Green Space Quality Analysis Using Machine Learning Approaches

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Green space is any green infrastructure consisting of vegetation. Green space is linked with improving mental and physical health, providing opportunities for social interactions and physical activities, and aiding the environment. The quality of green space refers to the condition of the green space.

Keywords: green space ; quality ; machine learning ; image classification

1. Introduction

Green space is defined as green infrastructure containing vegetated areas, including grass, lawn, flowers, trees, parks, gardens, and forests [1][2]. Green space plays a vital role in aspects of daily life. Firstly, green space is associated with humans' improved physical and mental health. Secondly, it provides opportunities for social interactions and encourages physical activities such as walking. Thirdly, green space helps the environment by improving air quality, increasing urban biodiversity, and assisting in microclimate regulation [3][4][5][6][7]. Thus, the monitoring, analysis, and evaluation of the quality of green spaces are critical.

Green space at the human perception level represents how people perceive and experience green space [8]. The survey conducted by [9] found that the visual appearance of green space was the most crucial aspect of green space users' satisfaction. Paper [10] demonstrated that green space quality tends to serve as a determinant of people's desire to utilize green space and the benefits they derive from doing so, which assesses the quality of green space seen at the human perception level of utmost importance.

The quality of green space refers to the condition of the green space. It measures how well the site is maintained and the amenities it provides to make it safe, appealing, and inviting to visitors [11]. According to the survey by [12], cleanliness, maintenance, quietness, and safety were the essential qualities of green space. Other studies have confirmed that cleanliness, maintenance, and safety are the essential qualities of green space [13][14][15][16]. There is convincing evidence that poor, or a lack of, maintenance, such as littering, vandalism and dirtiness, may negatively affect green space usage. Appearance, concerns about safety, and the social setting of green space are crucial to its desirability to users [11]. According to [17], the maintenance of green space is costly and requires hard labour. The maintenance tasks of green space include removing litter, watering the trees and plants, raking leaves, removing old and dying trees and plants, and planting new ones. Central Park in New York City spent approximately 22 million US dollars on staff, maintenance, and other operations in 2021 [18]. With the advancements in Machine Learning (ML), recent studies proposed building ML models to analyze and assess green space, which could be used to automate some of the maintenance or monitoring tasks—saving time and reducing costs and labour required as a result [19].

2. Green Space Quality Analysis Using Machine Learning Approaches

Green spaces are described as the ground that is partially or entirely covered with some form of vegetation [20]. Green space has the potential to contribute favourably to several of the most critical urban goals, including social inclusion, health, sustainability, and urban revitalization. Green space plays a crucial part in the day-to-day lives of residents. Environmental improvement through maintaining and expanding green space systems makes places more aesthetically pleasing and hospitable. It contributes to biodiversity preservation, promoting inward investment and increasing land values. Green spaces can catalyze broader communal and economic effects in a way that other neighbourhood facilities or structures cannot achieve. The fact that parks give free, open, non-discriminatory access 24 h a day, seven days a week and are apparent indicators of the quality of a neighbourhood were cited as significant aspects of their unique function [21].

Plants can indirectly influence the microbiome of the environment to which humans are exposed. Humans derive essential health advantages from the gut microbiome by controlling immunological balance and preventing chronic inflammation [20][22]. There is compelling evidence that higher accessibility to green space was linked to lower exposure to air pollution. Decreased exposure to air pollution and high accessibility to green space has proven to affect the cognitive development of children [20][23] positively. Increased exposure to green space has shown several physical health benefits, such as reducing the likelihood of cardiovascular and respiratory diseases in men, improved life expectancy, restoration of the brain's cognitive functionality, increased newborn babies' weight, lower risk of preterm birth, and higher self-reported health [20][23][24]. In addition, green space is proven to benefit mental wellbeing by improving mood and self-esteem, reducing stress levels, and reducing the risk of depression and anxiety [20][23][24][25].

Green space creates a communal area accessible to all segments of society. It can serve as the focal point of a community by providing numerous chances for social interaction, leisure, and recreational purposes. Few studies have shown the direct relationship between green space and health by improving social interaction [20][21][26]. Gardens can be a place for people to interact with each other; parks facilitate physical activities and leisure, and forests can be used for recreational activities. Isolated individuals are typically less healthy and more susceptible to stress, depression, and cardiovascular disease [26].

According to [27], urban green spaces help the conservation of biodiversity, making them an essential component of environmental protection. They provide various beneficial ecosystem services, including moderating climate extremes and reducing pollution by carbon sequestration. Carbon sequestration is the process of transferring and storing carbon dioxide in carbon pools [28]. Furthermore, green spaces help the environment by filtering dust, dirt, soot, smoke and liquid droplets, protecting the ozone layer against the ultraviolet (UV) radiation, lowering the impact of fierce winds, preventing erosion and pollution, and having beneficial effects on the natural water cycle, constraining storm-water runoff, protecting rivers from pollution, and reducing noise. They are necessary for the long-term sustainability of the environment [21][27]. According to [29], green space has been proven to help reduce the temperature in parks to lower than that in non-green areas.

3. Green Space Quality Analysis Using Traditional Methods

In a study conducted by [30], the authors proposed to find the relationship between the quality of green space and the frequency and duration of self-reported physical activities and self-reported stress, mental and physical health. The study surveyed 420 people in Aydin, Turkey's parks and urban greenways. The study considered several quality factors: the distance to green space, aesthetics, cleanliness, size, maintenance, shaded areas, lighting, and openness/visibility. The results of the survey were analyzed using multivariate linear regression. The first finding of this study showed that distance to green space was negatively correlated to the number of users and frequency of physical activities. Secondly, cleanliness and maintenance were positively associated with the frequency of physical activities in green spaces. Finally, the size of green space was associated with less stress, and open/visible green space was associated with better physical health. In the research by [31], the authors conducted a study to evaluate the quality of Bucharest's green spaces. The study surveyed 51 citizens about the five parks under investigation using questionnaires with ten questions in the city of Bucharest. The study evaluated the parks based on the following criterion: green space placement (pollution, distance from home, and territory expansion), green space use (existence of recreational facilities and working places), environment (presence of water sources, shades, and space for pets) and biodiversity (diversity of vegetation and bird species). The weight of each criterion was determined using the Analytic Hierarchy Process (AHP) method. Each criterion was assessed using a five-point Likert scale. The study's initial findings showed that the five parks evaluated in this study were polluted to some extent. Two parks were in the city centre, making them reachable. However, only three of the parks had the freedom to expand their territory. Subsequently, all the parks offered recreational facilities and working places within their territory. Furthermore, a water source and special pet space were available in all the parks. However, only two parks offered areas covered with trees (shaded areas). Finally, the species and habitats were not diverse in the assessed parks. The author conducted a study to evaluate the aesthetic quality of green space while considering a human multi-sensory perspective and presented a systematic way to capture green space images to estimate near-view scenic beauty. The study surveyed a random selection of 178 people by using photo panels and a questionnaire at different sites in the Hangzhou Flower Garden in Hangzhou City, China. The study considered the following criteria for assessing the aesthetic quality of green space: visual, auditory, tactile, and olfactory. The study took the quantitative holistic approach to assess the landscape aesthetic. The authors captured 420 photos of bonsais and flowers and grouped them into panels with 12 photos per panel. The garden visitors were shown panels at the sites where the photos were taken. Then, they were asked to rank the 12 photos on a scale of 1–10 on their ability to represent the site. Subsequently, the five best-representing photos were selected from each panel and randomly assigned to 14 panels with 12 photos per panel. The 14 photo panels were randomly shown to the respondents, who were asked to rank ten photos in each panel from best to worst in terms of visual quality. The study's findings demonstrated that scenic beauty could offer an environment for relaxation for garden users. In addition, the findings showed that green space offered various aesthetic qualities, such as: auditory, olfactory, tactile, and visual. Firstly, green space provided auditory diversity, which is not offered in urban environments. Secondly, green space offered natural fragrances, which respondents admired. Thirdly, respondents appreciated some elements of the green space more when they touched them due to their tactile qualities. Finally, a defined way of taking, selecting, and presenting photos in a panel could eliminate bias and professional inability. In a recent study conducted by [12] to analyze the association between different features of green space and perception of green space qualities using the results of a survey and GIS-based spatial metrics. The study surveyed respondents in the form of an online and on-site questionnaire to assess the perceived importance of green space qualities in Brussels between 2015 and 2016. The survey yielded 371 responses, of which 349 were complete and valid. The green space types studied here were 19th-century formal green spaces, public areas of housing projects, gardens, and spaces for community activities. The study considered nature and biodiversity, quietness, historical and cultural value, spaciousness, facilities, cleanliness and maintenance, and safety as quality factors under study. The survey results showed that cleanliness and maintenance, quietness, and safety are perceived as the most important qualities of green space, followed by adequate facilities and spaciousness. The research by [32] examined neighborhood residents' perceptions of the quality and useful purposes of green spaces concerning neighborhood satisfaction and wellbeing. The study surveyed two neighborhoods (De Hoogte and Corpus-Noord) in Groningen, Netherlands, using a paper-mailed questionnaire in June 2014. Out of the 2750 questionnaires distributed, only 276 were returned, and 223 were completed. The survey results were analyzed using statistical, mediation, and linear regression methods. The 95% confidence interval was calculated using the Monte Carlo method. The quality factors studied here were recreational facilities, amenities for a picnic, good natural features, the absence of litter, easy accessibility, and maintenance. The study results showed that residents with easy accessibility and usable green space were more content with their neighborhood. A study by [33] aimed to address the limitations of existing methods for assessing street greenery, such as questionnaires and field audits. The study aimed to use Google Street View (GSV) images to assess street greenery's eye-level quantity and quality. The study focused on the street greenery and evaluated the greenery, absence of litter, maintenance, and general condition by using a five-point scale. The data collection method was GSV images and field observation by a trained researcher. The study included a total of 240 streets in Hong Kong, China. The results indicated that the average quality of street greenery is 3.21 on a scale out of 5, indicating a relatively high quality. Furthermore, the findings showed that the quality of street greenery was linked to higher levels of physical activity in green spaces. The paper by [3] addresses the scarcity of existing multi-dimensional quality assessment tools for urban green spaces by developing and implementing the RECITAL tool. The study's objective was to assess the quality of green space and evaluate the reliability and internal consistency of the tool. The study focused on municipalities and urban areas. The quality factors assessed included surroundings, access, facilities, amenities, aesthetics and attractions, incivilities, potential usage, land covers, and animal and bird biodiversity. The study was conducted in Barcelona, Spain, where eight technicians conducted fieldwork, visiting between three and five green spaces per day, and completed a questionnaire for each space using the RECITAL tool. The study results showed that the tool was reliable, with an overall intraclass correlation coefficient (ICC) of 0.84, indicating a good reliability. The paper by [34] presented a study to create a tool to evaluate the quality of local green spaces known as "neighbourhood" green spaces. The study recognized that the current techniques for evaluating the quality of green spaces may not be suitable for smaller, local green spaces because these areas had different functions compared to the larger green spaces that people visit. The study's objective is to create a straightforward method to analyze and evaluate the quality of local green spaces, referred to as "neighbourhood" green spaces. The study focuses on neighborhood green spaces, and the quality factors assessed were appearance, maintenance, and the quality of various features. The data collection method used in the study was a survey conducted in Stoke-on-Trent, in the United Kingdom. The study was divided into three phases: phase 1 included four focus groups with 35 adults to gain opinions about local green space, phase 2 included a survey using a five-point scale on 635 adults to determine the appropriate weighting for various domain factors based on their relative significance, followed by testing for feasibility and reliability, and phase 3 included two researchers separately evaluating 28 local green spaces that met the established criteria for inclusion in the study. The study results showed that, according to survey participants, incivilities such as litter, dog waste, and vandalism were consistently deemed the most critical factors in determining the use of green spaces. The study by [35] aimed to analyze the relationship between physical activity and the access to high-quality urban green spaces. The study was conducted in Norwich, England and collected data from a questionnaire on self-reported physical activity levels of 4950 residents. The quality factors assessed included accessibility, maintenance, recreational facilities, amenity provision, signage and lighting, landscape, usage, and atmosphere. The study used multiple regression models to determine the relationship but found a lack of clear connections between leisure activities and green spaces. The paper by [36] aimed to investigate the relationship between the quality of green spaces and prosocial behavior in children over time. The study focused on the quality of green spaces such as parks, playgrounds, and play spaces and assessed the quality factor of availability using a questionnaire and a Likert scale. The study's results showed that the quality of green spaces had a positive relationship with prosocial behavior in children. This research addressed the lack of conclusive evidence regarding the connection between neighborhood green spaces and prosocial behavior in children.

4. Green Space Quality Analysis Using Machine Learning

A study by [37] presented a novel methodology for classifying urban green spaces using a two-level system. The study aimed to improve upon existing methods for quantifying vegetation, such as NDVI, which lacked the resolution to detect smaller details like the presence of trash. The study's objective was to classify the land's health level and the presence of contamination in the green space. The quality factors used in the study were "Healthy", "Healthy Contaminated", "Dry", "Dry Contaminated" "Unhealthy", "Unhealthy Contaminated", "No Vegetation", and "No Vegetation Contaminated". The data for the study was collected using a DJI Phantom 4 drone, which captured 9901 aerial images from parks, university campuses, suburban neighbourhoods, and forested areas. The images were taken from ground level at 20–30 m. There were 9001 images used for training, and 901 images were used for testing. The study's authors designed their deep neural network consisting of a convolutional neural network for extracting features from the images and a multilayer perceptron acting as a classifier. The performance metrics used were accuracy, precision, recall, and an F1-score. The study results showed that the test accuracy, precision, and recall was 72%, while the F1-score was 71%. The research by [8] aimed to develop a system for assessing the quality of urban street-level greenery using street-view images and deep learning. The key limitation with the existing methods, such as satellite and aerial imagery, was that they accurately quantified large-scale greenery but were weak at showing street-level greenery, including contours and features of ground plants. This research aimed to create a method for calculating and displaying the amount of visible greenery in urban areas at the street level. The researchers introduced the Panoramic View Green View Index (PVGVI) to do this. The research focused on parks and gardens, and assessed the quality factors like the visibility of greenery. The data source used in this research was the Cityscapes dataset, which contained recorded videos of streets from 50 different cities to benchmark the performance of their proposed method. Google Street View images were used to apply their proposed method to the study area. A total of 24,920 Google Street View images (1000 × 1000 pixels) were used in the study, which was conducted in Suita, Osaka, Japan. The algorithm used in this research was DeepLabV3+. The performance of the proposed method was evaluated using the mean intersection over union (mIoU), the root-mean-square error (RMSE), and the mean absolute error (MAE). The research results showed that the proposed method achieved an mIoU of 78.37%, an RMSE of 2.75%, and an MAE of 2.28%. The study by [38] presented a new machine-learning approach for evaluating the quality of street green space using street view images from Guangzhou, China. The study aimed to address the limitations of the current research methods for assessing green space quality, which was labour-intensive and time-consuming. Two thousand images were randomly selected for training purposes and were scored based on a 10-point scale of quality attributes by trained investigators. A random forest model was trained to automatically rate the images based on the proportion of 151 elements in the image segmentations. Two validation methods were used to evaluate the performance of the model, first the comparison of the automated scores with manually assessed images, and second by physical visits to residential neighbourhoods by three observers. The methods showed good consistency, whereby a Pearson correlation of more than 0.90 and an agreement percentage of over 85% was achieved. The study by [39] aimed to address the problem of urban planning practices overlooking the accessibility and visibility of street greenery. The study proposed to use Google Street View images to quantify street greenery and evaluated the discrepancy between visible greenery and street accessibility using space syntax. The study also evaluated the similarity between street greenery measurements, including visible and accessible greenery, and urban green cover obtained from satellite images. The study was conducted in Singapore using Google Street View images, a support vector machine (SVM) algorithm, and the scoring method of two urban planning experts to evaluate the results. Comparing the judgements of experts and the SVM showed a high level of accuracy with Cohen's Kappa coefficient values of 0.910 and 0.925. The study authored by [40], aimed to investigate the relationship between urban greenery and the time spent walking by pedestrians. The study specifically looked at the Green View Index (GVI), which measures the visibility of greenery from a specific position in neighbourhood streets. The study used a fully convolutional neural network for semantic segmentation (FCN-8s) to segment Google Street View (GSV) images, which were then used to calculate GVI. The model was trained on the Cityscapes dataset, with 22,973 images for training and 500 for validation. The study found that the model had a validation accuracy of 84.56%. The study by [41] examined the association between exposure to green and blue spaces in residential areas and geriatric depression in Beijing, China. The study aimed to address a gap in the knowledge about the relationship between the access to green and blue spaces and mental health in non-Western countries and the limitations of current methods for measuring exposure to these spaces. The study used deep learning techniques, specifically a fully convolutional neural network (FCN-8s), to segment street view images and compare the data to satellite imagery. The study trained the model using the ADE20K labelled image dataset and achieved a training accuracy of 81.4% and a test accuracy of 76.8%. In the study authored by [42], the problem addressed was that informal green spaces in urban areas, such as those used for recreation and forestry, are often small and not easily detected through aerial surveys. As a result, these spaces were often overlooked by government and city planners during surveys and planning. The study's main objective was to test the feasibility of using machine learning to detect informal green spaces in Google Street View photos by applying the method in the study area of Ichikawa, Japan and Ho Chi Minh City, Vietnam. The study used 24,553 Green Space View panoramic images from Ichikawa, Japan and Ho Chi Minh, Vietnam, and 1000 manually labelled pictures were used to train the model. The DeepLabV3+ model was employed to classify and detect green areas in the GSV images, and the model's accuracy was 65%. The paper by [43] aimed to develop models that could predict the health of turf grass from aerial images as a solution to the limitations of visual examination, which may be subjective and influenced by personal biases. The study used 187 images, collected using a camera mounted on an unmanned aerial vehicle (UAV), and the quality factors evaluated were hue, texture, colour, leaf blade width, and uniformity. Three deep learning models were used for the prediction, AlexNet, GoogleNet, and Inception-V3. The performance was measured using accuracy and loss, and the results showed that Inception-V3 had the highest average accuracy of 73.35% and the lowest loss of 40.25%. The paper by [44] aimed to address the challenge of measuring the relationship between people's perceptions of the built environment and their health. The study focused on green space in the form of streets and the quality factors of nature quality, beauty, relaxation, and safety. The researchers used a dataset called PlacePulse 2.0, which contained 1.1 million images, and applied a SIAMESE CNN network. The results showed an average accuracy of 70.53%. The study by [2] focused on developing a natural language processing (NLP) application and text mining tool to evaluate the quality of urban green spaces. The data source used in the study contained 16,613 TripAdvisor reviews of St. Stephen's Green Park in Dublin, Ireland. The model used was a support vector machine (SVM). The performance of the model was measured using the area under the curve (AUC), precision, recall, and an F1-score, which showed a high performance with an AUC of 97.2%, a precision of 97.1%, a recall of 99.7%, and an F1-score of 98.3%.

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