was used to calculate the potential trail-based demand score. The data were collected from the smart devices of 1010 hikers on Mount Mireuk from June 29, 2014, to March 25, 2023. All data list is described in Table 1.

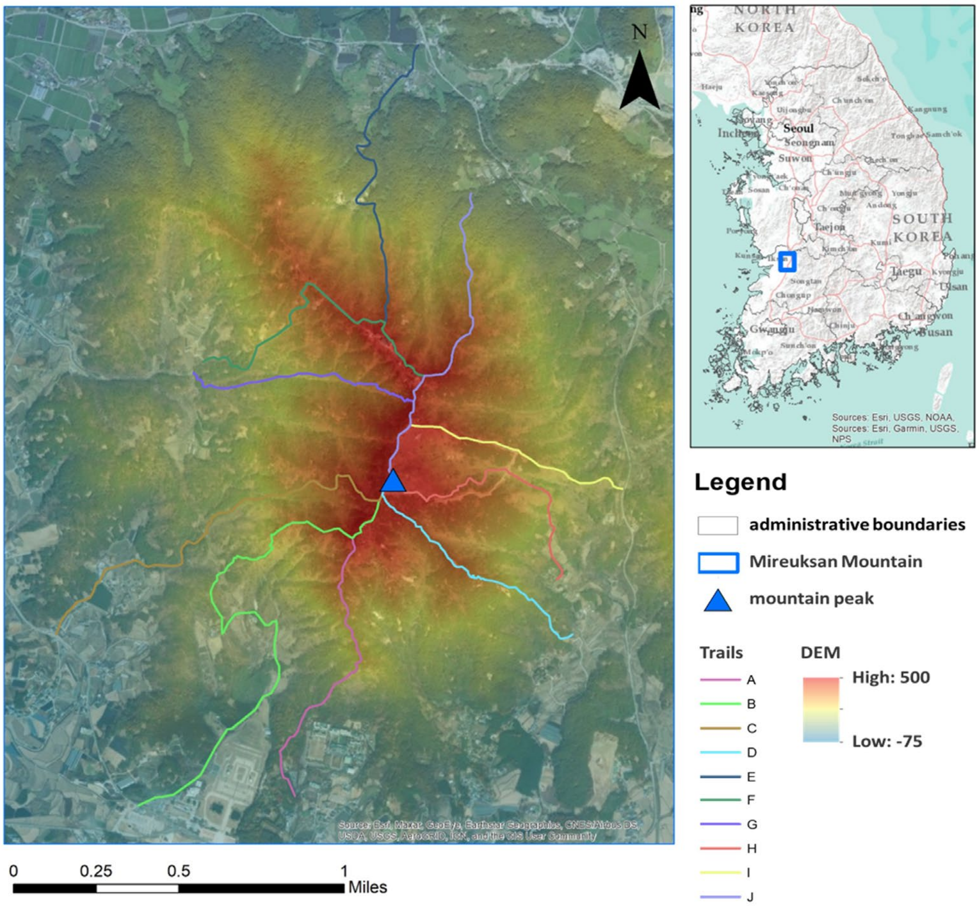


FIGURE 1 | Study area.

2.3 | Methodology

2.3.1 | Literature Review: Cultural ES Supply and Demand Estimation

Previous studies on cultural ES have utilized a range of data sources, including social media, interviews, surveys, forestry, and urban landscape data. These studies typically aimed to identify indicators serving as criteria for ES, such as pollinated crop yield or area, honeybee stocking rates, and the number of special species (Schulp, Lautenbach, and Verburg 2014; Breeze et al. 2014; Andersson et al. 2016). These indicators have been pivotal in quantifying the supply and demand of cultural ES (Burkhard et al. 2012; García-Nieto et al. 2013; Beichler 2015; Uthes and Matzdorf 2016).

A set of studies illustrated this approach by estimating the supply of cultural ES using factors such as proximity to roads and natural landscapes, while demand was quantified through sources such as geotagged social media data (Bing et al. 2021; Zhang et al. 2022). These studies indicated a strong correlation between supply and demand, underscoring the importance of spatial elements in cultural ES assessment. Other assessments, focusing on river basins, considered vegetation and geomorphic factors along with social media data for demand analysis, revealing mismatches between supply and demand and highlighting the complex dynamics of natural settings (Yoshimura and Hiura 2017). Further research employed the geographic information system (GIS) and the maximum entropy model (MaxEnt) to model potential user preferences for cultural ES using social media photos, demonstrating the integration of spatial analysis with user-generated data (Arslan and Örücü 2021).

In urban contexts, studies using indicators such as area, land type, naturalness, population density, and land development level revealed significant discrepancies between the supply of cultural ES and the demand, indicating the need for more effective supply strategies in regional development (Liu, Huang, and Yang 2021). For instance, research has identified and normalized various indicators related to cultural ES supply and demand to measure urban ES, such as the cooling capacity of green infrastructure and PM10 deposition for supply, and population residing within a certain distance from railroads and total population in commercial areas for demand (Cortinovis and Geneletti 2020). In rapidly urbanizing watersheds, there has been a case study that explored the spatial mismatch between cultural ES supply and demand in urban areas by combining a survey-based model (SolVES) with text analysis of social media reviews (Meng et al. 2020).

Another research stream using Bayesian belief network (BBN) models informed by land-use type, road density, and recreational data highlighted the crucial role of accessible transportation and green spaces in driving cultural ES demand (Wu et al. 2022). An additional approach that incorporated sentiment analysis of social media posts with demographic and

TABLE 1 | Data description.

Data	Resolution	Description	Data usage	Reference
Forest map	1:5000	Visual representation of the forest area such as tree species distribution and forest ecosystems in a specific area	Estimating all supply and demand score	National forest service
Land use and land cover map		Map that classifies and represents the land characteristics of a specific area, such as topography, soil, vegetation, etc.		Ministry of environment
National land and environment assessment map		Map created to evaluate sustainable national land and environment at the national level		Ministry of environment
Trail line data	Vector line	Vector data representing hiking trails in mountainous areas	Estimating trail-based supply and demand score	Iksan city local government
DEM (digital elevation model)	10 × 10 m	Spatial data that represent the elevation of the Earth's surface	Estimating trail-based demand score	Ministry of land, infrastructure, and transport
Hiking data	—	Time to reach the peak by each trail, speed per slope, break time during hiking, and break time at the peak point		Ramblr Inc
# Hiking visitors		Seasonal hiker count by trails		Ramblr Inc

socioeconomic indicators enhanced the understanding of the balance between supply and demand in cultural ES, demonstrating the multifaceted nature of assessing and addressing ES needs (Jo et al. 2021).

Most analyses of cultural ES supply–demand mismatches have primarily used methods of GIS mapping to compare spatial distributions (González-García et al. 2020; Tao et al. 2023) or statistical techniques comparing ranks or ES scores (Baró et al. 2015; Simelton and Viet Dam 2014). These studies often rely on social media data, which allows for indirect interpretation of demand, and compare it with supply for mismatch analysis.

However, there is a scarcity of studies that consider human micro-level activities, such as hiking or trekking, in measuring and analyzing cultural ES supply and demand mismatches. Some studies have focused on individual-level research, such as conducting surveys with questionnaires on hiking experiences to analyze the correlation between route choice and respondents' characteristics (Sherrouse et al. 2017; Havel et al. 2022). Others have mapped or predicted the demand for potential tourism destinations based on individual demographic features, socio-economic values, and climate change (Balbi et al. 2013; Plieninger et al. 2013; Paracchini et al. 2014). However, there have been very few cases where cultural ES was measured by simulating hiking on specific trails within a localized area, such as a single mountain, taking into account the unique characteristics and landscapes of each trail. Also, while studies on hiking simulations have been conducted (e.g., Gimblett, Daniel, and Meitner 2000; Cavens et al. 2004), it is hard to find studies that combine these simulations with methods for measuring cultural ES scores.

Developing such a framework that simulates individual cultural ES acquisition by hiking behaviors based on factors, such as trail types, slope, or weather changes, would enable the prediction of ES demand scores for each trail under various scenarios, such as seasonal variations or changes in tourist populations. Additionally, this approach could assess the cultural service scores hikers obtain in other mountains, even where no accumulated individual hiking data exist. This would provide valuable insights for regional forest policies. Therefore, in this study, we propose a framework for measuring cultural ES scores at a microscale (trail scale) using ABM.

2.3.2 | Overall Processes of Cultural ES Estimation of Supply and Demand

In this study, as illustrated in Figure 2, we conducted (1) ES supply estimation, (2) ES demand estimation, and (3) an assessment of ES supply–demand mismatch. ES focused on cultural ES, which were further divided into landscape and recreational services.

2.3.2.1 | ES Supply Estimation. Cultural ES supply estimation was conducted using two approaches. First, a map-based approach (map-based supply score estimation approach) was used, which has been commonly used in previous studies. This approach involves grid-based scoring using static spatial data, specifically attribute data from forest maps, land use and land cover maps, and national land and environment assessment maps. Next, participatory methods were employed to develop indicators, upon which Delphi scores were applied to these spatial data. Scores were assigned to each grid, resulting

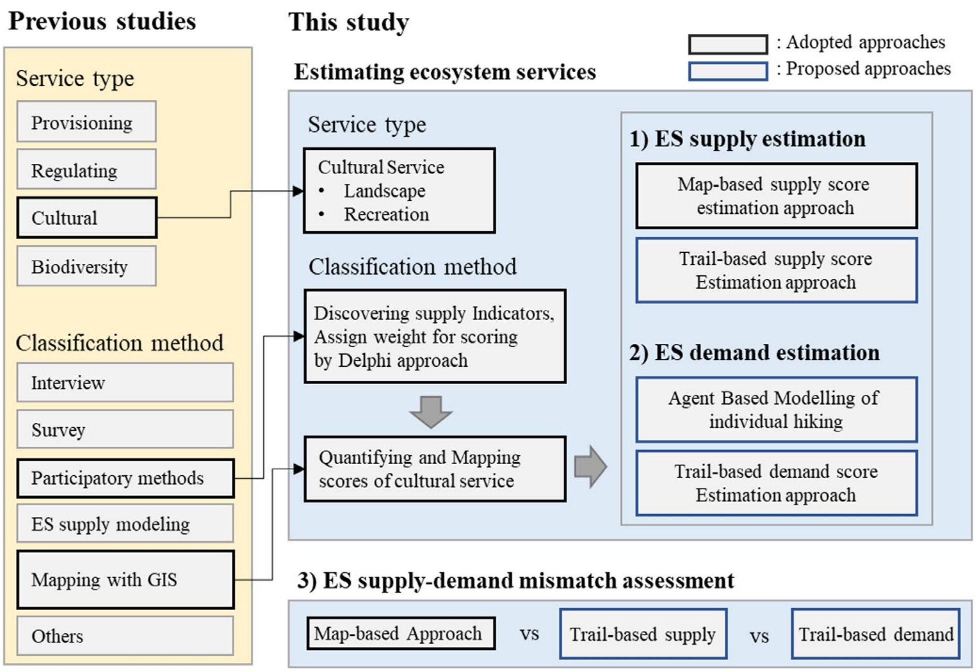


FIGURE 2 | Study design.

in a measurement of the overall supply score. Detailed processes are described in Sections 2.3.2 and 2.3.3.

Second, a new trail-based approach (trail-based supply score estimation) was proposed. This involves conducting a viewshed analysis for each trail on the target mountain and estimating the total potential amount of cultural ES supply within the visible range during hiking on each trail. Detailed descriptions of these processes can be found in Section 2.3.4.

2.3.2.2 | ES Demand Estimation. The calculation for the cultural ES demand score was obtained through ABM. This simulation approach estimated the potential total quantity of cultural ES consumed by individual hikers through their hiking activities on an individual scale. Since the score is based on hiking behavior simulations of individuals, it remains robust even with spatial relocation and produces consistent results, making it spatially explicit. Further details on these processes are provided in Section 2.3.5.

2.3.2.3 | ES Supply–Demand Mismatch Assessment. We assessed the mismatch between the supply and demand of cultural ES in two distinct stages. First, we compared map-based approaches to the trail-based approach in terms of supply estimation. Second, we identified the mismatch between the supply score derived from the trail-based approach and the demand score, also based on the trail-based approach, using real hiker visitation data.

2.3.3 | Classification Method: Participatory Delphi Analysis

We used a participatory method (e.g., Wolff, Schulp, and Verburg 2015; Martínez-Harms and Balvanera 2012) involving 15 domestic experts on forest ES. Among the various participatory methods available, we employed the Delphi method due to its effectiveness in efficiently synthesizing expert opinions and achieving consensus, particularly in situations where empirical evidence is limited or data are incomplete (Jorm 2015). To ensure the reliability and robustness of the results, 15 experts were selected from diverse fields, aligning with the general recommendation that a panel size of at least 10–15 experts is necessary for minimizing group errors and maximizing the credibility of the findings (Dalkey, Brown, and Cochran 1970; Rowe, Wright, and Bolger 1991; Birdir and Pearson 2000). Through this approach, we identified and quantified indicator values that served as criteria for scoring ES. The indicators were extracted from the attributes of the three thematic maps, as shown in Table 2. Through these indicators, we developed a land-use scoring matrix and calculated the expected value of cultural service supply. The detailed logic behind the scoring methodology for each thematic map is as follows.

Scores were assigned based on a focus on "accessibility" for recreation services and "conveyance of conservation value" for scenic (educational) services. In the case of recreation, factors limiting accessibility and usability of the natural environment influenced the score, whereas scenic services were evaluated with an emphasis on conservation value and educational potential. This differentiation in evaluation is intended to present a scoring system that reflects the distinct characteristics of each service rather than prioritizing consistency in scoring.

2.3.3.1 | Land Use and Land Cover Map. For recreational services in cultural ES, higher scores were assigned to areas suitable for recreation and tourism. Arid and semi-arid regions, where the presence of forests is limited and recreational opportunities are scarce due to residential, industrial, and commercial zones, were assigned a score of 0. Cultural and sports leisure facilities that provided minimal recreational services were assigned a score of 2. Agricultural areas,

TABLE 2 | Map types and summarized scoring criteria.

Map type	Attributes	Scoring criteria
Land use and land cover map	• Residential areas • Paddy fields • Fields • Forests • Grasslands • Wetlands • Water bodies	• Recreation: High scores assigned to areas suitable for recreation and tourism (e.g., forest scores: 10, agricultural area score: 7) • Landscape: Higher scores for areas with natural history or cultural value (e.g., forest score: 10)
Forest stock map	• Forest origin • Forest type • Tree species • Diameter class • Age class • Crown density • Height	• Recreation: Higher scores for areas with forests and excellent environments (e.g., forests score: 7, areas without tree species score: 0) • Education: Higher biodiversity and tree coverage score (e.g., forest score: 10)
National land and environment assessment map	• Vegetation conservation grade • Endangered species evaluation • Ecological grades 1–3	• Recreation: Scores based on natural environment quality (e.g., Grade 1 scores: 9, Grade 5 scores: 1) • Education: Scores reflect biodiversity and ecosystem stability (e.g., Grade 1 scores: 10, Grade 5 scores: 1)

particularly orchards, ranches, and fish farms, where experiential and tourism activities occur, were assigned a score of 7. Forested areas, including deciduous, coniferous, and mixed forests, were assigned a score of 10 because they provide excellent natural environments and are used for recreational and leisure activities. Natural environments such as grasslands, golf courses, tidal flats, natural marshes, inland waters, and marine areas, which may not have outstanding natural qualities but are, to some extent, managed and enable sports and leisure activities, were assigned a score of 8. Inland wetlands were assigned a score of 5 because recreational activities are deemed challenging in such areas.

For landscape services in the cultural ES, higher scores were assigned to areas suitable for education on natural history and cultural value. Arid and semi-arid regions, which have limited natural environments and basic educational infrastructure, were assigned scores of 1. Agricultural areas were mostly assigned a score of 5, but orchards, ranches, and fish farms, which enable experiential activities, were assigned a score of 6. Forested areas, inland wetlands, tidal flats, and other areas with high biodiversity were assigned a score of 10 to reflect rich natural diversity. Inland waters and marine areas, although also exhibiting high biodiversity, were assigned a score of 9 because direct observations in these areas may be more challenging than in forested areas, inland wetlands, and tidal flats. Natural grasslands, which minimize human intervention and maintain a well-preserved natural environment, were assigned a score of 7. In contrast, artificial grasslands, due to extensive human development and a lack of suitable habitats, were assigned scores of 3 for mining areas and other grasslands and 2 for sports fields.

2.3.3.2 | Forest Stock Map.

Higher scores were assigned to areas with forests and excellent natural environments suitable for recreational and tourism activities. Tree density, species diversity, forest coverage, and tree species composition were considered important for recreational services; however, no significant individual differences were observed. Therefore, a score of 7 was assigned to most areas. Areas with limited tree species, grasslands without tree species, and cultivated areas with no vegetation were assigned scores of 5 and 0, respectively. Stream order, stream length, and canopy density were considered indicators of excellent natural environments, and higher scores were assigned to areas with higher stream orders, longer stream lengths, and denser canopy cover.

Higher scores were assigned to areas with forests and excellent natural environments suitable for educational activities. Based on the same criteria used for recreational score calculation, areas with trees were assigned a score of 10 because of their high biodiversity. Non-forested and non-vegetated areas were assigned a score of 5. For tree species composition, both artificial and natural forests were assigned a score of 10. Natural forests possess high biodiversity and provide a stable ecosystem suitable for educational activities, whereas artificial forests may have relatively lower biodiversity but can still accommodate educational facilities, warranting the same score as natural forests. Areas without tree species, such as grasslands, were assigned a score of 5. Other factors, such as species diversity, stream order, stream length, canopy density, and elevation, which play important roles in providing educational services but to a lesser extent than other factors, were all assigned a score of 7. Areas without trees or where educational activities may be challenging, such as barren lands, were assigned scores of 3 and 0, respectively.

2.3.3.3 | National Land and Environment Assessment Map.

For recreational services, higher scores were assigned to areas with excellent natural environments that provided a wider range of services. However, compared to other services, the influence of biodiversity on the supply of recreational services is relatively low. The scores were as follows: Grade 1 (9 points), Grade 2 (7 points), Grade 3 (5 points), Grade 4 (3 points), and Grade 5 (1 point).

Similar to recreation, landscape services are manifested in excellent natural environments, and biodiversity has a significant influence on educational services. High biodiversity indicates a stable ecosystem and a wealth of available educational materials. Scores were assigned as follows: Grade 1 (10 points), Grade 2 (8 points), Grade 3 (6 points), Grade 4 (4 points), and Grade 5 (1 point).

2.3.4 | Map-Based Supply Score Estimation Approach

There are two main approaches for mapping ecosystems in the context of ES. The first approach involves assigning ES scores to irregular vector shapes and preserving the original information in the data (e.g., Portalanza et al. 2019). The advantage of this approach is that it retains the original shape and information of polygons. However, combining different layers with irregular polygonal shapes may lead to null values and difficulties in spatial interpretation, depending on the shape of the original polygons (Jo et al. 2020).

The second approach involves assigning scores to regular grid-shaped cells (Sharps et al. 2017; Benedetti et al. 2020). This approach helps to overcome the issue of null values and overlays. However, because we need to convert the irregular shape of polygons to regular grid-shaped cells, there is a possibility of losing information, resulting in an overestimation or underestimation of the values.

In this study, we used a method to overcome the underestimation or overestimation in the spatial mapping process by converting irregular polygon data into regular grid data using area-based weighting. This approach, proposed by Jo et al. (2021), involves intersecting irregular polygon data with the grid using the union operation and assigning a final score to each grid cell by multiplying the proportion of the area covered by the irregular polygon within the grid cell (Equation 1).

In this equation, i represents an irregular polygon, which is the original polygon contained within grid j. The score was calculated by multiplying the area of the polygon by the score of the corresponding polygon and dividing it by the area of the grid. Variable m represents the number of irregular polygons within the grid. Summing the scores of all irregular polygons within a grid yields the total score for that grid. With a total of n grids, the scores of all n grids were summed to obtain an overall score for the study area. The Delphi method was used to assign scores to each indicator selected from the forest, land use, land cover, and national land and environment assessment maps. These scores were then applied to 10×10 m grids to map the cultural, landscape, and recreational service scores.

$$T = \sum_{j=1}^{n} \sum_{i=1}^{m} \left(\frac{C_i \times A_i}{S_j} \right) \tag{1}$$

where T is total scores, n is the number of grids, m is the number of irregular shaped polygon i in grid j, C is the score of one grid, A is the area of the irregular shaped polygon, and S is the area of one grid.

2.3.5 | Trail-Based Supply Score Estimation Approach

To calculate the cultural ES supply score for Mireuksan using a trail-based approach, we divided 10 trails into 10 m intervals and generated observer points. Subsequently, we conducted a viewshed analysis at each observer point from origin to peak point (see Figure A1). Viewshed analysis involves measuring the number of grids within a visible area using a DEM from the observer's point (Wheatley 1995; Lake, Woodman, and Mithen 1998). The visible area is calculated based on the line of sight, considering various terrains of the DEM, such as hills or cliffs. The orientation was set to 360°, taking into account the maximum potential views that a person could see from that point in all directions. This approach enabled us to estimate the cultural service score for the observable viewshed, which varied at each point as hikers ascend the trail.

The method for calculating the total supply score is described in Equation (2). The supply score at each point j was computed by summing the grid-based scores (from Equation 1) of all raster grids C_j within the visible area at point j. Therefore, the total supply score T_s for each trail was the sum of the supply scores of all n observed points.

$$T_s = \sum_{j=1}^{n} \left(C_j \times \text{score}_j \right) \tag{2}$$

where C_j is the number of raster grids from observer point j and score_j is grid-based score in each point j.

Figure 3 illustrates the results of the viewshed analysis conducted for Trail A, Trail J, and all the trails combined. Each trail exhibited a distinct visible area. Trail A, running from south to north, predominantly showed a larger number of visible grids in the southern and southwestern regions. In contrast, Trail J, starting from the north, displayed a limited number of visible grids in the southern direction. When examining the viewshed results for all trails, it was evident that although the 10 trails were evenly distributed around the summit of the mountain, there was a higher concentration of visible grids in the west than in the east. Additionally, numerous non-visible areas were present, indicating areas that were not covered in any of the 10 trails. This result highlights the limitation of the map-based scoring approach, which calculates supply scores based on spatial data of the entire area without considering the trails and fails to adequately cover the realistic supply range of the ecosystem. Consequently, scoring should be conducted in a manner that considers higher supply scores in areas with higher frequency of visibility.

The lengths and observer points for each trail are presented in Table 3. The observer points included the endpoint, which was the peak point of the mountain. Therefore, the number of observer points was calculated by dividing the length by 10

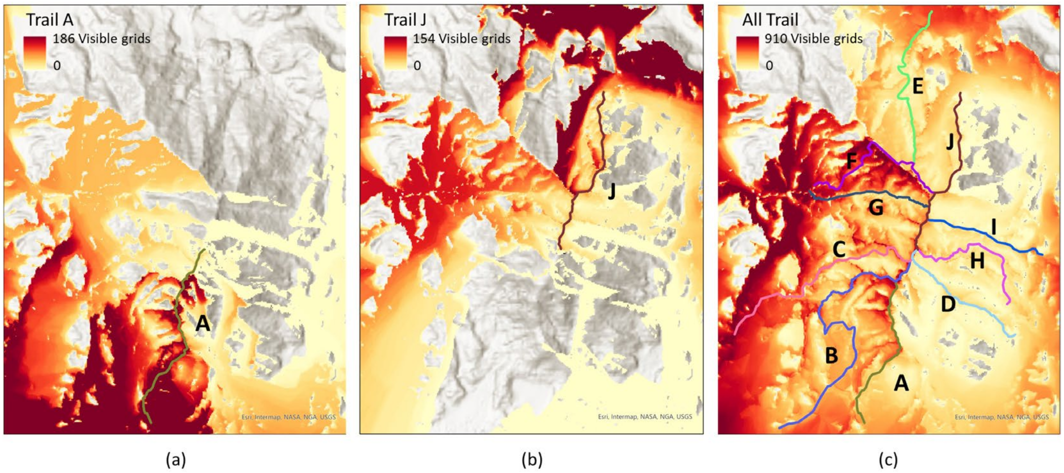


FIGURE 3 | Viewshed analysis result (a: Trail A, b: Trail J, and c: all trails).

TABLE 3 | Observer points in each trail.

Trails	Length (m)	# Observer points
A	2381.28	240
B	3907.98	392
C	2805.11	282
D	1713.89	173
E	3301.08	332
F	2812.52	283
G	2037.91	205
H	1757.41	177
I	1788.20	180
J	2055.23	207

and adding 1. Trail B had the longest length of approximately 3908 m, with 392 observer points. In contrast, Trail D had the shortest length, around 1714 m, with 173 observer points. As the lengths of the trails vary, there is a possibility that the supply score will be higher for longer trails. This reflects the fact that, in real-world hike scenarios, longer trails require more time to hike, resulting in higher exposure to the total amount of ES.

2.3.6 | Trail-Based Demand Score Estimation Approach

We quantified the potential cultural ES demand score for each trail by considering human microscale activities. To achieve this, we simulated individual hikes with ABM based on the actual hike record data in Mireuksan. Since the information on individual records varied across trails, we focused on Trails A, B, and F, which had the most abundant data, to quantify the demand score.

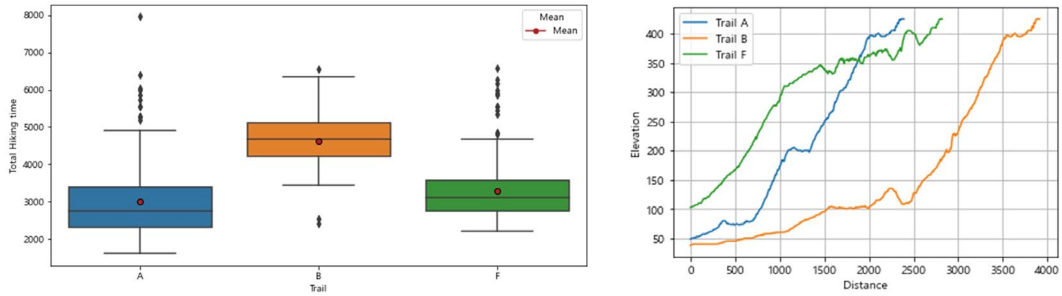
ABM is a simulation approach that enables the representation of individuals with unique characteristics and behavioral rules, enabling them to interact with their environment and other individuals (Crooks et al. 2018; Crooks 2015). ABM offers several advantages, including the ability to capture the individual decision-making processes of each agent (Helbing 2012; Train 2009), depict the diverse characteristics of each agent (Yin et al. 2014; Choi and Hohl 2023), and illustrate the interactions between agents and their surrounding environment (Zhang, Chan, and Ukkusuri 2009). ABM has been widely used in various social science disciplines to predict and understand phenomena related to cities, ecosystems, and natural systems that emerge from individual behaviors and interactions (Choi, Park, and Ji 2022; Filatova et al. 2013; Kang and Aldstadt 2019).

Figure 4 shows the differences in hike time (a) of 1010 hikers and elevation (b) with distance for each trail. Trails A, B, and F resulted in average hike times of approximately 3030 s (about 51 min), 4720 s (79 min), and 3110 s (52 min), respectively. The median hike times were 2840 s (about 47 min), 4800 s (80 min), and 3020 s (50 min), respectively. However, in the case of outliers, Trail A had the highest hike time of 7960 s (133 min), while Trails B and F recorded 6480 (108 min) and 6520 s (109 min), respectively. Trail B had the lowest starting elevation and longest horizontal distance, resulting in the longest total hike time. Statistical analysis of the t-test using the total hike time showed p-values of < 0.001 for all trail comparisons, indicating that conducting separate simulations for each trail is appropriate.

Equation (3) indicates the computation of the total ES demand score. Given that the hiking process of individuals is simulated, the factor of "time spent" that is affected by the slope and length of the trail should be considered. The score is the sum of the cultural ES scores of all the visible areas at point j, representing the total supply score that each agent can obtain at location j. Therefore, we calculated the total potential demand score for individuals by multiplying the elapsed hike time at each observer point by the corresponding score.

$$T_d = \sum_{j=1}^{n} \left(C_j \times \text{score}_j \times t_j \right) \tag{3}$$

where C_j is the number of raster grids from observer point j, score_j is grid-based score in each point j, and t_j is the time taken at each point j.



(a) (b)

FIGURE 4 | Trails A, B, and F (a: hiking time and b: elevation by distance).

The overview, design concepts, and details (ODD) of the individual hike simulations are listed in Table 4. ODD is a framework proposed by Grimm et al. (2010, 2020) that provides a structured format to describe the detailed processes and information of a simulation, facilitating the reproducibility and replicability of simulation studies.

The hike simulation included six parameters: (1) *stamina*: individual stamina, (2) *sta_decrement*: degree of stamina decrement, (3) *break_thres*: threshold stamina level for agents to start taking a break, (4) *break_time*: time duration of a break, (5) *vel_slope*: speed corresponding to the slope, and (6) *peak_break*: break time at the peak. The parameter value distribution for "*break_time*", "*vel_slope*", and "*peak_break*" are derived from the hiking data. Values are extracted from the distribution and assigned to each agent in the simulation.

At the beginning of the simulation, each agent is assigned values for the "*stamina*", "*sta_decrement*", and "*break_thres*" as parameters. They started hiking from the 0 m point of the selected trail and proceeded toward the peak at intervals of 10 m. During the hike, if the "*stamina*" value falls below the "*break_thres*", the agent takes a break for the duration specified by the "*break_time*" parameter, which is randomly selected from the data distribution. The hike speed corresponded to the velocity of the slope along the trail route. The data distribution of break time by trails and speed by slope is provided in Figure A2. Upon reaching the summit, the agent takes a break for the duration specified by the "*peak_break*" parameter. The total potential demand score for each individual is calculated by aggregating the scores collected at every 10 m point along the trekking route, including the time spent during breaks.

Due to the impracticality of obtaining specific observational data for individual parameters of "*stamina*", "*sta_decrement*", and "*break_thres*", a predetermined range of values was established. The parameter ranges designated for calibration included *stamina* (500–2000), *sta_decrement* (1–10), and *break_threshold* (0–100). We employed a parametric space searching methodology, which involved comparing the distribution of total hike time among hikers with the simulated results, to identify the parameter combination yielding the lowest root mean square error (RMSE) as per Crooks, Heppenstall, and Malleson (2018).

Monte Carlo simulations were executed 10,000 times across various parameter combinations for Trails A, B, and F. The calibration process determined the optimal parameter ranges to be *stamina* (1400–1600), *sta_decrement* (2–6), and *break_threshold* (10–40). The resulting RMSE values were 890.11 for Trail A, 732.09 for Trail B, and 598.35 for Trail C.

Figure 5 depicts the comparison between the simulated results using optimal parameter ranges and observed data patterns. Solid lines illustrate the simulation outcomes, while dashed lines correspond to the observed data patterns. The alignment between the two suggests a good model fit. Consequently, the calibrated optimal parameter ranges were implemented for simulating individual hiking activities.

3 | Results

3.1 | Map-Based Cultural ES Supply Score

The results of the map-based cultural ES supply score are presented in the choropleth map in Figure 6. The color classification method is based on Jenks' algorithm, which uses natural breaks (Jenks 1967). Red and blue indicate the high and low scores, respectively. In the figure, (a) represents the recreational service score, (b) represents the landscape score, and (c) represents the total cultural score, combining both services.

The recreational service supply score showed an average of 47.975 per 10×10 m grid, with a maximum value of 78.005 and a standard deviation of 30.292. The total score (sum of all scores) was 6,777,137.042. Spatially, the score distribution exhibited a radial shape, with higher scores observed in the areas surrounding the mountain than near the mountain peak. The assigned scores well reflect reality considering that recreational activities are more likely to occur at lower altitudes than at mountain peaks.

In contrast, the landscape score exhibited a less concentrated spatial pattern. This can be attributed to the complex spatial distribution of factors, such as vegetation, topography, and slope, which primarily influence the landscape. The landscape score had an average of 50.527, a maximum value of 89.007, a standard deviation of 33.273, and a total score of 7,145,082.331. As

TABLE 4 | ODD matrix for ABM.

Overview	
Purpose	Simulating each agent's hiking pattern based on multiple individual characteristics or physical environment such as stamina, trail distance, and slope
Entities, state variables, and scales	This simulation has one entity, which is "agent". Hiking pattern is decided by the parameters below 1. *Stamina* (X_1): Initialized stamina of agents when the simulation starts 2. *Sta_decrement* (X_2): Degree of stamina decrement for agents. A higher value makes them get tired more easily 3. *Break_thres* (X_3): Th threshold stamina level for agents to start taking a break during hiking. When the stamina decreases by the value of "sta_decrement" and reaches this threshold, agents take a break 4. *Break_time* (X_4): Break time for agents. If they take multiple breaks, each break is assigned a different duration 5. *Vel_slope* (X_5): Speed corresponding to each slope. As agents hike, their velocity is assigned based on the actual slope values 6. *Peak_break* (X_6): Break time at the peak. Each agent has a different duration for enjoying the scenery at the peak
Process overview and scheduling	At the beginning of the simulation, each agent undergoes the following movements and interactions during hiking time: 1. Initialization • Agents are assigned random values for "stamina", "sta_decrement", and "break_thres" parameters • Agents start at the 0 m point of the assigned trail 2. Hike • Agents move along the trail, progressing by 10 m at a time • Each agent is assigned a different speed based on the slope of the trail segment they are currently on • Agents move toward the peak, advancing by 10 m increments according to their assigned speed 3. Break • If an agent's stamina falls below the "break_thres" value during the hike, they take a break • When a break event occurs, the agent is assigned a "break_time" value, and their stamina recovers during break 4. Mountaintop observation • Upon reaching the peak, agents take a rest for the duration of the "peak_break" value • During the rest period, the potential demand score is accumulated every second
Design concept	
Basic principles	This model is basically an individual agent-based simulation modeling, which captures hiking patterns arising from an agent's movement based on multiple trails. This model does not simulate the action of going down the mountain to eliminate the complexity when the trail going up the mountain peak and the trail coming down are different
Sensing	Agents move along a trail and hike up to the peak point. They sense the trail's slope to determine their speed and consume stamina. When their stamina falls below a certain level, they take a break
Interaction	There are interactions between the agent (hiker) and the slope
Observation	The collected sensing data include (1) the time taken by agents at each 10 m interval on the trail, (2) the total break time during the entire hiking duration, (3) the time taken to reach the peak, and (4) the number of breaks taken. Monte Carlo simulations were conducted 1000 times for each trail, generating total hiking time distributions for each trail (A, B, and F) to validate the simulation results Y: Total hiking time for each trail (Y_1: ***trail A***, Y_2: ***tail B***, Y_3: ***trail F***)
Details	
Initialization	For the simulation initialization, the trail is selected, and the slope data from 0 m to the peak point of the chosen trail are allocated to the server. Subsequently, each agent is assigned values for "stamina", "sta_decrement", "break_thres", and "peak_break" parameters, and the agent is positioned at the 0 m point of the trail. Other agents remain uninitialized, as a single initialization is to create one agent
Parameter setting	The value range of each parameter is stated below. 1. Stamina (X_1): 500–2000, randomly assigned, calibration needed 2. Sta_decrement (X_2): 1–10, randomly assigned, calibration needed 3. Break_thres (X_3): 0–100, randomly assigned, calibration needed. 4. Break_time (X_4): Assigned from observed data distribution (Figure A2a). 5. Vel_slope (X_5): Assigned from observed data distribution (Figure A2b). 6. Peak_break (X_6): Assigned from observed data distribution (mean: 445.275 s, std.: 30)

a result, the landscape score was higher than the recreational service supply score.

The cultural ES supply score, which combines both the recreational and landscape scores, had an average of 98.452, a maximum value of 167.013, a standard deviation of 63.5, and a total score of around 1.39×10^7. Spatially, the scores were higher in the northern region than in the southern region. The distribution of the three scores exhibited a bimodal pattern, indicating a significant difference in the scores between the surrounding urban and mountainous areas.

3.2 | Trail-Based Cultural ES Supply Score

The results of the trail-based cultural ES supply scores are presented in Figure 7. The results are depicted in the following two distinct formats: (1) by aggregating the scores from all trails to generate a comprehensive large-scale map and (2) by constructing 10 subset maps, each representing an individual trail.

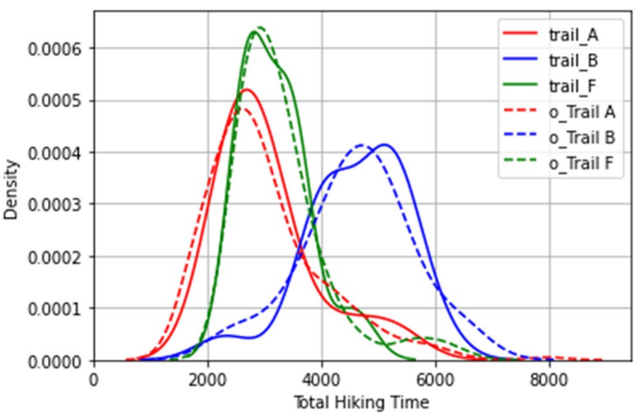


FIGURE 5 | Result of model validation with calibrated parameters.

In analyzing the aggregated scores from all trails, it was observed that the supply scores were predominantly concentrated on the western side, in contrast to the eastern side. This distribution notably differs from the map-based approach results, where supply scores were primarily concentrated on the northern side. The discrepancy can be further understood by considering a specific instance: when aggregating the scores across all 10 trails, the eastern side (more specifically, the northeastern region) of Trail J, except when hiking Trail J itself, was not within the visible range of any other trail. This led to a diminished total supply score for that area. Conversely, the map-based approach might not adequately account for such nuances, potentially overlooking vital aspects of human interaction and visibility within the landscape.

Across all trails, higher scores were observed at lower elevations than at higher elevations. The legend in the figure displays the score values on a 10×10 m grid. For relatively shorter trails, such as D, I, and J, the maximum score was below 25,000, whereas that of the longest trail, Trail B, exceeded 50,000.

The combined landscape, recreational, and total (cultural) scores of each trail are presented in Table 5. It reveals that the landscape score consistently exceeded the recreational score across all trails. Generally, there was a proportional relationship between the score rank and the trail length rank, suggesting that longer trails typically allow for extended hike durations and, consequently, greater exposure to cultural ES. For instance, Trail B, being the longest with a total length of approximately 3910 m, registered a cultural ES supply score of approximately 4.47×10^5. In contrast, Trail D, spanning 1710 m, recorded a cultural ES supply score of approximately 9.24×10^4, making Trail B's score approximately 4.8 times that of Trail D. However, Trail A ranked 2nd, notably higher in score despite its median length. This deviation suggests that factors beyond mere trail length, such as a wider view and diverse forest attributes, significantly influence the cultural service supply score.

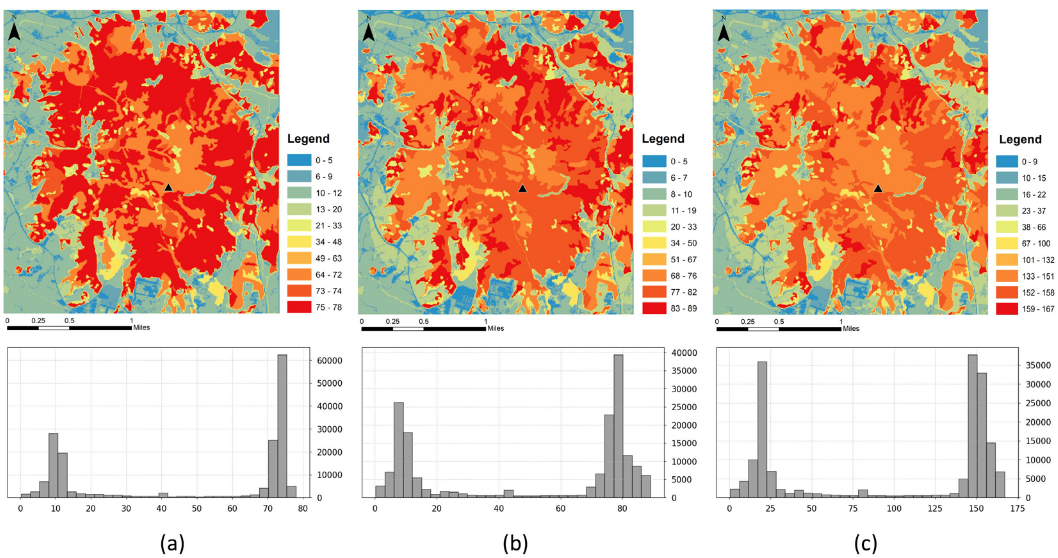


FIGURE 6 | Map-based cultural ES supply score: (a) recreation, (b) landscape, and (c) total culture.

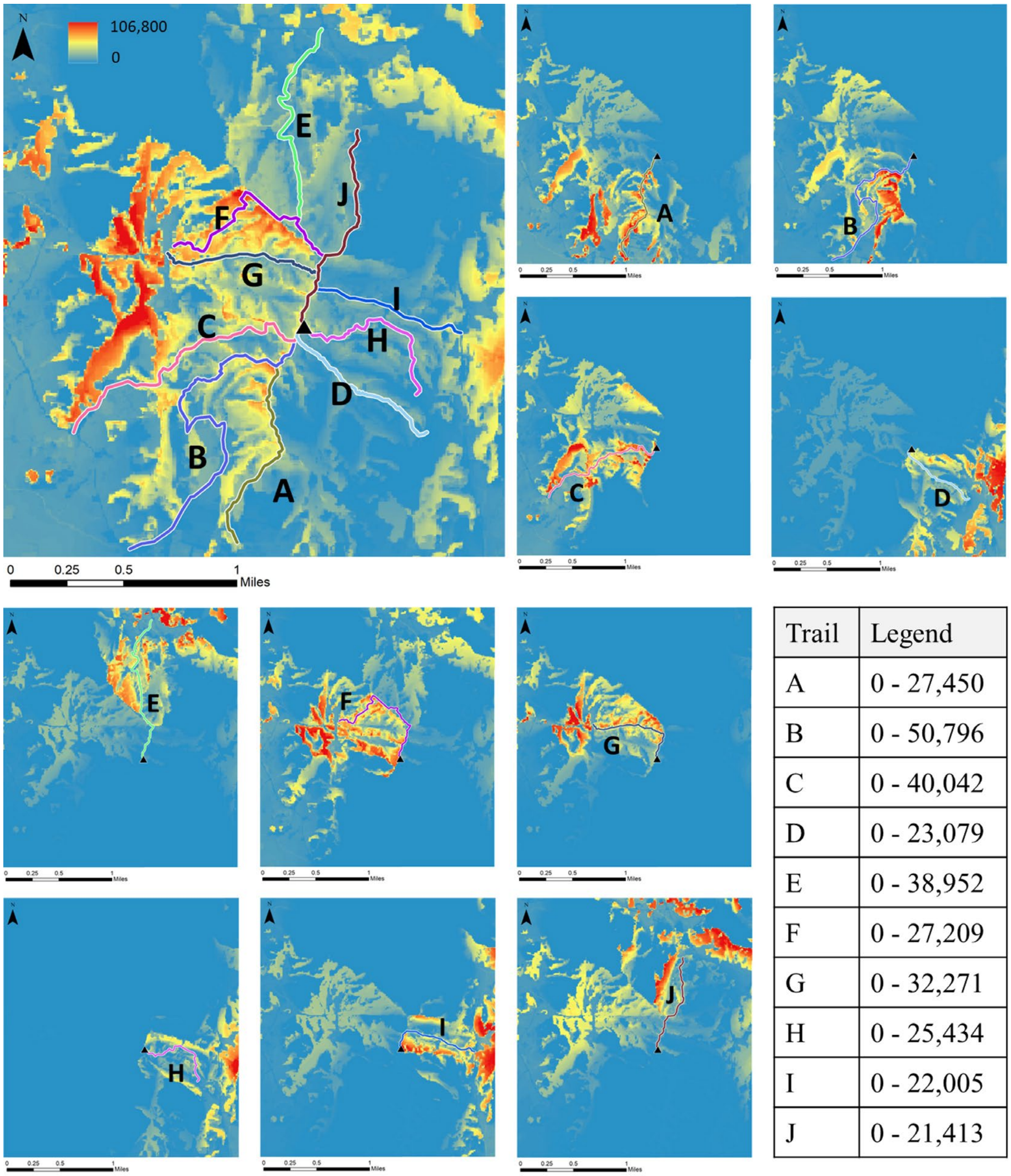


FIGURE 7 | Trail-based cultural ES supply score.

TABLE 5 | Trail-based cultural ES supply score (recreation, landscape, and total).

	Cultural ES supply score (10^5)				
Trails	**Recreation**	**Landscape**	**Total (Culture)**	**Score rank**	**Length rank**
A	1522.97	1564.86	3087.83	2	5
B	2194.30	2275.71	4470.01	1	1
C	863.75	911.47	1775.23	5	4
D	447.28	476.87	924.15	10	10
E	1407.47	1467.28	2874.75	3	2
F	870.10	917.90	1788.01	4	3
G	531.87	567.78	1099.65	7	7
H	455.45	485.67	941.11	9	9
I	462.36	493.12	955.48	8	8
J	537.37	573.69	1111.06	6	6
Average	929.292	973.435	1902.728		

3.3 | Trail-Based Cultural ES Demand Score

Figure 8 presents examples of individual hiking ABM simulation results. Subfigures 8a–c respectively show the time spent and break duration along Trails A, B, and F. Specifically, an agent hiking Trail A did not take any breaks until reaching the peak. In contrast, agents hiking Trails B and F each took one break during their hikes. The following subfigures, 8d–f, display the potential cultural ES demand scores accrued by the same agents. Generally, it was observed that as the elevation increased, hikers enjoyed a wider range of scenery and were exposed to a more diverse array of cultural ES, leading to higher demand scores at higher elevations. Also, the demand scores were also higher at breakpoints and peaks, corresponding to the longer durations spent at these locations.

As a result, Trail B exhibited the highest scores for recreation, landscape, and total scores, followed by Trails A and F (see Figure A3, which presents the distribution of potential cultural ES demand scores obtained by assuming multiple agents hike on Trails A, B, and F). The average cultural ES demand score for Trail B resulted in 1.15×10^{10}, with a maximum value of 2.295×10^{10} and a minimum value of 0.635×10^{10}. Trail A had an average score of 0.693×10^{10}, with a maximum value of 1.877×10^{10}. Trail F showed the lowest results, with an average score of 0.282×10^{10} and a maximum value of 0.797×10^{10}.

3.4 | Mismatch Analysis

3.4.1 | Comparison of Map-Based and Trail-Based Cultural ES Supply Score Results

In the trail-based approach, scores were computed at 10 m intervals along each trail and subsequently aggregated, yielding higher values compared to the map-based approach that assessed scores across the entire grid-based area. Consequently, a direct score comparison is not possible. To address this issue, supply scores from both approaches were normalized via min–max scaling, enabling a comparison of the relative proportions of landscape and recreation scores that constitute the cultural ES supply score (Figure 9).

Both approaches revealed that the landscape score contributed more significantly to the cultural ES supply score than the recreation score. Specifically, in the map-based approach, the landscape score comprised about 51.3% of the total, while the recreation score made up around 48.7%. In contrast,

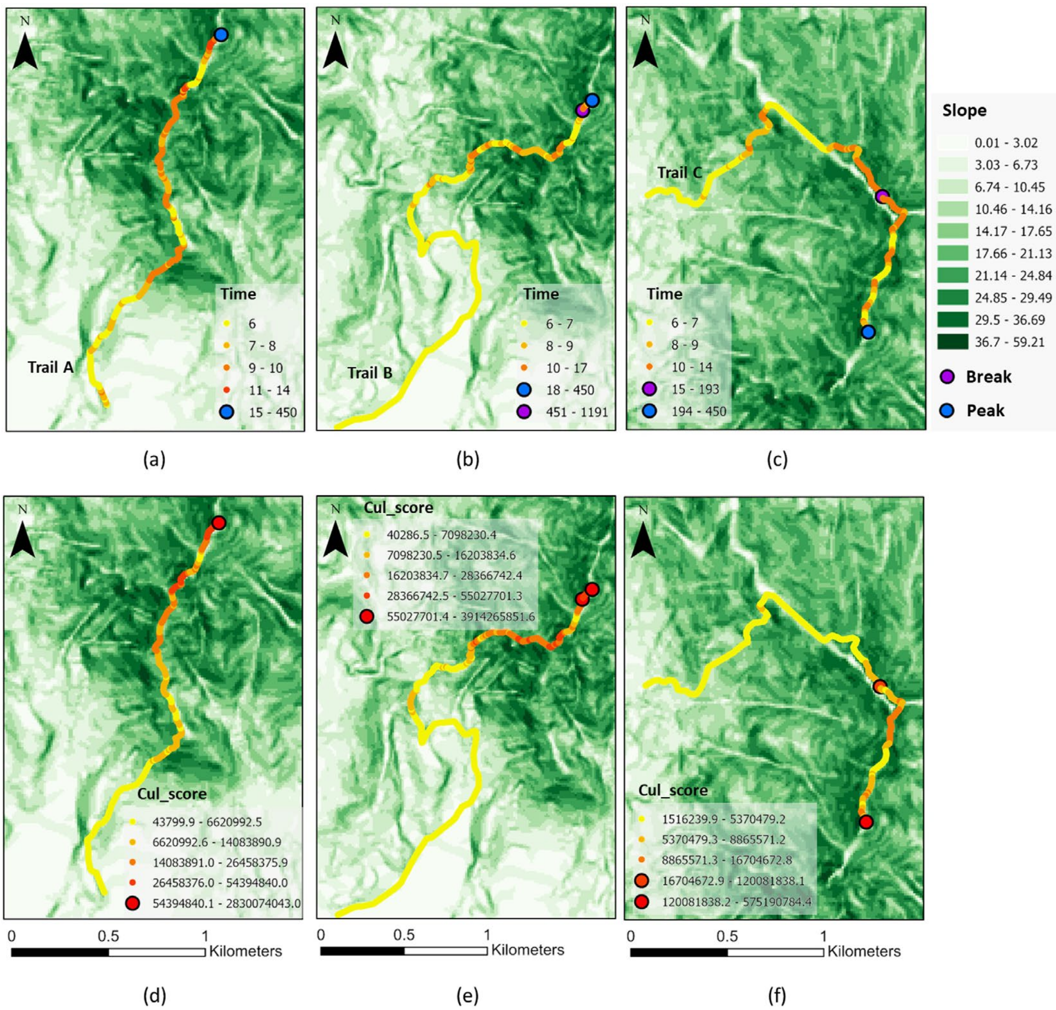


FIGURE 8 | Individual hiking simulation result of each trail (a, b, and c: 10 m intervals of spending time; d, e, and f: cultural ES demand scores on Trails A, B, and F).

individual trails displayed varying characteristics. For instance, Trail A had a slightly lower landscape score of around 50.6% and a higher recreation score of approximately 49.4%, with only about a 1% difference between the two. Meanwhile, Trails D, G, H, I, and J had higher landscape scores, roughly 51.5%, and lower recreation scores, about 48.5%, compared to the other trails.

This granularity of the trail-based approach allows for a more detailed analysis at the trail level, facilitating precise micro-level interventions in forest and cultural policies. For example, trails with higher landscape scores might focus on developing hiking-related industries or implementing policies to protect forest resources within their visible zones.

Figure 10 illustrates a spatial comparison of normalized cultural ES supply scores, achieved by subtracting the trail-based scores from the map-based scores. Notably, as the trail-based scores are predominantly higher on the western side, the comparative values result in negative on the western side and positive on the eastern side. Most areas on the eastern side display deviation values of 1, indicating that the map-based approach yielded larger scores compared to the trail-based approach in these regions. This marked difference highlights a significant divergence between the two methodologies. The discrepancy emphasizes the potential limitations of the map-based approach in accurately calculating ES supply scores, particularly its insufficient consideration of human activity and interaction with the environment.

3.4.2 | Mismatch Exploration Between Trail-Based Cultural ES Supply and Demand Score

To estimate mismatches between cultural ES supply and demand scores, our focus was on calculating demand scores through simulations using actual visitor data from Miruk Mountain across various seasons. We utilized seasonal hiker data as input (as shown in Table 6) and conducted ABM simulations with optimal parameters described in Section 2.3.5.

The mismatches between supply and demand scores are presented in Table 7. Among the trails, Trail B recorded the highest cultural ES supply score, approximately 4470×10^5. However, regardless of the season, Trail A consistently showed the highest ES demand score. Figure 11 compares the rankings of supply and demand scores, highlighting the

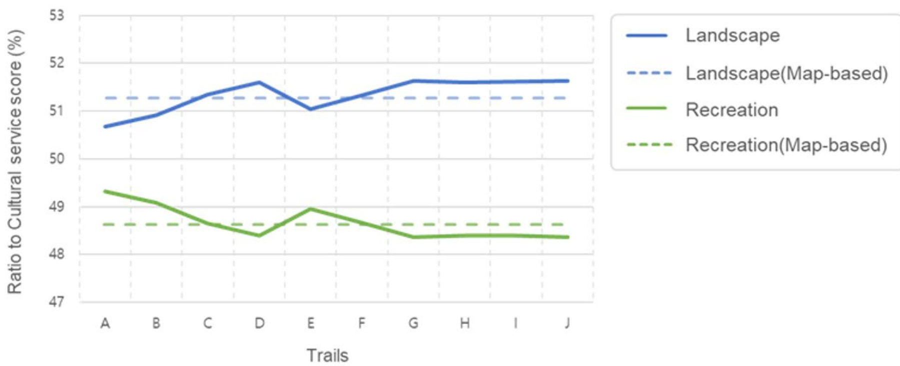


FIGURE 9 | Normalized supply score: map- and trail-based approaches.

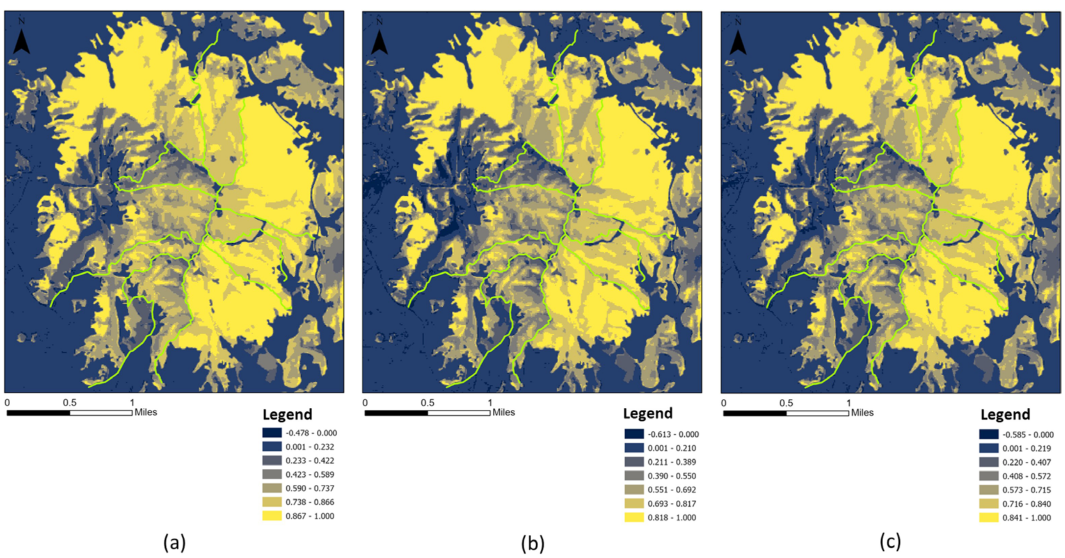


FIGURE 10 | Spatial comparison of cultural ES supply scores from map-based and trail-based approaches (a: recreation, b: landscape, and c: culture).

seasonal mismatches. For supply scores, Trail B consistently ranked first, followed by Trails A and F. In contrast, demand scores fluctuated seasonally. During spring, summer, and autumn, Trails A, B, and F ranked 1st, 2nd, and 3rd, respectively. However, in winter, these rankings shifted to 1st for Trail A, 3rd for Trail B, and 2nd for Trail F.

These results suggest that despite Trail B's higher cultural ES supply, Trail A experienced greater demand, likely due to factors such as better accessibility from main roads and reasonable hiking duration. Notably, in winter, Trail B's demand score was lowest, possibly due to longer hiking times. These findings underscore the importance of considering various factors, including hiker numbers, specific trails, and seasons, in policy decisions related to the allocation of cultural ES. For instance, policymakers in forest ecosystem service management could focus on Trail A for local residents with high demand for recreational services, as it consistently demonstrated high demand scores.

TABLE 6 | The number of hikers over seasons.

Season	Trail	# Hikers
Spring (March)	A	2778
	B	889
	F	1333
Summer (July)	A	2889
	B	333
	F	1222
Fall (October)	A	3445
	B	555
	F	1222
Winter (January)	A	2556
	B	111
	F	1111

4 | Discussion

4.1 | Bridging the Gap in Cultural ES Assessment

In this study, we propose trail-based frameworks for evaluating cultural ES scores. To calculate the supply score, we combined the maximum achievable landscape and recreation scores within each individual's viewshed along the trails. This approach allowed us to quantify the distinct amount of services supplied by each trail. Traditionally, the supply score has often been calculated using map-based approaches, where land-use data are spatially converted into scores. However, our comparison between the traditional map-based approach and the proposed trail-based approach revealed that the potential total cultural ES that individuals can perceive through their behavior significantly differs in spatial distribution from what is derived through simple mapping. This finding extends the work of Weyland and Laterra (2014), who emphasized the importance of dynamic, activity-based assessments in truly understanding the value of ES.

For the demand score, we built anABM based on recorded hiking data that tracks individuals' trail usage. This model enabled us to calculate the consumption of cultural ES by each agent as they hike along different trails. Recognizing the seasonal variations in hiking populations, we also demonstrated that the cultural ES acquired by individuals on these trails varies by season. This insight can directly inform policies aimed at organizing local events, such as festivals, that supply cultural ES, thereby establishing a spatially explicit link between cultural ES and cultural events. Our approach aligns with the work of Breuste, Qureshi, and Li (2013) and Breuste et al. (2013), who highlighted the need for more nuanced and localized ES assessments. Previous studies on demand scores have also focused on individual scales, often linking personal characteristics to destination choices. However, these studies predominantly took a broader perspective. In contrast, our research presents a method for modeling human activities on a microscale, focusing on local mountains or trails. This approach allows for a more localized understanding of how cultural ES is consumed, providing insights that are both specific and practical.

TABLE 7 | Comparison of trail-based cultural ES supply score and demand score.

			Demand score by season (10^{10})			
Category	**Trail**	**Supply (10^5)**	**Spring**	**Summer**	**Fall**	**Winter**
Cultural	A	3087.83	2233.77	2198.3	2319	1720
	B	4470.01	1009.12	374.41	512	150
	F	1788.01	374.57	276.28	331.1	298.8
Recreation	A	1522.97	1100.3	1081.8	1142	846.1
	B	2194.3	496.73	184.29	251.9	73.85
	F	870.1	183.37	135.02	162	146.1
Landscape	A	1564.86	1133.47	1116.5	1177	874
	B	2275.71	512.39	190.12	260.1	76.12
	F	917.9	191.19	141.26	169.1	152.7

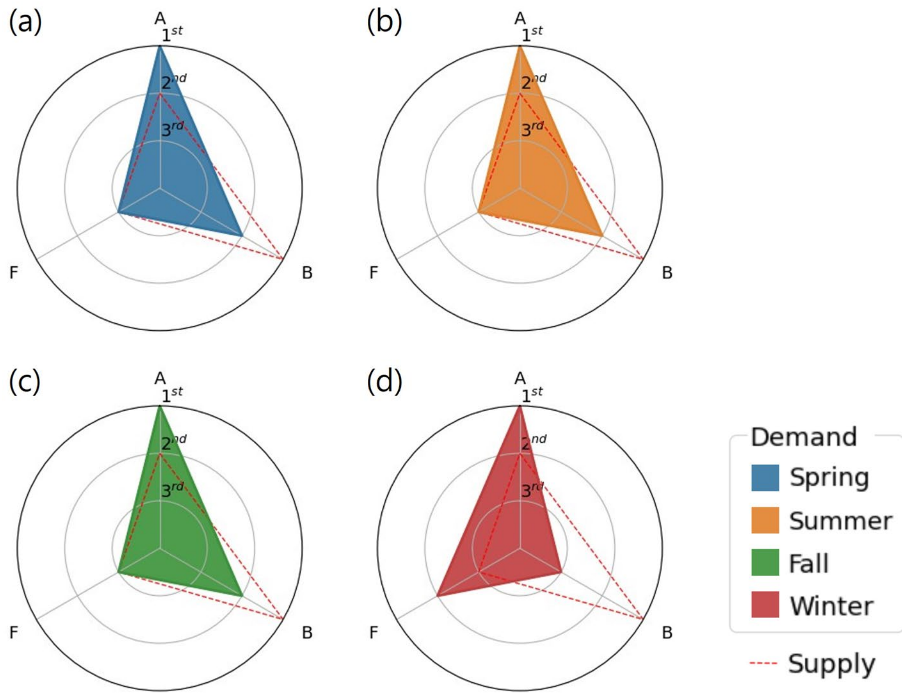


FIGURE 11 | Cultural ES supply and demand score rank by season.

4.2 | Implications for Policy and Environmental Management

In this study, the estimated ES supply score represents the potential maximum amount of cultural ES that each trail can provide, while the ES demand score indicates the potential amount of cultural ES that could be consumed by human activities on each trail. Therefore, from a policy perspective, the identified spatial mismatch between cultural ES supply and demand across different trails highlights the need for more targeted environmental and recreational policies. For example, if a trail has a high supply but low visibility or cultural consumption, resulting in a lower demand for potential cultural ES through actual hiking activities, this could necessitate specific management and policy interventions for that trail.

This could involve prioritizing certain trails for development conservation, a perspective supported by Schirpke et al. (2016). Such a targeted approach could significantly enhance the effectiveness of ecosystem service management and conservation strategies. Environmentally, our detailed analysis of cultural ES contributes to broader conservation efforts. By providing empirical evidence on how different trails and natural landscapes are used for recreational purposes, our study aids in sustainable land use planning. This is in line with the arguments presented by Maes, Paracchini, et al. (2012) and Bai et al. (2018), who emphasized the role of detailed ES assessments in supporting conservation policies.

4.3 | Addressing Methodological Limitations and Future Research Directions

Our study, although innovative, has limitations due to its reliance on specific datasets and the geographic focus on a particular mountain range. These constraints might limit the applicability of our findings to other regions. Future studies should aim to expand the geographic scope and integrate more diverse datasets, such as high-resolution satellite imagery or biodiversity indices, to enhance the accuracy and comprehensiveness of cultural ES assessments. This approach is in agreement with the recommendations of Andrew et al. (2015), who called for the integration of various data sources and refined spatial parameterizations for a more holistic understanding of ES.

Additionally, as more individual-scale hiking data are collected, it will be possible to conduct more accurate hiking simulations. Given that ABM allows for behaviors and interactions based on individual characteristics, more detailed data will enable a broader range of scenarios. In our study, we used a limited dataset of approximately 1000 hiking records to explore simple scenarios, such as differences in the cultural ES demand score based on seasonal population variations. However, with more detailed and extensive data, it would be possible, for example, to identify which trails are more heavily utilized for cultural ES consumption based on age-specific scenarios or to predict cultural service consumption levels across different times and locations for new hiking trails. Furthermore, future research is to apply validated hiking simulations to mountains where hiking data are challenging to collect, thereby estimating cultural ES scores in data-scarce areas.

Lastly, it is important to recognize that the scoring criteria for cultural ES may vary depending on regional context and future perceptions, such as those related to recreation or landscape. The scoring criteria in this study reflect the opinions of experts based on contemporary common sense. However, if the scoring system is updated in the future or applied to different regions, the results may differ. For example, if region A is famous for its dense coniferous forests and region B is known for its autumn foliage, the landscape scores assigned to coniferous and deciduous trees in each region may vary. Therefore, continuous research and updates to the scoring system are necessary. In conclusion, our study fills a gap in the field of cultural ecosystem service assessment by introducing a trail-based methodology that closely aligns with actual human activities at a mountain scale. This approach not only enhances the accuracy of cultural ES estimates but also provides actionable insights for policy-making and environmental management. By addressing the identified limitations and expanding upon our methodology, future research can continue to refine and improve the assessment of cultural ES, contributing to the sustainable management of natural resources.

5 | Conclusion

This study marks a significant advancement in the field of ES, introducing a trail-based methodology for accurately estimating cultural ES. By focusing on hiking as a specific human activity, we have provided a unique lens to understand how individuals interact with and benefit from natural environments.

The departure of our research from conventional methods is its core strength. Traditional approaches often overlook the subtleties of individual human behaviors and their direct impact on ES. In contrast, our methodology capitalizes on real-time data and ABM, grounding the estimation of cultural ES in actual human activities. This not only enhances the precision of ES assessments but also offers a detailed perspective on the use of different trails and natural landscapes for recreational purposes.

Our findings underscore the importance of integrating individual behaviors into ES assessments, a perspective that has not been thoroughly explored in previous research. This approach allows for more accurate and realistic estimations of cultural ES, reflecting the actual usage patterns and preferences of individuals. These insights are crucial for developing more effective environmental policies and management strategies, especially in the realm of sustainable tourism and natural resource management.

In conclusion, our study proposes a forward-thinking and practical framework for cultural ES assessment, emphasizing the need to consider direct human activities in eco-system service research. The methodology, by aligning closely with actual human usage patterns, represents a substantial leap forward in the accurate and effective management of natural resources. It contributes to the broader goals of environmental sustainability and conservation, offering a versatile tool for future applications in diverse ecosystems and geographical settings. Moving forward, addressing the identified limitations and exploring the applicability of this methodology in various contexts will be crucial in continuing to refine our understanding and management of ES.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Appendix

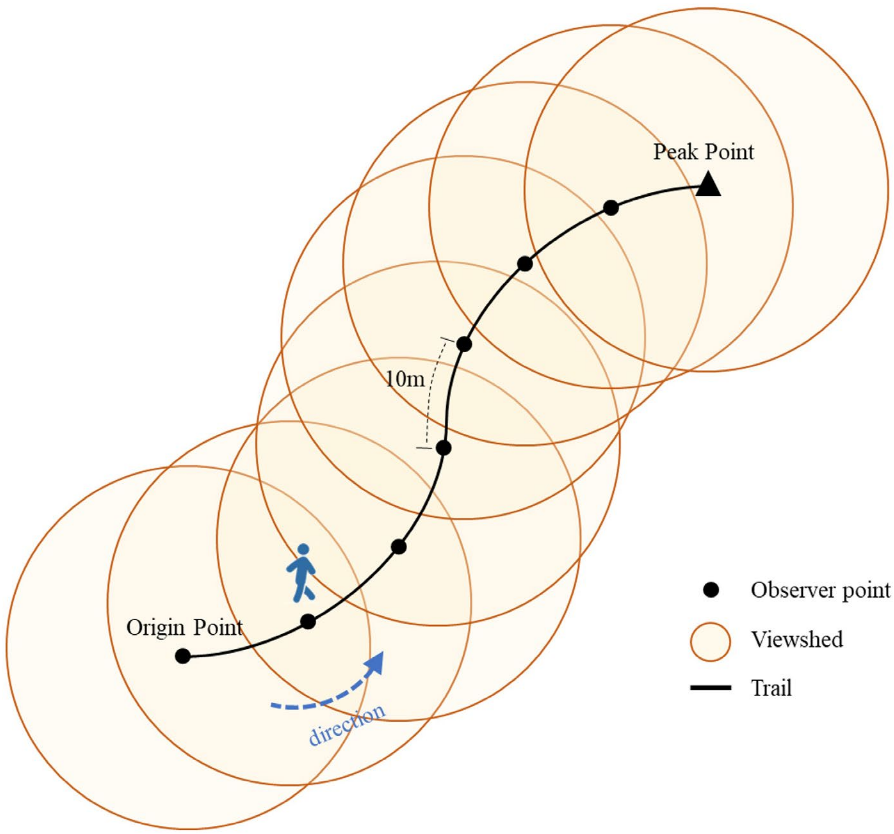

FIGURE A1 | Trail-based viewshed analysis.

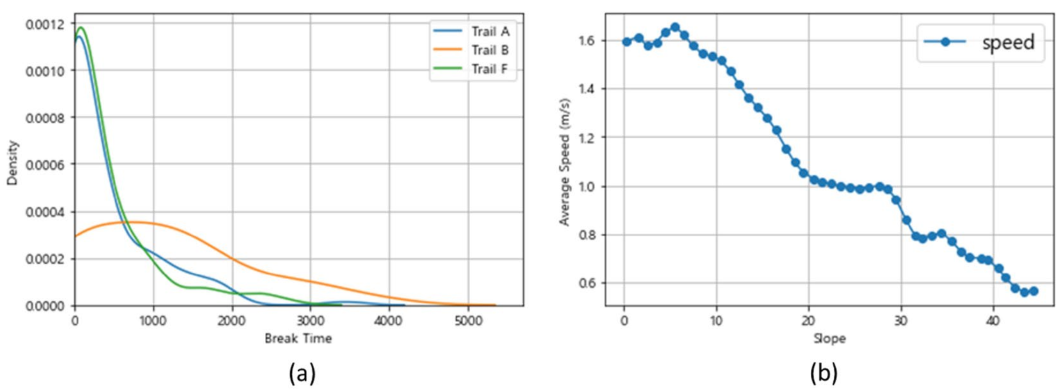

FIGURE A2 | (a) Break time by trails and (b) speed by the slope.

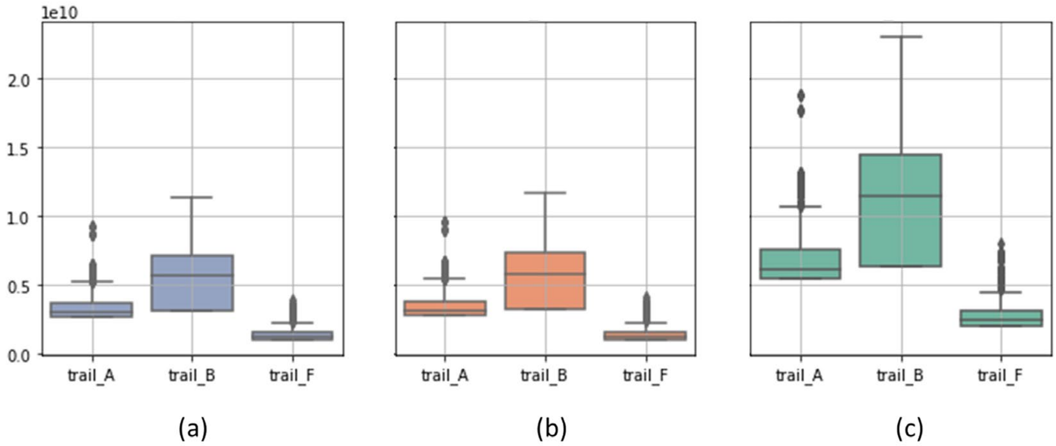

FIGURE A3 | Trail-based cultural ES demand score (a: recreation, b: landscape, and c: culture).