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ADAPTIVE FUZZY INTERFERENCE SYSTEM FOR QUANTIFYING THE EFFECT OF URBAN GREEN SPACE ON HUMAN HEALTH

Abstract: Urban green areas consist of intentionally preserved plantations, parks, and natural elements available to the public for recreation and relaxation. These places are good for people's health because they provide places that encourage physical activity, stress relief, and mental recovery. To evaluate their influence, urban green areas must be systematically categorised based on their measurable impact on human health. In this research, an Effect Quantifying Process using a Fuzzy Inference System (EQP-FIS) is used to figure out what effect this has by looking at two main factors: health improvements that have been shown to happen and the functional effect of being close to green spaces. The method finds the degree of connectivity between environmental effects and health-related recommendations. Low connectivity indicates limited health benefits, prompting targeted suggestions for improvement, whereas high connectivity supports the growth or replication of effective green spaces. The model's performance is verified using recommendation scores, effect rates, data availability, and analysis time.

Keywords: FIS, human health, recommendation score, urban green space

Introduction

Urban green space (UGS) is an open space used as a public park with many green plants. UGS provides a natural environment to urban people, including water features and plant life in a park [1]. UGS plays a major role in improving people's health. UGS promotes the mental and physical health range of people and also reduces the mortality ratio of urban residents [2]. UGS parks provide physical activities to reduce residents' stress and anxiety. An optimal planning model is used in UGS to improve the healthcare range of urban residents [3]. The planning model analyses people's actual health condition via an analysis process. The analysis identifies the blood pressure level, diabetes level, chronic disease, and physical condition of the UGS users [4]. The analysis process provides feasible information for healthcare improvement and development processes. UGS is mainly used to improve urban residents' self-rated health, and UGS provides the necessary surroundings and a peaceful environment to the users, reducing the negative impact on the

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residents [5]. The overall Self-Rated Health (SRH) rate is improved among urban residents, which enhances the performance range of people's physical health conditions.

Urban green spaces create a rapid impact on people, which improves their healthcare routine. UGS gains quantifying user interest, reducing and enhancing healthcare's improvement range [6]. A quantitative health impact assessment (QHIA) is used in urban areas to identify the actual impact of UGS on people.

The Fuzzy Inference System (FIS) is used to quantify the impact of urban green spaces on human health by analysing data on health improvements and environmental factors. Quantitative Health Impact Assessment (QHIA) evaluates how urban green spaces affect health outcomes like stress reduction, cardiovascular health, and overall well-being. The Analytic Hierarchy Process (AHP) analyses and ranks multiple criteria by pairwise comparisons, prioritising factors like accessibility, vegetation density, and health benefits. The AHP method helps determine the relative importance of different characteristics of green spaces in improving public health. These methods enable a data-driven assessment of urban green spaces, facilitating precise recommendations for optimising their design and distribution to maximise health benefits.

QHIA is used via UGS to identify users' health benefits [7]. The QHIA tool analyses the preliminary characteristics of the user's health and provides necessary data for the assessment process [8]. The QHIA increases the accuracy of the healthcare decision-making process, improving the users' mortality range. The QHIA tool reduces the latency in the health condition identification process [9]. An analytic hierarchy process (AHP) based evaluation method is used to evaluate the well-being level of urban residents. The AHP technique is mainly used here to identify the residents' characteristics and health condition patterns [10]. The AHP-based method identifies the quantifying interest of users over UGS and minimises the complexity in the further evaluation process. The AHP-based method provides proper datasets for healthcare planning, improving urban residents' well-being [11].

Various health impact assessment methods are used in UGS to detect the exact health condition of the users. Optimisation-based methods are commonly used to identify the well-being level of users [12]. A health impact assessment with benefits is used in UGS to verify the actual healthcare range of urban residents. The assessment method evaluates the urban planning strategies used in urban areas [13]. Urban planning strategies are mainly used to analyse the mental health, depression, stress, and anxiety levels of urban people. The planning strategies provide optimal information for the health impact assessment process [14]. Health impact assessment approaches are increasingly employed to evaluate the influence of Urban Green Space (UGS) on human well-being. Existing studies investigate UGS impacts from multiple analytical perspectives, including neurophysiological responses, user preference evaluation, and spatial accessibility analysis [15-17]. These complementary perspectives provide insights into the spatial and temporal characteristics associated with UGS exposure and human health outcomes. Such findings contribute to a more comprehensive understanding of the relationship between green space environments and the physical and psychological well-being of urban residents.

The existing approaches show a negative correlation between urban green space exposure and mortality, heart rate, and violence and a favourable correlation with concentration, mood, and activity. This research aims to determine the effects of urban green spaces on human mental health by examining their ability to cleanse the environment,

reduce the impact of congestion and other noise, and serve as gathering places for the residents.

The contributions of this paper are:

- To develop a real-time fuzzy-based correlation that dynamically links urban green space (UGS) utilisation with specific health improvements, surpassing the limitations of static evaluation methods.
- To create an adaptive decision-making framework that continuously refines UGS expansion, modification, or replication recommendations using live health and environmental data.
- To establish a precise quantification model using fuzzy inference rules, reducing uncertainty in health impact assessments compared to traditional QHIA and AHP-based methods.
- To design an integrated system incorporating multiple external data sources to minimise data latency, ensuring timely and effective urban development decisions.

The rest of the article is prearranged as follows: Review and research gap section discusses the related works, Proposed methodology: EQP-FIS framework section proposes the EQP-FIS system, Result and discussion section deliberates the experimental outcomes, and Conclusion section concludes the research paper.

Research questions:

- How does the presence and accessibility of Urban Green Spaces (UGS) impact various aspects of human health, including cardiovascular (CVD), mental illness (MI), and respiratory (RP) conditions?
- What is the role of physician recommendations and self-motivations in influencing the health benefits of UGS?
- How effectively can the proposed Effect Quantifying Process using a Fuzzy Inference System (EQP-FIS) assess and categorise UGS based on their health impact?
- What key factors determine the need for UGS expansion or replication?

Hypotheses:

- H1: Increased exposure to UGS positively correlates with improvements in cardiovascular, mental, and respiratory health conditions.
- H2: Physician recommendations and self-motivations significantly influence the effectiveness of UGS in improving health outcomes.
- H3: The EQP-FIS model accurately quantifies the impact of UGS on human health and provides reliable recommendations for expansion or replication.
- H4: UGS with high connectivity to health improvements exhibit a stronger justification for expansion and replication than those with low connectivity.

Review and research gap

Urban green spaces (UGS) have gained significant attention due to their positive impact on human health and well-being. Researchers have explored various assessment methods, including machine learning, fuzzy logic, and structural equation modelling, to evaluate the effectiveness of UGS in promoting physical and mental health. These studies

have provided valuable insights into urban planning, health monitoring, and ecosystem sustainability.

Yanez et al. [18] conducted a study to assess the health impact of urban green space interventions. They analysed the root causes of mental health issues and proposed an optimal solution to improve mental well-being. Their findings showed that well-planned green spaces significantly enhance mental health by reducing stress and anxiety. However, their research was mainly focused on specific urban settings, highlighting the need for broader validation across different environments.

Zhang et al. [19] introduced a new assessment method for UGS using a structural equation model (SEM). This approach helped evaluate the relationships between various factors influencing UGS effectiveness. Their study demonstrated an increase in the performance of UGS-based associations, making urban planning more effective. While SEM provided a structured evaluation, its adaptability to rapidly changing urban landscapes remained challenging. Future research could integrate real-time analytics for more dynamic assessments.

Hematian and Ranjbar [20] explored the role of UGS in mental health through a cross-sectional analysis. They focused on detecting people's emotional responses and micro-level behavioural patterns within green spaces. Their findings suggested that well-maintained UGS improves the quality of life by fostering relaxation and social interaction. However, their study lacked long-term monitoring, emphasising the need for longitudinal studies to track the sustained impact of UGS on mental well-being.

Wu et al. [21] investigated the role of vegetation in designing health-oriented urban green spaces. They used an analysis method to examine how greenery affects respiratory health, particularly in reducing pulmonary diseases and symptoms. Their study found that properly designed vegetation layouts contribute to healthier urban environments. However, the research primarily focused on respiratory health, leaving room for further exploration of broader health benefits such as cardiovascular improvements.

Olszewska-Guizzo et al. [22] proposed a revised contemplative landscape model (CLM) for UGS, incorporating electrocardiogram (ECG) data to assess the physiological benefits of green spaces. Their findings showed that exposure to well-designed UGS can improve mental and visual well-being. While the study provided valuable insights, it was limited in sample size, indicating the need for further validation with diverse populations.

Ali et al. [23] developed a health planning model for elderly individuals in UGS. Their approach suggested physical activities to reduce cardiac risks among older adults. Their study improved the accuracy of health planning and highlighted the benefits of UGS in promoting active aging. However, the model lacked personalised health tracking, suggesting a need for integration with wearable health technologies for better real-time monitoring.

Rajaram [24] introduced a real-time heart condition prediction model using frequency pattern mining and deep neural networks. This method enhanced cardiac risk detection accuracy by analysing physiological data patterns. The approach was effective for fast, real-time health monitoring. However, it required high computational resources, limiting its scalability in large-scale clinical applications. Future work could focus on optimising the model for broader accessibility.

Song et al. [25] assessed the ecological health of UGS using a landscape ecological health (LEH) model. Their study integrated factors such as patterns, functions, sustainability, and processes to suggest improvements for urban landscapes. While the

model increased the effectiveness of health assessments, it required complex calibration, making real-time applications challenging. Future research should focus on simplifying the model for wider adoption.

Benton et al. [26] explored low-cost interventions for improving UGS accessibility and health benefits. Their study used behavioural patterns of elderly individuals to optimise healthcare recommendations. The approach was effective in reducing assessment time and costs. However, it was primarily focused on older populations, leaving a gap in research for younger demographics.

Ding et al. [27] developed an analytic hierarchy process (AHP)-based fuzzy evaluation method for assessing UGS at the city level. Their findings demonstrated improved sustainability in urban planning. The method provided a structured approach for analysing green spaces but required significant computational resources. Future research could integrate AI-driven automation to reduce complexity and improve efficiency.

Wang et al. [28] proposed a machine learning (ML) approach for assessing UGS features such as accessibility, aesthetics, and availability. Their model enhanced urban planning efficiency by using data-driven insights. However, the method depended heavily on data quality, emphasising the need for better data integration techniques to improve accuracy.

Kim and Kwon [29] examined the impact of UGS on regional ecosystem services using a patch-based cellular automata model. Their study demonstrated increased accuracy in assessing ecosystem benefits. While their approach provided valuable insights, its real-time adaptability was limited, indicating a need for continuous monitoring systems.

The related works section summarises the previous works from different authors related to the proposed concept. Thus, the summary of the previous works is presented in Table 1.

Table 1

Summary of the previous works

Authors	Objective	Methods	Findings	Advantages	Disadvantages	Research gap
Yanez et al. [18]	Assessing the health impact of urban green space interventions	Analyses causes of mental health problems to derive optimal solutions	Improves users' mental health	Provides targeted solutions for mental well-being	Limited to specific case studies	Needs broader validation in diverse urban settings
Zhang et al. [19]	Evaluating urban green spaces using structural models	Structural equation model (SEM) to assess UGS pathways	Enhances UGS-based associations' performance	Provides a systematic evaluation framework	Limited adaptability to varying urban environments	Requires integration with real-time urban analytics
Hematian and Ranjbar [20]	Evaluating UGS from a mental health perspective	Cross-sectional analysis of emotional and micro features	Enhances quality of life	Provides insights into psychological well-being	Limited longitudinal assessment	Needs integration with AI-based mental health tracking

Authors	Objective	Methods	Findings	Advantages	Disadvantages	Research gap
Wu et al. [21]	Health-oriented vegetation design for UGS	Analysis method for pulmonary diseases and symptoms	Increases feasibility of healthcare systems	Links vegetation planning with respiratory health	Requires more empirical validation	Needs extended analysis for other health factors
Olszewska-Guizzo et al. [22]	Enhancing UGS through a revised contemplative landscape model (CLM)	Uses ECG data for health insights	Improves the visual quality of UGS	Integrates physiological data into UGS design	Limited sample size	Requires further validation with diverse populations
Ali et al. [23]	Developing an elderly health planning model for UGS	Suggests physical activities to reduce cardiac risks	Increases accuracy of health planning	Provides targeted interventions for the elderly	Lacks personalised health tracking	Needs integration with wearable health technology
Rajaram [24]	Real-time heart condition prediction using frequency pattern mining	Frequency pattern mining & deep neural networks	Enhances accuracy in heart condition prediction	Fast, real-time cardiac risk detection	Requires extensive computational resources	Needs validation in large-scale clinical settings
Song et al. [25]	Assessing landscape ecological health (LEH) in UGS	LEH model integrating patterns, functions, and sustainability	Improves health assessment process performance	Provides holistic UGS evaluation	Complex model calibration	Needs real-time dynamic assessment
Benton et al. [26]	Evaluating low-cost UGS interventions	Uses behavioural patterns of elders to reduce assessment latency	Enhances healthcare recommendation accuracy	Cost-effective intervention analysis	Limited to elder demographics	Needs broader application across age groups
Ding et al. [27]	Fuzzy evaluation of city-level UGS planning	AHP-based method for analysing green building characteristics	Improves sustainability in planning	Effective for large-scale UGS planning	High computational complexity	Needs integration with urban IoT data
Wang et al. [28]	Machine learning-based feature assessment for UGS streets	Assesses UGS aesthetics, availability, and accessibility	Enhances planning efficiency	Data-driven approach for UGS evaluation	High dependency on data quality	Requires multi-modal data fusion
Kim and Kwon [29]	Identifying regional ecosystem service impacts of UGS	Patch-based cellular automata model	Increases assessment accuracy	Enables ecosystem service modelling	Limited real-time adaptability	Needs continuous monitoring for impact validation

Analysing UGS becomes mandatory for validating its impact on human life due to changing work and human activities. Considering the positive impact on human health, the recommendations for peaceful environments must be expanded and coupled with phenomenal daily activities. If the impact is negative, modifications to the existing UGS are required to convert them into fruitful impulses. For both the above cases, intense real-time

data analysis is required. The above-discussed methods fail to connect the impact and recommendations between the health for real-time implication. This problem results in economic wastage or improper UGS installation. The precise impact analysis becomes mandatory for better insight for recommendation or modification, and the proposed process is designed for the purpose.

Proposed methodology: EQP-FIS framework

There is a need for more cities worldwide to put urban green space at the top of their policy listings. Urban Green Space (UGS) is land in a city covered in grass, trees, bushes, or other plants, partially or fully. Urban Green Space includes parks, community gardens, cemeteries, rooftop gardens, vertical gardens, fields, and trees. UGS is sometimes called a "blue-green zone" because it includes urban water like ditches, canals, rural waterways, rivers, and riverbanks. UGS makes cities less likely to flood, maintains cities cool in the summer, and increases wildlife. UGS supports healthier living conditions by reducing environmental stressors and enhancing opportunities for social interaction, and the proposed EQP-FIS framework is introduced to systematically quantify these health-related benefits.

The proposed process handles two data for analysis: the health improvements and the urban space effect. This effect is identified using space recommendations for health improvements from physicians/self-motivations. The data are taken from Yeh et al. [30] to analyse the spatial characteristics of urban green spaces and human health using exploratory analysis of canonical correlation. Yeh et al. revealed a dataset that includes outpatient consultation records from several hospitals in the Taipei metropolitan area. These records include cases of heart disease, mental illness, and breathing problems. The records include thousands of patient visits, which were grouped together using ICD-9 codes to make sure that health issues were always grouped together in the same way. The sampling method is based on how often people use outpatient services instead of how often they report to their homes. This allows for coverage across districts, but it may have some problems, such as not including socio-demographic information, not being able to access individual homes because of the Personal Information Protection Act, and not including people who don't regularly go to the hospital for care. Even with these limitations, the dataset is frequently utilised in spatial-health correlation studies due to its provision of spatially consistent, medically vetted records appropriate for developing UGS-health links.

The health and spatial datasets used in this study were derived from the publicly reported outpatient records and urban green space indicators analysed by Yeh et al. [30]. The data were utilised as secondary data and reprocessed through normalisation and population-based scaling to support the EQP-FIS computational framework proposed in this work. While Yeh et al. employed canonical correlation analysis to explore UGS-health associations, the present study introduces a fuzzy inference-based modelling framework for computational health impact assessment.

The data correlates the UGS and the health of people observed in the Taipei area. According to Taiwan's Personal Information Protection Act, doctors cannot disclose their patients' addresses. Only the hospital's physical locations are made clear in the outpatient dataset. This dataset integrated the outpatient identifiers for the common cold (ICD9 460) and flu (ICD9 487) with those for cardiovascular illness, mental disorders, and chronic

respiratory disease to account for the impact of patients from other districts. Using this combined data, researchers can determine the precise locations of typical cold and flu treatment centres in the homes of outpatients. The considered area and its scale are presented in Figure 1.

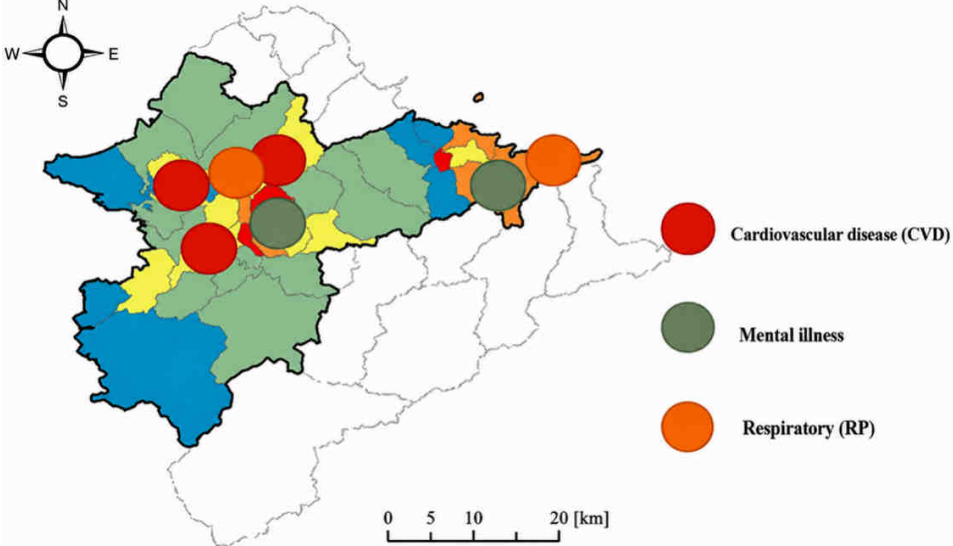


Fig. 1. Area considered and health problems

As presented in the Figure 1, cardiovascular (CVD), mental illness (MI), and respiratory (RP) are the health issues considered. Based on this information, the canonical correctional with health and UGS utilisation are tabulated in Tables 2 and 3.

Table 2

UGS utilisation data

Disease	[persons (min) · year ⁻¹]	[persons (max) · year ⁻¹]	Mean · 10 ⁵ persons	Mean access distance [m]
CVD	2,770	45,566	11,090.81	243.84
MI	821	14,735	3,683.97	96.7
RP	1,185	21,270	5,140.27	365.76

Depending on the physician’s recommendations and personal interest, the utilisation and aftermath effects of the health benefits are presented. The values personated rely on 100,000 persons/year in the UGS. The residential, vegetation, and recommendation factors are provided using a minimum range across various regions. This is required to handle the connectivity between the health issues (considered) and UGS effects. The interference system performs this connectivity assessment (Table 3).

Table 3 shows the structured Effect Quantifying Process employing a Fuzzy Inference System EQP FIS to estimate urban green space health effects. It describes the main process steps, their methods, and their implementation. The system uses fuzzy inference modelling, multi-source health and spatial data, and computational impact assessments to accurately and adaptively measure urban green space effectiveness in promoting public health.

Table 3

EQP FIS methodology data processing and computational assessment

Process stage	Methodological approach	Implementation details
Multi-source data acquisition	- Extracting outpatient health records and urban spatial data from multiple sources. - Establishing correlations between health outcomes and urban green space (UGS) exposure.	- Outpatient data filtered based on ICD-9/ICD-10 codes (CVD, MI, RP). - UGS parameters include spatial coverage, vegetation density, accessibility index.
Data preprocessing and integration	- Standardising datasets to ensure consistency across health and spatial records. - Implementing geospatial mapping for UGS-health impact correlation.	- Standardised using normalised spatial resolution and time-series data alignment. - GIS-based spatial overlay analysis applied to assess proximity effects.
Fuzzy inference-based modelling	- Defining membership functions for urban green space influence on health parameters. - Applying fuzzy rule-based logic to generate impact scores.	- Input variables: Distance to UGS, frequency of visits, patient health metrics. - Fuzzy rules: If distance < threshold & visit frequency high → Positive health effect.
Computational impact assessment	- Generating a UGS Impact Score (UIS) for different regions. - Estimating trends in health improvement using computational analysis.	- CVD patients residing within proximity to Urban Green Space (approximately 500 m) exhibit improved hypertension-related health indicators according to the EQP-FIS computational assessment. - Myocardial infarction (MI) cases in vegetation-rich urban environments show reduced depression-related consultation trends based on the model evaluation.
Model validation and performance evaluation	- Cross-verifying computed results with historical outpatient trends and urban environmental data. - Conducting sensitivity analysis of fuzzy parameters for model robustness.	- Benchmark comparison with traditional QHIA/AHP models. - Model performance metrics: Connectivity strength, prediction accuracy, recommendation reliability.

Data acquisition and integration

The proposed Effect Quantifying Process using a Fuzzy Interference System (EQP-FIS) focuses on classifying urban green spaces based on their consequences on human health to steer the sketch and expansion of such spaces. This proposed process employs two different sets of data for analysis: health improvements and the effect of urban spaces. The health improvement data includes physician recommendations, self-motivation, and other resources that indicate how an urban green space can improve human health. It consolidates the suggestions for human health enhancements and assesses the undeniable effects of these green spaces to establish precise recommendations or denote the necessity for expansion or replication. This evaluation of the procedure involves assessing recommendation scores, effect rates, data availability, and analysis time. This proposed process is diagrammatically illustrated in Figure 2.

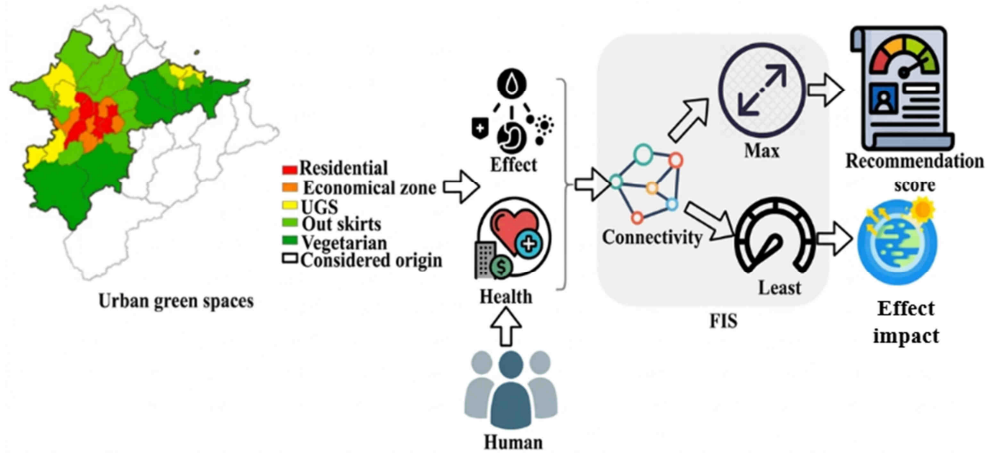


Fig. 2. Proposed process illustration

Urban green space and health impacts

Urban green spaces are analysed to evaluate the effectiveness of their impacts on human health. Urban spaces like parks, ecological spaces, etc., are analysed for further evaluation procedures. These green spaces positively affect human health, which helps enhance connectivity. Urban green spaces positively affect humans by reducing stress levels, providing fresh air, and reducing pollution. This analysing process of the green spaces helps further distribute efficacious recommendations to build up green spaces in the future. The production of positive effects on humans by building urban green spaces is evaluated in this procedure. This also analyses the effects on every human individual's health due to the urban green space. The following equations explain the process of analysing the urban green spaces for the evaluation process:

$$\left. \begin{aligned} \rho_m &= \rho_m(x_{m,1}, x_{m,2}, \dots, x_{m,n}) \\ \rho &= \left| \frac{x_1 \cdot m_1 + x_2 \cdot m_2 + \dots + x_n \cdot m_n}{x_1 + x_2 + \dots + x_n} \right| \\ &= \left| \frac{\sum_{n=1} x_n \cdot m_n}{\sum_{n=1} x_n} \right| \\ \rho_m(x) &= \int_0^1 \rho_m(x) dx \\ \rho_m^*(x) &= \begin{cases} 1 & x = m \\ 0 & \text{otherwise} \end{cases} \end{aligned} \right\} \quad (1)$$

where $\rho_m(x)$ represents the total number of urban green spaces considered for evaluation, ρ_m denotes the evaluation procedure applied to each space, and $\rho_m^*(x)$ refers to the resulting outcome derived from the evaluation step. This formulation separates the operational components and makes the assessment process more interpretable. ρ is denoted as the number of urban green spaces for the analysis process, m is represented as the evaluation procedure, x is denoted as the outcome of the urban green spaces. Now,

individual humans are inspected to evaluate their effects and health status after constructing urban green spaces. Now, individual humans are analysed to evaluate the positive effects on their health due to the urban green spaces. This consideration process happens for the further categorisation procedure. This helps determine the effects of the urban green spaces and the human health status due to this urban green space. The following relationships explain the analysis process for human categorisation:

$$\left. \begin{aligned} \alpha &= \{(x, \rho_m(x)) | x \in \alpha\} \\ \rho(x, y, \alpha) &= \left(-\frac{1}{2} \left(\frac{\|x - y\|}{\alpha} \right)^2 \right) \\ \rho(x, y, z, \alpha) &= \left(\left(\frac{x - y}{y - x}, \frac{\alpha - z}{\alpha - y} \right), 0 \right) \\ \rho(x, y) &= \begin{cases} 1 & \text{if } x = y \\ 0 & \text{if } x \neq y \end{cases} \\ \rho_{x \cap y} &= \rho_x(X) * \rho_y(X) \\ \rho_{x \cup y} &= \rho_x(X) \oplus \rho_y(X) \end{aligned} \right\} \quad (2)$$

where α is represented as the analysing process in human individuals, y is denoted as the current health status of an individual, z is represented as the effect of the urban green space on the human. The categorisation process takes place by consolidating the outcome of the analysing process. The effect and health status are classified based on the outcome of the analysis process. By estimating the urban green spaces (ρ), the factors such as the outcome of urban green space (x), the current health status of the humans (y), the effect of the urban space (z), analysing process (α) is determined for the estimation of the urban space effect

on humans $\left(\rho(x, y, z, \alpha) = \left(\left(\frac{x - y}{y - x}, \frac{\alpha - z}{\alpha - y} \right), 0 \right) \right)$. Now, the effects of urban green space on humans are determined by categorising it. In this process, the positive effect of the urban green space on humans is determined, and thus, the connectivity is evaluated using the fuzzy inference system.

Effect analysis process

The positive effect of urban spaces on humans mainly helps increase their mental health and peaceful surroundings. These urban green spaces also help enhance the surroundings with a peaceful habitat and fresh air. After this categorisation process, the connectivity is estimated for the further maximum connectivity determination processes. This positive effect also helps humans maintain their positive well-being. The following equations explain the process of determining the effects of the urban green space:

$$\left. \begin{aligned}
 \phi(x) &= \frac{1}{1 + e^{(-x)}} \\
 X &= \frac{1}{2}(\hat{y} - y)^2 \\
 M_{1+n} &= M_n - \nabla \phi(M_n)x \\
 \nabla \phi(M_n) &= \left[\frac{\partial \phi}{\partial M_1}, \frac{\partial \phi}{\partial M_2}, \dots, \frac{\partial \phi}{\partial M_n} \right] \\
 \phi_n &= \left(-\frac{1}{2} \left(\frac{\|x_n - y_n\|^2}{\alpha_n} \right) \right) \\
 \alpha(x_n) &= \sum_{n=1} y \phi(x_n) \\
 &= \sum_{n=1} y M_n
 \end{aligned} \right\} \quad (3)$$

Equations (3) express the determination of the effect generated by each urban green space on an individual. In this formulation, $\phi(x)$ denotes the effect identified for a specific human individual, while M_n represents the measurable improvement in mental or physical health attributed to green space exposure. Presenting the components separately allows the effect estimation process to be understood more clearly and highlights the contribution of each term. Where ϕ is denoted as the effects determined based on the individual human, M is represented as the improvements in the humans' mental health. The output of the urban green space is determined by analysing individuals. $(\alpha(x_n) = \sum_{n=1} y \phi(x_n))$. The consignment of positive effects is determined in an individual after the construction of green spaces. This effect is determined using urban green space recommendations for health improvements from physicians/self-motivations, etc. The effect analysis with the considered data is illustrated in Figure 3.

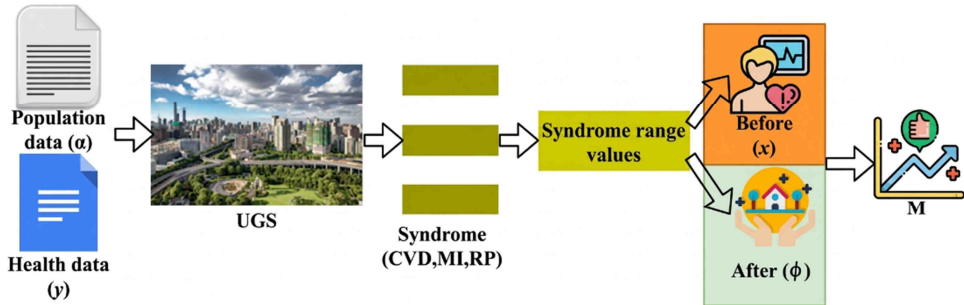


Fig. 3. Effect analysis process

The (α, y) is jointly utilised for the given syndrome (from the dataset, it is CVD, MI, RP) in any UGS of the considered region. The actual x (before UGS utilisation) and ϕ (after UGS utilisation) are accounted for in identifying M . The correlation values are fetched from the clinical information (data range) from the source. The M is further classified as min/max compared with the previous time-space (Refer to Fig. 3). The positive

effect is estimated by contemplating the health enhancements derived from the analysing process. Then, the fuzzy inference technique determines the space recommendations, positive effect, and connectivity. This is estimated when the effect determination process is contrived. The thresholds and membership function parameters employed in the fuzzy logic modelling were determined by the statistical distribution of the dataset and recognised standards in environmental health evaluation. We used the Taipei outpatient dataset to find distance-related thresholds, like how close UGS is to a person. The mean access distances for CVD, MI, and RP patients let us determine the boundary values for the membership functions. The linguistic categories ("low", "medium" and "high") were developed using triangular and trapezoidal membership functions, consistent with previous UGS-health correlation research that utilise analogous fuzzy scaling methods for spatial and behavioural variables. These choices for the parameters make sure that the fuzzy inference structure shows realistic gradients of health response to UGS exposure while also being in line with past empirical studies. Thus, the positive effects of urban green space for humans are explained by the following equation:

$$\left. \begin{aligned} \psi_{x,y}^1 &= \rho(x, y) \\ &= \sum_{n=1} \left(-\frac{1}{2} \left(\frac{\|x_n - z_n\|}{\rho_n} \right)^2 \right) \\ \psi_n^2 &= M_n \\ &= \prod_{n=1} \psi_{n,x,y} \\ \psi_n^3 &= M_n \cdot y_n \\ \psi_n^4 &= \sum_{n=1} \frac{M_n \cdot y_n}{M_n} \end{aligned} \right\} \quad (4)$$

where ψ is represented as the positive effects determined by the humans. Now, the health status of the human individual after the construction of the urban green space is determined in the categorisation process. The health status is the attribute that determines the connectivity between the effects and recommendations. The health status of the human residing in the urban green space reduces stress and anxiety. Greeneries lead humans to live peaceful lives. This is determined by comparing the health status of humans before and after the urban green spaces. The process of evaluating the health status of human individuals in the categorisation process is explained by the following equations:

$$\left. \begin{aligned} \frac{\partial K}{\partial y} &= (\hat{y} - y) \frac{M_n(x)}{\sum_{n=1} M_n(x)} \\ \frac{\partial K}{\partial \rho} &= (\hat{y} - y) \frac{y_n - \hat{y}}{\sum_{n=1} M_n(x)} \\ &= \left(\frac{\|x_n - z_n\|^2}{(\alpha_n)^3} \right) \\ \frac{\partial K}{\partial z_n} &= (\hat{y} - y) \frac{y_n - \hat{y}}{\sum_{n=1} M_n(y)} \\ &= M_n(x) \left(\frac{x_n - z_n}{\alpha_n} \right) \\ \frac{\partial K}{\partial y_n} &= (\hat{x} - y) \frac{x_n - \hat{x}}{\sum_{n=1} M_n(x)} \\ \frac{\partial K}{\partial y_n} &= M_n(y) \left(\frac{y_n - z_n}{\alpha_n} \right) \end{aligned} \right\} \quad (5)$$

$$\left. \begin{aligned} \xi_{XUY} &= \xi_X + \xi_Y \\ \xi_{XUY} &= \sum_{n=1} (\xi_X + \xi_Y) \\ \xi_{XUY} &= \sum_{\alpha=1} (\xi_X + \xi_Y) \\ \xi_{XUY} &= \xi_X - \xi_Y \\ \xi_{XUY} &= \begin{cases} \xi_X & m_x > m_y \\ \xi_Y & m_x \leq m_y \end{cases} \\ \xi_{XUY} &= \frac{m_x \cdot \xi_X + m_y \cdot \xi_Y}{m_x + m_y} \\ \xi_{XUY} &= \frac{\xi_X + \xi_Y}{2} \end{aligned} \right\} \quad (6)$$

where K is denoted as the health status of the human normally, ξ is represented as the human health status with the urban green space. The improvements in human mental health are determined by considering the comparison process $\left(\frac{\partial K}{\partial y_n} = M_n(y) \left(\frac{y_n - z_n}{\alpha_n} \right) \right)$.

The human health status with the urban green space is estimated by consolidating the outcome of the green space and the current health status of the humans $\left(\xi_{XUY} = \frac{\xi_X + \xi_Y}{2} \right)$. Now, with the help of the categorisation process, the connectivity is determined using the fuzzy inference system. The relationship between the health status and the urban space effect is determined by identifying the connectivity. The M observed for a range of peak density of 800 humans is presented in Table 4. This tabulation considers the values from the dataset and the above analyses.

Table 4

M observed from the source and computed

	Peak density	Avg. <i>y</i>	Avg. <i>z</i>	<i>M</i>
CVD	200	0.03	0.01	0.02↑
	400	0.041	0.018	0.023↑
	600	0.042	0.021	0.02↑
	800	0.038	0.015	0.023↑
MI	200	0.035	0.031	0.004↑
	400	0.041	0.038	0.003↑
	600	0.042	0.038	0.004↑
	800	0.048	0.041	0.007↑
RP	200	0.036	0.044	-0.008↓
	400	0.054	0.025	0.029↑
	600	0.041	0.031	0.01↑
	800	0.051	0.044	0.007↑

As presented in Table 4, the average *y* and *z* are computed per 100,000 persons in the maximum UGS space. The peak density observed across different *m* and days are summarised for identifying *M*. The positive improvements are identified if $y < z$ and the contrary is a negative impact. This means the UGS has less impact on health. Therefore, the changes in *m* and ϕ are obvious across multiple *K*. This is updated periodically between the successive peak densities. The fuzzy system makes use of fuzzy logic in deriving health improvements by the use of urban factors. The relationship between urban spaces and health is evaluated to determine connectivity. The process of estimating the relationship between the health improvements and then the urban space for the evaluation of the connectivity using FIS is explained by the following equations:

$$\left. \begin{aligned}
 &\eta: \{x|x \in Z, |x| \leq 1\}^n \rightarrow \{y|y \in Z, |y| \leq 1\}^n \\
 &\rho_x(x) = \eta(\rho_1(x), \rho_2(x), \dots, \rho_n(x)) \\
 &\quad = \sum_{n=1} M_i \rho_x \\
 &M_i \in \{x|x \in Z, |x| \leq 1\} \\
 &\quad \sum_{n=1} |M_i| = 1 \\
 &\rho_{x \rightarrow y}(Z, \alpha) = \rho_x(Z) \cdot \rho_y(\alpha) \\
 &m_{x \rightarrow y}(Z, \alpha) = m_x(Z) \cdot m_y(\alpha)
 \end{aligned} \right\} \quad (7)$$

where η is the relationship between health improvements and urban space, the connectivity is determined using the inference system by contemplating the improvements and space recommendations (Eq. (8)).

$$\left. \begin{aligned}
 &f \leftarrow 1 \\
 &\text{while } f < F \\
 &\quad g \leftarrow 1 \\
 &\quad \text{while } g < m_\alpha \\
 &\quad \quad \alpha_n \leftarrow F m_\alpha \\
 &\quad \psi_n = (G - 1)(2\Pi) / m_\alpha \\
 &\quad \phi_n \leftarrow 1/(m_\alpha - 1) \\
 &\quad \phi_n(\psi) \leftarrow 1/G(m_\alpha - 1) \\
 &\quad G \leftarrow G + 1 \\
 &\quad f \leftarrow P + 1 \\
 &\quad g \leftarrow G
 \end{aligned} \right\} \quad (8)$$

The health enhancements after the urban space construction and the positive effects help to assume the connectivity with the help of the fuzzy inference technique. The process of determining the connectivity is explained by the following Eq. (8) given above. Where f is denoted as the connectivity determined, g is represented as the fuzzy logic used to determine the connectivity. By considering the human effects and health improvements, the connectivity is determined ($\phi_n(\psi) \leftarrow 1/G(m_\alpha - 1)$). From the connectivity, the maximum positive and then the least connectivity are extracted to produce precise recommendations for further urban green spaces. First, the output values generated by the fuzzy inference are evaluated to estimate the high connectivity between urban space and health improvements.

Relationship factor analysis

The relationship factor and f between the UGS and the health issues are presented in Figure 4.

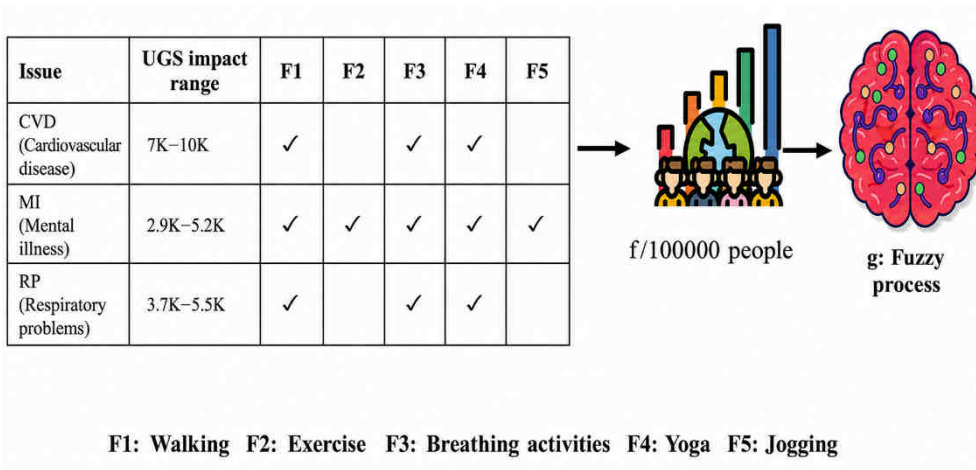


Fig. 4. Relationship factor and f analysis

In Figure 4, the 5 relationship factors (F1, F2, F3, F4, and F5) represent the works: Walking, exercise, breathing, yoga, and jogging. The issues reported are adaptable for a few relationship factors for which $f/100,000$ people are variable. This variation is

identified as min/max using g , for which further investigation is performed. The M is modified from this point for new impact assessment. The evaluated values from the connectivity determination process using the inference system are compared with the maximum connectivity achieved. This gives recommendations for further processing and helps in upcoming analysis procedures. The process of estimating the maximum connectivity by using the fuzzy inference technique is explained by the following relationships:

$$\left. \begin{aligned}
 \vartheta_m(x) &= m_x e^{(x)} \\
 Y = \psi(m) &= \begin{cases} 1 & \text{if } m = y \\ 0 & \text{if } m \neq y \end{cases} \\
 Y &= \alpha(m) \\
 &= \left\{ -\frac{1}{2} \left(\frac{(m-y)^2}{\phi} \right) \right\} \\
 Z &= |\xi(m)| \\
 &= \begin{cases} 1 & \text{if } Z(\phi) = Y \\ 0 & \text{otherwise} \end{cases} \\
 \xi(m) &= \psi
 \end{aligned} \right\} \quad (9)$$

where ϑ is represented as the maximum positive connectivity determined using the fuzzy inference system, e is denoted as the outcome of the connectivity estimation process. The maximum connectivity output ($\vartheta_m(x) = m_x e^{(x)}$) is evaluated by considering the determination process output (e), improvements in human health (m), and output of the urban space construction (x). The least connectivity is determined based on the connectivity output using a fuzzy inference system. Here, the area with low connectivity between the urban green space and health improvements is identified. The fuzzy inference helps extract the connectivity's lowest values, which have the lowest values in the determination procedure. This helps in understanding the urban space factors that have a low impact on the health improvements of human individuals due to the urban green space, and it also helps provide the awareness that may require further intervention to improve the health status of humans. The process of detecting the least connectivity by using the fuzzy inference system is explained by the following equations:

$$\left. \begin{aligned}
 x &= H * \psi \\
 y &= H * \psi \\
 Z &= |\xi(m)| \\
 &= \sum_{n=1} \left(-\frac{1}{2} \left(\frac{|(x,y) - \alpha|^2}{\psi} \right) \right) \\
 \sum_{n=1} (x,y) &= \psi \\
 \xi(m) &= \frac{1}{2} \left(\frac{\|(x,y) - \alpha\|}{\phi} \right) \\
 \xi(x,y) &= \|(x,y) - \alpha\| \\
 H(x_n) &= \sqrt{(H^x)^2 + (H^y)^2}
 \end{aligned} \right\} \quad (10)$$

where H is denoted as the least connectivity determined from the connectivity output, the recommendations are provided for future green spaces based on the maximum connectivity. This also provides precise information about human health improvements due to green spaces. The H and ϑ analysis for the varying health issues and peak density is analysed in Figure 5b.

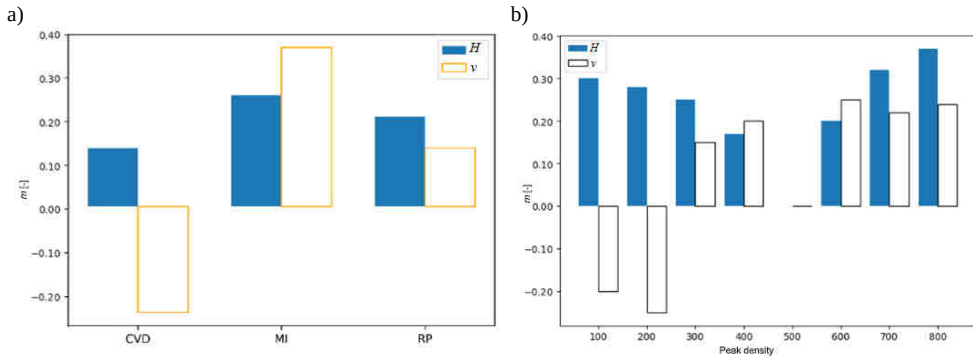


Fig. 5. H and ϑ analysis for health condition identification based on Urban Green Space indicators: a) variation across health conditions (CVD, MI, RP), b) variation with peak density levels

The H and v are classified using g as derived in Eqs (8) and (9). Based on the available data and its range, the $\xi(m)$ and $\xi(x, y)$ are validated. This validation relies on identical factors for which the least influencing factor is augmented. The augmentation is valid only if $Y = 1$ else $\xi(m) = \psi$ is the next validation factor. In this case, the new relationship for the varying peak densities is identified between v and H for optimal results. This process is required for new fuzzy classification without major recommendations (Refer to Fig. 5).

Recommendations for urban green space development

The maximum positive connectivity helps guide the precise, valuable recommendation regarding the construction of urban green spaces. These recommendations help enhance and optimise the urban factors that are obtained, which will help improve human health status. Adding more urban green space helps increase human health and well-being. The following Eqs explain the process of providing recommendations to build urban green spaces (11), (12):

$$\left. \begin{aligned}
 F &= \{f_1, f_2, \dots, f_{1-n}, \dots, f_m\} \\
 x_1 &= F_x \\
 n &= 2: |F| - 1 \\
 m &= 1: |x_n - 1| \\
 y_n &= x_{n-1} \setminus \{x_2\} \\
 F(y_n) &= F * G \\
 x_n &= y_n = F(x) * F(y) \\
 x_n &= \phi \\
 m &= 2: |G| - 1 \\
 m &= 1: |Y_{n-1}| \\
 x_n &= Y_{n-1} / \{y_2\}
 \end{aligned} \right\} \quad (11)$$

$$\left. \begin{aligned}
 \lambda_n(x, y) &= \frac{1 - |F(x) - F(y)|}{|F_{n+1} - F_{n-1}|} \\
 \lambda_n(x, y) &= \sum_{n=1} \left(\frac{-|F(x) - F(y)|^2}{2F_n} \right) \\
 \lambda_n(x, y) &= \sum_{n=1} \frac{\psi(x, y)}{\phi(x, y)} \\
 Z(F) &= \frac{\sum_{n=1} \psi_{x,y}(x)}{|F|} \\
 \sum_{n=1} Z(F) &= \frac{\sum_{n=1} \phi(x) + \sum_{n=1} \phi(y)}{\phi(x, y)}
 \end{aligned} \right\} \quad (12)$$

where λ is denoted as the recommendations provided, now, based on the least connectivity, the negative impact of the effect is determined. The connectivity determination process determines the lowest values, denoting the urban space factors with the lowest effects on human health. This determination process helps understand which urban environment characteristics require more intervention to mitigate their negative impact.

Effect impact assessment

Provided recommendations are generated to identify these urban factors and reduce their disadvantageous effects on human health, enhancing healthier and reassuring urban spaces for the well-being of human individuals. The process of determining the effect impact is explained by the following equations:

$$\left. \begin{aligned}
 J(Z) &= J(Z_x + Z_y) \\
 &= J(Z_x) + J(Z_y) \\
 \psi^2 x &= \sum_{n=1} (J^*) \\
 &= J[(Z - J[Z])[Z - J[Z]^*] \\
 \psi(Z_1, Z_2) &= J[Z_1, Z_2^*] - J[Z_1]J[Z_2]^* \\
 \sum_{n=1} J[Z] &= \frac{\sum_{n=1} J_{x,y}[Z]}{J}
 \end{aligned} \right\} \quad (13)$$

where J is represented as the effect impact, this process helps determine the precise recommendations regarding replicating urban green spaces. This process helps enhance the precise recommendation, analysis efficiency, and effect rate and reduces the analysis time. The fuzzy inference system helps detect the connectivity between the urban space recommendations and health improvements. The effect impact over the expansion/replication of the UGS is computed using the correlation factor provided in the dataset. Close to the identified dataset value, the proposed (computed) values are tabulated in Table 5 with the new e inputs.

Table 5

J analyses for λ

	Peak density	η	λ	$e(x:y)$	J
CVD	200	F1, F3, F4	0.098	(0.1:0.4)	-0.0015
	400	F1, F5, F3,	0.12	(0.12:0.52)	-0.001
	600	F1, F2, F3, F4, F5	0.057	(0.32:0.61)	-0.00048
	800	F1, F2	0.45	(0.25:0.58)	-0.00041
MI	F1, F3, F4	0.101	(0.31:0.69)	-0.0019	F1, F3, F4
	F3, F5	0.089	(0.38:0.7)	-0.0008	F3, F5
	F5	0.46	(0.5:0.62)	-0.0002	F5
	F1, F3, F5	0.38	(0.48:0.65)	-0.00021	F1, F3, F5
RP	F3, F5	0.32	(0.31:0.62)	-0.00155	F3, F5,
	F3, F4, F5	0.12	(0.12:0.52)	-0.0009	F3, F4, F5
	F1, F3, F5	0.15	(0.21:0.48)	-0.00045	F1, F3, F5
	F4, F5	0.25	(0.31:0.58)	-0.00033	F4, F5

Table 6

Time effect management in the EQP-FIS model

Factor	Methodological approach	Implementation details
Time-Series Data Integration	Structuring health and UGS data into short-term, mid-term, and long-term intervals	- Health records are analysed using weekly, monthly, quarterly, and annual timeframes. - Ensures correlation between UGS structural changes and health improvements over time.
Temporal weighting in fuzzy inference	Adjusting fuzzy membership functions to model delayed health effects	- Immediate effects (e.g., stress reduction) vs. long-term effects (e.g., cardiovascular improvements) are weighted differently - Fuzzy rules incorporate time-adjusted impact factors.
Lag correction via historical data correlation	Identifying and compensating for delays between UGS changes and health outcomes	- Uses historical trend analysis to map past UGS modifications to current health trends. - Applies correlation adjustment functions to align previous interventions with present data.
Dynamic model updating	Continuous recalibration of EQP-FIS using new health and environmental data	- System refines UGS impact scores based on real-time deviations in predicted vs. observed health effects. - Adaptive learning mechanisms adjust model parameters for enhanced accuracy over time.

For the varying peak density, the η, λ , and e based on S assessment presented in Table 4. This analysis equalises e on (z, y) for which new η is estimated. The UGS is utilised based on the available inputs. Based on the available inputs considering the deviations in the varying H, v , a further M assessment is performed. If the considered input is varied across multiple instances, then the achievable λ relies on η . This η is correlated with the data input for which M is estimated. Different from the previous input analysis,

only the positive M is used for recommending expansions. The negative M is used for providing modifications to the existing UGS utilisations.

Table 6, The Effect Quantifying Process using a Fuzzy Inference System (EQP-FIS), is a methodological approach that accounts for the time lag between urban green space (UGS) structural changes and their effects on human health. It incorporates time-sensitive modelling techniques to enhance accuracy. Four key strategies include time-series data integration, temporal weighting in Fuzzy Inference, lag correction via historical data correlation, and dynamic model updating.

Result and discussion

The discussion on recommendation score, effect rate, data availability, analysis time, and recommendation/ replication factor is presented in this section. The connectivity factor varies from 0.2, 0.4, 0.6, and 0.8 in this analysis. The X-axis variants area (m^2) and the peak density (persons/ m^2) are used in this discussion

Recommendation score

The upcoming green space construction recommendations are based on the maximum positive connectivity. It also provides recommendations for replicating urban green spaces in the environment. These recommendations provide information about the most important for enhancing the health of humans and space allocations in the environment. This also provides precise information about human health improvements due to green spaces. The maximum positive connectivity helps guide the precise, valuable recommendation regarding the construction of urban green spaces. The urban factors are enhanced by contemplating the outcome of the connectivity determination process, and thus, the outcome helps detect the maximum and least connectivity. These recommendations help enhance and optimise urban factors, which improve human health. By consolidating these ways, the recommendation score in the proposed method is efficacious (Fig. 6).

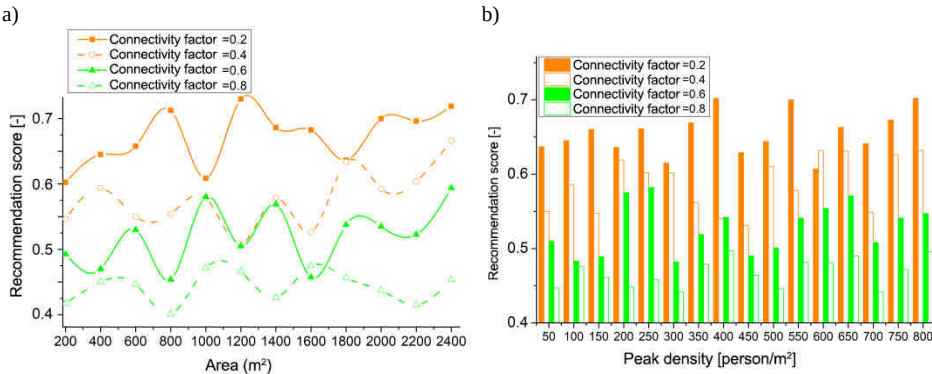


Fig. 6. Recommendation score assessment: a) low variability, b) high variability

Effect rate

The effective rate is determined by contemplating the human health status and urban green space effects on the environment and humans. The positive effect is extracted from humans due to the urban green spaces. At first, the health of humans is detected before and after urban green spaces, and then the difference in human health is detected. Positive effects such as lesser anxiety, reduced depression, and peaceful mental health are observed in individual humans. The positive effect and then the health status of the human are categorised to determine the connectivity between the space and recommendations. Thus, these are detected using the fuzzy inference system by extracting the maximum and least positive connectivity. The relationship between the effect and the health status of the humans is determined to estimate the effect rate. Urban green spaces provide more positive effects on humans and hence provide precise recommendations for replicating urban spaces in the environment (Fig. 7).

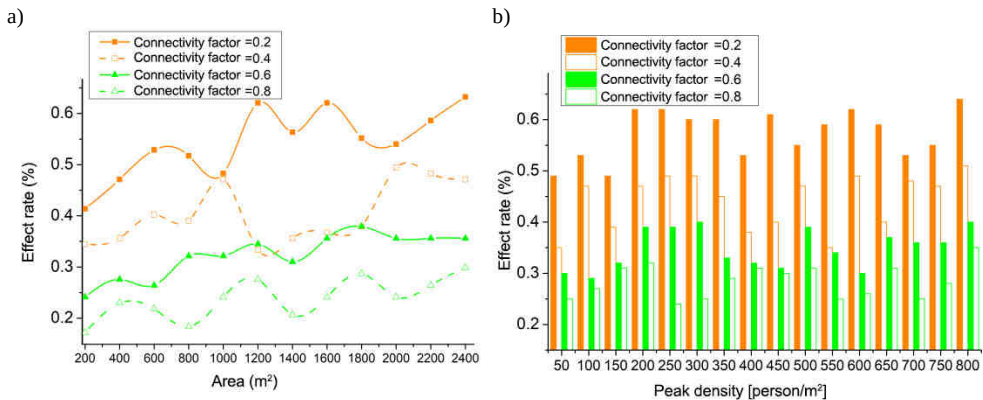


Fig. 7. Effect rate assessment: a) low variability, b) high variability

Data availability

The data availability is efficacious in the connectivity determination procedure, considering the positive effects and improving human health. It acquires more reliable data regarding urban green spaces to enhance connectivity by producing maximum positive outcomes. The consignment of positive effects is determined in an individual after the construction of green spaces. This effect is determined using urban green space recommendations for health improvements from physicians/ self-motivations, etc. The relationship between the health status and the urban space effect is determined by identifying the connectivity. The fuzzy system makes use of fuzzy logic in deriving health improvements by the use of urban factors. The availability of the data is enhanced by using the fuzzy inference system, and then the precise recommendation validation takes place according to the outcome of the connectivity (Fig. 8).

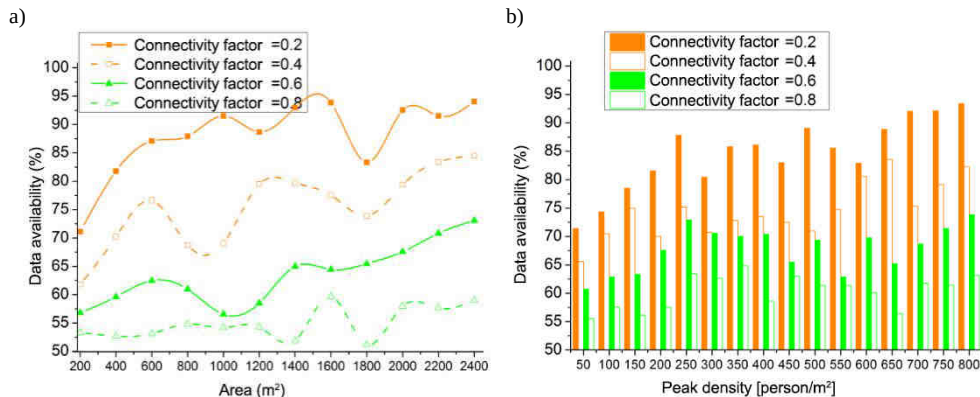


Fig. 8. Data availability assessment: a) low variability, b) high variability

Analysis time

The time taken for the analysis is not much due to the efficient process of the fuzzy inference technique. Effective data collection and significant analysis methods help reduce analysis time. In this proposed method, rapid data processing and analysis of the positive effect on humans are made with precise connectivity outcomes. This analysis process helps quickly determine the positive effect of urban green spaces on individual humans. With the help of the categorisation process, the connectivity is determined using the fuzzy inference system. The relationship between the health status and the urban space effect is determined by identifying the connectivity. By extracting the connectivity, the maximum and least effective impacts are determined for the further production of recommendations. By contemplating these analysis ways and data processing in the urban green space, the time taken for the analysis process is less in this proposed method (Fig. 9).

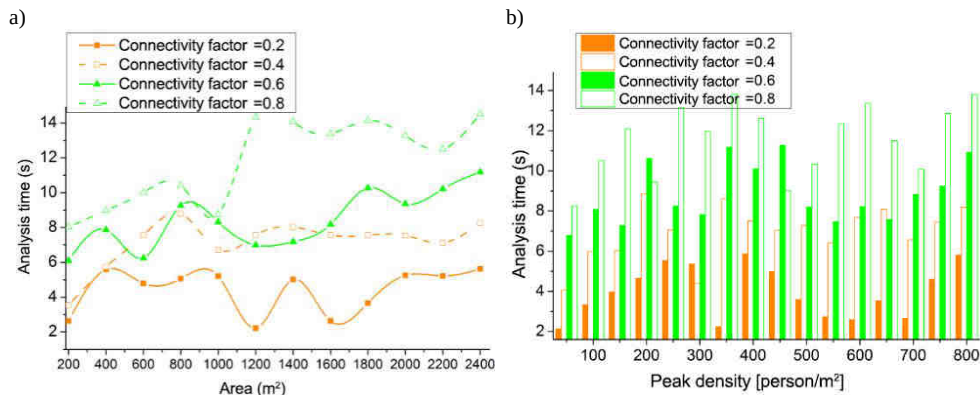


Fig. 9. Analysis time assessment: a) low variability, b) high variability

Expansion/replication factor

The expansion and replication factor is better when the precise recommendation score for the upcoming urban green spaces is produced. The recommendations produced for urban green spaces help establish a better replication factor, enhancing their effectiveness and positive impacts and enhancing the health status of the individuals. The connectivity outcome helps provide the maximum positive outcome, and the recommendations are established for the recommendation production. This also provides precise information about human health improvements due to green spaces. The maximum positive connectivity helps guide the precise, valuable recommendation regarding the construction of urban green spaces. This helps increase human health and well-being by replicating the more urban green spaces in the environment. This determination process helps understand which urban environment characteristics require more intervention to mitigate their negative impact (Fig. 10).

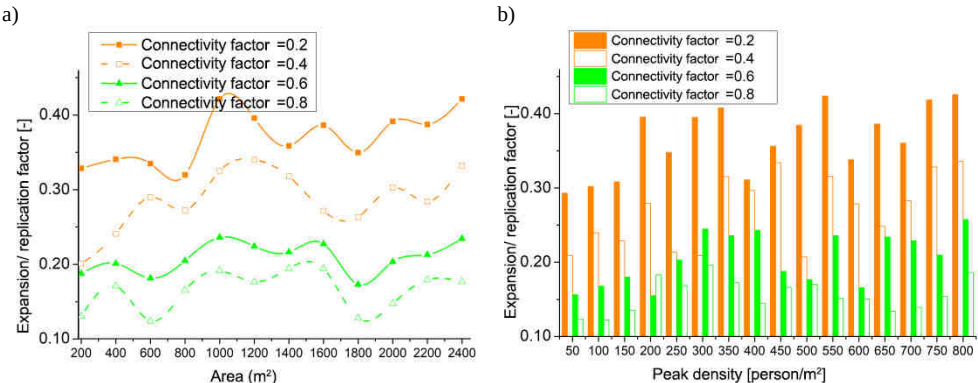


Fig. 10. Expansion/replication factor assessment: a) low variability, b) high variability

The Effect Quantifying Process using a Fuzzy Inference System (EQP-FIS) is a novel framework for evaluating the health impacts of urban green spaces (UGS). Using real-time environmental and health data, UGS exposure and health benefits are dynamically correlated. UGS’s impact on public health is quantified using fuzzy logic, enabling non-binary assessment models. The model provides data-driven UGS growth, modification, and optimisation recommendations to improve urban well-being. The findings help urban planners prioritise high-impact green spaces and implement sustainable urban development strategies using evidence-based policies. This research’s shortcomings include data dependency and availability, generalisation constraints, computational complexity, and socioeconomic factor neglect. EQP-FIS can optimise urban green areas and improve public health by resolving these constraints and enhancing the model based on empirical investigations.

Conclusion

The effect of urban spaces is extracted by evaluating the actual influences of these green spaces on individual humans. By consolidating these two inputs from the acquired

process, the fuzzy interference procedure regulates the connectivity between the effects and suggestions, which helps in the future process. If the connectivity between the effect and health is low, the effect is minimal or insignificant, and correct suggestions are provided accordingly for the further process. On the other hand, if the fuzzy interference process indicates a high level of interference, it suggests a strong connection between the effects and recommendations, indicating the need for space expansion or replication in other parts of the environment. The efficaciousness of the proposed process is evaluated using various factors, including recommendation scores, effect rates, data availability, and analysis time. These factors help in evaluating the precision and authenticity of the classification process. Therefore, the EQP-FIS technique provides a structured approach to classify urban green spaces based on their impact on human health.

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