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RESEARCH PAPER

A fuzzy-based emotion detection method to classify the attractiveness of urban green spaces

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Abstract

In European studies, the most used definition of Urban Green Spaces (UGS) is based on the European Urban Atlas, which includes public green areas primarily used for recreation and green areas adjacent to urban areas that are managed or utilized for recreational purposes. UGS play a vital role in creating sustainable and resilient cities, as they provide essential social benefits for the well-being and health of urban residents. Both planners and scientists acknowledge the importance of involving, actively or passively, citizens in defining criteria for designing and managing inclusive and functional UGS. According to a post-normal science approach, the integration of hard data from scientific sources with soft data gathered from citizens' engagement holds the potential to shape an innovative support system for public policies addressing significant, urgent, and uncertain challenges pertaining to UGS. Nowadays, the abundance of data generated through online reviews, opinions, and comments allows for collecting valuable information about people's opinions and sentiments towards UGS. This study proposes a methodological framework that utilizes emotion detection techniques to identify and analyze citizens' emotions concerning UGS through social reviews. To balance computational costs and classification accuracy, the framework introduces a fuzzy emotion-based classification method called FREDoC (Fuzzy Relevance Emotions Document Classification). This method incorporates a lightweight natural language pro-cessing (NLP) approach to detect and annotate terms associated with specific emotional categories within the text. The framework adopts the psycho-evolutionary classification approach based on R. Plutchik's observations of general emotional responses. This model is implemented within a Geographical Information System (GIS) for the purpose of categorizing UGS, specifically green parks, according both to WHO report key indicators and to the detected relevant emotions. The outcome is a novel classification model of UGS that can assist decision-makers in identifying the attractiveness of UGS as catalysts for urban transformation processes.

Keywords GIS · Urban green park · Emotion detection · Fuzzy relevance · Emotional categories

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1 Introduction

Urban Green Spaces (UGS) encompass a diverse range of green areas, including both permeable hard surfaces and predominantly "soft surfaces" [1, 2]. However, a universally accepted definition for UGS does not exist. In European studies, the most used definition is based on the European Urban Atlas [3] (EEA 2023), which includes public green areas primarily used for recreation, such as gardens, parks, zoos, suburban natural areas, forests, and green areas adjacent to urban areas that are managed or utilized for recreational purposes. These UGS play a vital role in creating sustainable and resilient cities [4] (UN 2023), as they provide essential social benefits for the well-being and health of urban residents [5, 6].

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According to a report from the WHO Regional Office for Europe in 2017 [7], the key characteristics of UGS include their size, land cover type, presence of water bodies, accessibility, presence of green vegetation, and usage. Planners and scientists acknowledge the importance of involving, actively or passively, citizens in defining criteria for designing and managing inclusive and functional UGS [8–11]. The scientific framework of post-normal science [12] places significant importance on the interconnection between science, society, and policymakers. The fundamental proposition of this model is to in-corporate diverse stakeholders in shaping a scientific problem, starting from formulating research questions, determining the appropriate methodology, and gathering relevant in-formation. This model embraces uncertainty as an integral component of the decision-making process, with a particular focus on exploring values, interests and urgency of the debated issues. In this perspective, the integration of hard data from international re-ports with soft data gathered from citizens' engagement holds the potential to shape an innovative support system for public policies addressing significant, urgent, and uncertain challenges pertaining to UGS.

Nowadays, the abundance of data generated through online reviews, opinions, and comments allows for collecting valuable information about people's opinions and sentiments towards UGS. To analyze these unstructured texts from the web, sentiment analysis (SA) and emotion detection (ED) techniques are employed, applying natural language processing (NLP) methods. SA aims to extract meaningful information and semantics from text, determining whether a citizen's attitude is positive, negative, or neutral [13]. ED, on the other hand, focuses on identifying feelings or emotions expressed by individuals. Emotion models can be broadly classified into two categories: dimensional, utilizing three parameters - valence, arousal, and power - to represent emotions [14]; categorical defining emotions discretely, categorizing them into four, six, or eight distinct categories depending on the specific model. These models provide a range of emotional states that can be used as labels for annotating sentences or documents. In the domain of emotion detection from social streams, researchers often rely on Ekman and Plutchik's widely used emotion model for annotation purposes [15, 16]. Furthermore, there are three main approaches to per-form SA and ED: lexicon-based, machine learning-based, and deep learning-based techniques [17]. The lexicon-based approach involves searching for specific emotion keywords associated with psychological states. The complexity of this approach lies in organizing the emotion vocabulary. Machine learning-based techniques utilize different machine learning models, such as Naïve Bayes, support vector machine, and decision trees, to analyze emotions. Deep learning is a subset of machine learning that involves multiple layers of interconnected neurons. These complex neural networks enable parallel processing, leading to faster and more efficient analysis. However, these last two approaches require extensive training phases that can be computationally expensive but are necessary to achieve high classification accuracy.

This study proposes a methodological framework that utilizes emotion detection techniques to identify and analyze citizens' emotions concerning UGS through social re-views. To balance computational costs and classification accuracy, the framework intro-duces a lexicon-based approach with a fuzzy emotion-based classification method called FREDoC (Fuzzy Relevance Emotions Document Classification). This method incorporates a lightweight natural language processing (NLP) approach to detect and annotate terms associated with specific emotional categories within the text. The framework adopts the psycho-evolutionary classification approach based on R. Plutchik's observations of general emotional responses [18]. It defines a three-dimensional hybrid model comprising primary, secondary, tertiary, and opposite emotions. This model is implemented within a Geographical Information System (GIS) for the purpose of categorizing UGS, specifically green parks, according both to WHO report key indicators and to the detected relevant emotions.

The classification results are presented as thematic maps, which illustrate the spatial distribution of hard indicators and of relevant emotional categories. The interconnection between these indicators allows, through the implementation in a GIS environment, to de-fine at least three categories of UGS, facilitating the identification of which are more attractive. The attractiveness level of a UGS is related to the concept of "ba" [19–21] referring to the capacity of a UGS, specifically green parks, to foster the emergence of relationships, facilitate knowledge creation processes and activate an enabling context.

Of relevance is the study of the potential of green parks to represent catalyst elements of urban transformation actions and regeneration processes.

This research intends to provide an assessment of the attractiveness of UGS, with specific attention to green parks, by taking into consideration both hard indicators that evaluate the physical state of the park, and soft indicators connected to the emotional states of the users.

The proposed method offers several key strengths, which are outlined below:

- Efficient and Fast: FREDoC provides quick computation times while offering a multi-classification of prevailing emotional categories associated with each UGS. It ensures reliable emotional category detection while minimizing the computational resources required for the analysis.

- Comprehensive Emotional Classification: The method enables a comprehensive classification of emotional relevance by considering the predominant emotional states ex-pressed by users. This classification provides valuable insights into the spatial distribution of emotional relevance across different categories.
- Integration with GIS: The proposed method is implemented in a GIS platform. Through spatial distribution, it's possible to define thematic maps expressing the inter-connections between hard and soft indicators to construct a final thematic map of attractiveness of urban green parks.
- Innovative UGS Classification: The proposed methodology aims to establish an innovative classification approach that can assist decision-makers in identifying the attractiveness of UGS as catalysts for urban transformation processes.

The subsequent sections of this paper are structured as follows: Sect. 2 provides an introduction to the FREDoC framework; Sect. 3 illustrates how our method is applied to classify UGS, in particular green parks, utilizing the relevant emotions extracted from web-based reviews; Sect. 4 presents the outcomes of our experiments carried out assessing the attractiveness of green parks located in the municipality of Naples, Italy. The paper ends with a conclusion in Sect. 5, in which potential future directions for research in this field are outlined.

2 Preliminaries

2.1 The FREDoC model

FREDoC is a fuzzy-based emotion multi-classification model proposed in [23] to classify documents measuring the relevance of each pleasant and unpleasant emotional category. In [24] FREDoC is applied in a GIS-based framework to assess pandemic, climatic and environmental multi-risks in urban settlements detecting the prevailing emotional states of citizen expressed in messages posted on the social network. In [25] FREDoC is applied to capture the relevance of pleasant and unpleasant emotions expressed by users in evaluations of urban service facilities.

An architectural schematization of FREDoC is shown in Fig. 1.

FREDoC uses a dictionary of emotional terms, called *Dictionary of Emotional Words*, built based on a model of emotional categories, in which each emotional category is associated in its inflectional form with terms referring to it.

Input of the model is a set of texts extracted from a data stream (*Selected texts*); the *Text parsing* function remove irrelevant terms in the texts and perform the stemming of words; then, it groups in a document all texts with common keywords, producing the *Corpus of documents*.

The *Term filtering* function annotates all the terms in the documents expressing emotions; to perform this process it analyzes if the terms, in its stemmed form, is included in the *Dictionary of Emotional Category words* as term belonging to an emotional category.

The *ECM construction* function measures the relevance of each emotional category, constructing the *Emotional Category Matrix* (ECM), a matrix whose elements represent the relevance of an emotional category in a document. The relevance is calculated by measuring the *Term Frequency and Inverse Document Frequency* index (TF-IDF).

Let D = {d1, d2, …dN} be the corpus of N documents, *f*(t, di) be the number of times the term t appears in the i*th* document di and n_i is the number of times all terms appear in the document d_i. In addition, let N_t the number of documents in which the term *t* appears at least once.

The TF-IDF index measuring the relevance of the term t in the i*th* document is given by:

$$\mathrm{TF-IDF}\left(\mathrm{t},\mathrm{d_i}\right)=\mathrm{tf}\left(\mathrm{t},\mathrm{d_i}\right)\cdot\mathrm{idf}\left(\mathrm{t},\mathrm{D}\right) \tag{1}$$

It is given by the product of two terms. The first term $\mathrm{tf}\left(\mathrm{t},\mathrm{d_i}\right)$, called *term frequency*, measures the frequency of the term t in document d_i. It is given by the formula:

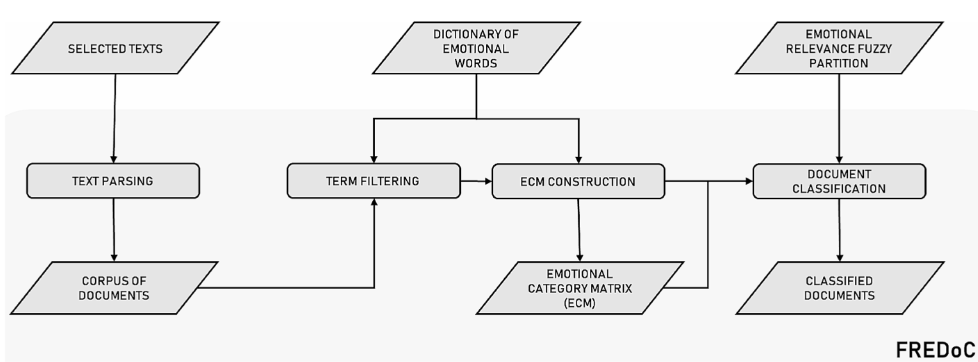

Fig. 1 Schema of the FREDoC model

$$\mathrm{tf}(\mathrm{t},\mathrm{d_i}) = \frac{\mathrm{f}(\mathrm{t},\mathrm{d_i})}{\mathrm{n_i}} \tag{2}$$

The last term *idf*(t, D), called *inverse document frequency*, measures, in decimal logarithmic scale, the relevance of the term in the corpus. It is given by

$$idf\ (t,\ D) = \log_{10}\frac{N}{N_t} \tag{3}$$

Let C = {c_1, c_2, …c_M} be the set of the M emotional categories and T_j be the set of terms referred to the *jth* emotional category c_j. The *ECM construction* function calculates the value:

$$TF?\,IDF\,(c_j,d_i) = \sum\nolimits_{t\in T_j} TF - IDF\,(t,d_i) \tag{4}$$

It groups the values of the TF-IDF index measured for the *ith* document and for all the terms belonging to the *jth* emotional category.

TF-IDF(c_j,d_i) measures the relevance of the *jth* category in the *ith* document. It is normalized in the closed set {0,1} applying the formula:

$$R(c_j,d_i) = \frac{TF - IDF\,(c_j,d_i)}{\sum\nolimits_{k=1}^{M} TF - IDF\,(c_k,d_i)} \tag{5}$$

R(c_j,d_i) is the function (i, j) of the EC matrix; it measures the relevance of the category c_j in the document d_i.

The *Document Classification* function classifies the documents using the *Emotional Relevance fuzzy partition*, a fuzzy partition of the domain {0,1} of the relevance of an emotional category in a document. It assigns to the emotion category a fuzzy relevance in the document given by the label of the fuzzy set of the Emotional Relevance fuzzy partition having the greatest membership degree.

The result of the classification is a dataset in which each document is assigned the relevance of all the pleasant and unpleasant emotional categories considered (*Classified documents*). The user can optionally decide to assign a threshold to the relevance of an emotional category, classifying the document according to the most relevant emotional categories.

2.2 The emotional relevance fuzzy partition

In this paragraph is described the Emotional relevance fuzzy partition used by FREDoC to fuzzify the relevance of an emotional category in a document.

Let X = {0,1} the domain of the normalized emotional relevance (5).

Let F = {A_1,A_2,…,A_n} a family of fuzzy sets on X. Following [22], F represent a fuzzy partition of X if none of his fuzzy sets are empty, and for each $\mathrm{x} \in \mathrm{X}$ the union of the membership degree of $_\mathrm{X}$ to the fuzzy sets of *F* is equal to 1. These two constraints are formally represented in Eqs. (6) and (7).

$$\forall\, A_i \in\ F\ \exists\, x \in\ X\ :A_i\,(x) \neq\ 0 \tag{6}$$

and

$$\sum\nolimits_{i=1}^{n} A_i\,(x) = 1\,\forall\, x \in\ X \tag{7}$$

where A_i : X → {0,1} is the membership function of the *ith* fuzzy set of the fuzzy partition.

In [23] the Emotional category fuzzy partition is constructed using triangular fuzzy number. In particular, the first fuzzy set is given by a R-function fuzzy number expressed by the couple (x_1, x_2) in the form:

$$A_1\,(x) = \begin{cases} 1 & x < x_1 \\ \frac{x-x_1}{x_2-x_1} & x_1 \leq\ x \leq\ x_2 \\ 0 & x > x_2 \end{cases} \tag{8}$$

the fuzzy sets $\mathrm{A}_2, \ldots, \mathrm{A}_{n-1}$ are given by triangular fuzzy numbers expressed by the triplet (x_{k-1}, x_k, x_{k+1}), in the form:

$$A_k\,(x) = \begin{cases} 0 & x < x_{k-1} \\ \frac{x-x_{k-1}}{x_k-x_{k-1}} & x_{k-1} \leq\ x \leq\ x_k \\ \frac{x_{k+1}-x}{x_{k+1}-x_k} & x_k \leq\ x \leq\ x_{k+1} \\ 0 & x > x_{k+1} \end{cases} \tag{9}$$

k =2,.,n−1and the last fuzzy set is given by a L-function fuzzy number expressed by the couple (x_{n-1}, x_n) in the form:

$$A_n\,(x) = \begin{cases} 0 & x < x_{n-1} \\ \frac{x-x_{n-1}}{x_n-x_{n-1}} & x_{n-1} \leq\ x \leq\ x_n \\ 1 & x > x_n \end{cases} \tag{10}$$

In Fig. 2 is shown an example of triangular number fuzzy partition where $n = 5$.

As an example, let $\mathrm{R}(\mathrm{c_j},\mathrm{d_i})$ = 0.18 be the relevance of the *jth* emotional category in the *ith* document, computed by (5).

The *Document classification* function fuzzifies this value assigning to the *jth* emotional category a fuzzy relevance in the *ith* document given by the term *Low* as the fuzzy set labelled *Low* is the one to which the relevance of the

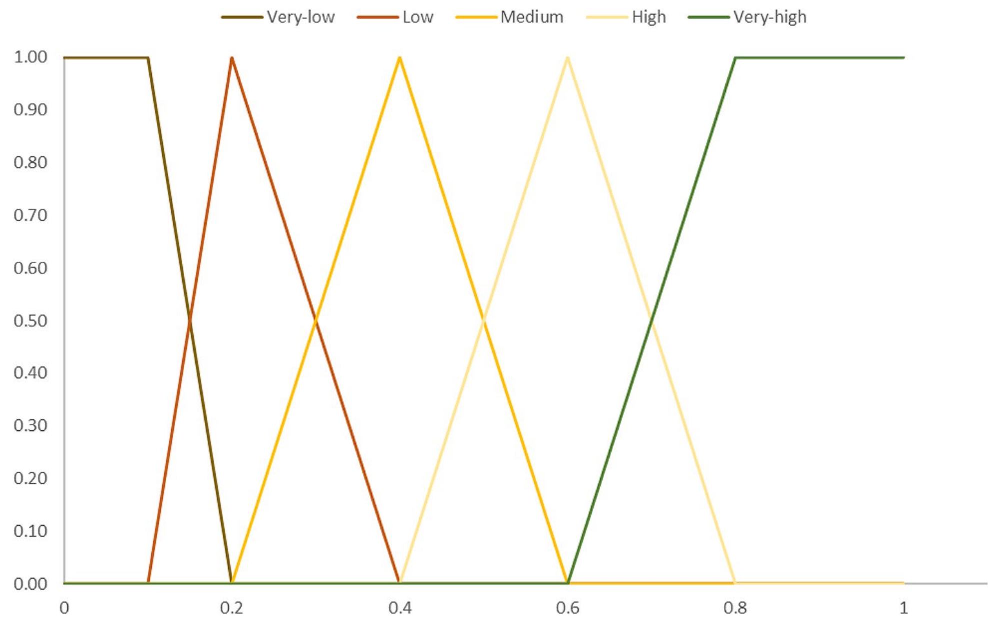

Fig. 2 Example of triangular number fuzzy partition applied to the emotional relevance

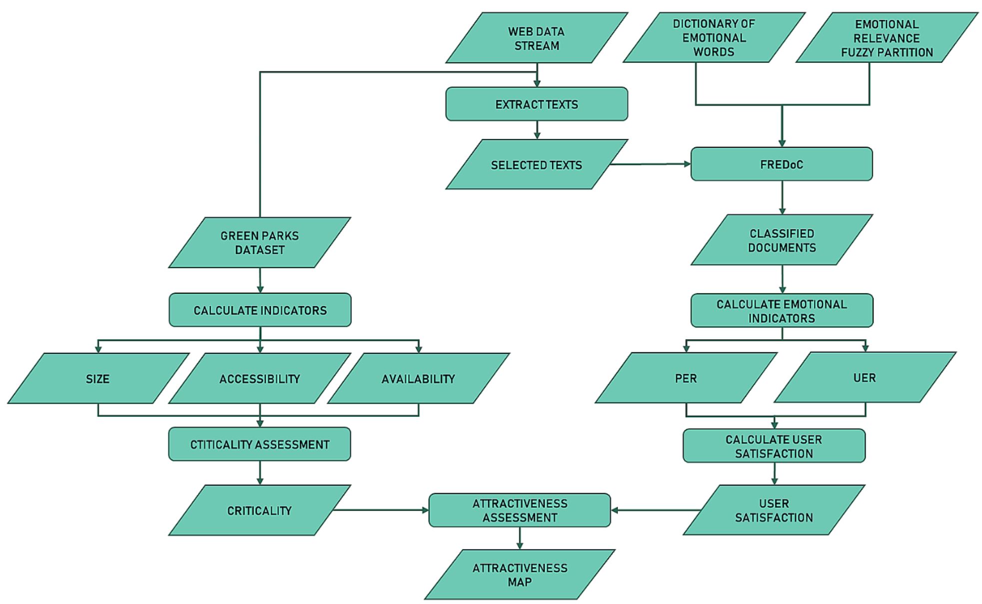

Fig. 3 Flow diagram of the proposed framework

emotional category belongs with the highest membership degree (0.80).

3 The proposed framework

Aim of the proposed GIS-based framework is to assess the level of attractiveness of green parks located in a study area based on both specific measurable indicators related to the landscape and service quality of the park, and the perceptions of citizens and users deduced from comments and reviews released on the web.

The Attractiveness is a synthetic indicator defined on a specific connected both to the criticality of the UGS on the basis of dimensional characteristics, accessibility and the presence of living vegetation, and to the state of mind of citizens and users, considering that the prevalence of pleasant emotional state of users with respect to unpleasant emotions implies a high attractiveness capacity of the UGS in terms of ability to be a pole of attraction for citizens and tourists.

The user of the framework is a decision maker who evaluates the attractiveness of green parks by taking into consideration both the physical characteristics and the perceptions and moods of citizens and consumers.

The flow diagram in Fig. 3 schematizes the framework.

The input dataset consists of the spatial dataset of green parks, including all the measurable characteristics necessary to calculate the set of physical indicators used to evaluating the criticality of green parks). According to the WHO Report [7], this research considers three physical indicators of green spaces: size, accessibility and availability.

Size refers to the physical dimensions of green parks, measured in square meters or hectares. The size of a green space has a notable impact on the activities individuals engage in within its bounds.

Accessibility is determined by the proximity of residential areas to green parks, considering the distribution of both green spaces and the population. Proximity plays a crucial role, as it assesses the spatial relationship between urban parks and the people living nearby. To accurately evaluate the accessibility of green parks, service areas are defined using network analysis techniques to identify accessible streets and evaluate the proximity of green parks to residences or neighborhoods. This approach provides a more comprehensive measure of proximity beyond simple linear distance calculations, as highlighted in the JRC Report on Measuring the Accessibility of Urban Green Spaces. The research draws upon the concept of the "15 minutes city," wherein most essential services can be accessed within a 15-minute radius from one's residence [26]. The indicator is obtained measuring the number of residents who live within the park service area.

Availability measures the presence of live, green vegetation in an area using the Normalized Difference Vegetation Index (NDVI). NDVI calculates the ratio between the difference and sum of spectral reflectance measurements acquired in the visible red and near-infrared regions. These measurements represent the ratios of reflected radiation to incoming radiation in each spectral band and can range between 0 and 1. The NDVI values span from -1 to $+1$. Values close to zero indicate barren areas with minimal or no vegetation, while higher positive values indicate the presence of more thriving vegetation. Conversely, more negative values generally indicate the existence of standing water, clouds, or snow.

The *Calculate Physical Indicators* function builds the three green park physical indicators: *Size*, *Accessibility* and *Availability*. The *Criticality Assessment* function aggregates the three physical indicators to evaluate the level of criticality of the green park. The higher it is, the worse its physical characteristics related to size, accessibility to the park and the presence of living vegetation are worse.

The *Attractiveness Assessment* function, based on the criticality and user satisfaction indicators, classifies the green parks in terms of attractiveness.

The *Extract texts* function extracts from the web texts posted by user related to each green park (for example texts posted in a social network or reviews inserted in web pages managed by providers). It returns the selected texts where each text is linked to the correspondent green park,

The *FREDoC* model is applied to classify the green parks based on the relevance of pleasant and unpleasant emotions. After text parsing all texts assigned to a green park are grouped in a document. Using the Dictionary of emotion words, all terms in the documents matched with terms in the dictionary in their stemmed forms are annotated; then the TF-IDF index of each emotional category is calculated. Each document is classified assigning the fuzzy relevance of all emotional categories in it, where the fuzzy relevance of an emotional category in a document is the fuzzified emotional relevance obtained using the Emotional relevance fuzzy partition created by the decision maker. The Calculate *PER/UER* function calculates two indices called Pleasant Emotions Relevance (PER) and Unpleasant Emotions Relevance (UER); they are two synthetic indices which summarize the relevance of, respectively, the pleasant and unpleasant emotions expressed by citizens and users.

The *Attractiveness assessment* function evaluates the attractiveness of the green parks based both on the criticality and on the PER and UER indicators. Finally, a resultant thematic map showing the attractiveness of the green parks (*Attractiveness map*) is constructed.

The PER and UER indices are calculated assigning, respectively, the most significant fuzzy relevance of pleasant and unpleasant emotions.

Formally, let $C_p = \{c_{p1}, c_{p2}, \ldots c_{ps}\}$ be the set of pleasant emotional categories and $C_u = \{c_{u1}, c_{u2}, \ldots c_{ut}\}$ be the set of unpleasant emotional categories, where $s+t=M$.

Let $FR(c_{pj}, d_i)$ $j=1,\ldots s$ be the fuzzy relevance assigned to the j*th* pleasant emotional category to the i*th* document. The Pleasant Emotions Relevance assigned to the document will be given by:

$$PER\ (d_i) = \max_{j=1,\ldots,s} FR(c_{pj}, d_i) \tag{11}$$

Similarly, let $FR(c_{uj}, d_i)$ $j=1,\ldots t$ be the fuzzy relevance assigned to the j*th* unpleasant emotional category to the i*th* document The Unpleasant Emotions Relevance assigned to the document will be given by:

$$UER\ (d_i) = \max_{j=1,\ldots,t} FR(c_{uj}, d_i) \tag{12}$$

The three physical indicators Size, Accessibility and Availability were partitioned into three classes using class rules applied in literature. Each of the three classes of the three physical indicators takes on three values: *Low*, *Medium* and *High*. Table 1 shows, for each indicator, the corresponding measure and the labels and the rules of the classes.

The Criticality indicator (Table 2) is obtained by combining the three physical indicators, assigning an order to the three classes (Low = 1, Medium = 2, High = 3). By adding

Table 1 Composition of the three physical indicators

Physical indicator	Measure	Class value	Class rules
Size	Green Park area	Low	Area ≤ 2 hectares
		Medium	2 hectares < Area ≤ 5 hectares
		High	Area > 5 hectares
Accessibility	Number of residents in the service area	Low	Number of residents ≤ 1000
		Medium	1000 < Number f residents ≤ 5000
		High	Number f residents > 5000
Availability	NDVI	Low	NDVI ≤ 0.3
		Medium	0.3 < NDVI ≤ 0.5
		High	NDVI > 0.5

Table 2 Composition of the criticality indicator

Numerical value	Criticality class
From 3 to 5	High
6 or 7	Medium
8 or 9	Low

the numerical values attributed to the three physical indicators, a value between 3 and 9 is obtained.

The greater attractiveness value (High) is attributed to green parks that have medium criticality and medium criticality and high user satisfaction. This is since green parks with the greatest potential attractiveness are those that arouse mostly positive emotions in users, and which can potentially become catalysts for nearby services and infrastructures, further reducing their level of criticality.

The Emotional relevance fuzzy partition used to fuzzify the relevance of the emotional categories is given by the seven fuzzy sets proposed in [23] and shown in Fig. 4; in [23] the authors showed that this fuzzy partition is well suited to comprehensively represent the relevance of an emotional category in a document.

The PER and UER indicators assume the greater value from Null to Very-high of the relevance assigned, respectively, to the emotional categories pleasant and unpleasant.

The User satisfaction indicator is obtained by combining the PER and UER indicators where is assigned an order to the seven classes: an ascending order is applied to the PER classes and a descending order is applied to the UER classes (Table 3).

The User satisfaction indicator is composed by classifying the numerical value given by the sum of the PER and UER numerical values, as shown in Table 4.

The final attractiveness indicator is categorized in three levels: *Low*, *Medium* and *High*. It is obtained by a combination of the Criticality and the User satisfaction indicators, as in Table 5.

Table 3 Classification of the PER and UER indicators

Class	PER value	UER value
Null	1	7
Low	2	6
Medium-low	3	5
Medium	4	4
Medium-high	5	3
High	6	2
Very-high	7	1

Table 4 Composition of the user satisfaction indicator

Numerical value (PER + UER)	User satisfaction class
From 2 to 5	Low
From 6 to 10	Medium
From 11 to 14	High

Table 5 Composition of the attractiveness indicator

Criticality class	User satisfaction class	Attractiveness class
High	Low or Medium	Low
Low	Low	Low
High	High	Medium
Medium	Low or Medium	Medium
Low	Medium or High	Medium
Medium	High	High

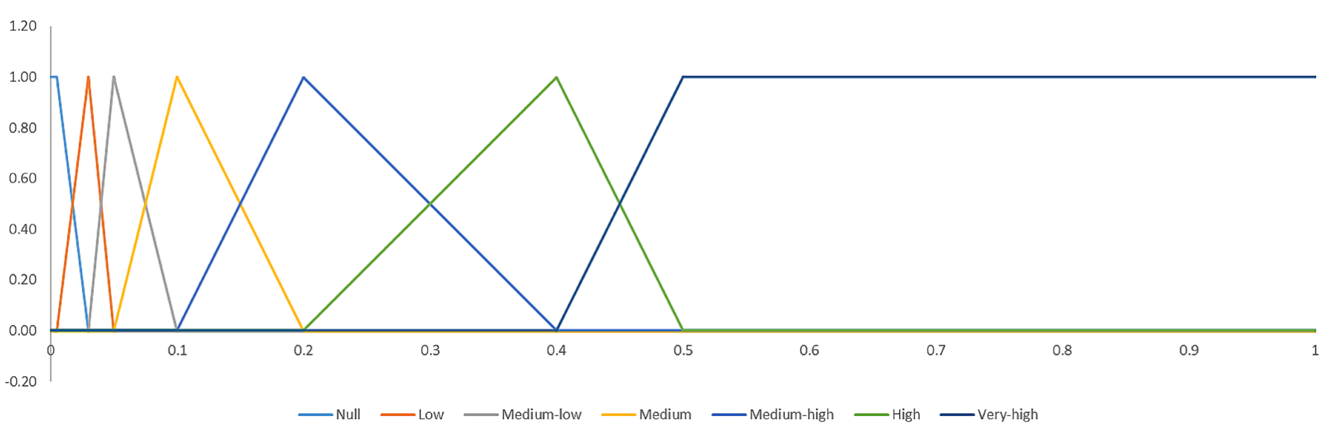

Fig. 4 The emotional relevance Fuzzy partition used

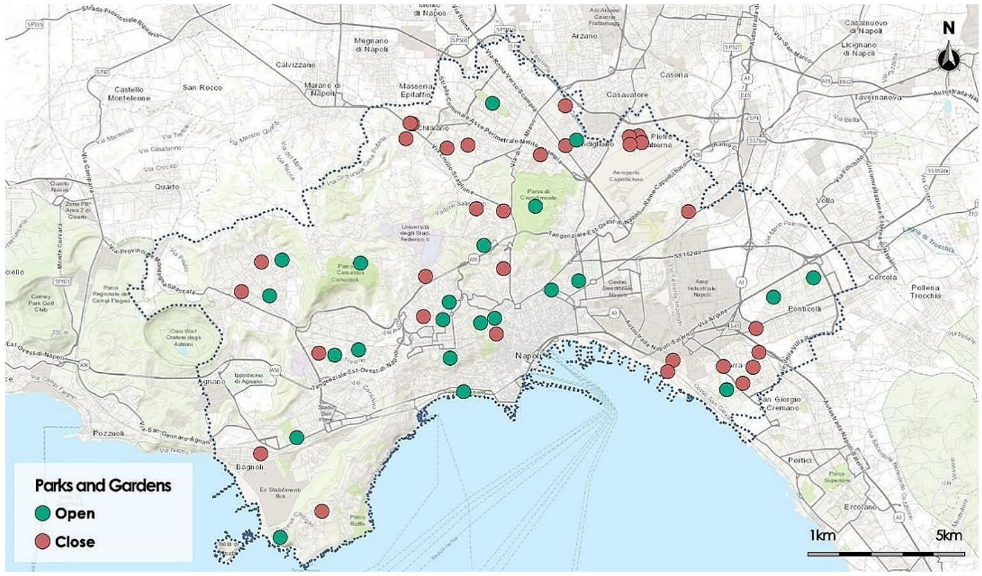

Fig. 5 Map of all public green parks in the city of Naples (Italy)

Green parks with *Medium* criticality and *High* user satisfaction have a *High* attractiveness. This is because green parks with the greatest potential attractiveness are those that arouse mostly positive emotions in users, and which can potentially become catalysts for nearby services and infrastructures, further reducing their level of criticality.

In next section are shown and discussed the results obtained executing the framework to evaluate the attractiveness of the green parks located in the municipality of Naples (Italy).

4 Results and discussion

We test the framework to assess the attractiveness of public green parks located in the municipality of Naples (Italy). The test is aimed at determining which of the open green parks can be, if enhanced, catalysts and attractors of users in using the surrounding services and infrastructures.

In the municipality of Naples there are 53 green parks. The map in Fig. 5 shows the green park entrances located in the map; only 22 green parks (displayed as green in the figure) are open; the other 31 (displayed as green in Figure) are closed or under renovation.

To detect the relevance of emotions were extracted for each open green park the reviews posted by users in the Google Review web pages from January 1, 2022, to May 30, 2023. Over 5000 reviews posted by users on the green parks in the city of Naples were acquired. After removing irrelevant terms in the texts, the Part of Speech tag assignment was performed, subsequently aggregating the texts that refer to a specific green park to form a document to be included in the Corpus of documents.

Table 6 Sixteen emotional categories classified as primary/secondary and pleasant/unpleasant

Emotional category	Primary/Secondary	Pleasant/Unpleasant
Joi	Primary	Pleasant
Trust		
Surprise		
Expectation		
Optimism	Secondary	Pleasant
Love		
Sadness	Primary	Unpleasant
Disgust		
Anger		
Fear		
Aggression	Secondary	
Submission		
Disapproval		
Contempt		Unpleasant
Remorse		
Awe		

The framework was implemented in the tool GIS ESRI ArcGIS pro suite; the topographic database in scale 1:5000 of the city of Naples was used to construct the road network and the Landsat 8 satellite images in the bands 4 (Red) and 5 (Near Infrared) were used to build the NDVI raster data. The population census data was extracted from the census data published by the Italian Institute of Statistics (ISTAT); they refer to the last census of the resident population carried out by census area.

The Dictionary of Emotional Words was created using the Plutchik's wheel of emotions [18], which is made up of eight primary and eight secondary emotional categories.

Table 6 shows the 16 primary and secondary emotional categories split up into Pleasant/Unpleasant.

The Dictionary of Emotional Words was built by analyzing the Italian language dictionaries of the synonyms of terms. Starting from the initial term consisting of the name of an emotional category, all the terms connected to it were iteratively extracted; the iterative process ended when all the synonyms of the currently analyzed terms had already been included in the dictionary. This process was accomplished for all sixteen emotional categories. Each term has been assigned its inflectional form.

To derive the Size indicator, the polygons corresponding to the 22 open green parks were extracted from the topographical database.

The Availability indicator was computed by constructing the raster dataset of NDVI from the Landsat 8 Red and Near Infrared images. Using zonal statistics operators, each green park polygon has been attributed the average of the NDVI values of the pixels enclosed in the green park surface.

The Accessibility indicator was computed by extracting the road network from the topographic database and determining service areas around each park, where a service area is given by an area from which the park entrance can be reached on the road network on foot in less than 15 min, considering an average speed of 3 km/h.

The classification rules in Table 1 were used to construct the maps of the three physical indicators.

In Fig. 6 the thematic maps of the three physical indicators are shown.

The maps show a significant presence of green parks with *Medium* availability (59%) and of green parks with *Medium* accessibility (45%).

Finally, Table 2 was used to construct the Criticality map of the 22 open green parks. Figure 7 shows the corresponding thematic map.

On the map 59% of the open green parks are classified as *Medium* criticality; 32% of them are classified as *Low* criticality and only 9% of them as *High* criticality.

The FREDoC model was implemented in the GIS platform to classify the relevance of the pleasant and unpleasant emotions detected in the reviews posted by users. The Emotional relevance fuzzy partition shown in Fig. 4 was used to fuzzify the emotional relevance of each emotional category.

The PER and UER indicators are calculated following (10) and (11); are assigned to each green park the highest fuzzy relevance of, respectively, the pleasant and unpleasant emotional categories.

In Fig. 8 are shown the analyzed green parks, classified by Pleasant Emotional Relevant (PER) indicator.

Most green parks belong to *Medium-high* classes (36%); there are four green parks classified as *Very high* (18%), 14% of them are classified as *High*, 27% of them are classified

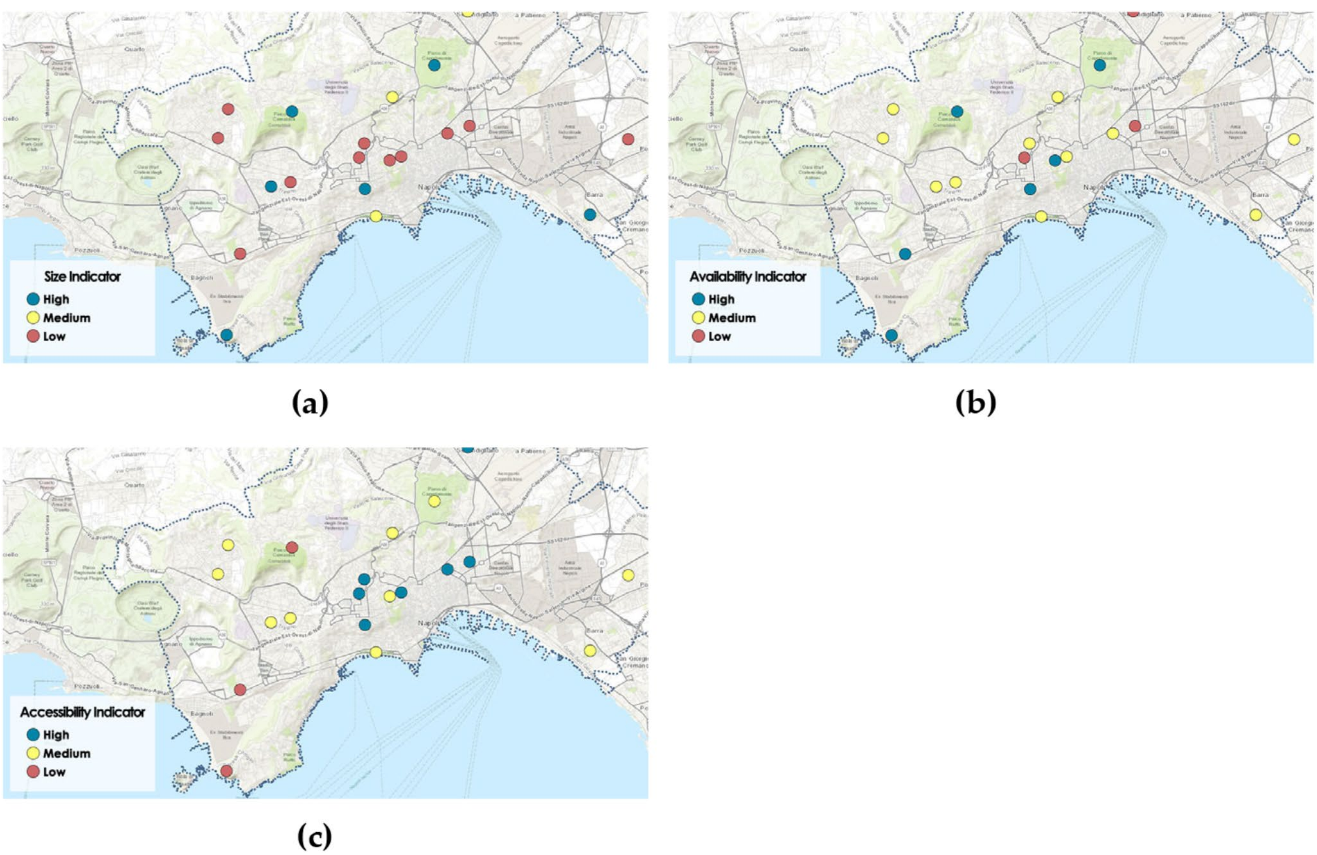

Fig. 6 Map of the three physical indicators: Size (**a**), Availability (**b**) and Accessibility (**c**)

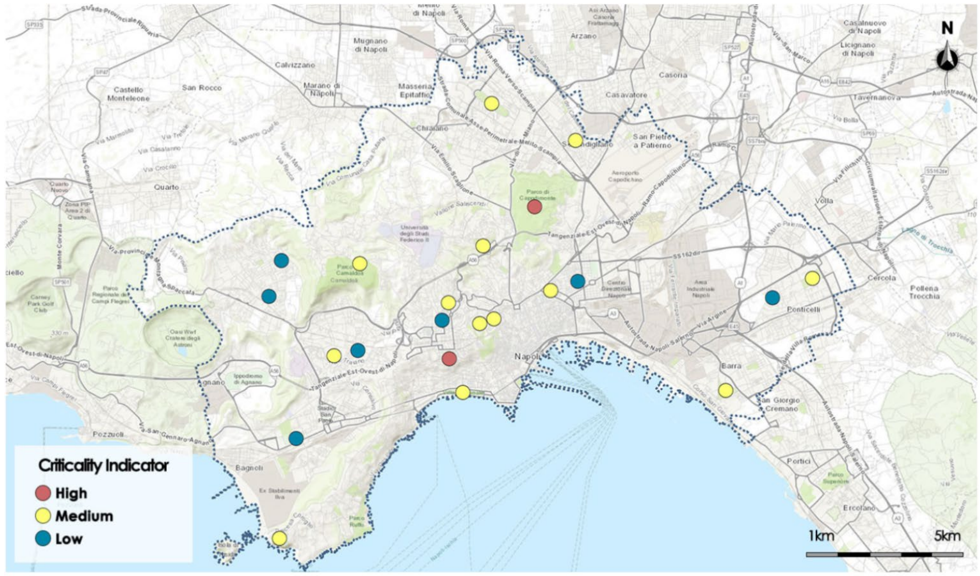

Fig. 7 Map of the criticality indicator

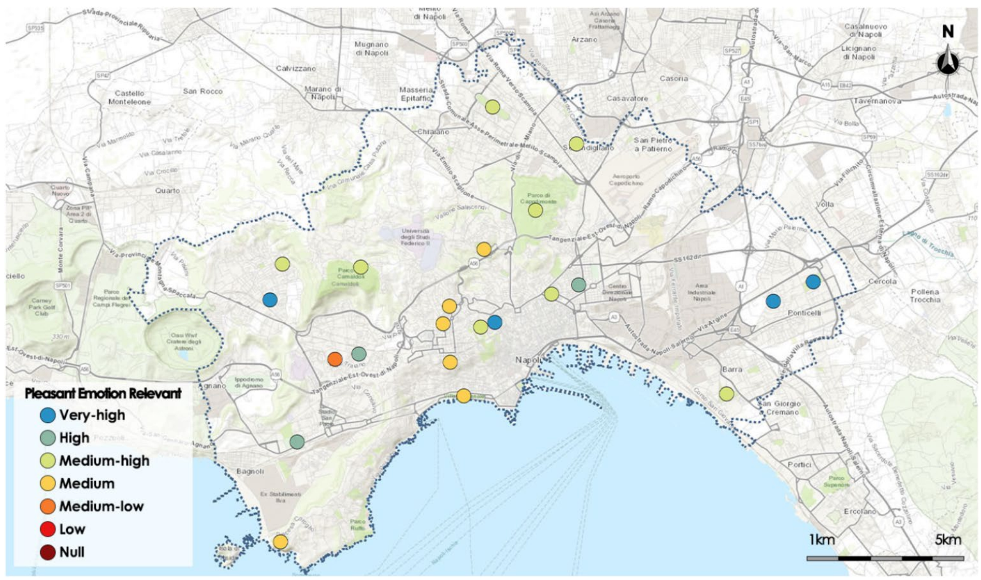

Fig. 8 Pleasant emotion relevance distribution of green parks in municipality of Naples, Italy

as *Medium*, while only one green park is classified with a *Medium-low* pleasant relevance (5%).

This result shows that there is strong feedback for the perception of positive emotional categories.

In Fig. 9 are shown the analyzed green parks, classified by Unpleasant Emotional Relevant (UER) indicator.

Almost all green parks are classified with an unpleasant emotional relevance above *Medium* (14% *Very-high*, 27% *High*, 45% *Medium-high*); only three green parks are labeled as *Null* (14%), since no prevalence of unpleasant emotional categories has been recorded for them. This result highlights the presence of a non-negligible relevance of unpleasant emotions for almost all of the green parks extracted from analyzed reviews. Only for three green parks this relevance is *Null*.

Therefore, although there are pleasant emotional states expressed by users for most open green parks, at the same time unpleasant emotional states are also present with significant relevance.

The User Satisfaction thematic map (Fig. 10) of the 22 open green parks was created using Tables 3 and 4.

Almost all green parks are classified with *Medium* level of satisfaction (81%), and the remaining 14% are classified with High; there is only one green park (5%) that is classified with *Low* level of satisfaction.

The final Attractiveness indicator thematic map is obtained by a combination of the Criticality and the User satisfaction indicators (Table 5). Figure 11 shows the corresponding thematic map.

Among all the green parks classified as *Medium* criticality, only the Ventaglieri green park is classified as *High*

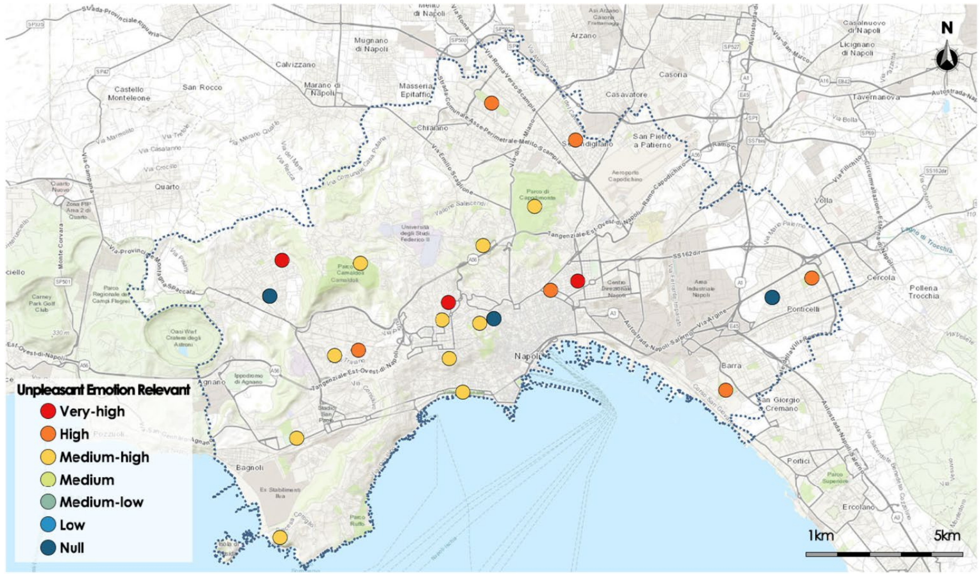

Fig. 9 Unpleasant emotion relevance distribution of green parks in municipality of Naples, Italy

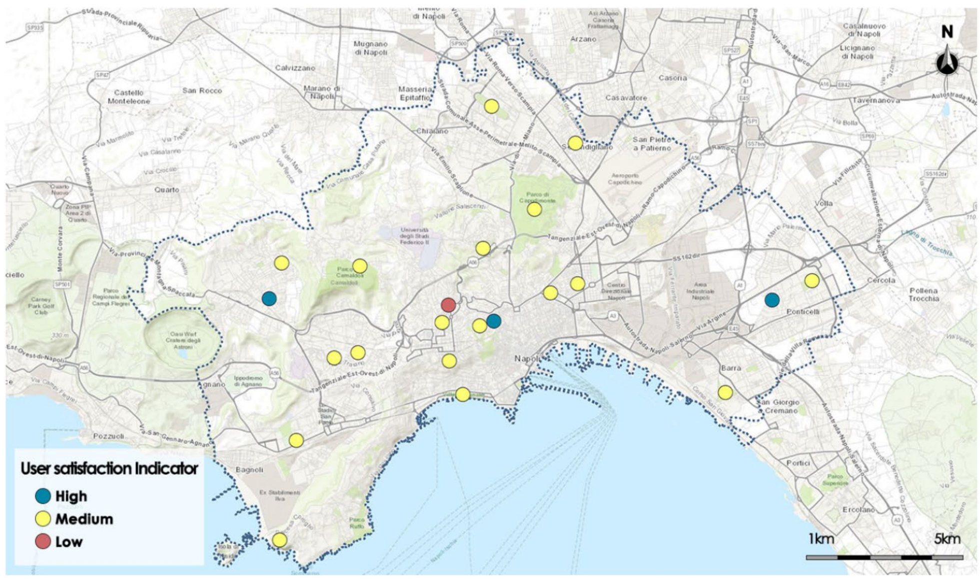

Fig. 10 User satisfaction distribution of green parks in municipality of Naples, Italy

attractiveness. It has a Low level of surface extension (Size), a *High* level of accessibility, and a *Medium* level of availability, all of which contribute to its *Medium* degree of criticality.

Furthermore, it is among the only three green parks classified with High user satisfaction as the values of the two indicators PER and UER for this green park are, respectively, *Very-high*, for the pleasant emotion relevance, and *Null* for the unpleasant emotion relevance.

The absence of unpleasant emotions reflects the effectiveness of the Ventaglieri green park as a service catalyst for the Avvocata district.

The result shows a potential investment in the urban development of services and infrastructure for the catchment area generated by the green park attractiveness.

Using a traditional approach, a decision-maker can evaluate the attractiveness of a green park, determining its criticality based on the three indicators of size, availability, and accessibility. Our framework integrates this approach with an emotion detection model that evaluates the prevalence of positive and negative emotions among users, providing an important and useful element for evaluating the potential attractiveness of open green parks.

Combining the criticality with the user satisfaction indicator, built by determining the relevance of the pleasant and unpleasant emotions of the users, the proposed framework provides a more complete assessment of the attractiveness of urban green parks, in which the moods of users are also taken into consideration. In the testing of the framework carried out on the urban green parks of the city of Naples, it emerged that, compared to approximately 22 urban green

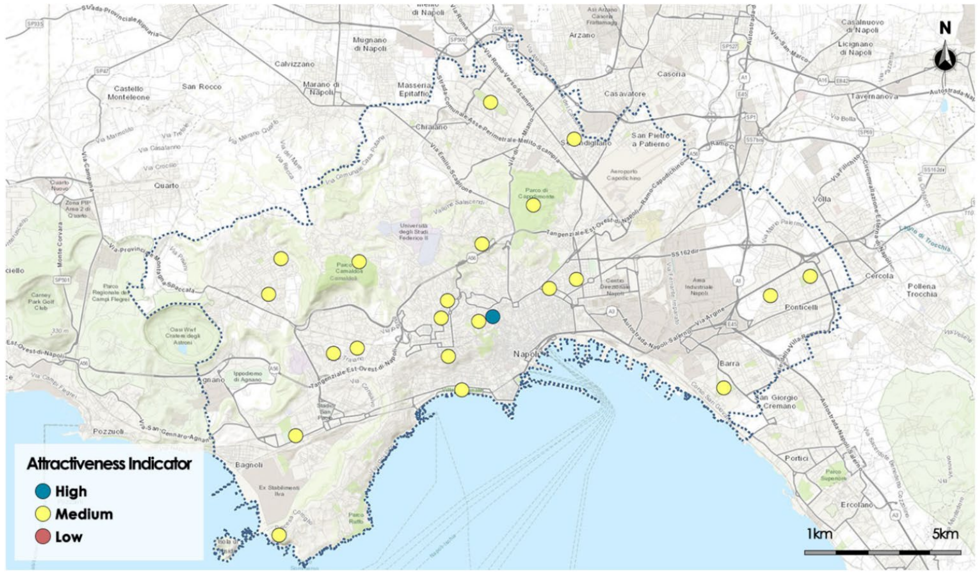

Fig. 11 Attractiveness distribution of green parks in Municipality of Naples, Italy

parks classified as medium criticality, the one with the highest attractiveness is the Ventaglieri green park, which represents the one with the optimal service catalyst.

This result highlights a benefit of the proposed framework compared to the basic model, in which the emotional states of the users are not captured, and the decision-maker makes his assessments taking into consideration only the criticality of the park.

5 Conclusions and future works

We propose GIS-based framework for the evaluation of the attractiveness of urban green parks carried out by taking into consideration both the main characteristics of the park such as its extension, accessibility and the abundance and diversity of vegetation, as well as the users' opinions and feelings, determined with the use of emotion detection techniques.

The FREDoC model has been implemented to classify the relevance of pleasant and unpleasant emotional categories expressed in the reviews submitted by users on the web. The sixteen primary and secondary emotional categories of Plutchik's wheel were considered and a fuzzy partitioning of the relevance of the emotional categories was used for document classification.

The attractiveness of green parks is assessed by taking into consideration two final indicators: Criticality, which measures how critical the state of the park is, based on the three physical indicators, and User satisfaction, which measures how much greater the relevance of pleasant emotions is than those unpleasant detected in reviews posted by users.

The goal is to select those green parks that have medium criticality but high customer satisfaction, as an attenuation of their criticality could make these parks catalysts in the use of surrounding services and infrastructures.

The framework has been tested to evaluate the attractiveness of urban green parks located in the municipality of Naples (Italy). The results showed that the green park with the highest attractiveness is the Ventaglieri park, a small park located in the central area of the city, which has a medium criticality, but for which there is a very high relevance of emotions pleasant and completely negligible of unpleasant emotions expressed by users.

In the future, we intend to evolve the research for the development of a Spatial Multi-Criteria Decision-Making system for assessing the attractiveness of UGS that takes into consideration hybrid criteria related both to the status and typology of green parks and to the relevance and diversity of emotions aroused in users.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Ethical approval This research does not contain any studies involving human participants performed by any of the authors.

Conflict of interest The authors declare no conflict of interest.

Informed consent Not applicable.

Competing interests The authors declare no competing interests.

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