Ecosystem Services 73 (2025) 101740

Contents lists available at ScienceDirect

Ecosystem Services

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

Full Length Article

Spatial patterns and interactions among multiple cultural ecosystem services across urban greenspaces

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ARTICLE INFO

Keywords:
Urban greenspaces
Cultural ecosystem services
Nature's contribution
Tradeoffs and synergies
Social media
Biodiversity

ABSTRACT

Urban greenspaces (UGS) deliver substantial benefits to human wellbeing by providing valuable ecosystem services. Prior research on UGS has been primarily focused on provisioning and regulating services, with comparatively fewer studies explicitly addressing cultural ecosystem services (CES), presumably due to conceptual and methodological challenges in their characterization and quantification. Social media data have emerged as novel datasets that could provide new insights into the quantification of these intangible, highly context-specific, but critically important CES. In this study, we merged multiple platforms, including TripAdvisor and Google Maps that are among the most comprehensive user-generated datasets, to map and quantify the spatial distribution of 11 CES. Employing named-entity recognition models, this study extracted 60,156 textual entities related to CES from scraped reviews, allowing us to categorize 30,599 reviews into different CES types across 426 urban greenspaces. Our research demonstrated substantial spatial heterogeneity in the presence and diversity of CES and identified six key CES bundles, revealing more occurrences of CES synergies than tradeoffs across UGS. Geographical random forest models were applied to determine the relative importance of natural landscape elements, biodiversity proxies, and human utility metrics in explaining the spatial heterogeneity of CES. We found that factors such as greenspace size, tree cover percentage, biodiversity, and water features emerged as strong predictors of CES provision. Our study provides a roadmap and research framework for understanding and quantifying CES in urban settings and has implications for the sustainable planning and management of UGS to improve social wellbeing through the contribution of diverse CES.

1. Introduction

Urban greenspaces (UGS) provide multiple environmental, social, and cultural benefits to humans (Jim and Shan, 2013). These benefits are often referred to as 'ecosystem services' (or nature's contribution to people) (Díaz et al., 2018; MEA, 2005), which exert profound impacts on human livelihoods and sustainability of cities (Hegetschweiler et al., 2017). Given accelerated urbanization across the globe (i.e., 68 % of world's population projected to reside in urban areas by 2050; Forman and Wu, 2016) and increasing social-environmental importance of UGS, it is critical to investigate and understand where, how, and under what conditions diverse ecosystem services are provided by UGS. Such knowledge can ultimately inform the design, planning and management of UGS, ensuring that they meet the diverse needs of urban residents and provide multiple ecosystem services.

Although social-environmental benefits from UGS are broad and multifaceted (Derkzen et al., 2015), their sustained cultural ecosystem services (CES) – defined as the nonmaterial benefits people obtain from nature through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experience – has been evolving. CES derived from UGS are particularly valuable due to their proximity to beneficiaries and their functions to improve physical health, mental wellbeing, and psychological resilience of urban residents (Bratman et al., 2019; Clark et al., 2014). In addition, most CES are subjectively valued, directly experienced, and intuitively appreciated, and are thought to inform people's preferences (Wardropper et al. 2020; Hui et al. 2024)

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https://doi.org/10.1016/j.ecoser.2025.101740
Received 6 November 2024; Received in revised form 6 May 2025; Accepted 11 May 2025
Available online 16 May 2025
2212-0416/

and held values (Gobster et al., 2007; Russell et al., 2013; Wardropper et al., 2020; Zhao et al., 2024). Hence, perceptions and appreciations of CES can be disproportionately important in improving environmental awareness and strengthening civic engagement by serving as places for rest and relaxation, exercise, and psychological restoration (Hartig, 2008). These nontangible benefits can consequently motivate and foster public support for sustainable management and conservation practices, especially in urban environments where natural habitats are likely fragmented and susceptible to anthropogenic influences (Haase et al., 2014; Plieninger et al., 2013). Ongoing urbanization and global changes have further highlighted the fundamental role that UGS could play in providing CES to promote urban resilience and sustainable urban development (Pulighe et al., 2016; Sikorska et al., 2023).

Nevertheless, there are ongoing debates about effective methodologies to measure CES, and a lack of robust theoretical frameworks that integrate CES into urban greenspace planning and management practices (Dickinson and Hobbs, 2017; MEA, 2005). Due to its intangible nature and complex relationships among biophysical, economic, societal, and cultural characteristics of UGS that underpin CES supply, CES remain notoriously difficult to assess and quantify, especially in a spatially explicit manner (Dickinson and Hobbs, 2017; Huynh et al., 2022). In particular, even fewer studies have focused on CES in urban settings characterized by substantial heterogeneity of socioecological dynamics, especially in highly urbanized metropolitan regions where complex human-nature interactions are commonly observed (Alberti et al., 2020; Yang et al., 2023). Such data and knowledge gaps preclude enhanced understanding of the spatial patterns, relationships, and drivers of CES. In addition, among existing research, few have taken a holistic approach that explicitly measures and analyzes multiple CES and their interactions across a range of different UGS (Cheng et al., 2022; Daniel et al., 2012). For example, current studies tend to focus on the supplying capacity of UGS for single or few CES (Nigussie et al., 2021; Shi et al., 2023), or the studies are localized in scale (Jones et al., 2020). Nonetheless, a holistic approach is crucial, given that ecosystem services are not independent of each other and may interact in intricate ways, producing synergies, tradeoffs, and bundles (i.e., multiple ecosystem services co-occurring repeatedly) (Bennett et al., 2009; Qiu and Turner, 2013). Hence, improved knowledge of interactions among a portfolio of CES from UGS can lead to more informed urban landscape decision-making, reducing tradeoffs, taking advantage of desirable synergies, and thus achieving holistically achieving multiple CES (Ma and Yang, 2025; Qiu et al., 2018; Turner et al., 2014).

Generalizable and scalable methodologies for accurately quantifying CES can enhance our understanding and help effectively incorporate these services into urban planning and sustainable development strategies. However, traditional non-economic approaches (e.g., social surveys, focus groups, qualitative interviews, public participation, and other instrumental assessments) (Csurgó and Smith, 2021; Heikinheimo et al., 2020; Marini Govigli and Bruzzese, 2023) face limitations in terms of capturing the intangible and incommensurable nature of CES (Winthrop, 2014), as well as generalizability and reproducibility across a large study area. Moreover, these methods also present additional challenges of framing effects of expressed values (e.g., question order or wording in the interview or questionnaire) (Satz et al., 2013), high labor and financial cost, limited sample size and the degree of representativeness (Lienhoop et al., 2015), and constraints pertinent to only selective CES.

In response to these challenges, georeferenced social media data has recently emerged as a promising alternative to quantify and assess ecosystem services, with more recent elevated interests in CES (Cao et al., 2022; Fox et al., 2021). Social media platforms like Flickr, Instagram, and X (formerly, Twitter) offer a rich and cost-effective source of perceptual data through user-generated content, including text, images, and videos (Arts et al., 2021; Chang and Olafsson, 2022; Wan et al., 2021). Specifically, textual content and natural language processing (NLP) techniques, especially when empowered by machine learning, can be advantageous to other types of crowdsourcing social media data to quantify CES. The rich, multidimensional descriptions available in textual content such as microblogs, tour reviews, and user-generated tags (Grzyb et al., 2021; Kong and Sarmiento, 2022) open new directions for assessing and understanding people's experiences of nature, landscape preferences, and perceptual landscape elements, and thus their sentiments towards and consumptions of CES (Cao et al., 2024; Havinga et al., 2024). The advancement of NLP, deep learning techniques (Le Guillarme and Thuiller, 2022), and transformer-based language models such as BERT (Berragan et al., 2023; Devlin et al., 2019) can especially offer promising avenues to process vast amounts of unstructured text to pretrain language representations to embrace big data to broaden the sample size and representations of CES in UGS. However, despite its value, social media data could suffer from inherent potential biases, including unequal representation of demographics (e.g., age, income, and digital literacy) (Y. Zheng et al., 2024), platform-specific user behaviors (e.g., Instagram's focus on visual aesthetics vs. TripAdvisor's review-driven ecosystem) (Toivonen et al., 2019), and geographic disparities in data density (Martí et al., 2019). These limitations necessitate strategic platform selection aligned with study objectives and integration of datasets from multiple platforms. User-generated review platforms such as Google Maps and TripAdvisor offer unique advantages for CES assessments, including: (1) spatially-explicit reviews tied to specific UGS, unlike the diffuse geotags of Twitter or Flickr; (2) detailed textual narratives on visitor experiences (e.g., aesthetics, recreation), which are critical for CES quantification (Kong and Sarmiento, 2022); and (3) broad user bases that, while still excluding non-tech-savvy populations (Owuor et al., 2023), capture diverse recreational and cultural engagements across urban areas. While prior studies have focused on platforms like Flickr for nature-based CES (Ghermandi et al., 2023), urban CES require platforms where users explicitly review multifunctional greenspaces—a strength of Google Maps and TripAdvisor.

Our objective was to leverage crowdsourcing review data and machine learning approaches to quantify and understand a wide range of CES across UGS to address their spatial patterns and interactions. We focused the analyses on Broward County (Florida, USA) as it is among the top 20 most populous counties in the U.S. and is experiencing accelerated urbanization with ~ 2 million current residents (2020 U.S. Census). Specifically, we mapped spatial heterogeneity of 11 CES (e.g., aesthetic value, experiential use, physical use, educational value, existence value) to ask: (1) What is the spatial pattern and hotspots of individual CES across UGS and which UGS provide the most diverse suite of CES? (2) Are there any consistent tradeoffs, synergies, and bundles among CES from UGS? and (3) What social and ecological factors explain the spatial distribution of CES across UGS?

2. Materials and methods

2.1. Study area

Our study was conducted in Broward County located in South Florida, USA. Broward County is Florida's second most populous county and ranks among the top 20 most populous counties in the U.S., with approximately 1.9 million residents (U.S. Census Bureau, 2021). The county spans 342,655 ha, of which 8.5 % is water, and includes 31 municipalities with urbanized areas covering 110,799 ha (U.S. Census Bureau, 2021). A sharp demarcation exists between its densely developed eastern urban core and the western Everglades Wildlife Management Area (Volk et al., 2017), creating a landscape where greenspaces are critically needed to balance ecological and human needs. Furthermore, we selected Broward County as our study area because it: (1) represents a highly urbanized landscape where UGS are much needed but face threats from ongoing urban development; and (2) serves as an exemplar subtropical and tropical urban system that remains overall less understood in the literature but is expected to harbor substantial levels of urban biodiversity and increasing flow of populations. Miguez et al.

(2025) has delineated the spatial boundaries of 639 UGS in Broward County, following Callaghan et al. (2020), where UGS are considered as urban landscapes that are managed and designated as parks or recreational spaces accessible to the public (Fig. 1). Full details of our definitions for defining and characterizing UGS can be found in Appendix S1.

2.2. Data sources and availability

Online reviews associated with UGS were extracted from TripAdvisor (https://www.tripadvisor.com/) and Google Maps (https://www.google.com/maps) using a browser automation tool named '*Selenium*' supported by Python. The review data from these two widely used platforms provide a globally scalable and complementary user-generated content and reviews with high spatial specificity for attractions, as well as detailed spatial records of interactions between humans and ecosystems (Ghermandi et al., 2023; Kong and Sarmiento, 2022). Specifically, TripAdvisor specializes in destination reviews, attracting users motivated to detail recreational and cultural experiences (Marine-Roig and Anton Clavé, 2016; Spalding and Parrett, 2019), while Google Maps integrates location-based reviews into daily navigation, capturing spontaneous UGS interactions (Mohamed and Kronenberg, 2025). We chose to combine data from both sources, also considering the complementarity of their reviews and the necessity to include as much data as possible to reflect a wide range of users from different socio-demographic groups (Owuor et al., 2023). We acknowledge the ethical considerations of web extraction and confirm that our data collection adhered to platform-specific guidelines and followed common academic practices (Ghermandi et al., 2023; Helbich et al., 2024). Reviews were aggregated for research purposes under fair use principles with no commercial intent. Data anonymization and aggregation protocols were implemented to protect user privacy and confidentiality.

Due to access restrictions, the maximum number of reviews of each UGS that could be extracted from Google Maps was 1,040, and this upper limit was reached for 30 UGS (out of 639 delineated UGS units), where reviews were sorted by Google's default "most relevant" algorithm, prioritizing popularity and recency. In other words, for this subset of $\sim 5\,\%$ UGS, we were only able to extract and use review data for 1,040 entries, which are considered the most recent and relevant experiences of visitors sorted by Google's algorithms. To assess the extent to which such upper limit can affect our characterization of CES, we performed additional sensitivity analyses (detailed in *Section 2.3*). For the TripAdvisor platform, no limit was imposed, and we were able to extract all reviews for all the studied UGS. The UGS locations were identified manually by matching identified UGS names and spatial boundaries to corresponding entries on Google Maps and TripAdvisor. To ensure spatial alignment, we cross-referenced UGS coordinates with Google Maps metadata and excluded facilities nested within larger UGS (e.g., park visitor centers). During our data collection, we found that 193 UGS out of the 639 delineated units had no valid reviews on either Google Maps or TripAdvisor. These UGS were excluded from our analyses due to the lack of user-generated content. In total, we collected 69,084 textual reviews across 454 UGS, including 60,552 reviews from Google Maps and 8,532 reviews from TripAdvisor. All reviews were extracted from December 2010 to October 2023.

2.3. Definition of CES and overall research design

Based on the extracted textual reviews, we extracted data to quantify CES associated with each UGS. Our definition of CES in this study was compatible with the most representative and adopted conceptual frameworks in the literature, specifically the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin-Young, 2018; Hirons et al., 2016), in which the physical, intellectual, and spiritual values of the natural environment were considered. To operationalize these concepts for manual annotation, we developed the working definitions for 11 CES categories (Table 1), explicitly linking CES categories to keywords and phrases in user-generated reviews. For example, aesthetic value was defined as artistic or sensory appreciation of landscapes, identified through references to natural features (e.g., "beautiful green leaves"), while physical use encompassed active engagement with UGS infrastructure, such as mentions of "walking paths" or "athletic fields." These definitions served as a prime rule for categorizing CES-related entities, ensuring consistency between theoretical frameworks and real-world expressions in textual data.

To address our research questions, we implemented a three-task workflow (Fig. 2). To address our first question (Task 1), textual review data from TripAdvisor and Google Maps were extracted as described above (*Section 2.2*). We then developed a review corpus annotated with the 11 CES types to create NER datasets that can further be used to train a BERT-based NER model. Afterwards, data from extracted reviews regarding CES were extracted to classify and quantify CES across all UGS (details on NER training and classification are in *Section 2.4*). To address our second question, in Task 2, we identified CES bundles for analyzing their interactions (i.e., tradeoffs and synergies) among multiple CES based on correlation analysis and cluster analysis

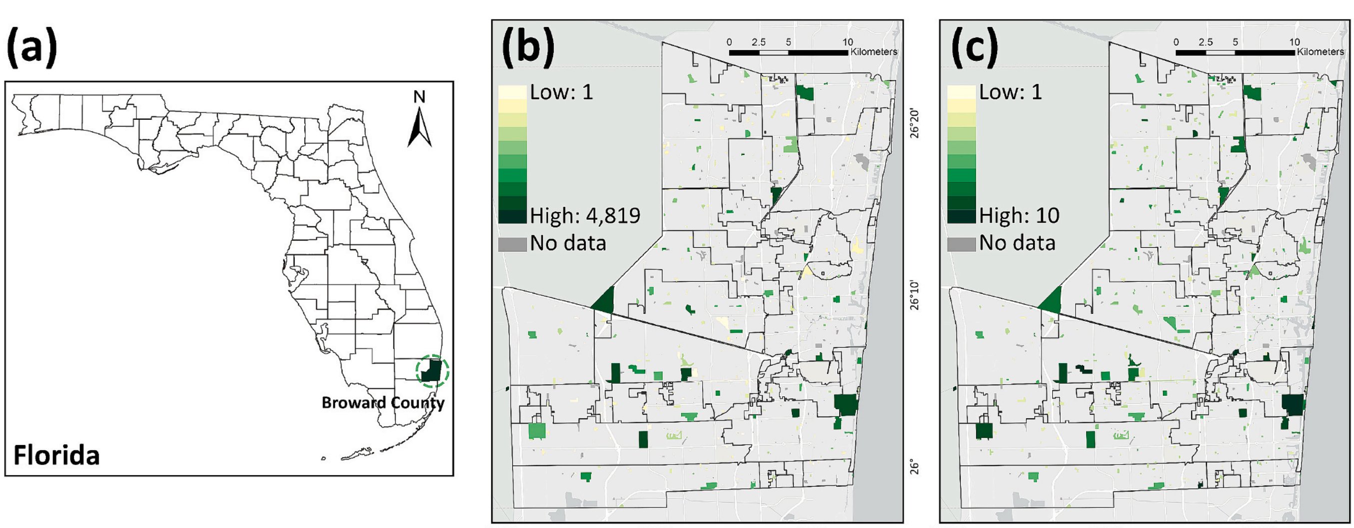
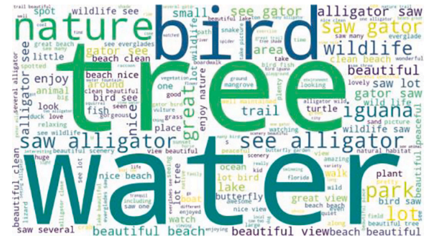
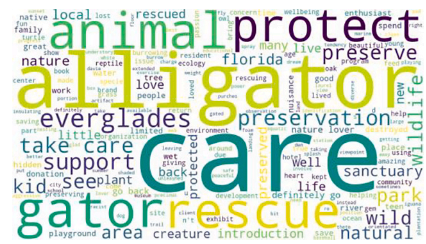
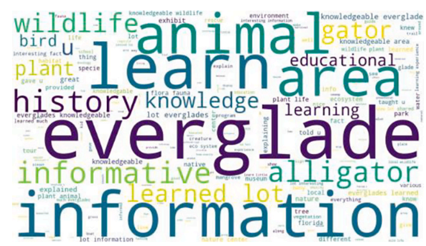
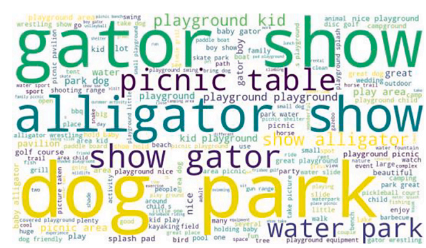
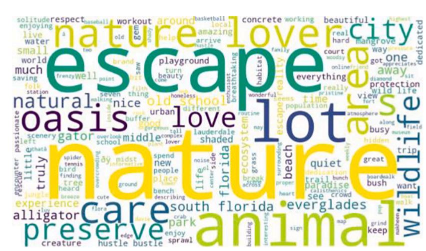
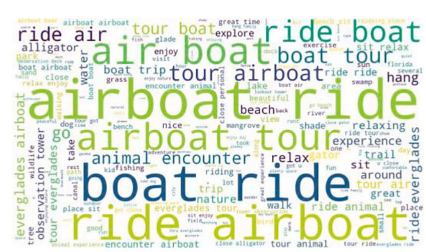


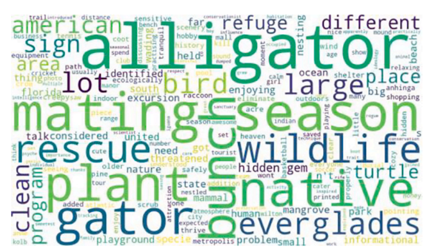
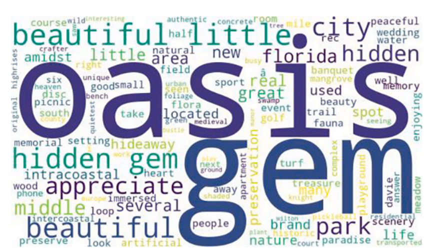
Fig. 1. (a) Location of our study region in Broward County, Florida, USA. (b) Total cultural ecosystem service (CES)-related reviews of each urban greenspace (UGS). (c) Total number of present categories of identified CES for each UGS. "No data" indicates UGS for which no CES-related reviews were found.

Table 1
Definition of cultural ecosystem services (CES) focused in this study and example of CES-related entities for model training.

CES	Definition	Example of entities	Word cloud of entities
Aesthetic value	Artistic representations of nature.	"…You can **see the beautiful green leaves of the red mangroves**; it is a bridge who brings you in the middle of the groves with a tower to observe the panorama…"	
Bequest value	Willingness to preserve plants, animals, ecosystems, and land-/seascapes for the experience and use of future generations.	"…Very happy to see Florida residents felt it was important in the 1970's to **preserve a little nature** so close to its popular beaches…"	
Educational value	Subject matter of educational value.	"…A great place to **understand the importance of the wildlife** and a history of the area both ecologically as well as architecturally…"	
Entertainment value	Benefits arising from various outdoor recreational activities.	"…This is a great place to **hold a picnic**, even in the evening…."	
Existence value	Enjoyment and philosophical perspective provided by the knowledge of, and reflections on, the existence of wild species, wilderness, or land-/seascapes.	"…Also enjoyed walking on their board walk and **feeling like being in the middle of the Everglades** and forgetting that I was just 10 min away from I to 95 and all the hub bub…"	
Experiential use	Experiential use of plants, animals, and land-/seascapes in different environmental settings.	"…Very nice camp site. not a lot of activities. great for **dog walking**…"	

(*continued on next page*)

Table 1 (*continued*)

CES	Definition	Example of entities	Word cloud of entities
Heritage value	Historic records of a place; cultural heritage preserved in different environmental settings.	"…He was very **informative about the history of the glades and the Seminoles**. We saw lots of birds which he told us interesting things about…"	
Physical use	Physical use of land-/seascapes in different environmental setting.	"…They have tours, gift shop, **workshops, lectures, tips on gardening for butterfly caterpillars**…"	
Religious value	Holy or spiritual places important to spiritual or ritual identity.	"…A beautiful spot to **meditate, relax**, and commune with the birds and nature…"	
Scientific value	Subject matter for scientific research.	"…This small park was **one of the last areas of undisturbed cypress swamp** in the county, and it was preserved, apparently, through the efforts of a group of local high school students…"	
Symbolic value	Emblematic plants and animals; national symbols.	"…This is **a great hidden little gem**. Very peaceful to walk the raised boardwalks in between lots and lots of spiders…"	

(detailed in *Section 2.5*). Finally, to address the third question, in Task 3, we examined the extent to which different factors (including landscape elements, biodiversity proxies, and human utility metrics) explained the spatial distribution of CES based on a geographical random forest model (detail in *Section 2.6*).

2.4. Classifying CES-related textual contents

After filtering CES-related content of extracted reviews, we found that some UGS ($N = 28$) did not contain any reviews that could be categorized into CES categories. Thus, we collected 60,156 textual entities related to CES that further allowed us to categorize 30,599 reviews into different types of CES within 426 UGS. The detailed classification of CES-related content within textual reviews aimed to build a dictionary containing each category of CES and its relevant keywords or phrases, following the methodology of previous studies (Benati et al., 2024; T. Zheng et al., 2024). We allowed for multiple CES designations for each review, because one user could express the enjoyment of several CES in one review. This process involved three main steps.

For Step 1 we selected a random sample of 20 % of the reviews from TripAdvisor as the model corpus dataset ($N = 1{,}710$) and manually annotated entities aligned with the 10 CES types using a span representationbased annotation platform with five domain experts in urban greenspaces and ecology. The training dataset contained 5,693 entities with more than 130,000 words. Notably, we focused on TripAdvisor data for training the classification model because its reviews were substantially longer (average 53.83 words per review) compared to Google Maps (average 12.24 words), providing richer contextual information for identifying nuanced CES categories.

For Step 2, we employed a BERT-based transformer model fine-tuned for classifying all remaining textual content related to each CES. While BERT was originally designed for tasks like traditional named-entity

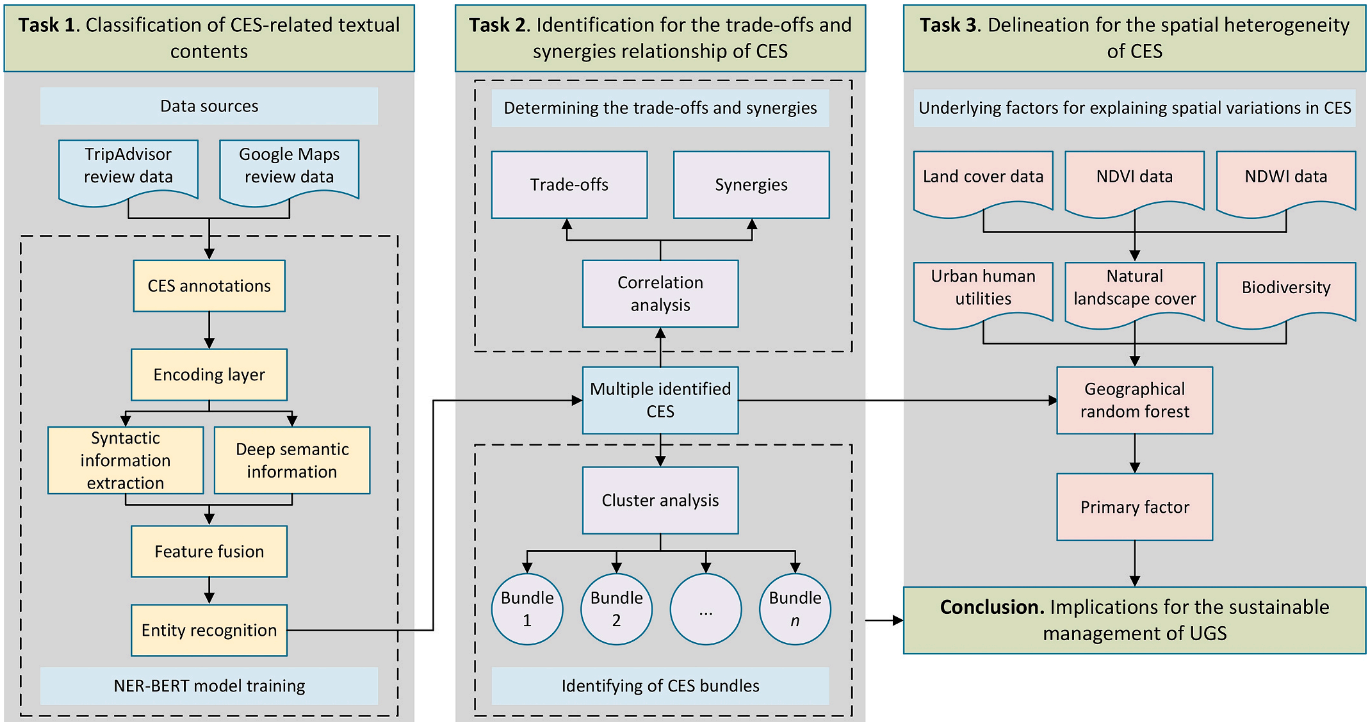


Fig. 2. Overall study design and research framework that uses crowdsourcing data to quantify cultural ecosystem service (CES) spatial patterns and interactions with three main tasks. Firstly, textual review data from TripAdvisor and Google Maps were extracted and were further extracted to classify and quantify for CES based on a NER-BERT model. Secondly, we identified CES bundles for analyzing tradeoffs and synergies among multiple CES based on correlation analysis and cluster analysis. Thirdly, we examined the extent to which different factors (i.e., landscape elements, biodiversity, and human utility) explained the spatial distribution of CES based on geographical random forest model.

recognition (Li et al., 2022), which identifies rigid categories such as locations or organizations, its contextual understanding and transfer learning capabilities make it adaptable for classifying diverse semantic categories such as CES. Compared to conventional sequence labeling models such as Conditional Random Fields or Long Short-Term Memory, BERT-based models better capture long-range contextual dependencies in text through transformer self-attention, though they require greater computational resources (Devlin et al., 2019). We adapted BERT's architecture by replacing its final NER classification layer with a custom layer trained to predict CES categories. We encoded the training data using an embedding layer and input it into an optimized BERT pre-training model. Then, we extracted the output from the Encoder layer, computed attention weights using the multi-headed self-attentive mechanism in the Transformer Encoder, and integrated syntactic features to enhance semantic understanding. We then fused this syntactic information with the last layer of the BERT output and obtained the predicted CES categories via a fully connected layer. The specific flow chart is also shown in Fig. 2. These steps were performed using the 'spaCy' library in Python. **Table A1** in the Supplement presents a comparison of manual detection and the automated annotation of CES based on the testing sets. Overall, we achieved a classification agreement of > 80 % in detecting most CES. This indicates that our automated approach for identifying and characterizing all the CES in UGS using textual review data is reliable and robust, with the reliability rate exceeding the recommended Cohen's kappa coefficient threshold of 0.6 for nearly all CES types.

We further created word clouds based on 'wordcloud' library in Python as shown in Table 1 to visualize the most representative keywords for each CES type as another way of intuitive validation. Given the scope of our study, we selected two numeric indicators to quantitatively characterize CES patterns: (1) total number of reviews in each CES category, which presumably correlates with the use of CES from UGS; and (2) total number of present categories of CES (i.e., total number of identified CES) in each UGS, which reflects the diversity of CES provided by each UGS. Based on these two indicators, we mapped the spatial heterogeneity of individual CES and total number of CES for each UGS. Specifically, for each UGS, we summarized the total number of reviews related to CES (Fig. 1**b**) and the total number of reviews for each individual CES (**Fig. A1** in the Supplement). Based on this, we were also able to calculate the number of identified CES types present in each UGS (Fig. 1**c**). For standardization, we further calculated the proportion of individual CES-related reviews to the total CES-related reviews of each UGS (Fig. 3). Furthermore, due to the infrequent occurrence of religious values CES, which only occurred in four reviews, we excluded this CES from aforementioned mapping and quantification as well as subsequent data analysis, and instead focused on the remaining 10 CES.

For Step 3, we further performed a sensitivity analysis on each UGS-assessed CES to estimate the minimum number of classified online reviews and the appropriate size of the training set needed to detect CES to ensure the robustness of our CES characterization by randomly selecting review subsets ranging from 1 % to 100 % of each UGS and recording the count of CES for each subset. Our analysis revealed that a minimum of 107 CES-related reviews were necessary to detect all 10 types of CES considered in this study (Fig. 4). Full details on our methodology for classifying CES-related textual content and the sensitivity analysis can be found in Appendix S2.

2.5. Identifying CES tradeoffs and synergies

Based on the textual content classification results, we mapped the spatial pattern of the number of CES-related reviews for each individual CES, and the number of present CES categories (i.e., total number of identified CES) for each UGS. To account for differences in total extracted reviews for each UGS, we standardized the indicator for each CES by calculating the proportion of individual CES-related reviews relative to all CES-related reviews. In addition, we performed pairwise

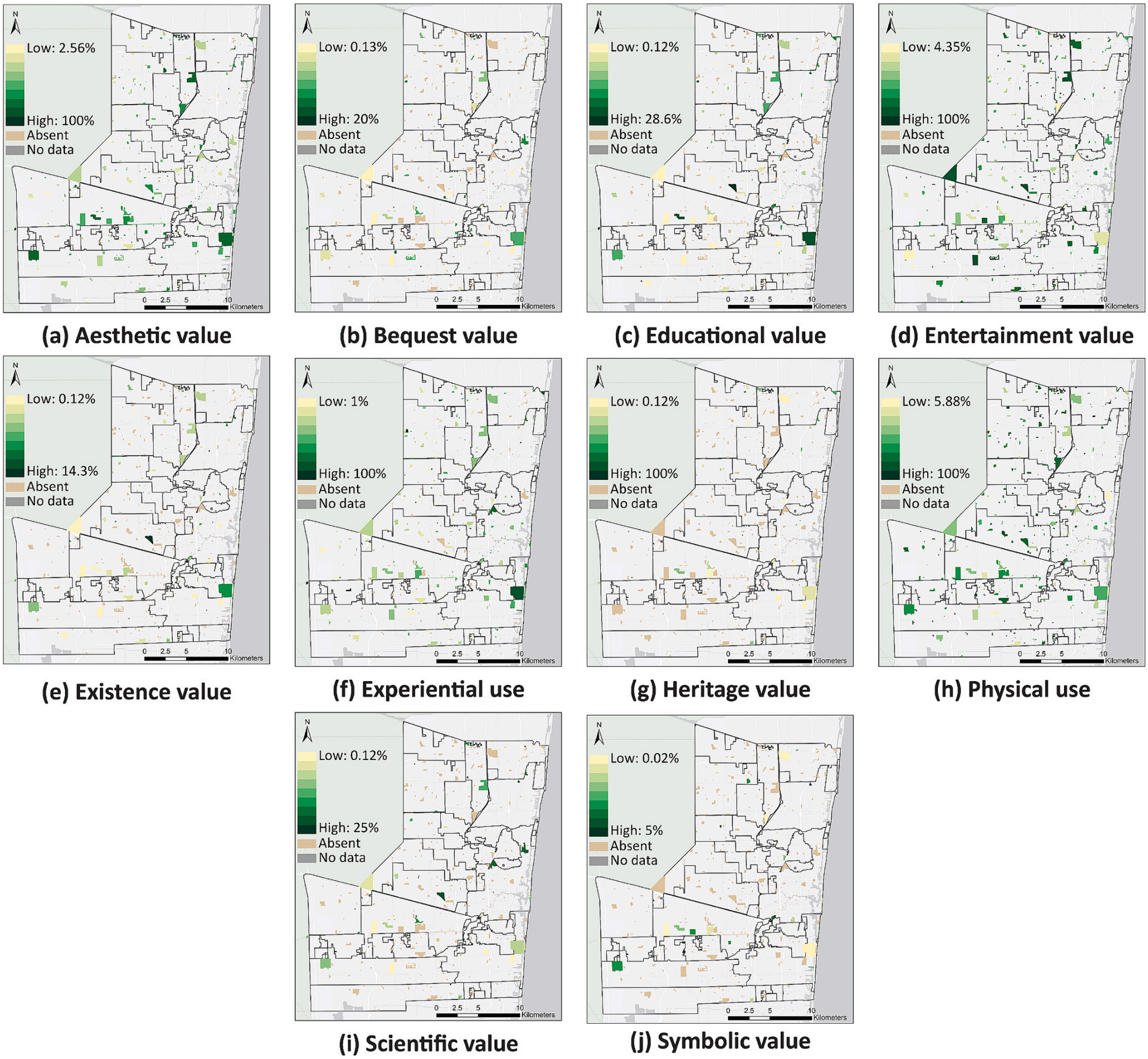


Fig. 3. Proportion of CES-related reviews within UGS: A comparison by CES category. In the legend, “No data” indicates UGS for which no CES-related reviews were found. “Absent” refers to UGS that had CES-related reviews but did not mention the specific CES being mapped.

Spearman correlation analyses on the proportion of various CES-related reviews to examine tradeoffs (i.e., negative correlations) and synergies (i.e., positive correlations) among CES. To avoid spurious results, we performed such analyses across (a) all 426 UGS, and (b) the most well-sampled UGS, defined as the top 25 percentile of UGS based on the abundance of CES-related reviews. This was done to help address the issue where certain UGS might be unable to detect those services, leading to too many zero values for specific CES.

We performed cluster analyses to identify CES bundles using a self-organizing map, an unsupervised competitive neural network with adaptive, self-organizing, and self-learning features (Dou et al., 2020; Qiu et al., 2021). We used the ‘*MiniSom*’ package in Python to learn and train the datasets of the proportion of individual CES-related reviews to all CES-related reviews to objectively create spatial unit clusters of UGS based on similarities in their supply capabilities. To avoid the local optimal solution, we set the training number to 10 times the number of spatial units, with the initial learning rate and the final learning rate as 0.05 and 0.01, respectively. Similar to the spearman correlation analyses, we also identified CES bundles across (a) all 426 UGS, and (b) the top 25 percentile of UGS based on the abundance of CES-related reviews. The cluster number that provided the largest inter-bundle dispersion, quantified using the silhouette width index (SWI), was used to determine the optimal cluster number. Finally, the optimal cluster results were mapped for each UGS to visualize the spatial pattern of the CES bundles.

2.6. *Analyzing factors that explain CES spatial heterogeneity*

To understand the underlying factors that explain spatial variations in CES of UGS, we considered three types of explanatory variables, including natural landscape cover, biodiversity proxies, and urban human utility metrics (Table 2). For assessing natural landscape

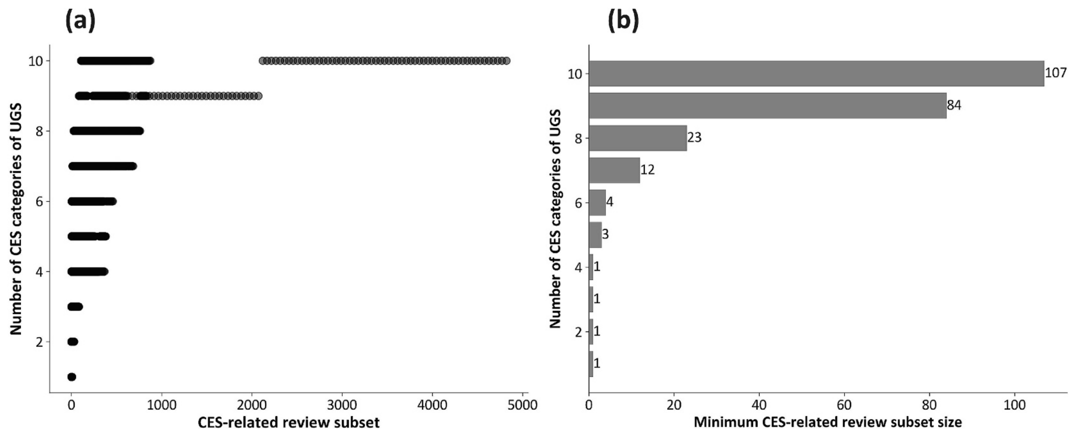


Fig. 4. Sensitivity analysis of CES detection of each UGS. (a) Each scatter dot represents one randomly selected review subset. For each subset, we recorded three key pieces of information: (1) the name of the UGS from which the subset was drawn, (2) the total number of reviews in that subset, and (3) the count of different CES types identified within that subset of reviews. (b) The minimum size of the CES-related review subset in relation to the detection of total number of CES categories.

Table 2
Statistics of explanatory variables for predicting CES spatial heterogeneity.

Variable category	Variable	Descriptions	Value across all UGS (N = 426)			
			Min	Median	Max	Std.
Total area of UGS		km^2	0.001	1.89	3.75	1.86
Natural landscape cover	Tree	Land cover data was derived from the global European Space Agency WorldCover dataset with a 10-meter resolution (Zanaga et al., 2022) and is expressed as the mean percentage of total UGS cover.	0	0.01	0.37	0.01
	Grassland		0	0.002	0.30	0.002
	Herbaceous wetland		0	0.004	0.50	0.004
	Mangroves		0	0.34	0.68	0.34
	Bodies of water		0	0.13	0.26	0.13
	NDVI	The normalized difference vegetation index (NDVI; Source: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_COMPOSITES_C02_T1_L2_8DAY_NDVI) and normalized difference water index (NDWI; Source: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_COMPOSITES_C02_T1_L2_8DAY_NDWI) were derived from Landsat 8 imagery with a 30-meter resolution and are expressed as the mean value for individual UGS.	0.06	0.34	0.54	0.01
	NDWI		0.06	0.40	0.47	0.07
Biodiversity utility		Based on citizen science data from iNaturalist (https://www.inaturalist.org/), biodiversity utility was quantified using species richness, with data filtered to remove captive organism observations to focus on naturally occurring biodiversity, and standardized on a scale from 0 to 1 as a proxy for biodiversity benefits (Miguez et al., 2025).	0	0.47	1	0.26
Human utility	Picnic area	Human utilities for each UGS were characterized based on the presence of eight amenity categories, with the total count of identified amenities per UGS rescaled on a scale from 0 to 1 to quantify the extent of amenities provided (Miguez et al., 2025).	0	1	1	0
	Playground		0	0	1	0
	Body of water		0	1	1	0
	Walk path		0	1	1	0
	Athletic facility		0	0	1	0
	Nature preserves		0	0.50	1	0.50
	Dog park		0	0	1	0
	Fitness center		0	0	1	0

elements within UGS, specifically the vegetation and water features, we selected several indicators: the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and percent coverage of various land cover types. The NDVI and NDWI maps were generated based on the Landsat 8 imagery with a 30-m resolution. The land cover data was derived from the global European Space Agency WorldCover datasets with a 10-m resolution (Zanaga et al., 2022), including 5 categories such as tree cover, grassland, herbaceous wetland, mangroves, and bodies of water. We examined multi-collinearity using pairwise Pearson correlation analyses (**Fig. A2**). While NDWI and water body coverage exhibited a moderate correlation (absolute value of correlation coefficient equals to −0.07), which is well below the commonly cited threshold for severe multicollinearity, we retained both variables because they further capture distinct hydrological aspects: the NDWI highlights open water features in satellite imagery, providing a continuous measure of water presence across an entire area, while water body coverage from land use products offers a discrete classification of permanent water bodies, making them distinct yet complementary metrics for assessing water features in a region (Zhang et al., 2023). We calculated the mean values of NDVI and NDWI for each UGS in 2021, as well as the proportion of each land cover type in UGS during the same year to ensure data consistency. Moreover, the biodiversity proxies and human utility metrics of each UGS were obtained from Miguez et al. (2025) with details shown in Appendix S4.

Lastly, we applied geographical random forest (GRF) model using the package '*SpatialML*' in R (Georganos et al., 2021) to analyze effects of included explanatory variables on CES in UGS. The GRF extends standard random forests by incorporating spatial lagged predictors to account for spatial non-stationarity, offering advantages over purely global models (e.g., ordinary least squares models) through localized interpretation while avoiding the linearity constraints of spatial regression models such as geographically weighted regression (Georganos et al., 2021). Our first analyses treated the number of present CES types (i.e., CES diversity) across each UGS as the dependent variable. We further utilized GRF to identify the most important factors explaining four key CES with the most abundant reviews: physical uses, entertainment values, aesthetic values, and experiential uses. We treated the proportions of these CES categories among all CES-related reviews as the response variables. To better understand how GRF addressed spatial heterogeneity, we mapped the spatial distribution of the standardized residuals. We also estimated spatial autocorrelation through local Moran's *I* to trace potential clustering in the residuals. Full details on the GRF and the determination of the fine-tuned hyperparameters can be found in Appendix S5**.**

3. Results

3.1. Overall characterization of CES detection

Our word cloud of CES-related entities (Table 1) provided visual and intuitive characterization of each CES. For example, the most representative labels of aesthetic values CES from the word clouds were associated with natural landscapes, including water features, vegetation, and biodiversity that was regarded as artistic representations of nature such as trees, water, birds, and species typical of Florida (e.g., alligators and iguanas). Keywords such as walking paths (18.16 % of entities identified as physical uses), dog parks (5.56 % of entities identified as entertainment values), athletic fields (5.66 % of entities identified as physical uses), and playgrounds (17.89 % of entities identified as entertainment values) were representative labels for entertainment and physical use CES to the public. Our word clouds (Table 1) also highlighted the different characteristics and roles that the UGS played in promoting other CES that include spiritual symbols, bequest and heritage values, and the educational and scientific research value of wild species and landscapes.

3.2. Spatial pattern of CES across UGS

Among all 10 analyzed CES, physical uses (46.29 % of reviews, $N = 14{,}166$), entertainment values (44.4 %, $N = 13{,}599$), aesthetic values (36.8 %, $N = 11{,}269$), and experiential uses (16.6 %, $N = 5{,}073$) were the most characterized and thus abundant CES across our studied UGS. However, there was substantial spatial heterogeneity in the number of CES-related reviews across UGS, with disproportionally more CES-related reviews in large and popular UGS (Fig. 1**b**). Further examination of the number of CES categories similarly showed spatial variations (Fig. 1**c**), with an average presence of 4.14 CES types across all UGS (standard deviation = 1.83). For example, compared to other UGS, Everglades Holiday Park, one of the most popular parks offering rich opportunities for airboat tours and animal encounters in our study region, showed the most noticeable presence of CES, with the highest number of both CES-related reviews (4,819) and total reviews (5,480). In examining the specific CES, Diamond Head Park of Cooper City stood out with presence of only aesthetic value (i.e., all CES-related reviews were attributed to this CES). The educational value CES was best represented by the Plantation Preserve Park and Linear Trail of Plantation, where a notable 28.6 % of its CES-related reviews were attributable to the nature-related experiences and conservation knowledges of UGS. Hotspot of entertainment value CES was found at the Lafayette Hart Park, where all CES-related review focused solely on recreational activities.

Our results further show an overall positive relationship between total extracted reviews and total CES-related reviews (**Fig. A3a** in the Supplement). Similarly, significant logarithmic positive relationships were found between the number of CES types vs. total reviews (**Fig. A3b** in the Supplement) and total CES-related reviews (**Fig. A3c** in the Supplement), suggesting that UGS with more CES-related reviews tended to provide a more holistic set of CES.

3.3. CES tradeoffs, synergies, and bundles

Overall, there were more positive correlations among different CES in UGS than negative correlations, indicative of more occurrences of synergies rather than tradeoffs among CES (Fig. 5 **and Fig. A4**). Specifically, CES of aesthetic value and educational value both showed positive correlations with six other CES (e.g., with bequest, existence value, experiential use, heritage value), and similarly, CES of existence value and experiential use also showed positive correlations with five other CES. In contrast, physical use CES showed negative correlations (i.e., tradeoffs) with four CES (e.g., aesthetic value, bequest value, entertainment value, and experiential value) (Fig. 5), and likewise, entertainment value also showed negative correlations with three other CES, such as aesthetic value, physical use, and symbolic value (Fig. 5). Across all CES, scientific value showed the least significant correlations (regardless of direction), which could potentially suggest a weaker tendency to spatially co-exist with other CES compared to other services.

Our cluster analyses showed that using six clusters best captured the variation in UGS based on the percentage of CES-related reviews. This was evident from the highest silhouette width index values of 0.228 for all UGS and 0.185 for the top 25 % of UGS. Consequently, we classified UGS into six groups, each representing a distinct CES bundle type. UGS belonging to the same CES bundle showed similar CES supply patterns (Fig. 6**a** of the top 25 percentile of UGS, and **Fig. A5a** of all UGS). For example, as for the two most frequent bundle types mapped onto the top 25 percentile of UGS, Bundle 1 (Fig. 6**b**, accounting for 39.0 % of selected UGS, $N = 41$) was characterized by dominance of aesthetic value, heritage value, and existence value yet with lower presence of bequest value. Bundle 2 (Fig. 6**c**, accounting for 41.0 % of those UGS, $N = 43$) comprised UGS that had very high entertainment value but with low symbolic value. Bundle 3 (Fig. 6**d**, $N = 2$) comprised UGS that had low aesthetic and entertainment values. UGS of Bundle 4 (Fig. 6**e**, $N = 9$) provided abundant aesthetic value and bequest value, with less presence of entertainment value, symbolic value, and physical use service. Bundle 5 (Fig. 6**f**, $N = 2$) encompassed UGS that had below average scientific value and entertainment value, but high bequest value. UGS in Bundle 6 (Fig. 6**g**, $N = 8$) were found to provide moderate-to-high levels of almost all types of CES, except for physical use. Similar CES bundle results were found for analyses conducted across all UGS (**Fig. A5**).

3.4. Factors driving spatial pattern of CES across UGS

Our analysis indicated that spatial clustering of model residuals was not evident in most areas, with residuals randomly distributed, suggesting that GRF effectively addressed spatial heterogeneity in most UGS (**Fig. A6** of the Supplement). The global variable importance scores from the random forest in **Fig. A7** of the Supplement and the average local importance values from the GRF model in Fig. 7**a** were analyzed to identify key predictors. Variables with the highest importance scores in both analyses—total area of UGS, tree cover percentage, biodiversity proxy, and mean NDWI index of UGS—were found as the most influential predictors of CES diversity across UGS. Moreover, the local model offered a spatially explicit representation of how the importance of variables differed across different UGS, as shown in Fig. 7**b.** Among these factors, tree cover percentage (25.4 % of UGS) and total UGS area (23.9 % of UGS) similarly served as the most important predictors. Interestingly, for the Everglades Holiday Park, which had the most abundant CES-related reviews, biodiversity proxy was the factor that most significantly influenced people's appreciation and enjoyment of different CES.

For four key CES categories, UGS size was consistently the most influential factor (21.05–27.23 % relative importance), aligning with overall CES diversity results. Biodiversity and tree cover served as particularly significant for aesthetic and experiential value, respectively, highlighting how different factors could influence specific CES values. Detailed results for individual CES categories are provided in Appendix S6 and **Fig. A8**.

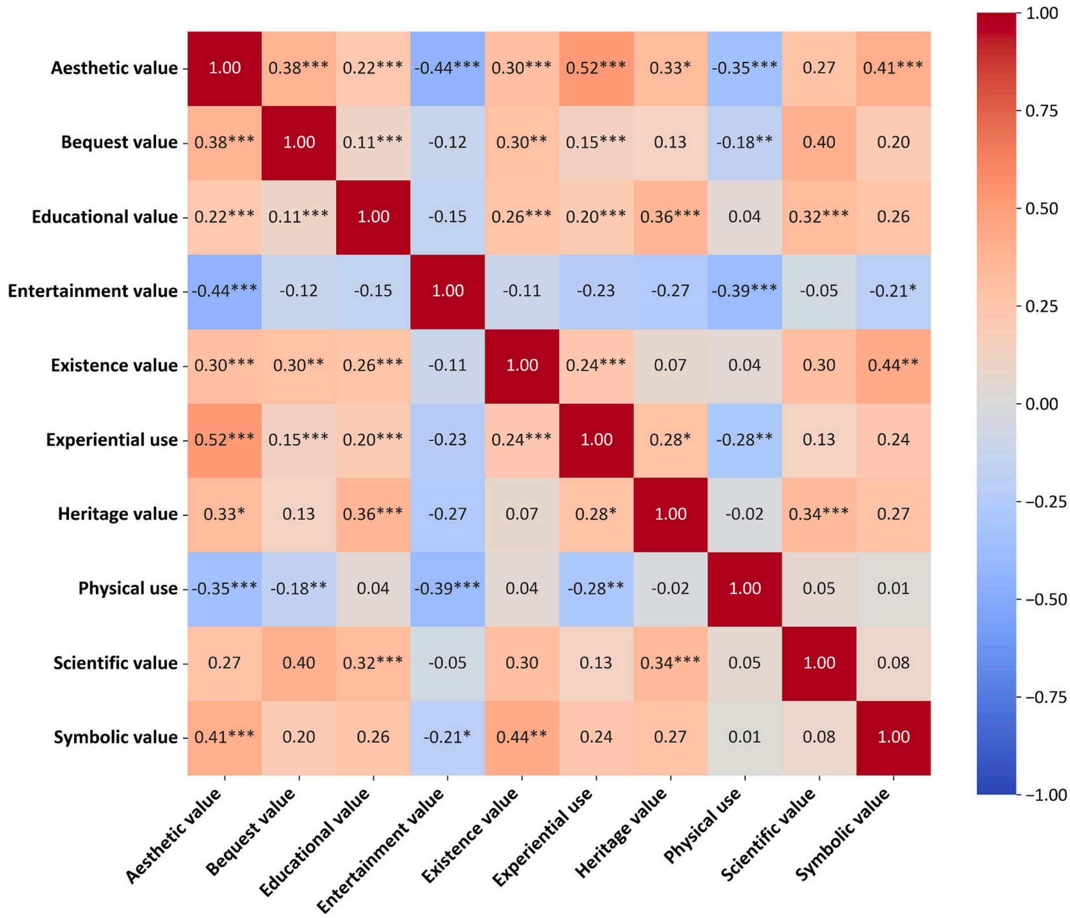


Fig. 5. Correlation matrix for the proportion of various cultural ecosystem service (CES)-related reviews to the total (Top 25 % UGS of most CES-related reviews). The results of all UGS can be found in Fig. A4 in the Supplement. Each cell contains the correlation coefficient followed by the significance level (*** for $p < 0.001$, ** for $p < 0.01$, and * for $p < 0.05$).

4. Discussion

4.1. *Characterizing CES of UGS using machine learning methods and crowdsourcing data*

By integrating machine learning approaches with extensive online reviews, we explored spatial patterns among a wide range of CES across different UGS and investigated the relative importance of various social and ecological factors that underly CES provision in UGS. Our study holistically investigated a portfolio of essential CES, their spatial patterns and interactions and determine how the interplay of different factors collectively influence the presence, supply, and diversity of CES across UGS, which is necessary for optimizing urban landscape design and achieving their multifunctionality. In addition, our corpus of CES based on multiple and complementary sources of crowdsourcing textual review datasets and advanced NLP techniques provided novel insights into the perception, use, and provision of multiple CES, which remain thus far less well understood. Further, our research also highlights spatially explicit implementation of machine learning methods by incorporating spatial dimensions and metrics directly into the modeling process of GRF. In tandem, our findings offer a more data-driven understanding of CES, moving beyond traditional survey-based methods to capture real-world user experiences at scale (Li et al., 2024; T. Zheng et al., 2024). Our research provides a framework to quantify and understand spatial patterns and interactions among CES, which can be applied to other landscape contexts besides urban settings, such as protected areas, national parks, or others.

4.2. *Understanding of CES synergies and tradeoffs in UGS*

Our research revealed more frequent occurrences of CES synergies than tradeoffs, indicating opportunities to manage UGS to simultaneously enhance multiple CES. Such results were conceptually similar to previous findings in other urban landscape contexts (e.g., Cheng et al., 2022). Specifically, the strongest positive synergies occurred in the interactions between aesthetic value and experiential value, which indicated that aesthetic enjoyment and some of the nature-focused recreational activities like observing wildlife highly overlap with use of urban parks. Management efforts, or interventions to improve aesthetic value of UGS are likely to enhance experiential value as well as other positively correlated CES (e.g., existence value and heritage value CES). Tradeoffs between aesthetic value vs. entertainment value and physical use CES were revealed, suggesting that certain entertainment- or physical use-focused activities may detract from the appreciation of natural beauty in UGS. These results align with our bundling analyses and with previous findings that highlight how certain activities could redirect people's attention away from the surrounding natural environment, potentially diminishing their capacity for aesthetic appreciation and engagement with the visual qualities of the greenspaces (Korpela et al., 2001; Schebella et al., 2017). It, to some extent, also alludes to the dichotomy between human-centered and nature-centered use and values towards landscapes that include UGS (Sweikert and Gigliotti, 2019; van Koppen, 2009).

Our analysis revealed the diversity and connections in the interactions among CES in UGS, identifying six different CES bundles that challenge current classification systems. Such understanding of complex

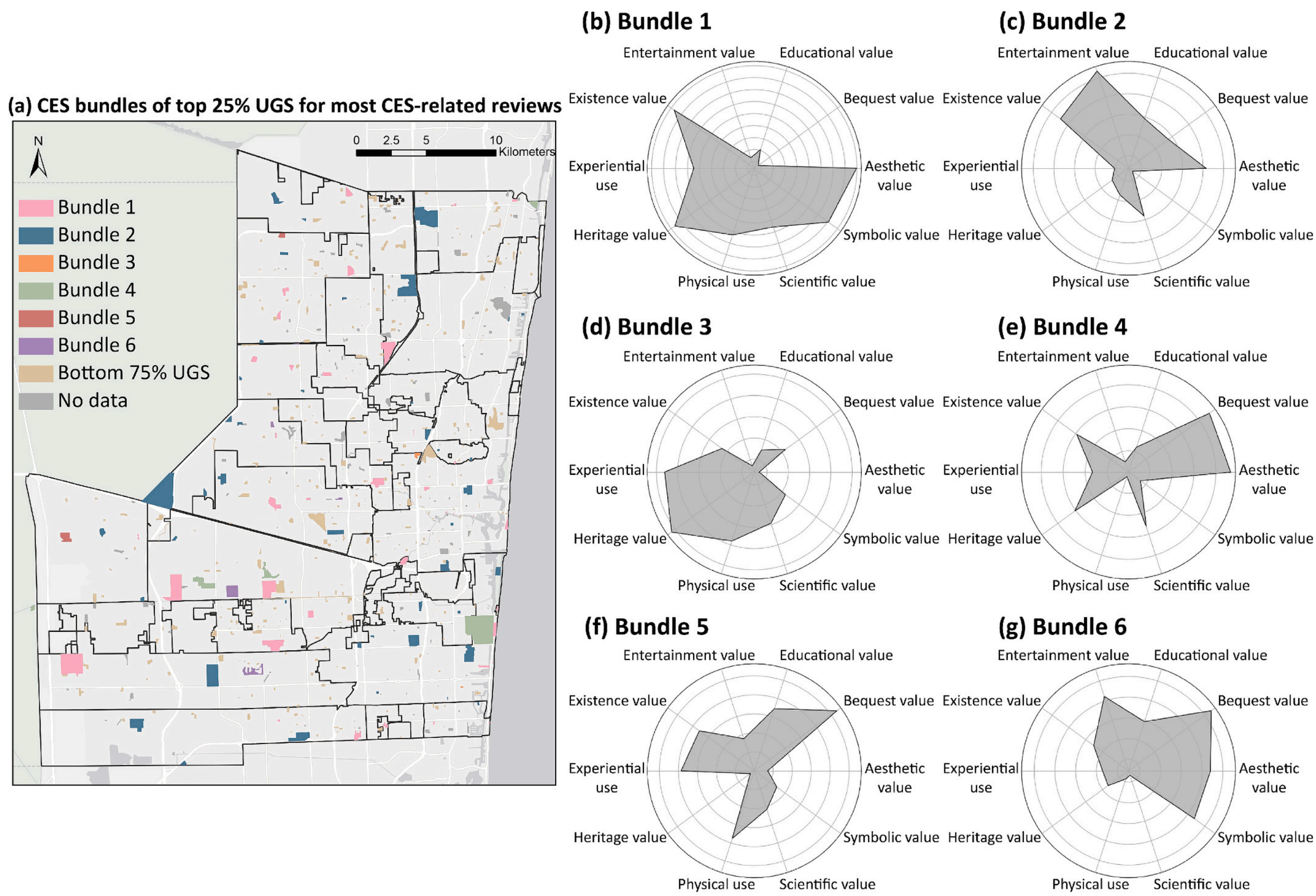


Fig. 6. (a) The spatial distributions of the six identified CES bundles across urban UGS. UGS included in the same bundle are highlighted in the same color. We chose to present here the results of the top 25 percentile of UGS based on the abundance of CES-related reviews. The results of all UGS can be found in Fig. A5 in the Supplement. (b)-(g) CES bundles and relative abundances of CES. The main CES in the six bundles are represented by rosette diagrams. The diagrams are dimensionless, as they are based on normalized data for each service, and a larger petal length indicates higher provision of a particular service. In the legend, "No data" indicates UGS for which no CES-related reviews were found.

CES interactions not only deepens our understanding of how people perceive and value urban nature, but also provides urban planners and managers with a powerful tool for optimizing greenspace design and urban landscape management, allowing them to strategically enhance synergies and mitigate tradeoffs among different cultural services (Plieninger et al., 2015). A strong co-occurrence of aesthetic value with spiritual-related values, particularly heritage, existence, and symbolic values, was observed in greenspaces, aligning with Cooper et al. (2016), who frequently coupled aesthetic and spiritual services, conceptualizing both as psychological benefits derived from human-nature interactions. According to our results, some of the CES found comparing to the divisions of current classification systems (i.e., CICES; Haines-Young and Potschin-Young, 2018) such as cultural heritage preservation, aesthetic appreciations, symbolic and existence interactions should rather be classified in the spiritual division. In the case of CICES, for instance, there are separate divisions for 'physical and intellectual interactions' and for 'spiritual, symbolic and other interactions'.

4.3. Key factors underlying CES provision across UGS

Our results revealed that natural elements, particularly water and vegetation features, tended to exert a positive effect on presence of aesthetic CES in UGS. There is a growing consensus on the significance of design in urban green and blue spaces, as these enhance the visual aesthetic appealing and promote landscape satisfaction of urban residents (Gascon et al., 2015; Li et al., 2020). The presence of and engagement with green and blue spaces is a positive indicator in the individualized or collectivized well-being, outdoor activities and pro-environmental behaviors (van Heezik et al., 2021). Water features are of particular importance due to their ability to captivate and evoke pleasant mental images (Völker and Kistemann, 2015). Reflections in water bodies could create a sense of spaciousness and tranquility, enhancing the overall aesthetic appeal (Deng et al., 2020). Furthermore, prioritizing trees, shrubs, and aquatic plants within greenspaces appears to be essential for maximizing resident satisfaction (Paudel and States, 2023). These diverse plant forms contribute to a multi-sensory experience that positively impacts landscape perception.

Biodiversity can be perceived by people within UGS, which also significantly influences CES by enhancing landscape aesthetics, promoting a sense of place, and potentially improving wellbeing (Cameron et al., 2020). Our study aligns with the findings of Qiu et al. (2013), who determined that highly biodiverse areas may not be the most preferred, with people often favoring more ornamental park settings that may have fewer ecosystem services. For example, among the top ten UGS with the highest biodiversity values, biodiversity served as the primary factor in the provision of CES diversity for only two greenspaces. This result highlights a potential conflict between recognizing the importance of biodiversity and traditional aesthetic preferences for UGS that appear neat and orderly. Thus, there needs to be a shift in how people perceive biodiversity to foster greater appreciation for their importance in ecosystem services provision. Importantly, our spatially explicit perspective and GRF allows us to further disentangle spatial variations

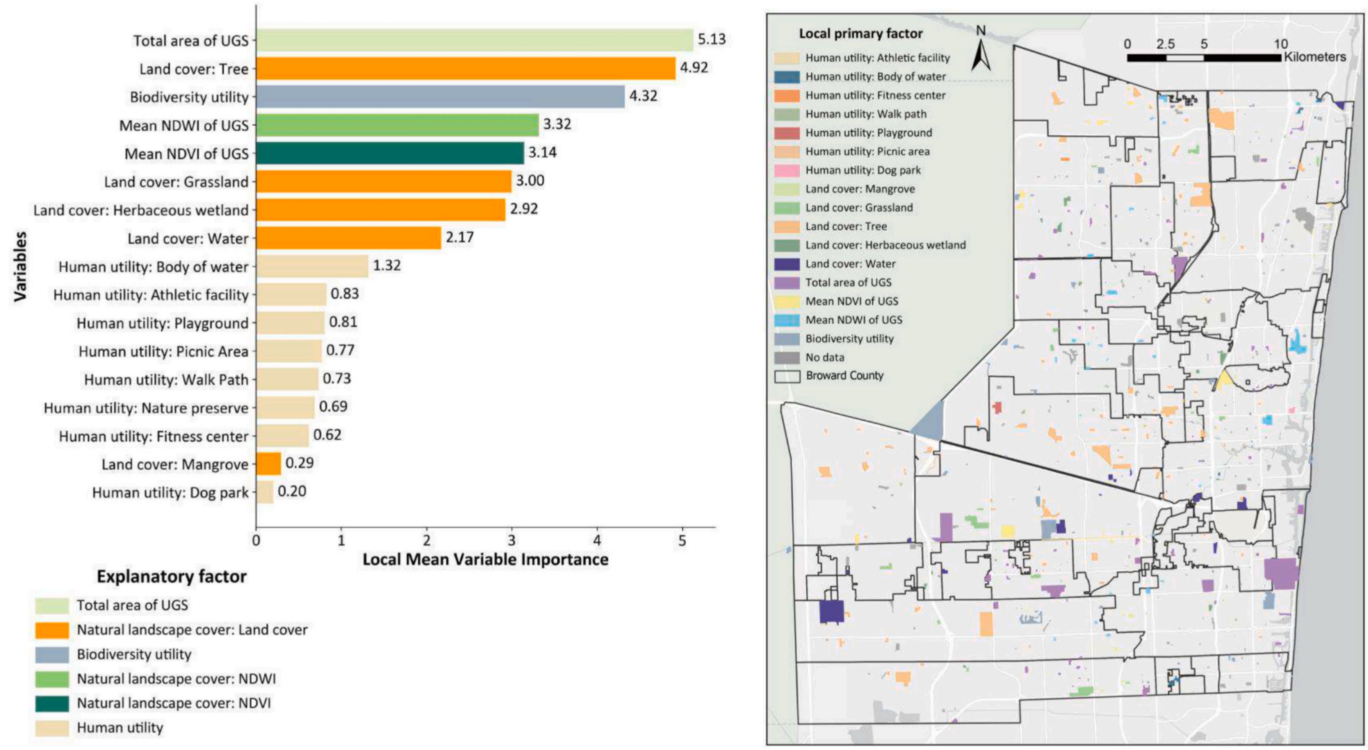


Fig. 7. (a) Aggregated variable importance of geographical random forest for predicting the number of CES categories of UGS. (b) Spatial distribution of importance of key factors for predicting the total number of CES categories present in each UGS. In the legend, "No data" indicates UGS for which no CES-related reviews were found.

in the relative ranking of factors driving CES across UGS, highlighting the importance of management and decisions at the scale of individual UGS to target factors that are mostly locally-relevant for providing CES.

4.4. Implications for UGS sustainable planning and management

Overall, all policies and management strategies in UGS (e.g., public facility planning and regional ecological protection) directed toward influencing human use of landscape resources should meet the wellbeing and cultural needs of the public (Dickinson and Hobbs, 2017). An integrated conservation strategy should be implemented that prioritizes the preservation of high CES-diverse regions and biodiversity hotspots, acknowledging potential spatial incongruences between these two conservation objectives. In greenspace management and landscape design, there is a strong need to develop ecological corridors within public spaces that integrate human activities with wildlife habitats (Beaugeard et al., 2021). A greater emphasis on landscape elements of UGS includes more expansive green areas, employing techniques such as multi-layered and vertical planting to maximize greenery, and thoughtfully integrating water scenes to create visual connections with the natural landscapes, which can lead to the simultaneous provision and improvement of multiple CES in UGS (Li et al., 2020). The capacity of greenspaces ecosystems and landscapes to supply direct or indirect benefits to society has long been assessed in landscape planning (Dade et al., 2020). Our study supports the view that a collaborative, integrated, and holistic assessment and evaluations of CES should become part of urban and regional landscape planning (Plieninger et al., 2013), thus incorporating synergies and tradeoffs in the form of CES bundles in relation to planning, design and management considerations.

4.5. Limitations and future research prospects

Our study addresses the under-investigated issues related to UGS and its CES, and opens the door for future research. First, digital divides can present challenges in researching the actual origin of landscape perceptions and the inclusivity of representation from a broader population through social media platforms (Cao et al., 2022; Hamstead et al., 2018). Our analysis only included UGS visitors who were also users of those review platforms. Therefore, further research is needed to investigate whether preferences observed in crowdsourced data sources, such as social media data, align with those identified in large-scale surveys (Choudhry et al., 2015). Furthermore, while necessary for considering representativeness and comparability based on the prior framework, this scope of the specific definition and selection criteria for UGS (Miguez et al., 2025) resulted in an analysis might not capture the full spectrum of CES from all urban green infrastructure types. The detailed rationale for these exclusions is provided in Miguez et al. (2025), and exploring CES in those excluded spaces remains an avenue for future research. Additionally, characterizing human utility based on specific amenity features facilitated a large-scale assessment across numerous UGS. We acknowledge that this characterization might simplify the complex reality of utility provision and not fully capture nuances like feature quality or size. Future research could employ more detailed metrics to enrich human utility assessments. Second, the exploratory variables were derived from a specific context in UGS of South Florida. A more generalized set of indicators can be formulated by exploring other UGS that vary in landscape elements and other socioeconomic contexts. This broader investigation would enhance the applicability and robustness of the findings across different geographic regions and social-environmental contexts. For example, a future study could include UGS across a climate gradient or different UGS in neighborhoods with varying socioeconomic demographics. Third, manually labeling named-entities to generate the initial corpus for CES-related entities is a time-consuming and labor-intensive task. However, combining weak supervision with limited manual labeling or unsupervised NLP techniques with knowledge bases could yield similarly convincing results while reducing effort. Fourth, our findings challenge existing classification systems (e.g., CICES) by revealing CES bundles that cross traditional categories. Thus, more future research is needed to determine whether other UGS and urban areas also exhibit these similar CES bundles for the sake of sensible classification frameworks (e.g., reconciling aesthetic/spiritual divisions) and improve indicator applicability across diverse urban landscapes.

5. Conclusion

Our study underscores the interactions among a wide range of CES in UGS by exploring the spatial heterogeneity of these critical services and their underlying drivers. Our results demonstrate the potential of integrating machine learning approaches and crowdsourced data to understand the complex relationships between UGS attributes and CES provision. Three key findings emerged. First, aesthetic, entertainment, physical, and experiential CES were the most characteristic UGS experiences, indicating urban residents' preferences of accessible recreation and sensory perceptions with nature. Second, synergies among CES were more dominant than tradeoffs. Third, factors such as UGS size, tree cover percentage, biodiversity, and water features were found to be strong predictors of CES diversity and provision. We envision a scenario in the future where as municipalities attempt to increase and bolster ecosystem services provided by UGS, and social media data, as demonstrated here, could provide a valuable means for tracking progress towards these urban policy and intervention goals. Our findings provide valuable insights for UGS planning and management, emphasizing the importance of conserving natural landscapes, promoting biodiversity, and incorporating human utilities to meet the community's cultural needs and enhance overall well-being.

CRediT authorship contribution statement

Haojie Cao: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Nataly G. Miguez:** Writing – review & editing, Investigation, Data curation. **Brittany M. Mason:** Writing – review & editing, Investigation, Data curation. **Corey T. Callaghan:** Writing – review & editing, Methodology, Conceptualization. **Jiangxiao Qiu:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization.

Declaration of competing interest

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

Acknowledgements

We acknowledge the financial support of this work from the U.S. Department of Agriculture (Project FLA-FTL-006277, FLA-FTL-006371, 2021-67013-33617) as well as partial funding support from the University of Florida School of Natural Resources and Environment.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2025.101740.

Data availability

Data will be made available on request.

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