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Monitoring Urban Green Space Using Remote Sensing Derived-vegetation Indices in Colombo District, Sri Lanka

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Abstract

This study investigated the use of Remote Sensing (RS)-derived vegetation indices for monitoring urban green spaces (UGSs) from Sentinel-2 RS multispectral imagery with a spatial resolution of up to 10 meters. Six vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Green Ratio (GR), and Transformed Vegetation Index (TVI) by using Google Earth Engine (GEE) platform. Derived the original and enhanced images were used to compare the aforementioned vegetation indices in order to assess four image quality parameters: Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), Standard Deviation (SD), and Correlation Coefficient (CC). The findings demonstrated the range of values for each vegetation index: NDVI (-0.398163 to 0.888742), EVI (-0.287905 to 0.615649), SAVI (-0.597015 to 1.00000), MSAVI (-0.495483 to 0.795898), GR (-0.199505 to 0.444334), and TVI (0.058906 to 2.32316). Among the indices, MSAVI exhibited the best fit with image quality parameters of PSNR, RMSE, SD, and CC measuring at 45.31, 0.0197, 0.06, and 0.9641, respectively. This outcome suggests MSAVI's better performance in estimating green vegetation areas compared to other indices in the study area. The study also discussed the limitations of using vegetation indexes to monitor UGS, including the influence of atmospheric conditions, sensor calibration, and data preprocessing techniques. Overall, this study is insightful which is valuable in terms of the effectiveness of different vegetation indices for UGS. The findings of this study can be used to inform future research on UGS monitoring and management, and to identify appropriate vegetation indices for RS applications in other areas.

Keywords: **Green space; vegetation; correlation; remote sensing**

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1. Introduction

Urban green spaces (UGSs) refer to extensive urban areas embellished with greenery, including parks, gardens, green belts, and street trees. These spaces are essential for providing leisure possibilities, upholding good living standards in urban environments, and enhancing the general wellbeing of urban dwellers. In addition, UGSs contribute significant global impact by delivering a range of services such as shade, ecological enhancements [35], green rooftops [2,5], alleviating heat islands [8,19], and improving both mental and physical health [17,21]. It also provides a number of co-benefits that are robust to the stress brought on by fast urbanization and resource-efficient. However, UGSs face escalating challenges from urbanization, climate change, other environmental strains, and the physical health of urban inhabitants [1,33,35,85]. Their importance has led to increased attention to monitoring their condition and quality to ensure their longevity. UGS research involves collecting, analyzing, and interpreting data in terms of their context, quality, and use. These data acquisitions contribute to the identification of factors affecting the quality and health of UGS, including aspects such as air and water quality, soil conditions and climate. Furthermore, it aids in evaluating the efficiency of management approaches and policies designed to conserve and enhance UGSs.
In general, the conventional approach for evaluating UGS involves analyzing the structural characteristics of individual species using the allometric method [27]. However, this method is known to be costly and time-consuming [1,24]. Consequently, RS technology is emerging as a cost-effective mapping and planning tool, providing a synoptic perspective for better monitoring of UGS and vegetation species monitoring compared to traditional methods [13]. Duan et al. [9] demonstrated the use of high-resolution optical RS data to model and quantify the spatial distribution of UGS in a rapidly urbanizing Chinese city. Their study found that UGS coverage varied and was significantly influenced by urban growth, land use and population density. Furthermore, it demonstrated the potential of RS in areas with insufficient green spaces to inform urban planning decisions. Similarly, Griscom et al. [10] used satellite-based data to map and assess global UGS coverage and its variation from 1985 to 2015. This study highlighted a global increase of 34% in UGS coverage over the indicated period in emphasis, with notable changes in regional and urban development, which allowed for Following due to ongoing global urbanization and areas at risk of green space loss. Recently, RS has gained increasing importance as a tool for studying UGS, which is important for the well-being of urban populations and the health of ecosystems. This technology provides accurate and up-to-date information on UGS quantity and quality, calculating green areas to cover, mapping vegetation in urban areas, tracking UGS changes.

RS technology is a valuable tool for estimating various aspects of UGS quality and health, including vegetation cover, abundance, and overall health. Zhang et al. [34] conducted a study using RS data to assess plant health and quality in UGS. The findings of this study highlighted the influence of factors such as vegetation type, age, activity, temperature, and precipitation on the quality of UGS, and emphasized the importance of proper monitoring and management. Furthermore, plants from RS provide valuable insights into the nature of UGS. This description provides information on the health and dynamics of vegetation cover in UGS, and allows the identification of areas of vegetation hardiness and the implementation of targeted strategies to improve their quality Quantitative analysis some have shown that RS-derived plants are effective in assessing UGS quality. For example, Chirichi et al. [7] used Sentinel-2 data and NDVI to evaluate UGS characteristics. Their study revealed lower NDVI values in areas with poor vegetation cover, demonstrating the potential of using NDVI to assess vegetation health. Common vegetation indices used to monitor UGS include Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI) NDVI is the main index used worldwide for vegetation monitoring coverage, calculated in the near-infrared (NIR) and red (R) reflectance differences, are generated by the ratio of their numbers, yielding values ranging from -1 to 1. Higher NDVI values are maintained indicates a dense vegetation cover [23]. In general, NDVI is widely used to assess vegetation cover, focusing on the R and NIR bands in the visible RS data [23] . These lines are particularly suitable for the analysis of specific leaf traits of canopy plants [22]. In their study, Henry et al. [12] utilized an allometric model to validate and quantify tree carbon content within urban vegetation through NDVI, emphasizing the growth of trees. Despite NDVI's natural ability to mitigate atmospheric influences, optimizing sensor effects is essential to understanding the relationship between UGSs' biospheric environments [37].

The effective management and monitoring of UGS are crucial aspects of urban planning and management. However, the rapid process of urbanization in recent years has altered the spatial arrangement of UGS. The depletion of these spaces will result in heightened levels of carbon in the atmosphere, deteriorated ecosystems, and elevated urban Land Surface Temperatures (LSTs) [4]. Consequently, it is imperative to evaluate the changes in UGS to facilitate sustainable city planning. In the past, UGS information was obtained by integrating expert knowledge and cross-validation techniques, employing both field and aerial surveys [36]. Presently, the utilization of higher-resolution satellite imagery, coupled with digital interpretation methods, allows for a more detailed delineation of UGS information. This advancement is integral to ongoing research endeavors and projects aimed at fostering sustainable and environmentally friendly urban development. Hence, this study delves into the application of vegetation-derived indices from RS data for monitoring UGS based on the five image quality parameters within the Colombo District of Sri Lanka.

2. Materials and Method

2.1. Choosing the Study Area

The research region spans from 6° 42′ 15″ to 6° 58′ 21″ latitude and79° 59′ 15″ to 80° 13′ 30″ longitude, encompassing an area of approximately 67,500 hectares (refer to Figure 1) featuring intermittent greenbelts. The Colombo District, under the pressure of recent urbanization and a burgeoning population, has witnessed a decline in green spaces. Over the past thirty years, this has led to a rise in city surface temperatures at a rate of 0.47 °C per year [43].

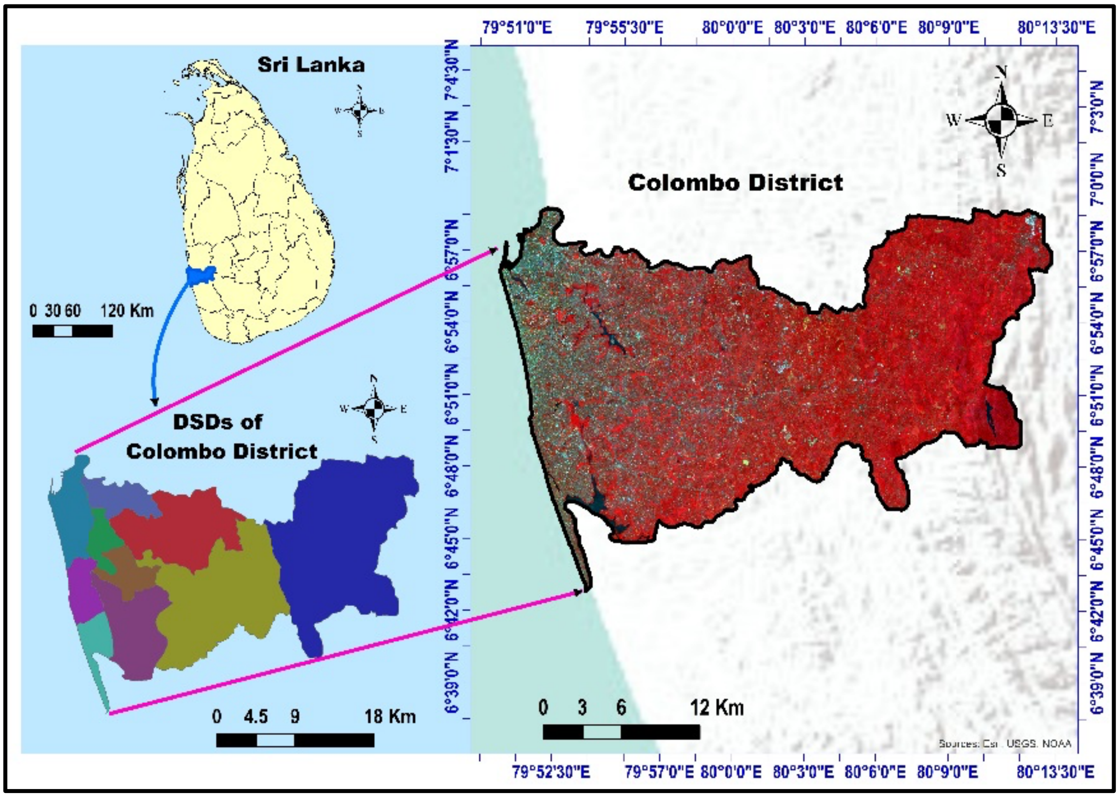


Fig. 1. Study Area

2.2. Using Sentinel-2 Satellite Images Through GEE for Different Vegetation Indices

Sentinel-2 RS data offers multispectral imagery with a spatial resolution of up to 10 meters and revisits the same area every 5 days. The spectral bands of Sentinel-2 span from visible to shortwave infrared across the electromagnetic spectrum, making it well-suited for vegetation mapping using NDVI values [11]. However, the Earth observation section of the European Union's Copernicus Program systematically monitors Sentinel-2 RS data using high-resolution optical imagery, primarily focusing on monitoring vegetation and coastal waters [18]. The mission plan encompasses a diverse array of spatial studies, including land use or land cover analysis, agricultural assessments, urban planning and management, and water quality evaluation.

Vegetation indices encompass mathematical formulations that utilize reflectance values across diverse segments of the electromagnetic spectrum to approximate the extent of vegetation cover and evaluate its state. Within RS, diverse vegetation indices are widely employed, furnishing invaluable insights into greenery patterns, processes, and trends across varied spatial and temporal scales. Recent advancements in RS technology, particularly Sentinel-2 MSI, have been validated for effectively monitoring alterations in vegetation stress within urban areas [37]. Furthermore, Sentinel-2 MSI offers precise data concerning vegetation stress at varying spatial resolutions, presenting dynamic vegetation conditions. However, a multitude of vegetation indices exist, each boasting distinct strengths and limitations. This study specifically delves into diverse vegetation indices and their practical applications, encompassing NDVI, EVI, SAVI, MSAVI, GR, and TVI using the GEE platform (see Table 1). This platform is powerful for calculating various vegetation indices like the aforementioned indices can be computed using GEE's vast satellite imagery archives and efficient processing capabilities.

Table 1. Different vegetation indices for Sentinel-2 image

Vegetation Indices	Formulas	References	Equations
NDVI	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{(\mathrm{NIR} + \mathrm{R})}$	[15,18,25]	(1)
EVI	$\mathrm{EVI} = \frac{2.5(\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + 6 * \mathrm{R} - 7.5 * \mathrm{B} + 1)}$	[32]	(3)
SAVI	$\mathrm{SAVI} = \left(\frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R} + 0.5}\right) * (1 + 0.5)$	[14,26]	(4)
MSAVI	$\mathrm{MSAVI} = \left(2 * \mathrm{NIR} + 1 - \sqrt{2 * \mathrm{NIR} + 1}\right)2 - 8 * (\mathrm{NIR} - \mathrm{R}))/2$	[16]	(5)
GR	$\mathrm{GR} = \frac{\mathrm{NIR}}{\mathrm{R}}$	[29]	(6)
TVI	$\mathrm{TVI} = \left(\frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} + 0.5\right)^{\frac{1}{2}}$	[6,28]	(7)

NIR-Near Infrared (Band 8), R-Red (Band 4), G-Green (Band 3)

2.3. Using Different Parameters for Image Quality

Image quality parameters play a crucial role in evaluating the precision and dependability of RS data. The accuracy of data interpretation and analysis heavily relies on the quality of the RS image. This study examines four frequently utilized image quality metrics: Peak Signal-to-Noise Ratio (PSNR), Root Mean Squared Error (RMSE), Standard Deviation (SD), and Correlation Coefficient (CC) (see Table 2).

The PSNR metric denoted in decibels (dB), acts as an indicator of the quality difference between an enhanced image and its original version. Typically, a higher PSNR value signifies superior quality, with values falling between 30 to 50 dB for 8-bit data and 60 dB for 12-bit data being common benchmarks [40]. PSNR computation involves comparing the maximum signal level in the image with the noise level to quantify image quality. A higher PSNR value implies better image quality. RMSE serves as a metric to assess disparities between two images, derived from the square root of the Mean Squared Error (MSE), reflecting processing efficacy through per-pixel changes. Resulting values range from 0 to 1, where values closer to zero suggest better-fitting models [41]. Similarly, SD quantifies the dispersion or range of pixel values within an image, computed by taking the square root of the variance of these pixel values [42]. A smaller SD suggests closely grouped pixel values around the mean, indicating minimal variability in the image. Lastly, CC measures the correspondence between two sets of pixels arranged by rank in different images, evaluating the disparity between enhanced and original images. The CC value, ranging from -1 to +1, signifies the presence and strength of an association between the pixels of the two images, whether positive or negative [40].

Table 2. Image quality parameters for vegetation indices

Image Quality Parameters	Formulas	Description	References	Equations
PSRN	$\mathrm{PSRN} = 10 * \mathrm{Log10}(\left(\frac{\mathrm{MAX_I}}{\mathrm{MSE}}\right)^2$	$\mathrm{MAX_i}$ - the highest pixel value in the image, and the MSE - the difference between the reference and test images	[30,39]	(08)
RMSE	$\mathrm{RMSE} = \sqrt{\sum \frac{(\mathrm{I_{ref}} - \mathrm{I_{test}})2}{\mathrm{N}}}$	$\mathrm{I_{ref}}$ - the pixel value in the reference image, $\mathrm{I_{test}}$ - the pixel value in the test image, and N - the total number of pixels in the image.	[3,20]	(09)
SD	$\mathrm{SD} = \sqrt{\frac{1}{\mathrm{N}} \sum (\mathrm{x} - \bar{\mathrm{x}})2}$	x - the pixel value in the image, $\bar{x}$ - the mean pixel value, and N - the total pixel count within the image.	[31]	(10)
CC	$\mathrm{CC} = \frac{\sum(\mathrm{Xi} - \bar{\mathrm{X}}\mathrm{i})(\mathrm{Yi} - \bar{\mathrm{Y}})}{\sqrt{\sum(\mathrm{x} - \bar{\mathrm{x}})2}\sqrt{\sum(\mathrm{Y} - \bar{\mathrm{Y}})2}}$	Xi ref and $\bar{X}$i - the pixel values in the reference and test images, respectively. Mean Yi and mean $\bar{Y}$ correspond to the average pixel values.	[3]	(11)

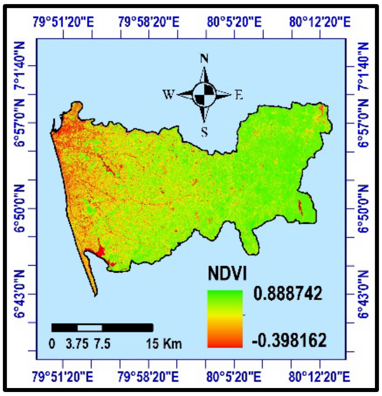
3. Results and Discussion

Various vegetation indices, such as NDVI, EVI, SAVI, MSAVI, GR, and TVI were utilized to evaluate the quality of UGSs. These indices were calculated based on Sentinel-2 RS data, enabling an estimation of the greenness and vitality of the green areas. The assessment aimed to measure ecosystem services like carbon sequestration potential and air quality improvements. The analysis revealed the effectiveness of MSAVI in monitoring UGSs among the diverse vegetation indices.

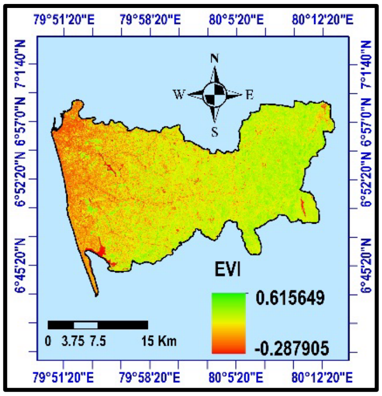
Based on the results, the vegetation index values exhibit a range: NDVI spans from -0.398163 to 0.888742, EVI ranges from -0.287905 to 0.615649, SAVI falls between -0.597015 to 1.00000, MSAVI spans -0.495483 to 0.795898, GR encompasses -0.199505 to 0.444334, and TVI extends from 0.058906 to 2.32316 (see Fig. 2.).

The PSNR results demonstrate that in the assessment of image quality parameters for vegetation indices, the highest PSNR values were 45.96, 45.31, 43.39, 38.43, and 37.18 for TVI, MSAVI, EVI, SAVI, and NDVI, respectively (see Table 4). Conversely, GR exhibited a notably lower value of 28.62 dB among all vegetation indices. However, Wald et al. [44] argue that the better quality of the enhanced image will be represented with higher PSNR values. Higher PSNR values in vegetation indices lead to improved results. Consequently, the enhanced images exhibit elevated pixel values in the mentioned vegetation indices compared to the original images. Thus, TVI and MSAVI emerge as superior image quality parameters for UGS.

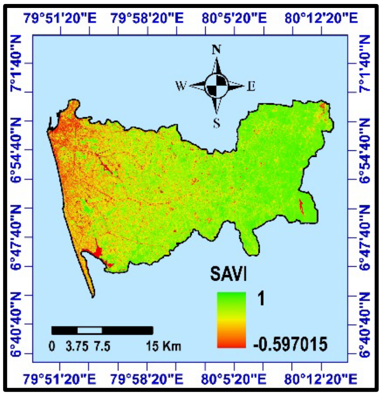
Similarly, the RMSE serves to evaluate the disparity between the vegetation index derived from RS data and the ground truth data, signifying accuracy. In this context, the RMSE values of MSAVI, EVI, TVI, SAVI, and NDVI are 0.0197, 0.0225, 0.0309, 0.0519, and 0.0757 respectively. RMSE acts as a filter for better-quality images, with a similarity index approaching zero. Notably, only the GR index demonstrated higher values of 0.2499 in this study. This outcome underscores that MSAVI showcased the most notable enhancement in image quality based on RMSE compared to other vegetation indices.



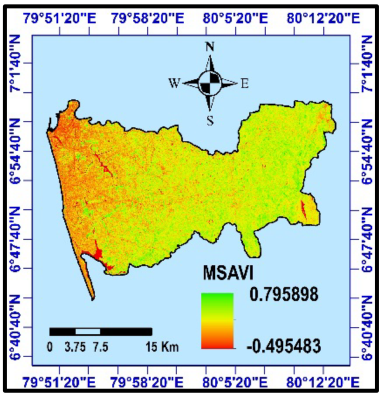
(a)



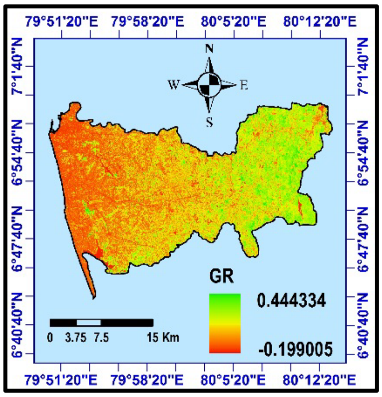
(b)



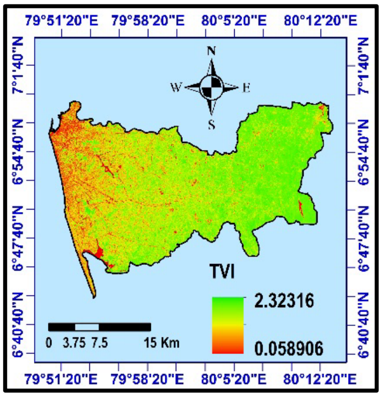
(c)



(d)



(e)



(f)

Fig. 2. (a) NDVI; (b) EVI; (c) SAVI; (d) MSAVI; (e) GR; (f) TVI.

Additionally, we utilized the SD to quantify the variability of the vegetation index derived from RS data. A smaller SD suggests that the pixel values closely cluster around the mean, indicating lower variability in the vegetation index. SD serves as a metric for how closely the data aligns with the mean. This investigation revealed that higher SD values were associated with increased variance in the enhanced results. This highlights minimal deviation in information content for the MSAVI, TVI, and EVI, with SD values of 0.06, 0.09, and 0.009, respectively. In contrast, the GR demonstrated a higher variation with an SD of 0.39, distinguishing it as having more variability among the vegetation indices (Table 3).

Table 3. Image quality of different vegetation indices.

Vegetation Indices/Quality Parameters	Peak Signal to Noise Ratio (PSRN)	Root Mean Square Error (RMSE)	Standard Deviation (SD)	Correlation Coefficient (CC)
NDVI	37.18	0.0757	0.11	0.9613
EVI	43.39	0.0225	0.09	0.9627
SAVI	38.43	0.0519	0.18	0.9617
MSAVI	45.31	0.0197	0.06	0.9641
GR	29.73	0.2499	0.39	0.8327
TVI	45.96	0.0309	0.09	0.9613

Ultimately, the CC is utilized to assess the correlation between the vegetation index derived from RS data and the ground truth data. A significant CC value suggests a strong linear correlation, confirming the precision of the vegetation index. The CC results demonstrate that the MSAVI shows a CC value of 0.9641, closely followed by the EVI at 0.9627, the SAVI at 0.9617, the SAVI at 0.9613, and the NDVI at 0.9613. Specifically for MSAVI, the CC value is noted at 0.9641, indicating a highly noticeable correlation between the pixel values in the original image and those in the enhanced image.

Based on these four image quality parameters, the MSAVI index has shown better performance for UGS in the study area. This suggests that MSAVI is effective in evaluating vegetation health and vigor in the context of UGS.

4. Conclusion

The study suggests that utilizing higher-resolution Sentinel-2 data, with appropriate atmospheric correction, allows for a more precise assessment of UGSs at an improved pixel scale. The research indicates that the MSAVI proves effective in evaluating the actual pixel values of green vegetation spaces within the study area. However, it acknowledges that MSAVI is less affected by atmospheric conditions compared to other vegetation indices like NDVI, GNDVI, EVI, SAVI, and TVI. In addition, MSAVI exhibits better CC values compared to the mentioned vegetation indices. Thus, MSAVI appears as the best method for UGS analysis by considering image quality parameters and comparing vegetation identifications This analysis method helps to distinguish between UGS in satellite image pixel-based classification analysis.

The findings of this study hold important implications for urban planning and management. The study shows that RS data provide valuable insights into the distribution and characterization of UGS, which are important for their development and management strategy. Furthermore, the study highlights the variability in the quality of green spaces within specific vegetation specifications, with the highest quality found in suburbs and the lowest in retail and residential areas Provided Integrating strategies such as increased tree and shrub planting, as well as green roofs and walls, can do wonders for improving the quality of the built environment.

However, it is important to acknowledge several limitations in this study. The resolution of the RS data used may not be sufficient to accurately identify small green areas or differentiate vegetation cover types Furthermore, the study used a supervised classification method, which can lead to classification errors. Future research should focus on refining the accuracy of vegetation descriptions from RS and developing new methods to better monitor UGS using RS data.

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