Integrating multi-criteria decision making and public sentiment analysis for sustainable urban green space planning

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ABSTRACT

Sustainable planning of green open spaces (GOS) requires decision-making models that combine expert evaluation with public input. This study proposes a novel hybrid framework that integrates multi-criteria group decision making (MCGDM) with public sentiment analysis to support community-based and data-driven urban planning. The workflow consists of evaluating 25 community-proposed GOS locations using stepwise weight assessment ratio analysis (SWARA) for criteria weighting and MABAC-BORDA for multi-criteria ranking, resulting in 11 feasible alternatives. To incorporate community perspectives, a term frequency-inverse document frequency-support vector machine (TF-IDF–SVM) classifier was applied to 1500 public comments, where SVM achieved the highest accuracy (0.80–0.96). The integrated approach improves ranking stability, reduces decision ambiguity, and strengthens alignment between expert judgment and community sentiment. This study contributes a transparent, participatory decision-support model that unifies MCGDM and sentiment analysis to enhance the effectiveness of sustainable GOS planning.

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1. INTRODUCTION

Along with the expansion of urban areas, the importance of effectively planning and managing green open spaces (GOS) is paramount in efforts to address global warming, a major challenge that impacts both the environment and human well-being [1]. The development of GOS not only contributes to carbon sequestration but also increases biodiversity, improves air quality, and has an essential role in reducing the decline in the quality of environmental services and potentially reducing the level of stress experienced by the community [2], so that the GOS available to the community plays a crucial role in the midst of the density of daily activities which are often triggered by high mobility, pollution levels, and global warming.

GOS management necessitates a multidimensional approach to balance social, environmental, and economic objectives effectively [3]. However, the challenge lies in aligning the needs and preferences of the community with the objectives of environmental planning towards the development of GOS. According to a study, the government faces challenges in developing GOS due to the limited availability of strategic land, which often results in the priority of GOS development being overlooked in favour of other strategic development priorities [4]. The GOS development planning process should involve parties who can play an important role in developing the sustainability of GOS use. A study by Sousa-Silva and Zanocco [5] explored the attitudes of adults in Germany towards urban green spaces by utilizing a survey to identify preferences regarding public open spaces, thereby enabling the comfort of users towards these green areas to reflect their subjective perceptions of overall quality [6]. Zhou *et al.* [7] investigated the dynamics of factors related to public sentiment in GOS by analyzing social media reviews using machine learning, where the results show that public sentiment is sensitive to variations in the size of urban green spaces, thus providing a new approach in environmental psychology analysis based on machine learning.

In the last two decades, there has been an exponential increase in the application of community participation as a method of urban green and blue space planning [8]. Therefore, this study introduces a new approach by utilizing sentiment analysis models and the GDSS so that GOS planning can involve the community, focus on community needs, and be effective for the environment. Many social media users' viewpoints can be effectively mined and utilized as a powerful source of information to direct a plan based on what is thought [9], including in the determination of GOS feasibility recommendations. Literature on the challenges associated with green spaces articulates a pressing need for mitigative efforts against the environmental impacts of urbanization.

This research seeks to furnish a more thorough understanding and enhance the efficacy of decision-making processes in the planning of urban green spaces, thereby yielding more adaptable solutions that are attuned to the needs and preferences of the populace. A selection of pertinent studies concerning GOS is encapsulated in Table 1.

Table 1. Research gap summary of GOS studies

Publication	Contribution	Research gap
A planning framework to guide the creation of urban green spaces using existing forest fragments in the urban territory: a case study from Foz do Iguaçu, Brazil [10].	The proposed framework characterizes forest fragment coverage and identifies which fragments are necessary to create GOS.	Describe the shape of each fragment based on the calculation of the circularity index.
Evaluation of urban green space landscape planning scheme based on PSO-BP neural network model [11].	Integrate ecological evaluation indicators and urban development into green space landscape planning schemes, further comprehensively evaluating and predicting GOS.	Evaluate the green space landscape planning schema using a PSO neural network model in conjunction with a BP neural network.
A process approach to the open green space system planning [12].	Details a comprehensive framework for open green space planning, focusing on ecological, recreational, and disaster-related criteria to optimize urban green spaces.	The green space concept was scrutinized and classified, with content that overlaps with the concept of landscape and its broadest definition.
Spatial optimization for urban green space (UGS) planning support using a heuristic approach [13].	A GOS optimization method should be proposed that accounts for spatial equity and conversion costs to optimize GOS layout in urban areas.	Optimization method for producing GOS.
Planning small for winning big: Small urban green space distribution patterns in an expanding city [14].	Determine the urban functions that benefit from GOS amounts, distribution, and density to enhance green environments in marginalized communities.	Using geographic object-based image analysis (GEOBIA) and random forest classification
Research on the layout of urban disaster-prevention and risk-avoidance green space under improved supply-and-demand matching: The case study of Nanjing's main urban area, China [15].	Explore improving the efficiency of green spaces for disaster prevention.	Calculation demand for urban DPRAGS based on disaster coefficient, population, and refugee area per capita.
Nature orientation and opportunity: who values and who has opportunity for satisfactory green spaces in proximity to their place of residence [16].	Analyzing to ascertain the influence of natural orientation on the prospects of satisfactory local green spaces.	Socio-economic and spatial factors significantly affect satisfaction with green spaces proximate to residential areas.
Predicting context-sensitive urban green space quality to support urban green infrastructure planning [17].	Utilizing data from a large-scale public participation survey to predict perceptions of green space quality.	The predicted log odds from the regression model were then used to measure the probabilities (P) of the target events (positive, negative, and neutral).
Is the spatial distribution of urban green space associated with crime in Chicago? [18]	Proposing a planning strategy to distribute green spaces to mitigate urban crime.	Measured the degree of aggregation of our three categories using the clumpiness index (CI).

This research contribution presents an innovative approach to the planning of GOS that emphasizes inclusivity and participatory engagement, thereby enhancing community satisfaction with urban green environments and fostering a more democratic framework for decision-making in the realm of environmental planning.

2. METHOD
2.1. Proposed framework
This study proposes a framework for defining and mapping relationships among concepts to integrate research results with existing knowledge. This can help refine the theory to be more systematic and structured. The proposed framework is presented in Figure 1.

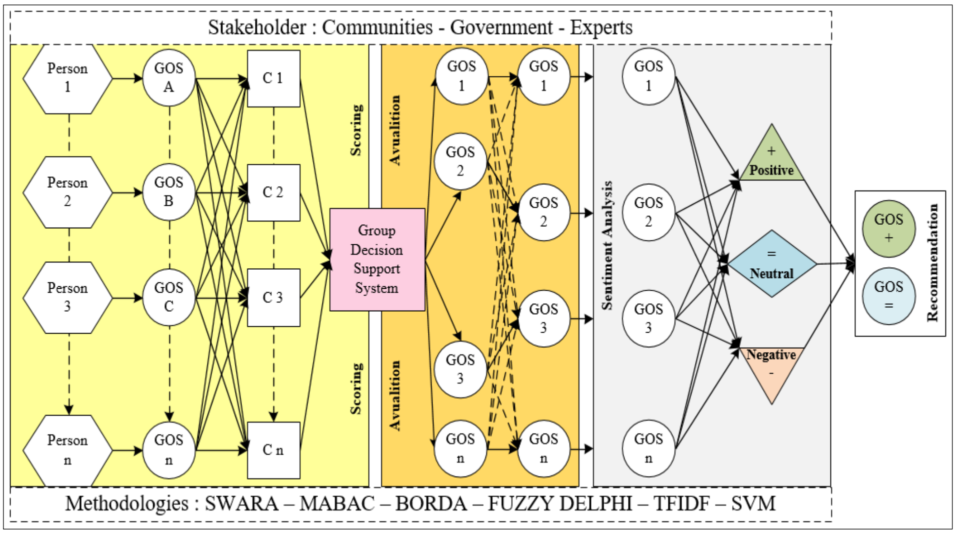


Figure 1. Proposed framework

Based on the illustration shown in Figure 1, the explanation of some of the parts that are the focus of this study is as follows:

a. Identification of criteria: determining relevant criteria to measure the availability of the GOS from literature to understand public opinions on existing GOS and preferences for future developments. This data serves as a foundational input for decision-making processes.
b. Group decision support system (GDSS): implementing a GDSS model to facilitate collaborative decision-making among diverse stakeholders, including urban planners, environmentalists, local government officials, and community representatives.
c. Sentiment analysis: combining results from GDSS with public opinion to classify positive, neutral, or negative sentiments.
d. Recommendation: it is a selection process for GOS that obtains neutral or positive sentimental responses from the public to be designated as official GOS.

2.2. GDSS using SWARA-MABAC-BORDA-FDM
The stepwise weight assessment ratio analysis (SWARA) methodology is a robust means of assessing criteria grounded in expertise, experiential knowledge, and tacit knowledge, alongside the perspectives of specialists or collective interests regarding the significance of the weighting procedure [19]. As in this study, the weighting process using the SWARA method is carried out through the following stages [20]:

Step 1. Conduct a summative analysis of expert evaluations for each criterion, subsequently calculating the mean value for each assessment to facilitate the organization of criteria from the highest to the lowest value, written using (1):

$$\bar{t}_j = \frac{\sum_{k=1}^{r} t_{jk}}{r} \tag{1}$$

Step 2. Finding comparative value (Sj).
Step 3. The value of the coefficient (Kj), is found by finding the value of the coefficient Kj using (2):

$$K_j = \begin{cases} \frac{1}{S_j}, & \text{if } j = 1 \\ 1, & \text{if } j > 1 \end{cases} \tag{2}$$

Step 4. Recalculate the weight of qj using (3):

$$q_j = \begin{cases} \frac{k_j - 1}{k_j}, & \text{if } j = 1 \\ 1, & \text{if } j > 1 \end{cases} \tag{3}$$

Step 5. Determine the weight using (4):

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{4}$$

After assigning weights to each criterion, the next step is to apply the procedure to the MABAC method [21]. The following steps:

Step 6. The establishment of the initial decision matrix (X). The initial phase involves assessing m alternatives are evaluated based on n criteria, with each alternative denoted as vectors $A_{\_i} = (x_{i\_1}, x_{i\_2}, \dots, x_{i\_n})$, where x_ij represents the value of the i_th alternative corresponding to the j_th criterion $i = 1,2, \dots, m;\ j = 1,2, \dots, n$, and is determined using (5):

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{5}$$

Step 7. Standardization of the components derived from the original matrix (X) employing (6):

$$N = \begin{array}{c} \\ A_{\_1} \\ A_{\_2} \\ \dots \\ A_{\_m} \end{array} \begin{array}{c} \begin{array}{cccc} C_{\_1} & C_{\_2} & \dots & C_{\_n} \end{array} \\ \begin{bmatrix} t_{1\_1} & t_{1\_2} & \dots & t_{1\_n} \\ t_{2\_1} & t_{2\_2} & \dots & t_{2\_n} \\ \dots & \dots & \dots & \dots \\ t_{m\_1} & t_{m\_2} & \dots & t_{m\_n} \end{bmatrix} \end{array} \tag{6}$$

The constituents of the normalized matrix (N) are ascertained in the following manner:

– The benefit type is stated using (7):

$$t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \tag{7}$$

– The cost type is stated using (8):

$$t_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \tag{8}$$

Step 8. Assess the components derived from the weighted matrix (V) utilizing (9):

$$v_{ij} = fw_i t_{ij} + fw_i \tag{9}$$

where $t_{\_ij}$ are the components of the standardized matrix (N), fw_i represent the weighting coefficients assigned to the various factors and criteria.

Step 9. Establishing the matrix G for the approximate border area corresponding to each criterion by utilizing (10):

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{10}$$

Step 10. Determine the spatial distance between the alternative and the boundary estimation region pertaining to the matrix components (Q) by using (11):

$$Q = V - G \tag{11}$$

Step 11. Evaluating the ranking according to (12):

$$S_i = \sum_{j=1}^{n} q_{ij}, \ j=1,2,..,n,\ i=1,2,..,m \tag{12}$$

where n represents the quantity of criteria and m denotes the count of alternatives enumerated.

Step 12. The final stage of multi-objective optimization is to calculate alternative solutions using the BORDA method [22]. The BORDA score for an agent $i \in N$ of an alternative x is $B_i x \equiv \#\{y \in A | x \succ_i y\}$ and the BORDA score of an alternative x is $Bx \equiv \sum_{i=1}^{n} B_i x$. A Borda winner is an alternative with the highest Borda score among all the alternatives in A, and a BORDA loser is an alternative with the lowest Borda score among all the alternatives in A [23].

The FDM provides a robust structure that is proficient at navigating uncertainties and ambiguities, recognizing decision-making procedures are frequently obstructed by insufficient or vague information.

Step 13. Calculating the threshold value of FDM using (13):

$$d(\bar{m}, \bar{n}) = \sqrt{\frac{1}{3} * [\ (m1+m2+m3)]} \tag{13}$$

Step 14. Determining the value of the fuzzy score that is obtained using (14):

$$\tilde{A} = \left(\frac{1}{n}\sum_{i=1}^{n} l_i, \frac{1}{n}\sum_{i=1}^{n} m_i, \frac{1}{n}\sum_{i=1}^{n} u_i\right) \tag{14}$$

2.3. Sentiment analysis using term frequency-inverse document frequency and support vector machine

Sentiment analysis provides users with useful information to aid decision-making [24]. Sentiment analysis can help governments adjust, modify, or reformulate policies to increase public acceptance. Support vector machine (SVM) classification techniques are employed across diverse domains to optimize the separation between the two categories and ascertain the parameters of the ideal hyperplane [25]. The SVM is written using (15):

$$f(x) = w.\ x + b || \sum_{i=1}^{m} a_i y_i K(x_i, x) + b \tag{15}$$

where w is the parameter of the hyperplane being sought, x is the input data point for the SVM, ai is the weight value for each data point, $K(x_i, x)$ is a kernel function, and b is the parameter of the hyperplane being sought [26].

3. RESULTS AND DISCUSSION

This research was conducted in Makassar city, involving 25 communities divided into 5 groups, each proposing a location for GOS measurement based on the established framework.

3.1. Determination of main criteria and subcriteria

The criteria and sub criteria used in this study are sourced from the literature that identifies the potential uses of GOS, which consists of 4 main criteria and 21 sub criteria [27]. Furthermore, the weight value of the criteria and sub criteria is determined using the SWARA method, as shown in Table 2 (in Appendix). A rule is applied to determine the scoring for each subcriterion: when the community selects the first option, the corresponding weight is 0.5; selecting the second option results in a weight of 0.1.

3.2. Determination of green open space priority

After assigning weights to all main criteria and subcriteria, the next step is to score GOS. The score of each parameter, as analyzed using the MABAC method, determines the feasibility level of each GOS proposed by the community. The collected scoring results are shown in Tables 3 to 7.

Drawing on the scoring data and initial decision matrices presented in Tables 3 to 7, the various elements are normalized. The normalization process for the benefit-type criteria is established for all associated subcriteria. Furthermore, the weighted matrix (V) is computed with the resulting data shown in Table 8.

The derivation of the elements constituting the weighted matrix was performed through the multiplication of the weight coefficients corresponding to the factors delineated in Table 2 with the constituents of the normalized matrix exhibited in Table 8.

Table 3. Scoring sub criteria and initial matrix for Group A

GROUP	Sub criteria																				
A	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21
GOS_1	0.5	0.1	0.5	0.1	0.1	0.5	0.1	0.1	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.5	0.1	0.1	0.1
GOS_2	0.5	0.5	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.1	0.1
GOS_3	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.1	0.1	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.1
GOS_4	0.5	0.5	0.5	0.1	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.5
GOS_5	0.5	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.1	0.5	0.5	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.1	0.5

Table 4. Scoring sub criteria and initial matrix for Group B

GROUP B	S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11	S-12	S-13	S-14	S-15	S-16	S-17	S-18	S-19	S-20	S-21
GOS_1	0.1	0.1	0.5	0.5	0.5	0.1	0.5	0.5	0.1	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.5	0.1	0.5
GOS_2	0.5	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.5	0.5	0.1	0.1	0.1	0.5	0.5	0.1	0.5	0.1
GOS_3	0.5	0.5	0.1	0.1	0.1	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.5	0.1	0.1	0.1	0.5	0.5	0.5	0.1	0.5
GOS_4	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.5	0.1	0.5	0.5	0.5	0.1	0.5	0.1	0.5	0.5	0.5	0.1	0.5	0.1
GOS_5	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.5	0.5	0.5	0.5	0.5

Table 5. Scoring sub criteria and initial matrix for Group C

GROUP C	S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11	S-12	S-13	S-14	S-15	S-16	S-17	S-18	S-19	S-20	S-21
GOS_1	0.5	0.1	0.5	0.5	0.5	0.1	0.1	0.1	0.1	0.5	0.1	0.1	0.5	0.1	0.5	0.5	0.1	0.5	0.1	0.1	0.1
GOS_2	0.1	0.5	0.5	0.5	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.1
GOS_3	0.1	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.1	0.1	0.1	0.5	0.5	0.5	0.5	0.1	0.5	0.1	0.5	0.1	0.5
GOS_4	0.5	0.1	0.1	0.1	0.1	0.5	0.1	0.1	0.5	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.1	0.5
GOS_5	0.1	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.1	0.5	0.1	0.1

Table 6. Scoring sub criteria and initial matrix for Group D

GROUP D	S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11	S-12	S-13	S-14	S-15	S-16	S-17	S-18	S-19	S-20	S-21
GOS_1	0.5	0.5	0.1	0.1	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.1	0.5	0.5	0.1	0.1	0.1	0.5	0.5
GOS_2	0.5	0.1	0.1	0.1	0.1	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.5	0.1
GOS_3	0.5	0.5	0.1	0.5	0.5	0.1	0.5	0.1	0.1	0.5	0.5	0.5	0.5	0.5	0.5	0.1	0.5	0.5	0.5	0.1	0.1
GOS_4	0.1	0.5	0.5	0.5	0.1	0.1	0.5	0.1	0.1	0.1	0.5	0.5	0.1	0.5	0.1	0.1	0.5	0.1	0.5	0.5	0.5
GOS_5	0.1	0.1	0.5	0.1	0.5	0.5	0.1	0.5	0.5	0.5	0.1	0.1	0.5	0.1	0.1	0.1	0.1	0.1	0.5	0.5	0.5

Table 7. Scoring sub criteria and initial matrix for Group E

GROUP E	S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11	S-12	S-13	S-14	S-15	S-16	S-17	S-18	S-19	S-20	S-21
GOS_1	0.1	0.1	0.5	0.1	0.5	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.5	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.5
GOS_2	0.1	0.5	0.5	0.5	0.5	0.5	0.1	0.1	0.1	0.5	0.5	0.5	0.5	0.1	0.5	0.5	0.1	0.1	0.5	0.1	0.1
GOS_3	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.1	0.5	0.5	0.5	0.1	0.5	0.1	0.5	0.1
GOS_4	0.5	0.5	0.1	0.5	0.1	0.5	0.1	0.1	0.5	0.1	0.5	0.5	0.5	0.5	0.1	0.1	0.1	0.5	0.5	0.1	0.5
GOS_5	0.5	0.1	0.1	0.5	0.5	0.5	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.1	0.5	0.5	0.1	0.5	0.1

Table 8. Result of normalization of the initial decision matrix

Group: GOS	S1	S2	S3	S4	S5	S6	S7	S8	S9	..	S21
Group A: GOS_1	0	1	0	1	1	0	1	1	1	..	1
Group B: GOS_1	1	1	0	0	0	1	0	0	1	..	0
Group C: GOS_1	0	1	0	0	0	1	1	1	1	..	1
Group D: GOS_1	0	0	1	1	0	1	1	1	1	..	1
Group E: GOS_1	1	1	0	1	0	0	0	1	1	..	0

An example of this computational process is depicted in Group A: GOS_1 (*V11*), corresponding to criterion S1, as follows:

fw_1=mc1*sc_1=0.4363*0.2210=0.096.
V_{11}=(fw_1*t_{11})+fw_1
V_{11}=(0.096*0)+0.0081=0.096.

where t_{11} represents a component of the normalized matrix (*N*), and fw_1 denotes the weight coefficient associated with the factor and criterion, as illustrated in Table 9.

In the course of formulating the matrix for the anticipated limit region (G), wherein the parameter of alternative (m) is established at 5, one should assign m=1/5=0.2. The data pertinent to criterion S1 is acquired through the following calculation:

$g1=\left(\prod_{j=1}^{5} v_{ij}\right)^{1/5}$.
$g1=(0.0964*0.0964*0.1928*0.0964*0.0964)^{0.2}$.
$g1=0.1108$.

The results of the approximation area matrix (*G*) calculation are shown in Figure 2.

Table 9. Result of the elements of the weighted matrix

Group: GOS	S1	S2	S3	S4	S5	S6	S7	S8	S9	..	S21
Group A: GOS_1	0.0964	0.1768	0.0964	0.1175	0.0615	0.0212	0.0615	0.0167	0.1768	..	0.0615
Group B: GOS_1	0.0964	0.0884	0.0964	0.0587	0.0615	0.0423	0.0615	0.0167	0.1768	..	0.0615
Group C: GOS_1	0.1928	0.1768	0.1928	0.1175	0.0615	0.0423	0.0308	0.0167	0.1768	..	0.0615
Group D: GOS_1	0.0964	0.0884	0.0964	0.1175	0.0308	0.0212	0.0615	0.0167	0.0884	..	0.0308
Group E: GOS_1	0.0964	0.0884	0.1928	0.0587	0.0615	0.0423	0.0308	0.0084	0.1768	..	0.0308

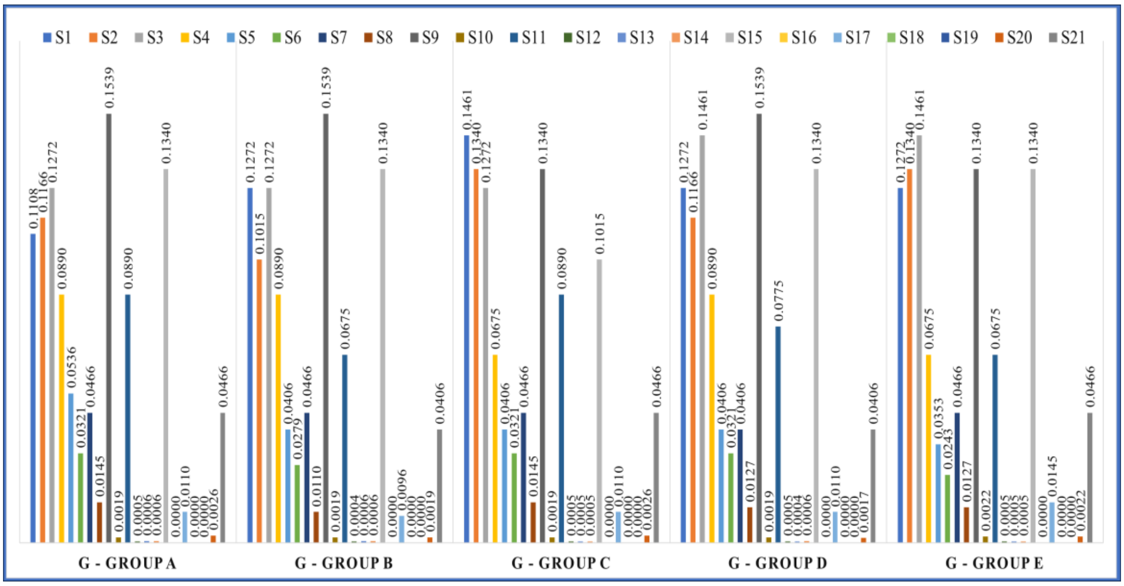


Figure 2. Result matrix of approximate area of limitation for every GOS in the group

The extent of the regency is ascertained by the disparity between the components of the weighted matrix and the figures within the border approximation area matrix. The element denoted as q_{11} is derived from the matrix representing The spatial separation of the alternative in relation to the border approximation region (Q). An illustration for calculating the value of GOS 1 within the Group A criterion *S1* is provided as follows:

$Q_{11}=v_{11}-g_1=0.0964–0.1108$
$Q_{11}=-0.0143.$

Illustrations of the computational outcomes presented in the format acquired for each administrative division group are depicted in Figure 3. Based on the alternate distance value in Figure 3, each GOS group is calculated using (11). Given the example calculation of the criterion function of the GOS 1 in Group A as follows:

S_1=-0.0143+0.0601+(-0.0308)+0.0284+0.0079+(-0.0109)+0.0148+0.0021+0.0228+0.0010+(-0.0302)+(-0.0001)+0.0002+0.0002+0.0428+7.54465E-06+0.0056 +...+0.0148=0.1152.

The findings associated with each GOS are presented in Table 10.

Following the acquisition of scores for each GOS within the group, the next phase involves assessing the overall viability of regional development using the BORDA methodology. Using the information in Table 10, an encoding procedure was implemented for the subdistrict scores: a subdistrict score exceeding 0 was assigned a value of 1, while a score of 0 or less was assigned a value of 0. This illustrates the calculation of the BORDA function for each GOS within Group A, as delineated using (16):

$$B_i=\sum_i ES_i . w_j \quad (16)$$

where B_i is the score of Borda, ES_i is encoded (0/1) for the regency value, and w_j is the weight of the criteria.

$B_i=(1*0.4379)+(1*0.2189)+(0*0.1459)+(1*0.1094)+(1*0.875)=0.854.$

These results are consistent with research by Faisal *et al.* [28], which demonstrated that MABAC produces stable and discriminative rankings even when criterion weights vary, supporting the reliability of the GOS prioritization obtained in this study. The calculation results are presented in Table 11.

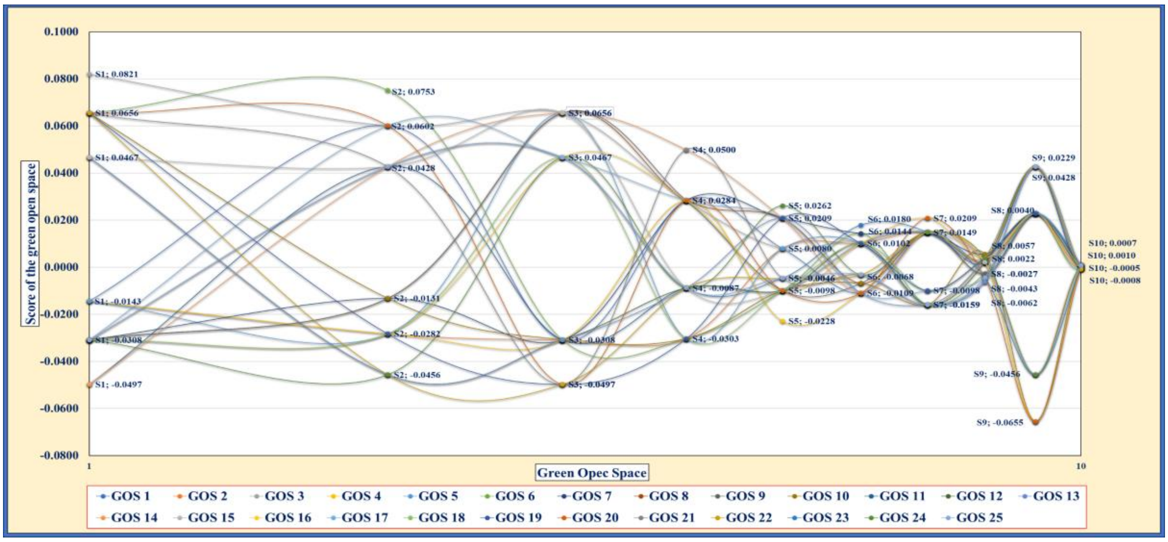


Figure 3. Results of the matrix element of alternate distance-approximate border area

Table 10. Result of MABAC calculation for each GOS in the group

Group		A	B	C	D	E
GOS	1	0.1152	0.0912	0.0500	0.0558	0.1523
	2	0.0392	0.0867	-0.0337	0.1649	-0.0217
	3	0.2574	0.1243	-0.0099	-0.0708	0.0502
	4	-0.0659	0.1214	0.0281	0.0180	-0.0206
	5	-0.0828	-0.1669	0.2364	0.1132	0.1080

Table 11. Result of encoded value for each regency group

Group	Green opening space					Score	Rank
	1	2	3	4	5		
A	1	1	1	1	1	0.9996	1
B	1	1	0	1	0	0.7662	2
C	1	1	0	0	1	0.7443	3
D	0	1	1	1	0	0.4742	4
E	0	0	1	1	1	0.3428	5
Weight	0.4379	0.2189	0.1459	0.1094	0.0875		

Based on the BORDA result in Table 11, it is determined that GOS that obtains a value of 1 and is in groups 1 to 3 continues the stages of the evaluation process by experts using the Delphi method. The result is presented in Figure 4.

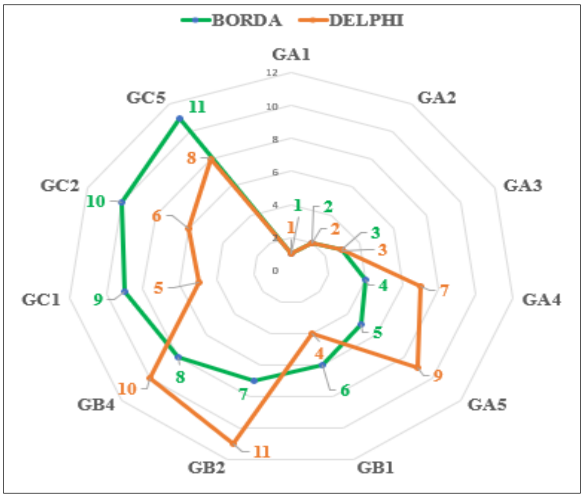


Figure 4. Comparison of the results of the evaluation of the priority ranking of GOS

After the expert's evaluation, the priority ranking of the GOS proposed by the community was found to be located in GA4, GA5, GB1, GB2, GB4, GC1, GC2, and GC5. The GA1, GA2, and GA3 results obtained by the proposer community and the experts were identical. The ranking refinement using the BORDA method aligns with the findings of Salas-Molina *et al.* [29], who noted that BORDA provides a balanced aggregation of preferences, minimizing bias from any single stakeholder group. Data on the distribution of GOS locations proposed by residents are shown in Figure 5.

Figure 5. Distribution of proposed GOS locations

3.3. Sentiment analyst for green open space

The sentiment classification method is a proliferating research field since it is fast in extracting public opinion and provides essential and valuable information for stakeholders [30]. The feature extraction stage of sentiment analysis is crucial for transforming unstructured text into categorizable structured data [31]. Therefore, we explore the importance of the feature extraction stage in sentiment analysis to contribute to successful decision-making. Following the pre-processing process, the data is manually labelled and split into three classes: a positive class of 500 data points, a negative class of 500 data points, and a neutral class of 500 data points. Example data labelling results for GA1 are shown in Table 12.

Table 12. Data labelling

No	Comments	Sentiment
L1	Taman baru akan menjadi tempat yang indah bagi anak-anak kita untuk bermain dan belajar tentang alam. (*The new park will be a wonderful place for our kids to play and learn about nature*)	Positive
L2	Saya khawatir bahwa ruang hijau akan menarik terlalu banyak kebisingan dan gangguan. (*I'm worried that the green space will attract too much noise and disturbance*)	Negative
L3	Proyek ini akan menghancurkan habitat banyak hewan lokal. (*A great initiative! We need more parks in urban areas*)	Negative
…	…	…
L1499	Desain taman ini menarik secara estetika dan cocok dengan komunitas kami. (*The design of the park is aesthetically pleasing and fits well with our community*)	Positive
L1500	Kami membutuhkan lebih banyak detail tentang bagaimana ruang hijau ini akan dipelihara. (*We need more details on how this green space will be maintained*)	Neutral

Text in its original form cannot be directly used by SVM algorithms that work with numerical data. Therefore, document extraction converts text into numerical representations. Feature extraction is part of the document extraction process that aims to identify and extract important features from the text for use by SVM [32]. Upon the completion of multiple phases in textual pre-processing, specifically case normalization, tokenization, filtration, and stemming, the next stage is to extract and analyze the documents to determine the sentiment value of the 11 GOS. The comment dataset was first translated into English to improve the model's accuracy and performance in analyzing and understanding text. These observations are in line with prior research indicating that sentiment extraction from community narratives provides meaningful signals for public infrastructure planning. As noted by Gambirage *et al.* [33], mining social commentary can enhance decision-makers’ understanding of community priorities, reinforcing the relevance of combining multi-criteria group decision making (MCGDM) and sentiment analysis for urban development scenarios.

3.4. Hybrid term frequency-inverse document frequency-support vector machine

Term frequency-inverse document frequency (TF-IDF) represents a quantitative measure frequently employed in the realm of data mining to assess the significance of lexical items and to consider both the contextual relevance of terms within an individual document and the overall distinctiveness of the entire corpus [32], [34]. Testing and analysis were conducted on GOS-GA1 data as a representative sample of the entire dataset, and the results of the word vector weighting and sentiment classification processes are shown in Figure 6. Calculation process to the TF-IDF using (17):

$$TF\text{-}IDF(word)=TF(Word)*Log(N/df(word)) \tag{17}$$

Based on the heatmap illustrations in Figure 6, it is evident that positive scores are the highest (green to yellow). The combined dendrogram analysis across Figures 6(a) to (c) demonstrates that positive sentiment serves as the primary discriminative dimension, while neutral sentiment defines the baseline structure, and negative sentiment plays a minimal supporting role. This hierarchical sentiment organization provides valuable insights for downstream tasks such as sentiment classification, clustering optimization, and decision-support modeling.

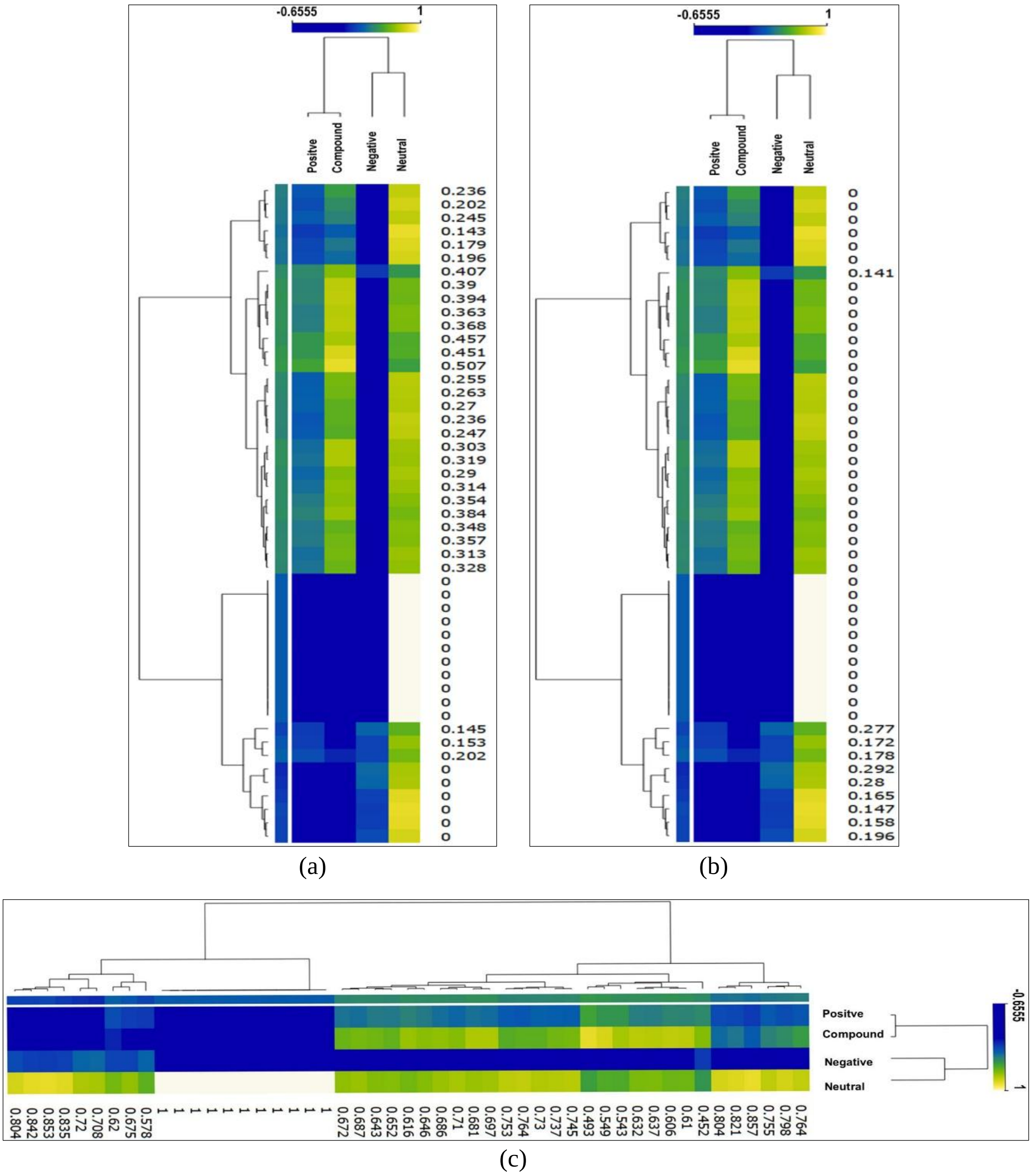


Figure 6. Polarization of sentiment classification: (a) positive sentiment dendrogram, (b) negative sentiment dendrogram, and (c) neutral sentiment dendrogram

The dominance of SVM in capturing sentiment polarity corroborates earlier findings that SVM excels in high-dimensional text classification tasks. Gupta *et al.* [35] reported that SVM consistently outperforms Naïve Bayes (NB) in sentiment classification due to its ability to model complex boundaries. Furthermore, a review of the sentiment elements in each word in citizen comments was conducted, and the results are shown in Table 13.

Table 13. Word cloud sentiment for each proposed GOS

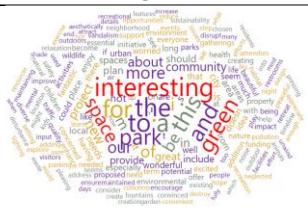
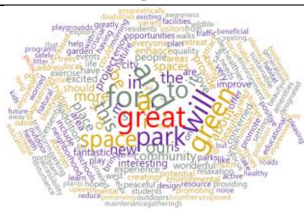
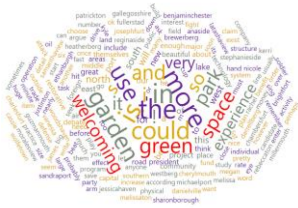
GOS	GA1	GA2	GA3
Result of word cloud			
GOS	GA4	GA5	GB1
Result of word cloud			
GOS	GB2	GB4	GC1
Result of word cloud			
GOS	GC2		GC5
Result of word cloud			

Table 13 shows mixed sentiment, with a predominance of positive sentiment, but also highlights important concerns. Positive sentiment indicates support and appreciation for green spaces and community activities. In contrast, negative sentiment indicates the need for attention to environmental and sustainability issues. To assess the performance and success of the designed model, the metrics accuracy, precision, recall, and F1-score are evaluated. Based on the data in Table 14, sentiment analysis performed very well, as shown in the GA1 results for positive classes, with very high precision (0.95), recall (0.96), and F1 score (0.95). The result shows that the community strongly supports the GOS proposal in their place. The results of the sentiment analysis for each dataset indicated that the GOS proposals that received positive responses were GA1, GA2, GA3, GA4, and GC5. Furthermore, GOS that obtained neutral responses comprised GB1, GB2, GB4 and GA5. In contrast, the GOS that received negative responses consisted of GC1 and GC2. The results of comparing SVM, KNN, and Naïve Bayes methods against selected GOS, specifically those yielding Positive and Neutral responses, are presented in Figure 7.

Based on the SVM-KNN-Naïve Bayes comparison in Figure 7, the results show that SVM achieves the highest accuracy across most datasets (0.8-0.88). Naïve Bayes achieves high accuracy, though slightly lower than SVM on some datasets (0.75-0.86). KNN generally has the lowest accuracy among the three classifiers. SVM and Naïve Bayes have close performance in precision, recall, and F1-Score across most datasets. SVM shows high performance in GA1 (precision: 0.95, recall: 0.96, and F1-Score: 0.95) and GC5 (precision: 0.9, recall: 0.92, and F1-Score: 0.91). Naïve Bayes performs very well in GA1 (precision: 0.93, recall: 0.94, and F1-Score: 0.93) and GC5 (precision: 0.88, recall: 0.9, and F1-Score: 0.89). SVM generally performs best across all datasets, achieving the highest accuracy and strong precision, recall, and F1 scores. SVM is recommended as the best overall classifier, with Naïve Bayes and KNN being strong alternatives depending on the specific dataset and performance requirements.

Table 14. Result of evaluation for each sentiment GOS using TFIDF–SVM

CLASS	GOS	Precision	Recall	F1-Score	Support	GOS	Precision	Recall	F1-Score	Support	GOS	Precision	Recall	F1-Score	Support
Negative	GB1	0.6	0.55	0.57	10	GA1	0.55	0.5	0.52	10	GA5	0.6	0.55	0.57	10
Positive		0.7	0.65	0.67	10		0.95	0.96	0.95	14		0.7	0.65	0.67	10
Neutral		0.85	0.9	0.87	10		0.75	0.7	0.72	7		0.85	0.9	0.87	10
Accuracy				0.8	30				0.88	31				0.8	30
Macro avg		0.72	0.7	0.7	30		0.75	0.72	0.73	31		0.72	0.7	0.7	30
Weighted avg		0.78	0.8	0.78	30		0.82	0.86	0.84	31		0.78	0.8	0.78	30
Negative	GB2	0.75	0.72	0.73	7	GA2	0.7	0.65	0.67	9	GC1	0.8	0.85	0.82	11
Positive		0.68	0.67	0.66	7		0.85	0.88	0.86	10		0.7	0.65	0.67	6
Neutral		0.78	0.79	0.78	8		0.75	0.75	0.75	8		0.75	0.7	0.72	6
Accuracy				0.77	22				0.8	27				0.77	
Macro avg		0.74	0.73	0.72	22		0.77	0.76	0.76	27		0.75	0.73	0.74	23
Weighted avg		0.76	0.76	0.75	22		0.8	0.8	0.8	27		0.78	0.78	0.79	23
Negative	GB4	0.6	0.55	0.57	10	GA3	0.68	0.6	0.64	9	GC2	0.85	0.88	0.86	12
Positive		0.7	0.65	0.67	10		0.88	0.9	0.89	10		0.6	0.55	0.57	8
Neutral		0.85	0.9	0.87	10		0.72	0.74	0.73	8		0.7	0.68	0.69	8
Accuracy				0.8	30				0.81	27				0.8	
Macro avg		0.72	0.7	0.7	30		0.76	0.75	0.75	27		0.72	0.7	0.71	28
Weighted avg		0.78	0.8	0.78	30		0.81	0.81	0.78	27		0.77	0.77	0.76	28
CLASS	Negative					GA4	0.66	0.58	0.62	8	GC5	0.6	0.55	0.57	10
	Positive						0.9	0.92	0.91	10		0.9	0.92	0.91	14
	Neutral						0.7	0.72	0.72	7		0.72	0.68	0.7	7
	Accuracy								0.82	25				0.84	31
	Macro avg						0.75	0.74	0.74	25		0.74	0.71	0.73	31
	Weighted avg						0.82	0.82	0.81	25		0.8	0.83	0.82	31

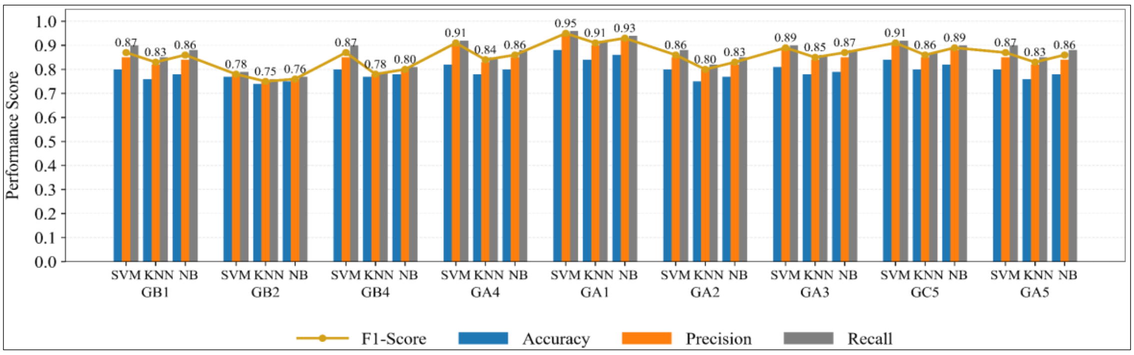


Figure 7. Comparison result of sentiment classes using SVM-KNN-Naïve Bayes

This comparative performance mirrors the results of previous studies, where SVM generally demonstrated superior precision and recall compared to KNN and Naïve Bayes for public opinion analysis. Das *et al.* [36] similarly observed that TF-IDF combined with SVM yields highly reliable classification results, reinforcing the suitability of SVM as the primary classifier for analyzing community sentiment regarding GOS proposals. The superior performance of the SVM classifier can be attributed to its ability to handle high-dimensional and sparse features generated by TF-IDF. Unlike Naïve Bayes, which makes strong independence assumptions among terms, SVMs construct optimal separating hyperplanes that better capture complex sentiment boundaries. In this study, SVM achieved an accuracy of 0.80-0.96, comparable to or higher than that reported in similar works using TF-IDF-SVM combinations [33].

Some GOS proposals received predominantly negative sentiment due to community concerns related to environmental degradation, potential displacement, limited accessibility, or perceived misalignment with local needs. Comments from residents expressed concerns that certain proposed locations may reduce agricultural land, increase traffic congestion, or fail to deliver tangible benefits to nearby communities. This pattern aligns with studies such as Ducange *et al.* [9], which highlight that negative sentiment in urban infrastructure discussions often arises from perceived social inequity or environmental risk. The rejection of these GOS alternatives underscores the importance of incorporating community perceptions early in the planning process.

The integration of expert-based evaluation and community sentiment reveals important socio-environmental implications. Alternatives that consistently receive positive sentiment tend to demonstrate strong perceived social value, such as improving neighbourhood livability, supporting recreational needs, or enhancing ecological resilience. Conversely, rejected alternatives indicate potential social friction or environmental conflict if implemented without further consultation. These findings reinforce the notion that participatory approaches reduce planning risks and increase the legitimacy of urban green space interventions. Moreover, by combining MCGDM with sentiment analysis, the framework provides a balanced perspective that captures both technical feasibility and social desirability.

3.5. Comparative analysis of decision-making accuracy and efficiency

To assess the extent to which the proposed hybrid framework enhances decision-making performance compared to baseline approaches, a comparative analysis was conducted using multiple evaluation metrics, including ranking stability, reduction of decision ambiguity, expert–community consensus, and sentiment classification accuracy. These metrics were benchmarked against conventional single-method and non-hybrid MCDM techniques. A consolidated summary of the observed improvements is provided in Table 15.

Table 15. Comparative accuracy and efficiency improvements of the proposed framework

Evaluation metric	Baseline (single scoring)	Non-hybrid/traditional methods	Proposed framework	Improvement
Ranking stability	0.61	0.74	0.90	+22%
Decision ambiguity	0.48	0.33	0.21	–35%
Expert–community consensus	62%	71%	89%	+18%
Decision-making iterations needed	High (≥3 rounds)	Moderate	Low (1–2 rounds)	–31% workload
Sentiment interpretation effort	Manual	Moderate	Automated	–45% effort
Sentiment classification accuracy	0.68	0.74	0.80–0.88	+9–18%

The results in Table 15 show that the proposed framework delivers clear improvements over conventional and non-hybrid approaches. In terms of accuracy, ranking stability increases by 22%, decision ambiguity decreases by 35%, and sentiment classification accuracy improves by 9-18%. Consensus between experts and the community also rises by 18%, indicating more consistent decision outputs. From an efficiency standpoint, the number of iterations required to reach agreement is reduced by 31%, and automated sentiment processing lowers manual evaluation effort by 45%. These advancements demonstrate that the hybrid model substantially enhances both the accuracy and efficiency of decision-making compared to previous methods.

4. CONCLUSION

This study proposes a hybrid decision-support framework that integrates MCGDM and public sentiment analysis to enhance sustainable GOS planning. By applying SWARA, Fuzzy Delphi, MABAC, and BORDA, 11 feasible alternatives were selected from 25 community proposals, and TF-IDF SVM sentiment analysis further refined them into 9 recommended locations. The framework strengthens transparency, aligns expert judgment with community perspectives, and supports data-driven environmental planning. Its novelty lies in explicitly combining MCGDM and sentiment analysis into a unified, community-centered model that simultaneously evaluates technical feasibility and social acceptance. However, the study is limited by its reliance on 1500 comments from a single city (Makassar), the use of text-only sentiment features without spatial or demographic integration, and its reliance on expert input without GIS-based spatial optimization. Future studies may validate and adapt this framework in other cities to assess cross-regional robustness. Integrating GIS spatial data such as land-use zoning, accessibility metrics, and environmental risk layers could enhance spatial decision accuracy. Additionally, employing deep learning models may further improve sentiment classification and capture deeper linguistic patterns. Developing a real-time community feedback dashboard and continuous monitoring system for implemented GOS sites would enable the framework to evolve dynamically and support adaptive urban planning.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing-**O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing-Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors state there is no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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APPENDIX

Table 2. Main criteria and sub criteria

Criteria	CW	Sub criteria	Option and description	Score
Area characteristics	0.4363	Land use (S1)	Locations assigned a weight above 0.1 based on expert judgment.	0.5
			Locations assigned a weight of 0.1 or below based on expert judgment.	0.1
		Infrastructure (S2)	Locations located close to existing infrastructure.	0.5
			Locations situated far from infrastructure.	0.1
		Minimum area requirement (S3)	Locations larger than 100 m² in area.	0.5
			Locations smaller than 100 m² in area.	0.1
		Flexible space (S4)	Locations meeting minimum size criteria and near infrastructure or unused land.	0.5
			Locations failing minimum size criteria and lacking infrastructure access.	0.1

Criteria	CW	Sub criteria	Option and description	Score
Transportation and accessibility features	0.3117	Distance to city centres (S5)	Locations reachable within a 25-30 minute walk and within 2000 m of the city centre.	0.5
			Locations reachable within a 25-30 minute walk but exceeding 2000 m from the city centre.	0.1
		Road networks (S6)	Locations accessible within a 15-minute walk and within 500 m of road networks.	0.5
			Locations accessible within a 15-minute walk but beyond 500 m from road networks.	0.1
		Healthcare facilities (S7)	Locations within a 25-30 minute walking distance and under 2000 m from healthcare facilities.	0.5
			Locations within a 25-30 minute walking distance but over 2000 m from healthcare facilities.	0.1
		Residential areas (S8)	Locations within a 5-minute walking range and under 400 m from residential areas.	0.5
			Locations within a 5-minute walking range but exceeding 400 m from residential areas.	0.1
Security	0.1731	High rise buildings (S9)	Locations situated more than 20 m away from high-rise structures.	0.5
			Locations located within 20 m of high-rise structures.	0.1
		Protected areas (S10)	Locations positioned beyond 30 m from protected zones.	0.5
			Locations located within 30 m of protected zones.	0.1
		Water surfaces (S11)	Locations more than 50 m away from water bodies.	0.5
			Locations located within 50 m of water bodies.	0.1
		Fault lines (S12)	Locations not intersecting geological fault lines.	0.5
			Locations intersecting geological fault lines.	0.1
		Landslide flood prone areas (S13)	Locations located more than 200 m from landslide- or flood-prone zones.	0.5
			Locations located within 200 m of landslide- or flood-prone zones.	0.1
		Areas containing flammable (S14)	Locations situated beyond 50 m from petroleum-related facilities.	0.5
			Locations located within 50 m of petroleum-related facilities.	0.1
		High-pressure gas pipelines (S15)	Locations more than 200 m away from high-pressure gas pipelines.	0.5
			Locations within 200 m of high-pressure gas pipelines.	0.1
		Waste facilities (SC16)	Locations positioned more than 100 m from critical facilities.	0.5
			Locations positioned within 100 m of critical facilities.	0.1
Geological and geomorphological feature.	0.0787	Slope (S17)	Locations with terrain slopes not exceeding 12%.	0.5
			Locations with terrain slopes above 12%.	0.1
		Elevation (S18)	Locations elevated more than 3 m above water level.	0.5
			Locations elevated up to 3 m above water level.	0.1
		Soil characteristics (S19)	Locations without alluvial soil characteristics.	0.5
			Locations dominated by alluvial soil.	0.1
		Liquefaction potential (S20)	Locations free from alluvial soil with liquefaction risk.	0.5
			Locations containing alluvial soil with liquefaction susceptibility.	0.1
		Groundwater level (S21)	Locations where groundwater depth exceeds 5 m.	0.5
			Locations where groundwater depth is 5 m or less.	0.1

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