Urban Forestry & Urban Greening 95 (2024) 128289

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

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

Original article

Evaluating implied urban nature vitality in San Francisco: An interdisciplinary approach combining census data, street view images, and social media analysis

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ARTICLE INFO

Keywords:
Urban Green Space
Deep learning
Big data
Socio-economic factors
Flickr

ABSTRACT

Urban green spaces (UGS) are vital in modern cities, offering extensive health, social, and environmental benefits. However, traditional research methods primarily focus on UGS distribution and aggregation through 2D mapping, often neglecting the quality and vitality of urban natural environments. This limited approach hampers our full understanding of the complex issues and opportunities surrounding UGS. This study proposes a novel concept of Implied Urban Nature Vitality (IUNV) and evaluation framework that offers a comprehensive lens to understand better and evaluate the manifold human-urban-nature interactions in modern cityscapes. Based on our IUNV framework, an interdisciplinary investigation is conducted to show the distribution and population-level perceived IUNV in San Francisco by leveraging a triad of data sources: census, street-built environment, and social media data. Utilizing census data, we analyze socio-economic influences on UGS distribution and IUNV, including factors such as education, age demographics, income, and ethnicity. Street view imagery (SVI), analyzed with advanced image recognition algorithms, serves as a proxy for visual and physical aspects of IUNV, highlighting features like trees, sky, buildings, and roads. This analysis paints a granular picture of UGS's spatial distribution and physical attributes, facilitating an objective measure of IUNV. Subsequently, we analyze Flickr photos related to urban natural areas, examining their distribution and identifying thematic clusters that illuminate various aspects of UGS vitality. Lastly, we combine computer vision and manual review to define 12 IUNV themes from architecture and nature, eco-friendly gatherings, to cultural performance, exploring the relationship between the vitality clusters and the independent variables. The main findings are: (1) Macro-level factors (e.g., accessibility level, land use mix level, road density, population density, etc.) are the dominant variables influencing IUNV.; (2) Street view factors play key roles in IUNV. Through this holistic IUNV analysis, the study shed light on the complexities of urban green space planning and management, informing future urban development strategies towards greater vitality and, by extension, environmental and social sustainability.

1. Introduction

1.1. Urban nature vitality

The expansion of cities and increasing urban density raise concerns about adverse effects on residents' physical and mental health (Hummel, 2020). Urbanization impacts health through air pollution, noise, reduced physical activity, and increased social isolation (Liu et al., 2022; Uttara et al., 2012). Urban Green Spaces (UGS) including parks, gardens, and tree-lined streets, are pivotal to urban quality of life. (Dong et al., 2022; Lopes and Camanho, 2013). UGS underpin the ecological, social, and economic vitality of cities, acting as the lungs of urban areas, enhancing air quality (De Ridder et al., 2004), reducing the impact of urban heat islands (Xu et al., 2022), promoting biodiversity (Faeth et al.,

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https://doi.org/10.1016/j.ufug.2024.128289
Received 26 November 2023; Received in revised form 6 February 2024; Accepted 14 March 2024
Available online 15 March 2024

2011), supporting social cohesion (Mouratidis and Poortinga, 2020), and offering recreational havens for city residents (Park and Ewing, 2017). Such knowledge is essential for urban planning and development towards social and environmental sustainability.

While benefits have been identified with the mere presence of UGS, a growing body of literature suggests that the presence and vitality of such spaces are important determinants of human well-being (Mouratidis and Poortinga, 2020). Some previous research studied urban vitality and explored its relationship with other built environment factors through big data-based methods (Chen et al., 2021; Li et al., 2022). Other researchers measured the small public space vitality through the people's density, trajectories, and duration of stay (Niu et al., 2022; Wang et al., 2022,2022). However, research on the vitality urban nature vitality remains relatively sparse. The diverse composition of green infrastructure, including large parks, community gardens, and street trees, holds significant potential for supporting resident vitality. The vitality of UGS refers to their capacity to provide a range of benefits and services to urban dwellers, which indicates that vibrant green spaces enhance social cohesion, promote physical activity, and improve mental health among residents. Several studies have identified various factors that shape the distribution patterns of green spaces (Boulton et al., 2018; Kabisch, 2019). Population density and land use patterns play a crucial role, as densely populated areas with limited open spaces often experience a lack of UGS (Li et al., 2017). Implied Urban Nature Vitality (IUNV) is based on the premise that collecting data from city users to understand the value of UGS is fundamentally connected to their interactions with urban dwellers and the socio-economic context of the city. IUNV, therefore, embodies a more comprehensive approach to assessing urban nature by combining objective measures, such as the distribution and physical attributes of green spaces, with subjective perceptions that are gleaned from community involvement and social media analysis (Kabisch et al., 2015; Lin et al., 2014). By acknowledging the complex interplay between the physical environment and human perception, IUNV offers a comprehensive framework for understanding and enhancing UGS's role in urban ecosystems.

1.2. Census data, Street View Imagery (SVI), and social media data for vitality measures

We broaden the investigation to encompass three data sources: census data for socioeconomic insights, SVI for visual and physical attributes of UGS, and social media data for population-level perspectives, collectively offering comprehensive insights into UGS distribution. Current literature has proved that census data provides insights into socio-economic factors affecting UGS (Lopes and Camanho, 2013; Wüstemann et al., 2017). SVI enhances our visual understanding of UGS by identifying key features of the built environment (Chen et al., 2020; Chen and Biljecki, 2023). Geotagged photos and posts from social media reveal residents' interactions and sentiments toward UGS, providing a nuanced view of urban nature vitality (Ghahramani et al., 2021; Chen et al., 2022; Roberts et al. 2018).

Socio-economic disparities can also result in unequal access to UGS, as lower-income neighborhoods may have limited green infrastructure compared to wealthier areas (Pinto et al., 2021). The direction of the causality in this relationship may even be inverted, with access to UGS having been suggested to raise real estate values, rendering areas with stronger access more well-off than areas with less such development (Chen et al., 2022). Urban planning policies and zoning regulations significantly impact UGS provision and the inclusion of green spaces in development projects (Pallathadka et al., 2021).

Prior research has explored various determinants of urban green space distribution and vitality, utilizing census data, SVI analysis, and geographically explicit social media information to harmonize these determinants. Census data has been valuable for understanding demographic and socioeconomic characteristics and their influence on urban green spaces, revealing patterns and disparities related to income, education, race/ethnicity, and age.

SVI is a valuable tool for assessing UGS quantity, quality, and spatial distribution. Computer vision algorithms can automatically identify UGS features, like parks and green infrastructure elements, and capture UGS conditions, such as maintenance and safety. This technology enables large-scale UGS analysis by segmenting images to extract urban elements and using classification techniques to categorize images based on content, facilitating the study of UGS distribution and its relationship with IUNV.

Moreover, crowdsourcing in urban planning enables the capture of diverse perspectives and local knowledge of urban green spaces beyond what official records may provide. The use of user-generated geographic information, particularly from social media platforms, has gained prominence in understanding UGS's usage and preference and demonstrated the potential of measuring IUNV (Heikinheimo et al., 2020). Social media platforms such as Flickr, Instagram (Y. Song et al., 2020, 2020), and Twitter have become valuable sources to study user experiences related to parks and recreational spaces. By analyzing social media posts, such as geotagged photos and user check-ins, researchers can identify popular UGS destinations, recreational activities and map UGS distribution patterns using platforms such as OpenStreetMap (OSM) (Cui et al., 2021; Ghahramani et al., 2021). Social media analysis also allows for real-time monitoring of UGS trends and identifying emerging issues or opportunities. For example, researchers have explored the link between UGS attributes and user sentiments expressed through social media platforms, shedding light on UGS's perceived vitality and quality (Ma et al., 2021). By involving citizens, crowdsourcing adds depth and richness to understanding urban green spaces beyond what official records may provide.

Integrating census sources, SVI with other geospatial data, such as land use data, socioeconomic data, environmental data, and social media analysis, can enhance the understanding of the contextual factors influencing UGS vitality. By linking SVI with these datasets, researchers can examine the relationship between UGS characteristics and various contextual factors, such as neighborhood demographics, land use patterns, and environmental conditions (Sun et al., 2021).

1.3. Research gaps

The study aims to address several literature gaps identified above. Firstly, this research will explore the relationship between urban features and UGS distribution in San Francisco, aiming to uncover disparities in accessibility across various demographic groups through census data and SVI. A complete understanding of these disparities can better equip designers to design and allocate urban green spaces more equitably.

Secondly, although previous studies have examined the physical attributes of UGS, our study emphasizes the importance of subjective perceptions and preferences captured through social media analysis. This study will also explore the role of social media data in shaping the distribution and vitality of UGS in San Francisco, providing a more comprehensive understanding of the factors contributing to urban green spaces' success.

San Francisco, a densely populated city in California, is celebrated for its diverse urban landscape and commitment to environmental sustainability. Despite its relatively small geographical area, the city boasts an extensive network of parks, open spaces, and green streets. However, the distribution and accessibility of these UGS are not uniform across the city, leading to disparities in the benefits enjoyed by different communities. This research provides a holistic understanding of the factors influencing UGS distribution and vitality in San Francisco by analyzing the relationships between census data, SVI indices, and social media data. The main research questions are: 1) What are the dynamics of the interactions between the socioeconomic data (education, age, income, ethnicity, health, etc.), the street view index, and the social media data? 2) What types of vitality can be clustered through the spatial analysis of social media images, and what are their characteristics?

While some elements of these questions have been investigated by the previous studies identified above, the novelty of this investigation involves using a more comprehensive viewpoint, combining three strategies that are well-supported in the literature to help shape a more nuanced understanding of UGS concerns related to equity. This study employs a tri-pronged approach: census data, street-level image analysis, and spatially explicit social media analysis. This methodology aims to provide a more nuanced understanding of UGS, particularly concerning equity concerns, by revealing insights that might be less apparent when using more singular research methods.

2. Methodology

2.1. Study area & research flow

This study centers on San Francisco, examining IUNV and its influencing factors through the lens of census tracts as spatial units. Excluding two relatively isolated regions, Census Tracts 9804.01 and 179.03, we utilize the remaining 240 spatial units for our research. San Francisco, a densely populated metropolis on the American West Coast, spans an area of 121.4 km^2. According to data predictions from the United States Census Bureau, San Francisco's population in 2022 was estimated to be 808,437 (U.S. Census Bureau, 2022).

Simultaneously, it stands as a cultural, commercial, and financial hub in Northern California, renowned for its diverse cultural makeup and community structure (Chion, 2009). San Francisco hosts conventional public parks and green spaces, and since 2005, it has also initiated the development of various smaller parks. These additions aim to supplement the city's open green spaces, thereby supporting the activity requirements of its residents (Littke, 2016). Consequently, San Francisco provides an ideal research scope for understanding the relationship between urban street spatial patterns, nature vitality, and the distribution of green spaces.

The workflow of this study shows three steps (Fig. 1).1: Data acquisition and preparation, data processing, and spatial data statistics. In the data acquisition and preparation section, we create a comprehensive dataset including road network and land-use data from OpenStreetMap (OSM), SVI from Google Maps, social economic data from the census, and social media photos from Flickr. In the data processing section, we use GIS, computer vision, and unsupervised machine learning methods to process the vector data and image data. In the last section, we set up dependent and independent variables and establish the spatial regression model to explore the variables that affect urban nature vitality. Images from Flickr are used to illustrate the IUNV for the study area.

2.2. Independent variables calculating

2.2.1. Census data: social-economic measurement

Urban character is deeply interconnected with its residents (Ravenscroft, 2000). Expanded upon by Lan et al. (2020) and Paköz et al. (2022), Jacobs's seminal urban vitality theory underscores the critical role of youth in energizing urban vitality (Jacobs, 1961). Concurrently, race and ethnicity, as foundational elements of urban life, create diverse combinations that influence urban vitality (Wilder, 2020). The youth, as

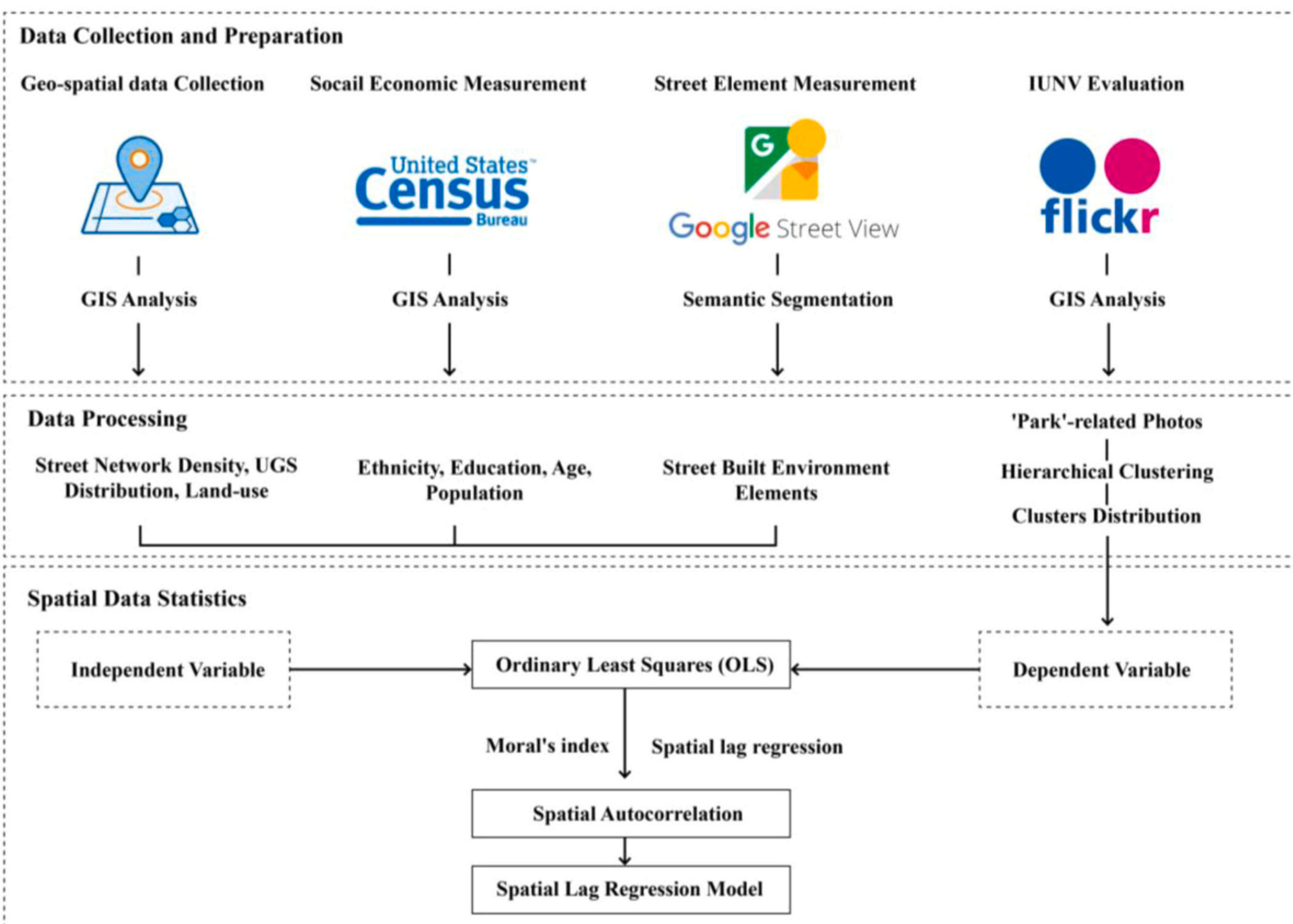


Fig. 1. Research method and framework.

the primary workforce and consumer base, and being the predominant social media users, significantly enhance economic growth and urban vitality. In contrast, an aging demographic presents challenges to sustainable development, affecting the city's liveliness (Jarzebski et al., 2021). Considering these insights, we derived socio-demographic data from the CDC's Social Vulnerability Index 2020 project, which is based on statistics from the American Community Survey five-year estimates from 2016 to 2020. For San Francisco, this data is summarized on a census tract level. We have selected nine variables, including total population, population below 150% of the poverty line, population 25 years and older without a high school diploma, population aged 65 and older, population aged 17 and younger, Black/African American population not Hispanic or Latino, Hispanic or Latino population, Asian population not Hispanic or Latino, and American Indian or Alaska Native population not Hispanic or Latino. These variables encompass aspects such as population size, poverty status, educational attainment, age distribution, and ethnic composition, among other.These variables were primarily selected based on practical concerns regarding information available from census data and are not intended to be an exhaustive set of all variables affecting UGS vitality. This selection aims to provide a comprehensive overview of factors contributing to describing IUNV in the spatial units. Fig. 2 and Table 1 comprehensively explain all the census variables.

2.2.2. SVI: objective built environment elements

The significance of urban nature vitality extends beyond parks and large green spaces to include small green areas adjacent to streets, street trees, and linear green spaces, all of which are vital for improving the ecological quality and well-being of city dwellers (Kong & Nakagoshi, 2006; Li et al., 2015). We conducted SVI to quantify street-level built environment elements (Fig. 3). Google Street View (GSV) offers a comprehensive dataset of detailed and reliable street images (Kang et al., 2020). Initially, we sourced road network data from OpenStreetMap (OSM) renowned for its extensive user-generated mapping database. We extracted points at regular 10-meter intervals along the streets of San Francisco, yielding a total of 26,810 distinct points. We utilized GSV Static API (https://developers.google.com/maps/documentation/streetview/overview) to derive images with constant camera settings (Li et al., 2018; Qiu et al., 2022). Each point served as a vantage point for capturing GSV images, culminating in a dataset of 26,810 SVIs.

After the image collection phase, we employed the ADE20K (Dong et al., 2023; Yang et al., 2023) dataset for image segmentation which is a

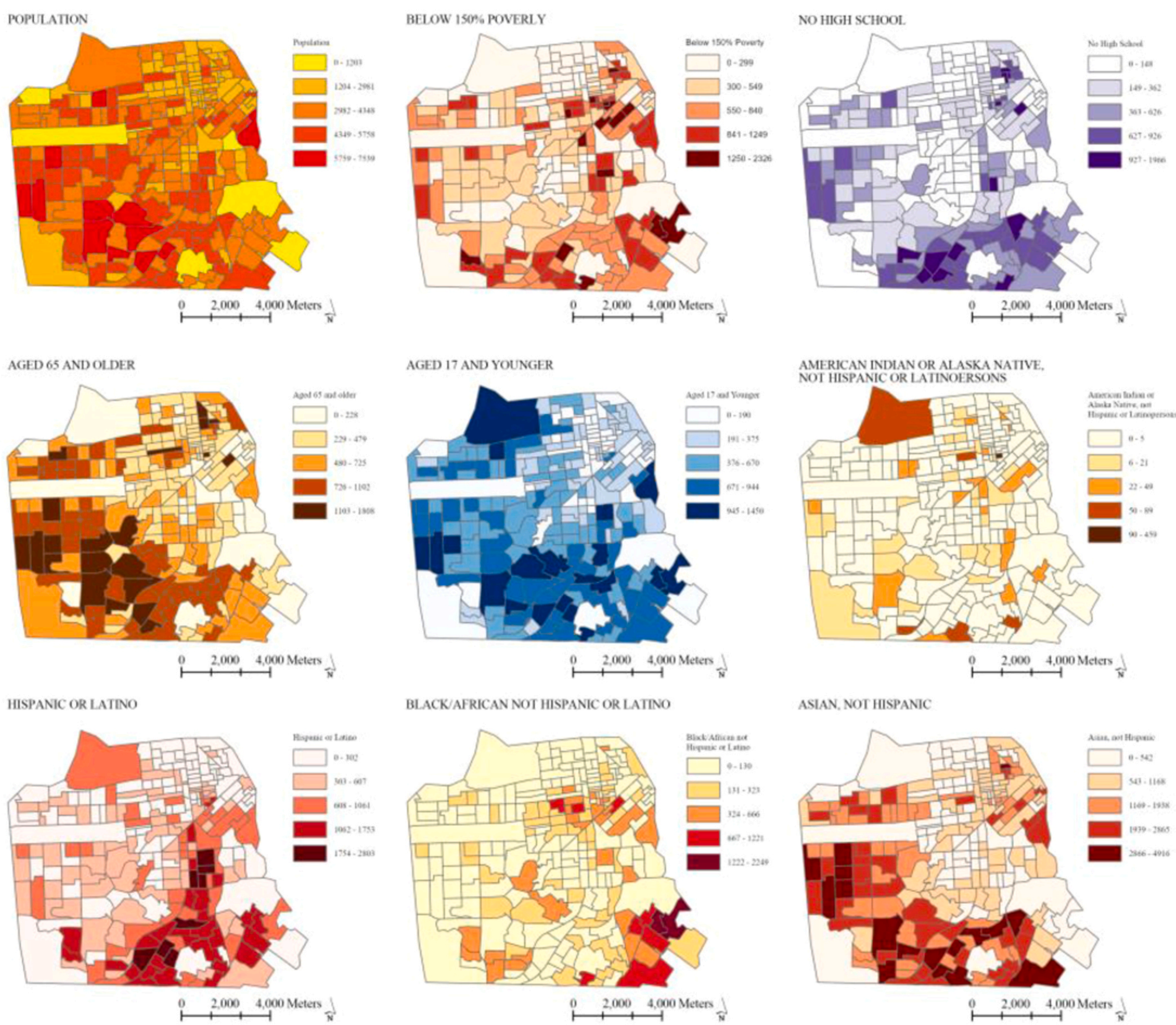


Fig. 2. Social economic measurement (education, ethnicity, age, population).

Table 1
All the census variables (N=241).

	Population	Below 150% Poverty	No High School
Description	Population estimate,2016–2020 ACS	Persons below 150% poverty estimate,2016–2020 ACS	Persons (age 25+) with no high school diploma estimate,2016–2020 ACS
mean	3816.286307	550.9128631	345.7178423
std	1403.009404	386.9644965	352.6527613
min	0	0	0
max	7518	2326	1966
	Aged 65 and Older	Aged 17 and Younger	American Indian or Alaska Native, not Hispanic, or Latino persons
Description	Persons aged 65 and older estimate, 2016–2020 ACS	Persons aged 17 and younger estimate,2016–2020 ACS	American Indian or Alaska Native, not Hispanic or Latino persons estimate,2016–2020 ACS
mean	629.8257261	490.8423237	4.336099585
std	389.5993063	343.0836512	11.44402609
min	0	0	0
max	1808	1450	89
	Hispanic or Latino	Black/African American, not Hispanic or Latino	Asian, not Hispanic
Description	Hispanic or Latino persons estimate, 2016–2020 ACS	Black/African American, not Hispanic or Latino persons estimate,2016–2020 ACS	Asian, not Hispanic or Latino persons estimate,2016–2020 ACS
mean	515.9626556	176.3112033	1319.556017
std	471.7130866	264.9966325	1027.781582
min	0	0	0
max	2803	2249	4916

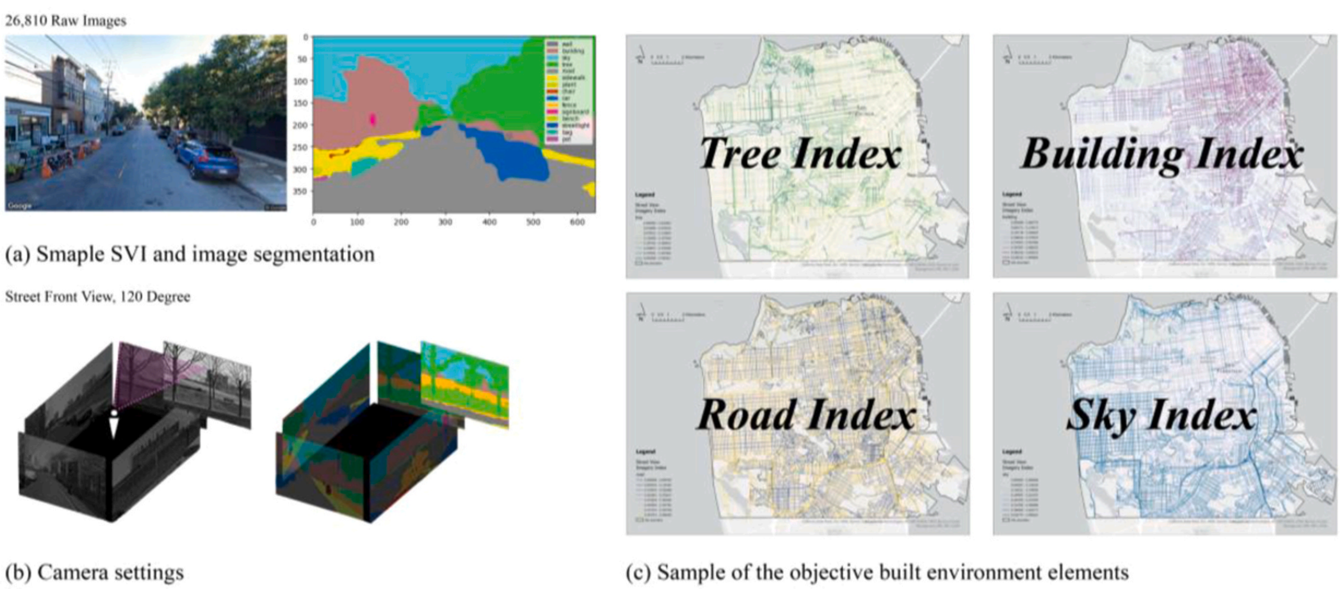


Fig. 3. The framework of objective built environment elements using SVI.

well-established dataset for computer vision with approximately 150 different object categories labeled for pixel-level semantic segmentation. Leveraging this tool, we divided each image into distinct segments (Fig. 3a). The camera setting is street front view and 120 degrees (Fig. 3b).

Following the image segmentation phase, we imported the segmented images into ArcGIS Pro 3.0. Within the GIS environment, we averaged the proportions of buildings, sky, trees, roads, etc. for each street (Eqs.1–4). This operation resulted in a spatial dataset where each street is associated with the average proportions of these elements (Fig. 3c).

$$P_{building} = \frac{1}{n}\sum_{i=1}^{n} \text{Building}_{n} \quad \{i \in (1, 2, \cdots, n)\} \tag{1}$$

$$P_{road} = \frac{1}{n}\sum_{i=1}^{n} \text{Road}_{n} \quad \{i \in (1, 2, \cdots, n)\} \tag{2}$$

$$P_{tree} = \frac{1}{n}\sum_{i=1}^{n} \text{Tree}_{n} \quad \{i \in (1, 2, \cdots, n)\} \tag{3}$$

$$P_{sky} = \frac{1}{n}\sum_{i=1}^{n} \text{Sky}_{n} \quad \{i \in (1, 2, \cdots, n)\} \tag{4}$$

2.2.3. Other independent variables: UGS accessibility, road density, and land use entropy

Moreover, we also calculated the UGS accessibility, road density, and land use entropy as independent variables. Research shows that urban residents in the US walk 1.3 mi, or just over 2 km, on average, during recreational walking trips, suggesting that 1000 m is the maximum average distance that most urban residents would walk to a park (Nesbitt et al., 2019). We conducted the OSM dataset to identify 442 distinct UGS in San Francisco by categorizing 'leisure park' attributes. We measured the UGS service distribution within 1000 m of each block group center in ArcGIS Pro 3.0 (Fig. 4a).

Built environment, at a macro-level scale. has shown an effective contribution to IUNV (Chen et al., 2023; Li et al., 2022). Including macro-level factors can help assess micro-level features' effects on explaining IUNV. Herein, we measured two factors: land use entropy, and road density. Land use diversity is an important element that significantly influences urban nature vitality (Fuller and Moore, 2017; Yue et al., 2019). To quantify a region's land use mix level, land use entropy is a commonly used metric that reflects the diversity level of land use. Ranging from 0 to 1, a higher number of land use entropy means relatively equal and diverse land use balance, while a land use entropy close to 0 represents only one type of land use (Chen and Song, 2020). In our case, we followed the method of Song et al. (2013). The calculation formula is as follows, where pj is the percentage of each land use type j and k is the total number of land use types (Eq. (5)):

$$Entropy = -\frac{\left(\left[\sum_{j=1}^{k} Pj \cdot InPj\right]\right)}{Ink} \tag{5}$$

Previous studies have indicated that street configuration significantly enhances IUNV (Li et al., 2022). Alterations in street configuration can impact urban functionality, land utilization, and accessibility levels. Therefore, road density is taken into consideration. A higher road density indicates more complex road conditions in a land parcel. This metric is calculated as the following formula, where L is the total length of each block and S is the area of this block respectively (Eq. (6)):

$$Roaddensity = \frac{L}{S} \tag{6}$$

2.3. Dependent variables: IUNV evaluation by social media photos from Flickr

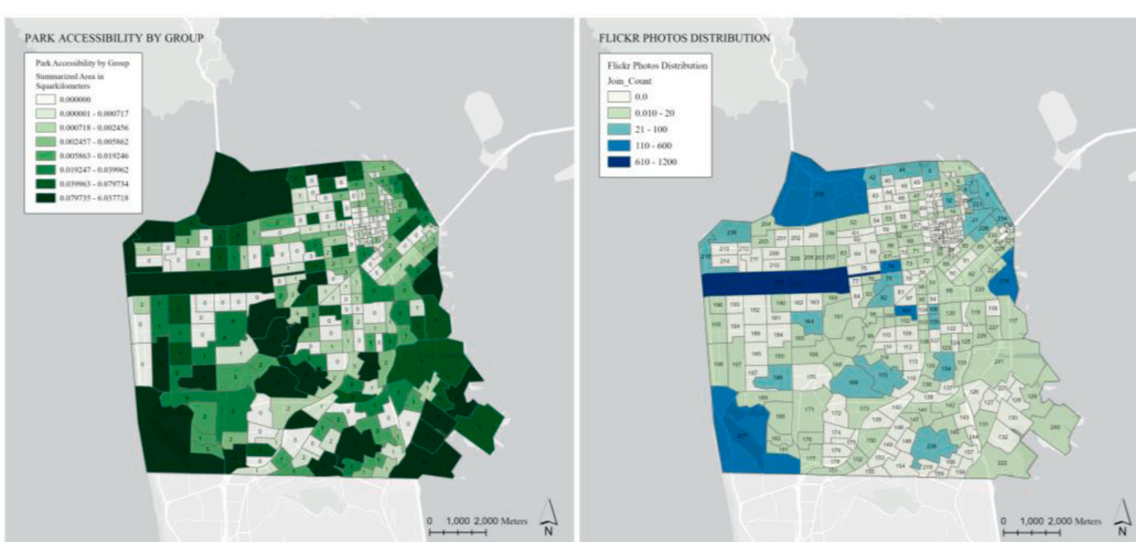
2.3.1. Flickr data collection to evaluate IUNV

Social media data is increasingly utilized to explore how citizens engage with urban spaces. The geotagged comments and photos can relate to citizens' emotions, mobility, and activity. Photos from social media in urban green spaces are a comprehensive source to explain people's use and preference (Matasov et al., 2023). We leveraged Flickr, a popular image-sharing platform in North America, to evaluate the popularity of San Francisco's parks. Flickr's extensive collection of geotagged and timestamped photos offers a rich source to understand public interest and engagement in urban spaces (X. P. Song, Richards, He, et al., 2020; Stahl Olafsson et al., 2022). Hence, we collected data from Flickr, subjected it to spatial analysis in ArcGIS Pro 3.0, and drew conclusions based on the quantity of photographs associated with different parks.

Initially, we developed a custom Python script designed to crawl Flickr and download images of parks, with the specified timeframe set from 2013 to 2022. Our systematic data collection approach yielded a comprehensive dataset of 4180 images, each implicitly representing a public interaction with the urban nature depicted. In addition to the download links for the images, we collected the ID, geotag (latitude and longitude), date, and user tag for each photo. The semantic meaning of image labeling was found helpful in revealing user preference in previous studies (Zhang et al., 2023). After the image categorization process, we created a spatially explicit dataset that depicted the distribution of Flickr images based on the blocks unit using ArcGIS Pro 3.0 (Fig. 4b). It is worth noting that these images are widely distributed in large parks, but also encompass a variety of other urban natural spaces, including linear green spaces, neighborhood parks, and streets lined with trees.

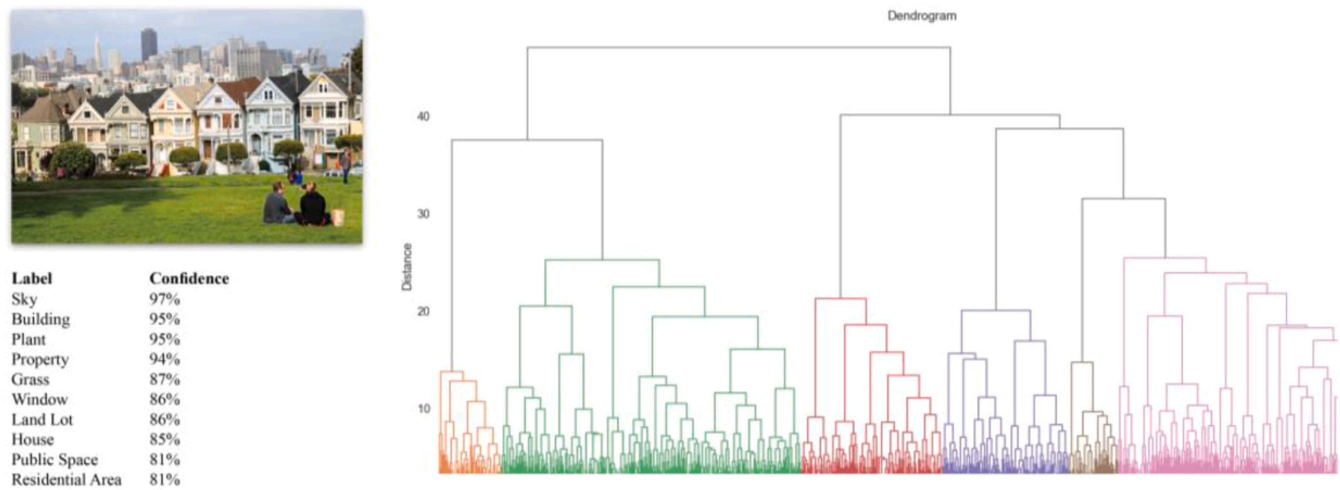
2.3.2. Flickr photos labeling and clustering to evaluate IUNV

We employed the Google Vision API to process a total of 3434 social media images scraped from Flickr after cleaning. The learning model is a powerful image analysis tool developed by Google that identifies objects, people, text, scenes, and a broad spectrum of product categories within images (Ghermandi et al., 2022) as shown in (Fig. 5a). This automated tagging process, grounded in deep learning, empowers platforms to handle vast amounts of visual data efficiently, ensuring content remains both relevant and organized. Utilizing this technology, we extracted each image's top ten labels with the highest confidence.



(a) Park accessibility by group (b) Flickr photos distribution by group

Fig. 4. Park accessibility and Flickr photos distribution by groups.



(a) Sample of image labeling (b) Hierarchical clustering

Fig. 5. The method of image labeling and hierarchical clustering.

This process allowed us to delve into each picture's core elements and key features.

Subsequently, we performed Hierarchical Clustering on these labels (Fig. 5b), which is a statistical method used to assess and group data samples into a series of clusters defined by similarity or distance (Song et al., 2020). One of the major advantages of this method is that it can be performed without a predefined number of clusters, affording us flexibility in exploring patterns within the data structure. We adopted the Average Silhouette Score as a measure to determine the optimal number of clusters. This is a quantitative tool for assessing the quality of clustering, considering both cohesion (i.e., similarity within the same cluster) and separation (i.e., difference between different clusters). The silhouette score ranges between −1 and 1, with values close to 1 indicating that the sample is well-matched to its cluster and poorly matched to neighboring clusters.

2.4. Data statistics

Exploring the association between independent variables and IUNV, this project encompasses three steps: (1) Calculating the Pearson correlation between independent variables to avoid collinearity; (2) Applying multilevel OLS regression models; (3) Checking Moran's I to assess spatial autocorrelation and ensure the validity of the model in capturing potential geographical patterns or dependencies in the data.

2.4.1. Pearson correlation

Pearson correlation coefficient measures the linear correlation between a list of independent variables X and dependent variable Y. This coefficient, denoted as r, ranges from −1 to +1, with +1 indicating a perfect positive linear relationship, 0 indicating no linear correlation, and −1 indicating a perfect negative linear relationship. The mathematical formula is shown below:

$$r = \frac{\sum (X - \overline{X})(Y - \overline{Y})}{\sqrt{\sum (X - \overline{X})^2}\sqrt{\sum (Y - \overline{Y})^2}} \tag{7}$$

The coefficient was calculated using the "corr" method from the Pandas library within the Python programming environment. This method computes the Pearson correlation by default when applied to a DataFrame object, providing a correlation matrix for all pairs of columns in the data set. The significance of the correlation coefficients was then evaluated to determine the strength and direction of the linear relationships. To enhance interpretability, the resulting correlation matrix was visualized using a heatmap generated by Seaborn's heatmap function, which offers a color-coded representation of the correlation coefficients, allowing for an intuitive grasp of the data's underlying structure.

2.4.2. Ordinary least squares (OLS)

Ordinary Least Squares (OLS) regression is a fundamental method in statistical modeling and econometrics for estimating the unknown parameters in a linear regression model. The OLS method minimizes the sum of squared errors (SSE) between the observed and predicted values (Pan et al., 2021). For each independent variable, it assigns a coefficient corresponding to case of minimum SSE. The equation represents OLS and the coefficient estimation matrix:

$$\hat{\beta} = (X^{'}X)^{-1}X^{'}Y \tag{8}$$

Herein, three OLS models were built to assess the isolated influence of different sets of independent variables: (1) Model 0: macro-level variables as independent variables; (2) Model 1: micro-level variables as independent variables; (3) Model 2: all the variables were fed into the model to do correlation analysis. R-squared was employed to interpret and compare the three models. With higher R-squared, the higher accuracy of a model in terms of explaining the association between independent and dependent variables. The processing was conducted by python package statsmodels.

2.4.3. Global Moran's I

Since spatial autocorrelation can influence linear models' performance, we used global Moran's I to examine whether the blocks have the issue of spatial autocorrelation (MORAN, 1950). It is defined as:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_i (X_i - \overline{X})^2} \tag{9}$$

A higher absolute value of Moran's I indicates a higher level of spatial autocorrelation. After that, Lagrange multipliers are useful metrics to decide which spatial regression model should be applied, including spatial lag model (SLM) and spatial error model (SEM). A spatial error model (SEM) with full variables was built to examine the correlation between features and IUNV further. All statistics were computed in R 2022.12.0.

3. Result and discussion

3.1. Socio-economic interactions with IUNV

GIS analysis in Fig. 7 revealed significant correlations between socio-economic conditions and IUNV. Demographic factors, including education level, ethnic diversity, and age distribution, influenced IUNV in diverse ways. For instance, Machin and Van Reenen (1998) analyzed educational inequality, investigating the determinants of limited educational engagement and highlighting the clear link between family income and educational participation starting from secondary education. This observation, together with our findings that regions with lower high school diploma achievement correlate with IUNV, suggests that the level of education and economic constraints are limiting factors (Kromydas, 2017). Conversely, younger populations in areas like South Beach and Mission Bay exhibited higher IUNV, likely due to their engagement with mobile technology and social media.

3.2. Social media perception learning of IUNV

Our clustering analysis determined that the highest average silhouette score 0.04615 occurred with the data partitioned into 12 clusters. This indicates that dividing the data into 12 clusters most accurately represents its intrinsic structure and patterns. Fig. 6(a) and (b) show the top 5 labels and the word cloud of each cluster.

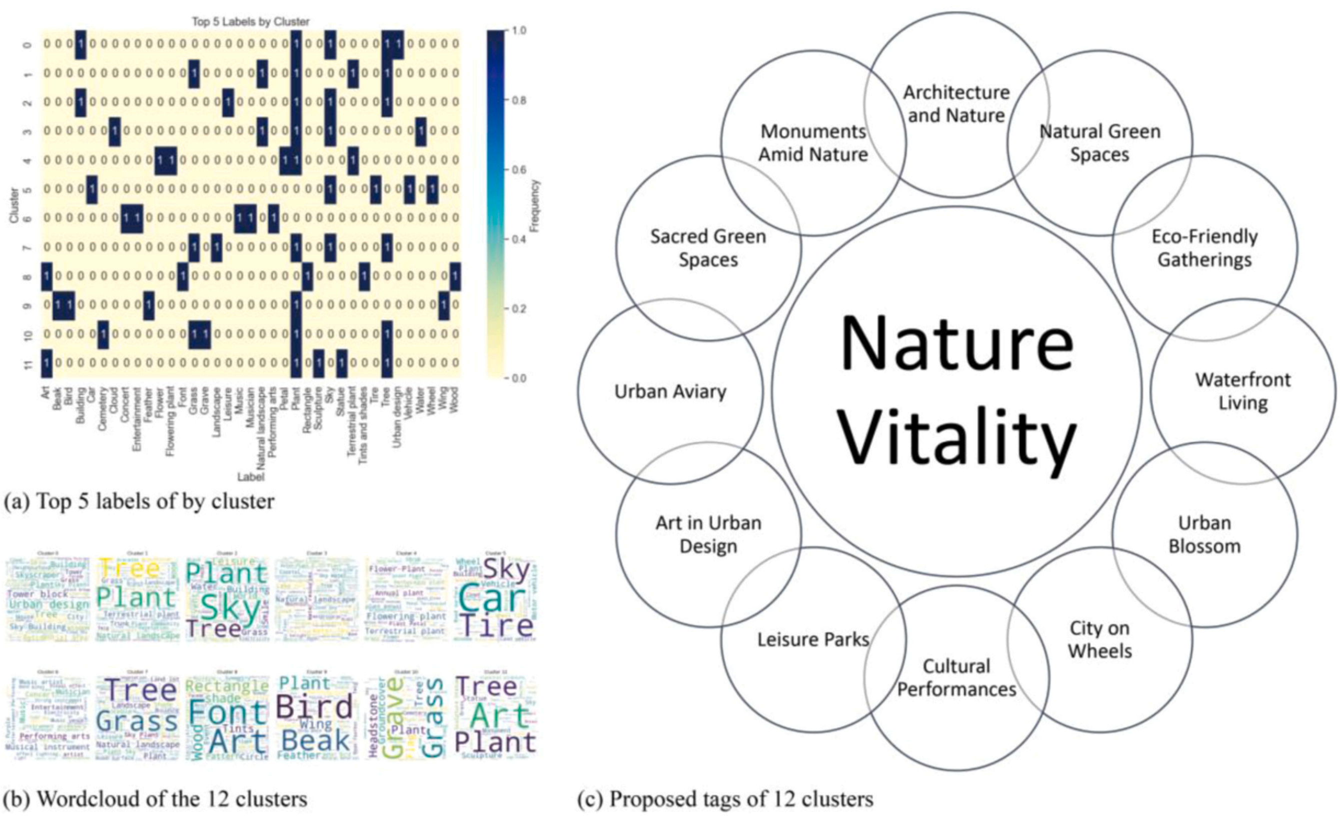
Additionally, we conducted a statistical analysis of the top ten representative labels for these 12 clusters and listed them in Table 3. This process aided in identifying the primary characteristics of each cluster, thus facilitating a deeper understanding and interpretation of the different clusters. Finally, we manually browsed through the images in each category to gain a more intuitive understanding of their respective features and differences. Based on this process, we defined a 'vitality' type for each category of images (Fig. 6c). Each representing a unique facet of IUNV. The twelve categories are: "Architecture and Nature", "Natural Green Spaces", "Eco-Friendly Gatherings", "Waterfront Living", "Urban Blossom", "City on Wheels", "Cultural Performances", "Leisure Parks", "Art in Urban Design", "Urban Aviary", "Sacred Green Spaces", and "Monuments Amid Nature", collectively cover a broad spectrum of urban features (Table 2). From the representative labels, we discerned that these categories occur in various urban natural spaces, including parks, streets, lakes, coasts, etc. These range from the amalgamation of natural elements within urban infrastructure to the cultural dynamism evident in various musical and artistic performances. Each of these categories, in its unique way, contributes to a comprehensive understanding of IUNV, encompassing physical characteristics and socio-cultural and environmental aspects.

3.3. Evaluation of key factors influencing IUNV

3.3.1. Correlation heatmap

In this section, we constructed a Pearson correlation matrix to examine the associations among all variables involved in this project, including six variables of macro-level category and 15 variables of street view features (Fig. 7). Owing to the variation in data units and ranges, we normalized the raw data to a range between −1 and 1 prior to conducting the correlation analysis. This normalization step aids in checking for multicollinearity issues and select variables with explanatory power.

At the macro level, population density and road density were found to have a positive association. The variables exhibiting the least negative correlation were road density and population. Similarly, land use entropy and sky coverage also demonstrated a comparable negative correlation. Among street view variables, an increase in the ratio of trees corresponds to a decrease in the proportion of visible sky. This association is empirically valid as a wider tree canopy naturally reduces the area of the visible sky. Chair and mountain show a positive correlation,



(a) Top 5 labels of by cluster

(b) Wordcloud of the 12 clusters

(c) Proposed tags of 12 clusters

Fig. 6. Result of the 12 IUNV clusters.

Table 2
Social media photos representative labels and clusters.

ID	Representative Labels	Number	Proposed Cluster Tag
Cluster 0	Building, Sky, Tree, Urban design, Plant, Tower block, Window, Skyscraper, Cloud, Daytime	501	Architecture and Nature
Cluster 1	Plant, Tree, Natural landscape, Grass, Terrestrial plant, Wood, Trunk, Sky, Groundcover, Landscape	368	Natural Green Spaces
Cluster 2	Sky, Plant, Tree, Leisure, Building, Electricity, Grass, Event, Cloud, Smile	511	Eco-Friendly Gatherings
Cluster 3	Sky, Water, Natural landscape, Cloud, Plant, Lake, Tree, Horizon, Water resources, Coastal and oceanic landforms	447	Waterfront Living
Cluster 4	Plant, Flowering plant, Flower, Terrestrial plant, Petal, Annual plant, Groundcover, Shrub, Botany, Herbaceous plant	225	Urban Blossom
Cluster 5	Wheel, Tire, Vehicle, Car, Sky, Plant, Building, Motor vehicle, Window, Tree	175	City on Wheels
Cluster 6	Entertainment, Performing arts, Concert, Music, Musician, Musical instrument, Music artist, Artist, Purple, Electricity	80	Cultural Performances
Cluster 7	Plant, Tree, Sky, Grass, Landscape, Natural landscape, Cloud, Building, Leisure, Land lot	617	Leisure Parks
Cluster 8	Font, Art, Rectangle, Wood, Tints and shades, Parallel, Pattern, Circle, Slope, Screenshot	277	Art in Urban Design
Cluster 9	Beak, Bird, Feather, Wing, Plant, Perching bird, Twig, Sky, Water, Songbird	77	Urban Aviary
Cluster 10	Cemetery, Plant, Grave, Grass, Tree, Headstone, Sky, Groundcover, Land lot, Cloud	76	Sacred Green Spaces
Cluster 11	Sculpture, Art, Statue, Tree, Plant, Monument, Sky, Grass, Classical sculpture, Building	80	Monuments Amid Nature

which can be explained by the scenic nature of these locations.

Foundation and sculpture also commonly occur together. The sky is the main street view variable that interacts with macro-level features. Blocks with a higher density of individuals under 17 and elderly populations appear to have greater sky exposure. Blocks with highly mixed land use and dense road connectivity tend to have less sky view. Because all variables do not have extremely high Pearson correlation with others, it is presumable that there is no multicollinearity issue, and the variables can be passed to further analysis via regression.

3.3.2. Multilevel regression analysis

OLS model performance was assessed using the r-squared value. A value closer to one indicates a stronger explanatory power of the independent variables for the dependent variable (IUNV). The SEM model was evaluated using the Akaike Information Criterion (AIC), where a lower absolute AIC value indicates a better model fit. We considered P-values of <0.005 and <0.050 highly significant and statistically significant, respectively.

Table 3 presents the results from the multilevel regression analysis. When comparing intra-OLS results, it became evident that including street view features significantly enhanced the explanatory power of IUNV, but the improvement was limited. It was important to note that macro-level variables still dominated the vitality level. Among these macro-level factors, accessibility demonstrated the most significant positive association with IUNV, followed by land use entropy, which exhibited a negative relationship. These results demonstrate that people in our study site were likelier to go places with convenient transport and relatively pure land uses. Compared with aging communities, areas with more teenagers tended to have higher IUNV levels.

The presence of sculptures and trees were the two most powerful street view features affecting IUNV. These results demonstrated that IUNV tended to be higher in places with higher proportions of greenery, aligning with the social media clustering analysis, where clusters with trees and natural characteristics had the highest frequencies. and places with sculptures. However, sculptures, though less common in our clustering analysis, significantly increased IUNV in the areas where they appeared. Both trees and sculptures showed a moderate correlation with accessibility and land use entropy, suggesting these macro-level variables may partly explain their observed impact on IUNV.

The presence of people negatively correlated with IUNV across all models, indicating that crowded environments might detract from the perceived vitality. Walls and fences negatively influenced activity willingness, while chairs had a positive correlation, highlighting the importance of open, recreational spaces for enhancing vitality. As indicated in Table 4, the Moran's I value of −0.013550, close to zero, suggests a nearly random distribution of block variables. The MSE model's findings were similar to those of the OLS models, suggesting no significant improvement in interpretability.

4. Conclusion

4.1. Implications for landscape and urban planning

This research introduces a novel concept and evaluation framework for Implied IUNV, integrating multi-dimensional data to uncover the underlying mechanisms, as evidenced in San Francisco. Using social media photos combined with computer vision techniques has been pivotal in understanding human activities and events in urban nature (Ghermandi et al., 2022; Y. Song et al., 2022; Tan et al., 2023). In this research, we integrate supervised labeling, unsupervised clustering, and qualitative tagging to quantify the types of vitality and better understand their coherence and implications, providing valuable insights for urban planning. The findings from this study have significant implications for urban planners and policymakers. By leveraging the IUNV framework, city planners can identify and prioritize areas within the urban landscape that enhance urban nature vitality. This approach can guide the allocation of resources and efforts towards areas that will yield the most significant impact on urban liveability and sustainability. For instance, integrating urban green spaces, such as parks, community gardens, and street linear greenery, can be optimized to enhance the social and ecological benefits they provide to urban residents.

Moreover, using social media data and computer vision techniques offers a novel way to engage with community members and understand their preferences and behaviors in urban natural settings. This participatory approach can lead to more inclusive and responsive urban planning, ensuring that the development of urban green spaces aligns with the needs and desires of the community (Zhang et al., 2021). In conclusion, the IUNV framework and its application in San Francisco provide a valuable model for other cities aiming to enhance urban nature vitality. Integrating multi-dimensional data, including social media content and computer vision analysis, offers a comprehensive and dynamic understanding of urban nature interactions. This approach can significantly contribute to developing more livable, sustainable, and resilient urban landscapes worldwide.

4.2. The effect of macro and micro level factors on IUNV

Through analyzing socio-economic, environmental, and population-level perception learning data, we have identified the following key findings: At the macro-level, previous research indicated the relationship between IUNV and land use intensity (Xia et al., 2020). We further identified a negative impact of land use entropy (diversity or heterogeneity) on IUNV.

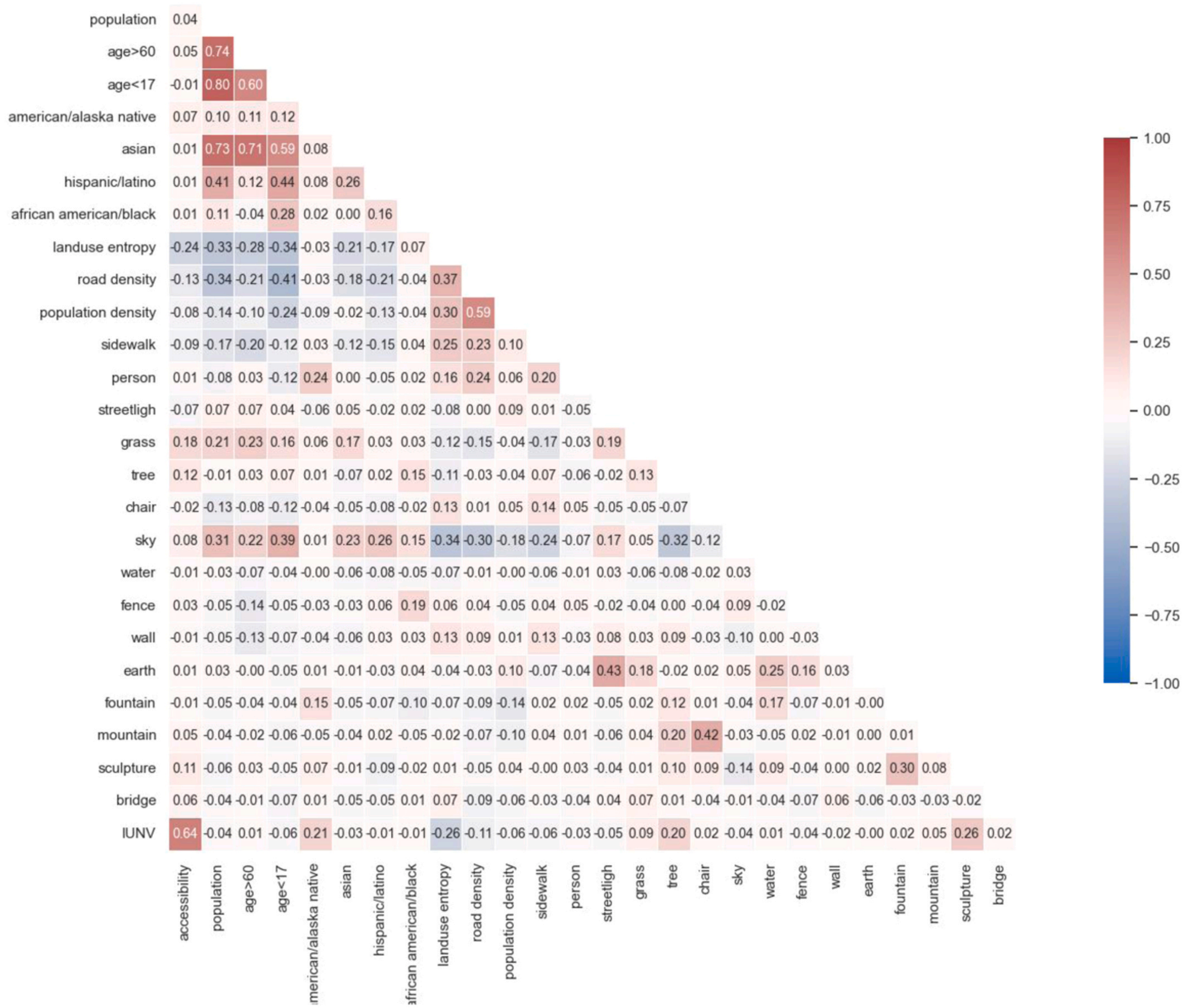


Fig. 7. Correlation matrix among all variables.

4.2.1. *Macro-level factors*

At the macro level, accessibility appears to be the most significant factor, which aligns with previous findings on the positive effect of influencing IUNV (Zhu et al., 2020)). Urban green space located in places with easier accessibility appears to have higher vitality.

Land use intensity is closely related to IUNV, as in five Chinese megacities (Xia et al., 2020). However, contrary to some previous studies stating that land use entropy positively relates with IUNV, this research generates a negative relation between the two factors. As observed in the case of Suzhou, this conflict can be explained by the mixture of land uses in this project because different types of urban natural space have different reactions to land uses (Ma et al., 2023). To moderate the negative impacts of land use entropy and exaggerate the benefits of accessibility, as pointed out by Elliott et al. (2020) and Pietta & Tononi (2021), improving the importance of green infrastructure and re-naturing cities is necessary for increasing the IUNV. Moreover, our findings suggest that urban planning strategies that balance land use diversity and safety can significantly enhance urban vitality. Integrating green spaces within diverse urban landscapes can mitigate the negative impacts of land use entropy, promoting a sense of well-being among residents.

4.2.2. *Micro-level factors*

At the micro-level, our analysis revealed a positive correlation between the presence of trees and sculptures and IUNV, highlighting the practical value of greenery and recreational areas within urban landscapes. From the model results, the R^2 increased after street view features were involved when comparing Model 0 and Model 2. This finding is consistent with previous studies underscoring the importance of human-perceived built environment for evaluating urban vitality (Wu et al., 2023). However, the influencing magnitude was relatively weak, showing macro-level factors were still the main component dominating the IUNV. Our study contributes a nuanced understanding of the factors influencing urban green space vitality through the synergistic effects of combined analysis and modeling. Urban designers gain valuable insights by integrating spatial autocorrelation analysis, regression, and clustering analysis with street view features. Our research adds depth to the literature on the determinants of urban green space vitality. We demonstrate the promise of integrating these analytical methods into a spatially explicit model, showcasing how such an approach can provide actionable insights for designers and policymakers. Specifically, our findings are relevant to San Francisco urban environments, offering guidance on resource allocation to ensure the effective integration of

Table 3
Multilevel regression model comparison.

Model predictors	Model 0 – Baseline		Model 1 - SVs		Model 2 - Full		Model - Full	
Method	OLS		OLS		OLS		SEM	
Variables	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
CONSTANT	0.0520	/	0.0051	/	0.0600	/	0.039	/
Macro-level								
Accessibility	0.4889	<0.001**	/	/	0.4700	<0.001**	0.518	< 2.2e-16**
Age>60	0.0050	0.802	/	/	0.0022	0.915	-0.003	0.849
Age<17	-0.0366	0.062	/	/	-0.0332	0.112	-0.022	0.166
Landuse entropy	-0.0735	0.013*	/	/	-0.0759	0.015*	-0.038	0.080*
Road density	-0.0311	0.434	/	/	-0.0195	0.640	-0.013	0.698
Pop density	0.0199	0.556	/	/	0.001	0.998	-0.004	0.885
Street Views								
Sidewalk	/	/	-0.0131	0.567	0.0027	0.883	-0.006	0.687
Person	/	/	-0.0092	0.828	-0.0162	0.634	-0.002	0.925
Street light	/	/	-0.0499	0.305	-0.0007	0.984	0.018	0.579
Grass	/	/	0.0401	0.327	-0.0173	0.597	0.004	0.885
Tree	/	/	0.0942	0.004**	0.0515	0.053*	0.042	0.052*
Chair	/	/	0.0242	0.697	0.0278	0.565	0.029	0.474
Sky	/	/	0.0335	0.364	-0.0150	0.646	-0.014	0.586
Water	/	/	0.0150	0.799	0.0045	0.922	0.011	0.766
Fence	/	/	-0.0206	0.542	-0.0224	0.402	-0.011	0.585
Wall	/	/	-0.0283	0.644	-0.0139	0.772	-0.023	0.595
Earth	/	/	0.0109	0.833	-0.0077	0.850	-0.019	0.577
Fountain	/	/	-0.0700	0.158	-0.0519	0.185	-0.053	0.117
Mountain	/	/	-0.0133	0.762	-0.0225	0.513	-0.018	0.534
Sculpture	/	/	0.1613	<0.001**	-0.1169	<0.001**	0.104	<0.001**
Bridge	/	/	0.0104	0.821	0.0138	0.706	-0.015	0.618
R-squared	0.434		0.121		0.490			/

Table 4
Moran's I Summary.

Global Moran's I SummaryMoran's Index	-0.013550
Expected Index	-0.004184
Variance	0.000199
z-score	-0.664122
p-value	0.506612

principles such as equity, livability, and sustainability.

4.3. Understanding vitality through social media and machine learning

4.3.1. Leveraging social media data for urban nature vitality analysis

The innovative use of social media data harnesses the power of digital footprints and offers a new perspective on public engagement and preferences in urban spaces (Matasov et al., 2023). The collection and analysis of images from Flickr, each representing a unique interaction with urban nature, provide a comprehensive view of how these spaces are utilized and valued by the public. Mapping the distribution of these images reveals insightful spatial patterns in park popularity and usage (Richards, He, et al., 2020). Integrating social media imagery and machine learning techniques in evaluating urban nature vitality provides a comprehensive and innovative approach to understanding and enhancing urban spaces.

4.3.2. Image labeling and clustering: a deep dive into urban space usage

The application of Google Vision API for automated image labeling and the subsequent hierarchical clustering of this data is a notable methodological innovation. This process efficiently handles a large volume of visual data and allows for a nuanced analysis of the content within these images (Ghermandi et al., 2022). The formation of 12 distinct clusters, each representing a unique aspect of IUNV, is a pivotal finding of this study. These clusters capture the diverse expressions of urban nature vitality in San Francisco. The combination of quantitative and qualitative analysis, including manual browsing and categorization of images, enriches our understanding of nature vitality, highlighting urban spaces' physical, socio-cultural, and environmental dimensions (Zhang et al., 2023).

4.3.3. Implications for urban planning and policy

The insights gained from this study have significant implications for urban planning and policy. The variety of IUNV categories identified can inform urban planners in creating spaces that resonate with a broad spectrum of public interests. The popularity of certain clusters suggests specific public preferences, guiding the design of urban spaces that foster naturalistic experiences, recreational opportunities, and aesthetic appreciation (Song et al., 2020; Stahl Olafsson et al., 2022). Additionally, this research underscores the potential of social media data as a tool for urban planning, offering real-time insights into public trends and preferences. This approach paves the way for more dynamic and responsive urban design strategies, ensuring that the evolving needs of urban residents are effectively addressed.

4.4. Possible limitations and opportunities for future research

Despite providing valuable insights into the distribution and vitality of UGS in San Francisco, this study has several limitations. Firstly, the sample size is relatively small, focusing only on San Francisco, which might limit the applicability of our findings to a broader geographical scope. Future studies could consider investigating more diverse cities to provide a more comprehensive understanding of UGS distribution and vitality.

Secondly, using social media data might not represent all population groups, especially older adults who may not use social media extensively. Thus, the perception and interaction with UGS might be skewed towards a younger demographic. This limitation can be addressed by incorporating other data collection methods, such as surveys or interviews, to capture a wider range of user perceptions.

Thirdly, unsupervised learning clustering comes with a certain level of imprecision. While machine learning algorithms can process large amounts of data quickly and efficiently, their output depends on the quality and representativeness of the input data. Fourthly, this study did not account for the temporal changes in the data. Future research could include time-series analysis to understand the dynamism and temporal variations in UGS distribution and vitality.

Lastly, our study focused primarily on the physical built environment and vitality without considering perception, which can significantly influence vitality outcomes. Future studies should incorporate perception-based measures to provide a more holistic understanding of UGS vitality. Understanding the physical environment alone is insufficient; perceptions play a crucial role in determining the success and vitality of UGS. As such, further research is needed to delve deeper into the relationship between perceptions and physical environment attributes.

4.5. Summarize

This study introduces and applies the concept of IUNV, offering a novel perspective for understanding and assessing the vitality of UGS. Our research delves into the various factors influencing the vitality of these spaces, thereby providing deeper insights for urban planning and sustainability. By integrating census data, SVI, and social media analysis, this study uncovers how socio-economic factors such as education level, age structure, income level, and ethnic distribution affect the distribution and vitality of urban green spaces. These findings highlight the importance of considering socio-economic backgrounds in the planning and managing urban green spaces.

Furthermore, this research employs advanced image recognition technology to analyze SVI, quantifying the physical characteristics of urban green spaces, such as trees, sky, buildings, and roads. These features collectively contribute to the vitality of urban green spaces. This method provides an objective tool to understand urban green spaces' spatial distribution and physical attributes more intricately. By defining 12 themes of urban green space vitality and exploring their relationship with various independent variables, this study further deepens our understanding of the complexity of urban green spaces. These themes range from architecture and nature to eco-friendly gatherings and cultural performances, revealing how urban green spaces interact with urban residents' lives on different levels. Through this comprehensive IUNV analysis, the study sheds light on the complexities of urban green space planning and management, guiding future urban development strategies to enhance urban green spaces' vitality, thereby promoting environmental and social sustainability.

CRediT authorship contribution statement

Ruilin Sun: Visualization, Software, Methodology, Conceptualization. **Shuying Guo:** Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation. **Yuxuan Cai:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Mingze Chen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xiwei Shen:** Writing – review & editing, Supervision. **Yang Song:** Writing – review & editing, Supervision.

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.

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