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ORIGINAL ARTICLE

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Multi-Index spectral analysis of urban green space categories in Bengaluru using Sentinel-2 Data

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ABSTRACT

The rapid densification of metropolitan areas in the Global South has precipitated a critical decline in urban green spaces (UGS), necessitating advanced monitoring frameworks that transcend simple binary vegetation mapping. This study presents a typological classification and multi-index spectral characterization of UGS in Bengaluru, India, utilizing high-resolution Sentinel-2 multispectral imagery. A comprehensive seven-class typology was developed to distinguish between distinct ecological and governance categories, including Urban Forests, Managed Public Parks, and Institutional Green Complexes. Spectral health was assessed using a suite of indices- Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and Normalized Difference Built-up Index (NDBI) to capture the structural heterogeneity of these spaces. Results indicate a stark spatial imbalance in the city's green cover. The landscape is co-dominated by Grassland/Scrubland Systems (30.77%) and Neighborhood/Community Parks (30.39%), reflecting a fragmented network of transitional and residential open spaces rather than contiguous ecosystems. In contrast, high-ecological-value Urban Forests remain critically fragmented, occupying only 2.20% of the classified area. Spectral analysis reveals that while Institutional Green Complexes (10.96%) function as vital ecological refugia with moderate-to-high vegetation density (μ_NDVI=0.56), Avenue Plantations exhibit significant urban stress (μ_NDVI=0.26) and high interaction with built-up surfaces. These findings demonstrate that a multi-index approach provides a more nuanced assessment of urban ecological quality than single-index methods, highlighting the urgent need to protect institutional lands and restore fragmented forest patches for sustainable urban planning.

KEY WORDS

Urban green space; Sentinel-2; Spectral characterization; Google Earth Engine; Normalised Difference Vegetation Index (NDVI); Urban typology

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Introduction

Urbanization and ecological transformation

The rapid acceleration of urbanization in the Anthropocene has fundamentally altered global land-use patterns, precipitating a critical decline in natural ecosystems within metropolitan regions [1,2]. In the Global South, this transition is particularly acute, where demographic pressures and infrastructure expansion frequently outpace environmental planning [3,4]. Bengaluru, one of India's fastest-growing metropolitan cities, exemplifies this urban-ecological conflict. Historically celebrated as the "Garden City" for its extensive network of parks and lakes, the metropolis has undergone a radical transformation into the "Silicon Valley of India," characterized by massive impervious surface growth [5,6]. Remote sensing analyses have consistently documented the fragmentation of Bengaluru's vegetation, revealing a stark inverse correlation between built-up density and green cover [7,8]. Longitudinal studies indicate that this uncontrolled sprawl has led to the depletion of water bodies and vegetation, severely impacting the region's environmental quality, while also altering land-surface-temperature patterns in Bengaluru [9-12].

Methodological advancements and limitations

The application of remote sensing in urban environmental monitoring has evolved significantly with the advent of high-resolution satellite missions and cloud computing [13]. Sentinel-2 Multispectral Instrument (MSI) imagery has been widely applied in urban vegetation mapping because it effectively captures vegetation spectral characteristics while maintaining sufficient spatial detail (10 m) for heterogeneous urban landscapes [14]. Furthermore, the emergence of Google Earth Engine (GEE) has democratized planetary-scale geospatial analysis, enabling researchers to process multi-temporal datasets without local computational constraints [15,16]. However, existing monitoring frameworks often rely heavily on the NDVI to delineate vegetation. While NDVI is effective for general biomass estimation, it exhibits significant limitations in complex urban environments, often saturating in high-biomass areas or failing to distinguish between distinct green space typologies [17].

Research gap and typological necessity

Despite the abundance of geospatial studies regarding Bengaluru's urbanization, a critical gap remains in the typological spectral characterization of its green spaces. Existing literature has largely focused on quantifying the spatial decline of vegetation, with limited attention given to the qualitative assessment of specific UGS categories using a multi-dimensional classification framework. Integrating ecological function with governance attributes is essential for improving policy relevance and urban planning applicability [18,19]. There is a paucity of research that systematically differentiates between distinct typologies such as institutional green complexes versus managed public parks using high-resolution multispectral data. This study addresses this gap by adopting a classification approach that emphasize ecological function, accessibility, and governance context [20].

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Study objectives

To address these limitations, this study employs a multi-index spectral analysis to characterize the quality and distribution of UGS in Bengaluru. The specific objectives are:

- To develop a robust seven-class typology of UGS based on ecological structure and management context.
- To employ Sentinel-2 multispectral imagery to capture vegetation spectral characteristics at a high spatial resolution, enabling the detection of fragmented urban green patches [21].
- To execute data processing using GEE, leveraging its cloud-based computational capacity for efficient geospatial analysis.
- To characterize the spectral health of each typology using a combined analysis of NDVI, EVI, SAVI, and NDBI [22].

Materials and Methods

Study area

The study focuses on the administrative jurisdiction of Bengaluru, the capital of Karnataka, India. Geographically located in the southeastern part of the Deccan Plateau at an elevation of approximately 900 meters above mean sea level, the city experiences a tropical savanna climate with distinct wet and dry seasons. The region's topography is characterized by undulating ridges and valleys, which historically supported a cascading system of tanks and lakes interconnected by storm-water drains (rajakaluves). Once renowned as the "Garden City" for its dense canopy and favorable microclimate, Bengaluru has experienced unprecedented urban densification, leading to the fragmentation of its ecological infrastructure [8]. The study area encompasses the Bruhat Bengaluru Mahanagara Palike (BBMP) limits, covering an area of approximately 741 km², which exhibits a complex mosaic of dense built-up zones, remnant forests, and transitional peri-urban vegetation (Figure 1).

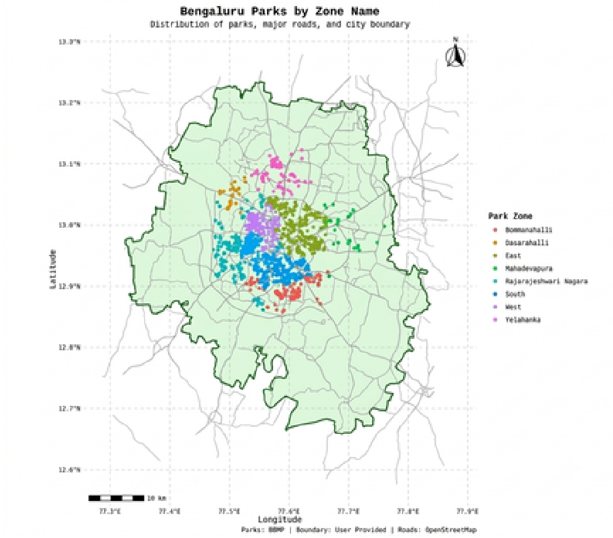

Figure 1. Map of the study area showing the administrative boundary of Bengaluru and the spatial distribution of major zone wise parks.

Data acquisition and processing platform

All geospatial processing was conducted on the GEE cloud computing platform, which facilitates the analysis of planetary-scale datasets without local computational constraints [15]. The primary dataset used was Sentinel-2 Multispectral Instrument (MSI) Level-2A surface reflectance imagery. Sentinel-2 was selected for its high spatial resolution, freely available Level-2A surface reflectance product, and proven suitability for urban vegetation and urban ecosystem-service mapping [14,23]. To ensure spectral accuracy, images were filtered for the dry season (January to March 2024) to minimize cloud contamination and phenological variability, with a cloud cover threshold of <10% [24].

Typological classification framework

To move beyond binary vegetation mapping, this study developed a seven-class typology (Table 1) based on ecological structure, spatial configuration, and land use function. This classification aligns with global urban forestry standards while adapting to the specific governance context of Indian cities [19].

Table 1. Typological classification of UGS in Bengaluru.

Class	Typology	Description
Type I	Urban Forest and Reserved Natural Systems	Relatively undisturbed vegetation patches with dense canopy cover, including protected forests.
Type II	Managed Public Parks and Botanical Gardens	Formally maintained recreational green spaces characterized by structured landscaping.
Type III	Institutional Green Complexes	Vegetation within large campuses such as universities, research institutions, and defense establishments.

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Type IV	Lake–Riparian Systems	Vegetation associated with wetlands, lakes, and surrounding buffer zones.
Type V	Grassland or Scrubland Systems	Open vegetation areas characterized by sparse canopy cover and mixed soil exposure.
Type VI	Neighborhood or Community Parks	Smaller residential green spaces serving localized populations.
Type VII	Avenue Plantations or Linear Greens	Roadside tree corridors and linear vegetation strips embedded in the transport network.

Spectral characterization and index calculation

To assess the qualitative differences between these typologies, four distinct spectral indices were computed for every pixel. These indices were selected to capture different dimensions of vegetation health, canopy structure, and urban interaction.

Normalized Difference Vegetation Index (NDVI)

Used as the primary proxy for chlorophyll content and biomass density [25]

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Enhanced Vegetation Index (EVI)

Corrects for soil background signals and atmospheric influences, providing superior sensitivity in high-biomass areas where NDVI often saturates [17].

$$EVI = 2.5 \times \frac{(NIR - Red)}{(NIR + 6 \times Red - 7.5 \times Blue + 1)}$$

Soil-Adjusted Vegetation Index (SAVI)

Incorporates a soil adjustment factor (L=0.5) to minimize soil brightness effects in sparsely vegetated areas like scrublands [26].

The value L=0.5 was selected as a compromise factor that provides optimal soil adjustment across the full range of vegetation densities encountered in this study, from high-biomass forests to sparsely vegetated scrublands [26]. While L can theoretically vary from 0 (high vegetation) to 1 (sparse vegetation), the intermediate value of 0.5 ensures consistent comparability across all seven typologies without requiring pixel-specific calibration.

$$SAVI = \frac{(NIR - Red) \times (1 + L)}{(NIR + Red + L)}$$

Normalized Difference Built-up Index (NDBI)

Delineates built-up areas to quantify the level of urbanization and its encroachment on green spaces [22].

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)}$$

The computation and interpretation of these indices followed standard digital image-processing principles for remotely sensed data [27].

Methodological workflow

The workflow involved pre-processing Sentinel-2 tiles to mask clouds and shadows using the QA60 band. The defined spectral indices were then calculated for the composite image. A supervised classification approach utilizing the Random Forest algorithm was employed to map the seven typologies, trained on a dataset of reference points derived from high-resolution Google Earth imagery [2,8,28-30]. Finally, zonal statistics were extracted to compute the mean and standard deviation of each spectral index across the identified classes to evaluate their "spectral fingerprints" [31].

Results

Spatial distribution and typological dominance

The supervised classification of Sentinel-2 imagery yielded a high-resolution typological map of Bengaluru, revealing a landscape defined by significant fragmentation rather than contiguous green cover. The Classified Urban Green Space Map (Figure 2) illustrates a distinct core-periphery gradient, where structured parks are confined to the city center, while the periphery is dominated by transitional scrublands.

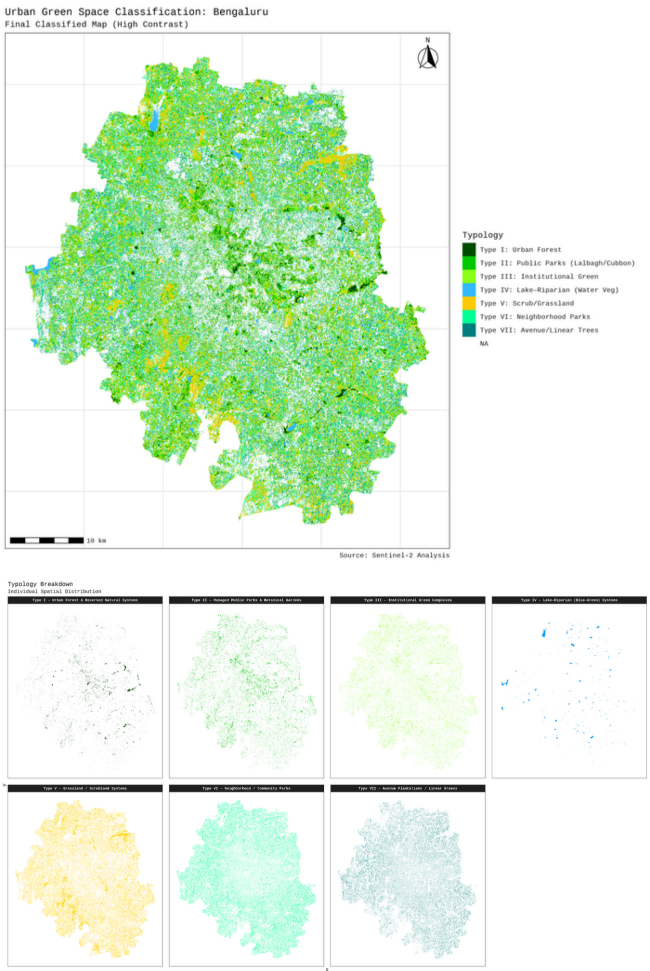

Figure 2. Classified Urban Green Space Map of Bengaluru (2024) derived from Sentinel-2 data. Note the dominance of Type V (Scrubland) in the peripheral zones and the fragmented distribution of Type VI (Neighborhood Parks) in the residential core.

The spatial statistics (Figure 3) quantify this imbalance. Contrary to the "Garden City" narrative, the landscape is co-dominated by Grassland/Scrubland Systems (Type V) and

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Neighborhood/Community Parks (Type VI), which account for 30.77% (39.35 km²) and 30.39% (38.86 km²) of the total classified area, respectively. In contrast, high-ecological-value Urban Forests (Type I) are critically scarce [8,20], occupying only 2.20% (2.81 km²), primarily restricted to defense lands and protected reserves.

It should be noted that these percentages and area calculations (Table 2) represent only the classified urban green space within the BBMP administrative boundary (741 km²), not the entire municipal area. The values reflect the proportional distribution of identified green space typologies rather than total city coverage.

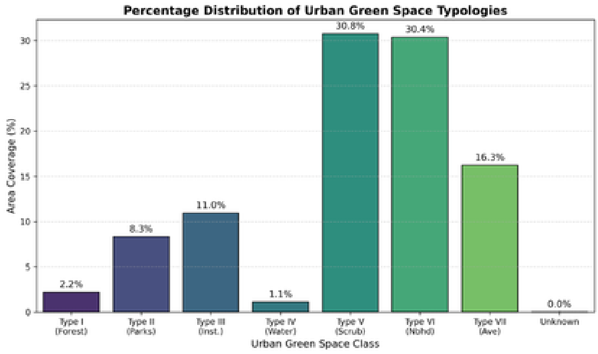

Figure 3. Percentage area distribution of UGS typologies. The extensive coverage of Type V and Type VI highlights the prevalence of transitional and fragmented green spaces over contiguous forests.

Spectral characterization and index performance

The multi-index analysis (Table 2) provides a robust quantitative assessment of vegetation health. Urban Forests (Type I) exhibited the highest vegetative vigor (μ_NDVI=0.72±0.05), validating their role as the city's primary carbon sinks.

Interestingly, Managed Public Parks (Type II) maintained a mean NDVI of 0.64, statistically comparable to forests, suggesting that active maintenance in parks like Lalbagh effectively mimics natural forest spectral signatures [25].

Table 2. Descriptive Statistics of Spectral Indices by UGS Class (Mean ± Standard Deviation).

Class	Typology	NDVI (Mean)	EVI (Mean)	SAVI (Mean)	NDBI (Mean)
Type I	Urban Forest	0.72 ± 0.05	0.48 ± 0.04	0.45 ± 0.03	-0.23 ± 0.06
Type II	Managed Parks	0.64 ± 0.08	0.39 ± 0.07	0.38 ± 0.06	-0.12 ± 0.09
Type III	Institutional Greens	0.56 ± 0.11	0.34 ± 0.09	0.33 ± 0.08	-0.05 ± 0.10
Type IV	Lake-Riparian	-0.12 ± 0.15	-0.05 ± 0.12	-0.08 ± 0.10	-0.10 ± 0.11
Type V	Scrubland	0.47 ± 0.18	0.18 ± 0.10*	0.28 ± 0.12	0.01 ± 0.14
Type VI	Neighborhood Parks	0.35 ± 0.12	0.23 ± 0.10	0.23 ± 0.09	0.06 ± 0.13
Type VII	Avenue Plantations	0.26 ± 0.09	0.18 ± 0.08	0.18 ± 0.07	0.08 ± 0.11

*(Note: EVI values for scrubland systems reflect moderate vegetation density with inherent spectral variability due to mixed soil-vegetation pixels).

The spectral distinctions are visually corroborated in Figure 4, which presents the comparative bar charts of the indices. While NDVI and SAVI follow similar trends, EVI highlights the extreme variance in Scrublands (Type V), confirming the "mixed pixel" effect noted in Table 2. It is important to note that the negative mean NDVI observed for Type IV (Lake-Riparian Systems, μNDVI = -0.12) reflects the predominance of water pixels in the sample set, as sampling points were primarily located on open water surfaces rather than the vegetated buffer zones. This explains the divergence from typical riparian vegetation signatures, which would otherwise exhibit positive NDVI values due to bank-side vegetation.

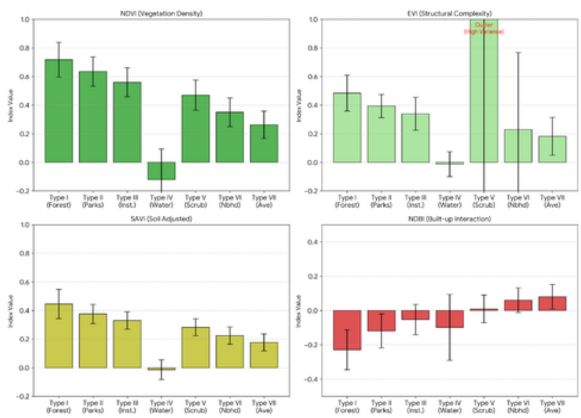

Figure 4. Comparative spectral indices (Mean ± SD) for the seven UGS typologies. Note the high variance in Type V EVI, reflecting its heterogeneous composition.

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To visualize these values in a spatial context, Figure 5 presents a multi-panel zoom of the Indian Institute of Science (IISc) campus. The transition from the high biomass signal in the NDVI panel to the structural detail in the EVI panel demonstrates the utility of multi-index mapping in resolving dense urban canopies.

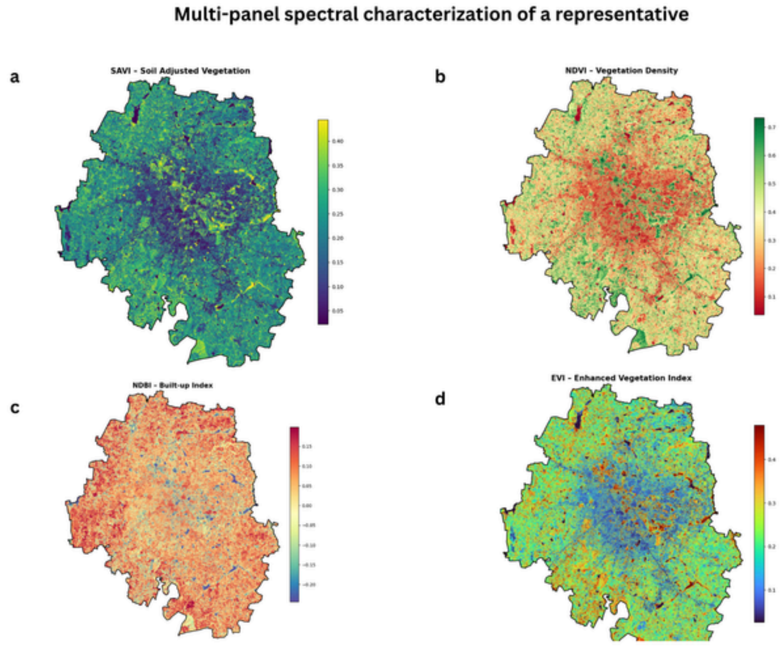

Figure 5. Multi-panel spectral characterization of a representative(A) SAVI; (B) NDVI showing biomass density; (C) EVI revealing canopy structure; (D) NDBI delineating the built-up interface.

Institutional refugia vs. public fragmentation

The analysis identifies Institutional Green Complexes (Type III) as the city's de facto ecological anchors (μNDVI = 0.56). The Hierarchical Clustering Dendrogram (Figure 6) places Type III in a cluster closely related to Type I and Type II, statistically separating it from the "stressed" urban classes (Types VI and VII). This confirms that restricted-access campuses (e.g., defense lands, universities) effectively preserve biodiversity and mature vegetation structure that are often reduced in the public urban realm by land conversion, fragmentation, and management pressure [7, 32-35].

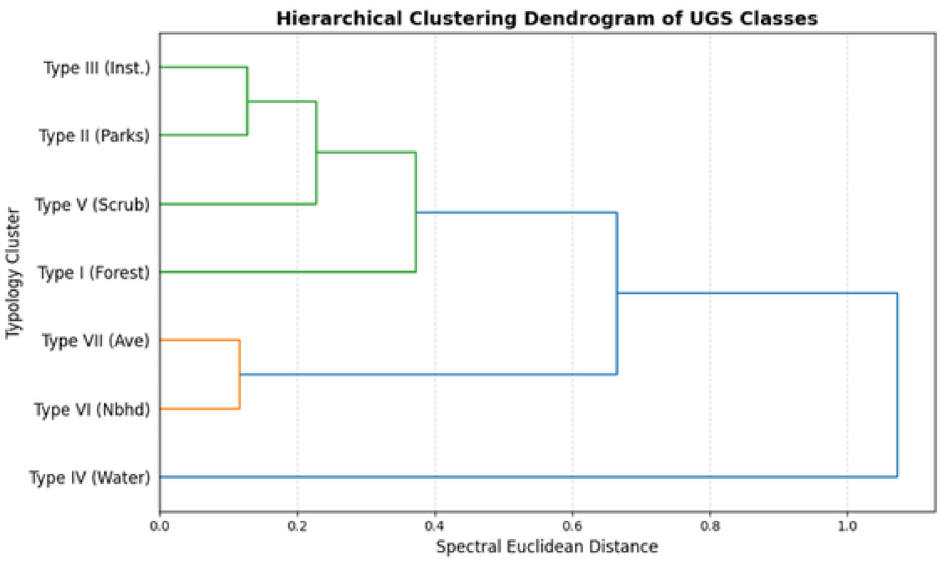

Figure 6. Hierarchical clustering dendrogram (Ward's method) illustrating spectral similarities. Note that Institutional Greens (Type III) cluster with Forests, while Neighborhood Parks (Type VI) cluster with transitional Scrublands.

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Urban stress and the spectral fingerprint

The multi-dimensional analysis effectively diagnoses "urban stress" in Avenue Plantations (Type VII). As illustrated in the Radar Chart (Figure 7), Type VII is spectrally pulled toward the NDBI axis (μNDBI = 0.08), unlike the vegetation-skewed Type I. This visualizes the "impervious surface interaction" described by Yuan and Bauer [36]. Furthermore, the Parallel Coordinate Plot (Figure 8) traces the trajectory of each class across all four indices. The crossing lines reveal a stark inverse relationship: as typologies shift from Forest to Avenue, the vegetation signal (NDVI/EVI) plummets while the built-up signal (NDBI) spikes. This strongly suggests that street trees in Bengaluru are physiologically compromised by root compaction and heat stress, rendering them less effective for microclimate regulation than park trees [37-39]. However, it is important to acknowledge that the low NDVI values observed for Avenue Plantations (Type VII) may partially reflect the spatial resolution limitation of Sentinel-2 (10m), where individual pixels typically encompass mixed land cover (tree canopy + asphalt road), rather than solely indicating biological stress of the trees themselves.

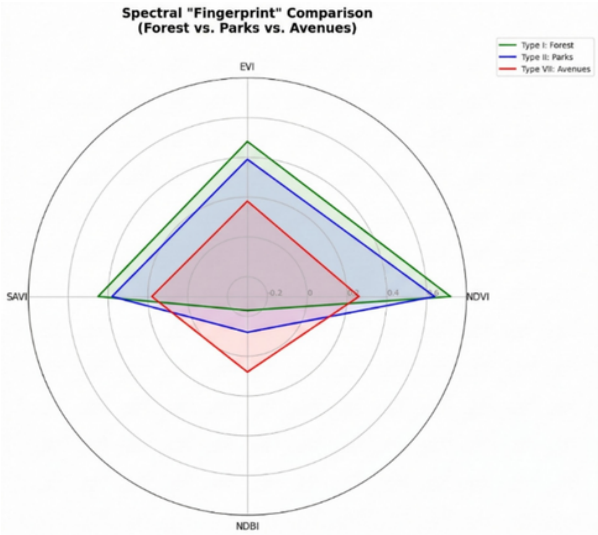

Figure 7. Radar chart illustrating the distinct "spectral fingerprints" of UGS typologies. Type I extends along the NDVI/EVI axes, whereas Type VII is skewed towards NDBI.

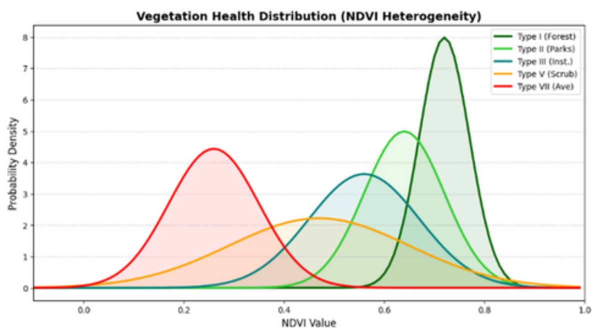

Figure 8. Parallel coordinate plot illustrating the inverse trajectory of spectral indices. The distinct "X" pattern demonstrates the trade-off between vegetative health (NDVI) and urban intensity (NDBI).

Policy implications

The spectral data indicates a "quantity-quality" trade-off. While Neighborhood Parks (Type VI) are spatially abundant (30.39%), their spectral health (μNDVI = 0.35) is significantly lower than that of Managed Parks (Type II) (μNDVI = 0.64). This suggests that the current network of civic amenity sites is under-managed and ecologically fragmented [20,40,41]. Policy interventions must therefore prioritize the ecological restoration of Type VI spaces to mimic the structural complexity of Type II parks, ensuring that the dominant green infrastructure of the city functions as a viable ecosystem. The spectral similarity between Type VI (Neighborhood Parks, μNDVI = 0.35) and Type V (Scrubland, μNDVI = 0.47) evident in their clustering in Figure 6 reflects the poor maintenance conditions prevalent in civic amenity parks, where dry grass patches and high soil exposure mimic scrubland signatures rather than managed vegetation [20,38].

Conclusion

Synthesis of findings

This study has executed a high-resolution, multi-index spectral characterization of Bengaluru's UGS, challenging the conventional binary narratives of vegetation loss. The typological analysis reveals that the city's green cover is no longer defined by the contiguous canopy of the "Garden City" era but by a highly fragmented mosaic of Grassland/Scrubland Systems (Type V, 30.77%) and disjointed Neighborhood Parks (Type VI, 30.39%). While the quantitative extent of these categories appears substantial, the spectral health assessment indicates significant qualitative deficits. The multi-index analysis confirmed that Urban Forests (Type I) the most ecologically functional typology is critically scarce (2.20%; μNDVI = 0.72) and spatially polarized, whereas the dominant Neighborhood Parks function spectrally closer to transitional scrublands than to managed reserves.

Methodological implications

The study validates the necessity of moving beyond single-index monitoring frameworks. The application of the NDBI alongside standard vegetation indices (NDVI/EVI) proved instrumental in diagnosing "urban stress." Specifically, the detection of high NDBI values in Avenue Plantations (Type VII) successfully quantified the impact of impervious surface interaction, a stressor that standard NDVI often obscures. The distinct "spectral fingerprints" identified in the hierarchical clustering analysis demonstrate that institutional, recreational, and remnant forest typologies provide fundamentally different ecosystem services and thus require differentiated management strategies. A key methodological limitation concerns the spatial resolution of Sentinel-2 (10m), which creates inherent pixel mixing in heterogeneous urban environments. This is particularly relevant for Avenue Plantations (Type VII), where the 10m pixel typically encompasses both tree canopy and impervious road surfaces, potentially conflating spectral signals and complicating the interpretation of vegetation health. Future studies employing sub-meter resolution imagery could better isolate tree-level physiological conditions from land-cover mixing effects.

Policy recommendations

Based on the spatial and spectral evidence, three strategic interventions are recommended for Bengaluru's urban planning policy:

Ecological networking of type VI

Given that Neighborhood Parks (30.39%) constitute the largest

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managed green inventory, urban local bodies (BBMP) must prioritize "corridor connectivity" projects. Linking these isolated pockets through greenways or vegetated storm-water drains (rajakaluves) can transform disjointed patches into a functional ecological network.

Legal protection for institutional refugia

Institutional Green Complexes (Type III) were identified as the de facto biodiversity reservoirs of the city. These zones (university campuses, defense lands) require specific legal designation as "Urban Eco-Sensitive Zones" to prevent their conversion into commercial real estate, a trend currently threatening their integrity.

De- Paving avenue corridors

To address the severe spectral stress observed in Type VII (Avenues), a policy of "de-paving" root zones is essential. Replacing impervious concrete curbs with permeable interlocking pavers can reduce root compaction and lower the NDBI signal, thereby improving the long-term survival of street trees.

In conclusion, Bengaluru's ecological future depends on shifting focus from the mere quantity of green space to the quality of its connectivity and structure. Preserving the remaining Urban Forests while actively upgrading the spectral health of the dominant Neighborhood Parks offers the most viable pathway toward a resilient urban ecosystem.

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Disclosure Statement

No potential conflict of interest was reported by the author.

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