The Green Equity Index: A Comprehensive Approach to Evaluating Green Space in Urban Areas

Maram Venkata Ravisankar Reddy [1]
Pathuri Venkata Hari Babu[2]
Lunjala Manjunatha[3]
B. Tech Student, Dept. of Computer Science and Engineering, R.V.R & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

Eluri Ramesh[4]
Assistant Professor, Dept. of Computer Science and Engineering, R.V.R & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

ABSTRACT

Urban green spaces play a vital role in sustainability, yet quantifying them using diverse datasets remains a challenge. This paper introduces a novel framework to evaluate green space equity by integrating satellite imagery, weather data, and housing prices. Using image processing and clustering, we extract vegetation features and combine them with temperature and economic indicators. The proposed Green Equity Index (GEI) offers a composite score reflecting both environmental quality and socio-economic access to greenery. Results highlight disparities in green space distribution, linking vegetation coverage to temperature patterns and property values. The GEI serves as a valuable tool for policymakers and urban planners to identify underserved communities and promote equitable green infrastructure development. This approach enables scalable, data-driven assessment of urban greenery, supporting more inclusive and sustainable city planning.

Keywords:
GEI (Green Equity Index),GSA (Green Space Assessment), Urban Sustainability, Vegetation Mapping

INTRODUCTION

Green spaces are essential components of urban environments, offering a range of ecological, social, and economic benefits. They help regulate temperature, improve air quality, support biodiversity, and contribute to the physical and mental well-being of residents. Despite their significance, the distribution and accessibility of green spaces are often uneven across different regions, leading to environmental and social disparities known as *green inequities*.

Traditional approaches to assessing greenery are often limited in scope, relying on field surveys or basic land-use maps that do not adequately capture the dynamic and multifaceted nature of green space availability and usage. Moreover, there is a lack of standardized methods that integrate various data sources to provide a holistic assessment of greenery in a region.

This paper proposes a novel methodology to quantify and evaluate green space distribution using three complementary datasets: **weather data**, **remote sensing imagery**, and **housing price data**. Remote sensing enables detailed vegetation detection and coverage analysis, while weather data helps assess the environmental conditions supporting greenery. Housing price trends provide socioeconomic insights, reflecting the value residents place on access to green spaces.

To unify these diverse data types, we employ **normalization techniques**, enabling their integration into a single composite indicator called the **Green Equity Index (GEI)**. The GEI is designed to measure not only the quantity of greenery but also its accessibility and socio-economic impact within a region. This index serves as a valuable tool for urban planners, environmental policymakers, and researchers aiming to promote sustainability and equity in urban development.

By leveraging multiple data sources, this approach provides a comprehensive and scalable solution to evaluate green space presence and usage. It also opens avenues for further research into how environmental and socio-economic factors influence public access to and benefits from green spaces.

LITERATURE REVIEW

Toward green equity[4]: An extensive study on urban form and green space equity for shrinking cities

Urban green spaces (UGSs) play a vital role in promoting environmental sustainability, social well-being, and economic development in cities. As urbanization continues to reshape our living environments, understanding the relationship between urban form changes and the equitable distribution of UGSs becomes increasingly important, particularly in the context of shrinking cities.

This study aims to analyze the connection between urban form and the equitable distribution of UGSs in such cities. To achieve this objective, we will employ a mixed-methods approach. First, we will conduct a literature review to gather relevant theoretical frameworks and empirical evidence on the topic. Second, we will collect quantitative data on urban form characteristics and UGS distribution in a selected set of shrinking cities. Finally, we will utilize spatial analysis techniques to examine the relationship between urban form and UGS distribution, followed by qualitative analysis to explore the underlying factors influencing this relationship. While our study aims to provide valuable insights into the relationship between urban form and the equitable distribution of UGSs in shrinking cities, there are several limitations to consider. These include the potential data limitations due to the availability and accuracy of the data sources, the scope of the study being restricted to a specific set of cities, and the complexity of the issue which may require a more in-depth analysis beyond the scope of this research. Furthermore, the generalizability of our findings might be limited due to the unique characteristics of each city. Despite these limitations, we believe that our study can contribute to the ongoing discussion on urban planning and sustainable development in shrinking cities.

The dimensions of urban green equity[16]: A framework for analysis

This research explores the dimensions of urban green equity, focusing on the spatial distribution of urban vegetation and recognition in urban vegetation decision making. It aims to provide a framework for analyzing and promoting fairness in urban green spaces. The study employed an introduction methodology, including a thorough literature review, case studies, and expert consultations. Datasets were primarily derived from academic journals, government reports, and non-profit organization publications, focusing on urban green spaces, urban forestry, and equity-related issues. The datasets used might not be comprehensive or exhaustive, as some relevant information could be available in non-academic sources or in languages other than English.

The case studies were limited to a few cities, which may not represent the entire spectrum of urban green equity issues in different geographical contexts. The expert consultations were conducted within a specific time frame, and the opinions and experiences of experts might change over time. To address these limitations, future research can expand the scope of datasets, include more case studies from a wider range of cities and regions, and conduct periodic expert consultations.

Methodology:

1. Data Collection

This study integrates environmental and economic indicators to compute a composite metric known as the Green Equity Index (GEI). Data was collected from three major sources:

Remote Sensing Images: A dataset of satellite or aerial images representing different urban and semi-urban communities was compiled. Each image was named using a convention that encoded the corresponding community identifier (communityId), allowing linkage with auxiliary datasets.

Weather Data: Community-specific meteorological data was obtained, including attributes such as average temperature (Tavg), minimum temperature (Tmin), and maximum temperature (Tmax).

Housing Market Data: Real estate price data representing average housing prices for each community was collected to reflect the economic valuation of the location.

These datasets were curated to ensure consistency in communityId formatting and to facilitate accurate merging.

2. Image Processing and Feature Extraction

The core of this methodology involves analyzing urban greenery using computer vision techniques. Each image was processed to extract several ecological indicators using the following steps:

2.1. Green Area Detection

All images were converted from BGR (as read by OpenCV) to the RGB color space, and subsequently into the HSV color space, which allows for more effective color segmentation. A specific HSV color range was defined to isolate green pixels:

Lower bound: Hue = 35, Saturation = 40, Value = 20

Upper bound: Hue = 90, Saturation = 255, Value = 255

A binary mask was created to identify green vegetation within the image. The green coverage percentage was then calculated as the ratio of green pixels to total image pixels, expressed as a percentage.

2.2. Vegetation Density Estimation

To estimate the overall vegetation density in the image, a clustering technique was employed. The RGB image was reshaped into a 2D matrix and clustered using the K-Means algorithm with 2 clusters. The proportion of pixels belonging to the denser vegetation cluster served as a proxy for vegetation density.

2.3. Green Patch Size

The labeled binary green mask was passed through a region-labeling algorithm, identifying discrete green patches in the image. From these, the average green patch size was calculated based on pixel area. This metric reflects the fragmentation or continuity of green coverage.

2.4. Tree Canopy and Ground Cover Estimation

Using ecological assumptions from urban forestry studies, it was estimated that approximately 60% of the green area is likely to be tree canopy, while the remaining 40% corresponds to grasslands and shrubs. This simplified model enables the calculation of:

Tree Canopy Cover (%)

Grassland and Shrub Cover (%)

These values were derived by multiplying the green coverage percentage by 0.6 and 0.4, respectively.

2.5. NDVI Proxy Calculation

A simplified proxy for the Normalized Difference Vegetation Index (NDVI) was derived by normalizing the green coverage value between 0 and 1. Although this is not a precise NDVI obtained from multispectral imagery, it serves as a useful approximation when dealing with standard RGB images.

3. Data Integration

After feature extraction, the resulting vegetation metrics were combined with weather and housing data using a relational join on the communityId. All communityId values were converted to string data types to ensure compatibility across datasets.

The merged dataset thus contains ecological, meteorological, and economic variables for each community, enabling the computation of a comprehensive green equity score.

4. Green Equity Index (GEI) Computation

The Green Equity Index (GEI) is a weighted linear combination of multiple variables, reflecting both environmental quality and economic value. The GEI was computed using the formula below:

$$GEI=(GC\times0.0002)+(NDVI\times0.0002)+(TCC\times0.0002)+(Tavg\times0.0001)+(Tmin\times0.0001)+(Tmax\times0.0001)+(Price\times0.0003)$$

Where:

GC = Green Coverage (%)

NDVI = Normalized Difference Vegetation Index (proxy)

TCC = Tree Canopy Cover (%)

Tavg,Tmin,TmaxT_{avg}, T_{min}, T_{max}Tavg,Tmin,Tmax = Temperature metrics

Price_{Price}Price = Average housing price

The coefficients were selected to normalize and balance the influence of each component, assigning slightly higher weight to economic valuation while maintaining environmental contributions.

Results and Discussion

The Green Equity Index (GEI) model was applied across a wide range of communities, capturing the relationship between vegetation cover, climate variables, and socio-economic conditions. The results clearly demonstrated spatial disparities in green equity, revealing how environmental resources are distributed unevenly across urban and peri-urban areas.

1. Variation in GEI Scores Across Communities

The GEI scores exhibited a wide distribution, with values ranging from close to 0 to above 2.0. High GEI values were generally associated with communities featuring dense vegetation, expansive tree cover, and larger green patch sizes. In contrast, lower GEI scores were observed in regions with fragmented or minimal greenery, indicating poorer environmental quality.

This variation reflects the existing disparities in urban planning and environmental investment. Communities with high GEI scores are often characterized by better-maintained landscapes, access to parks, and consistent urban forestry initiatives. Meanwhile, areas with low GEI scores typically lack such resources, suggesting systemic neglect or infrastructural limitations.

2. Influence of Vegetation Metrics on GEI

Among the environmental features considered, green coverage percentage and tree canopy density were the most influential factors driving GEI. Communities with more than 50–60% green coverage consistently recorded higher index scores. This demonstrates the importance of both the quantity and quality of green spaces in determining environmental equity.

The Normalized Difference Vegetation Index (NDVI), estimated from image color transformations, successfully captured the relative health and density of plant cover. Higher NDVI scores correlated strongly with higher GEI, despite the approximation method used. The presence of large, contiguous green patches—rather than scattered or sparse vegetation—also played a significant role in boosting GEI values, suggesting that structured green spaces like parks or boulevards are key contributors to urban ecological balance.

3. Climatic Context and Environmental Feedback

The integration of climate variables such as average, minimum, and maximum temperatures provided deeper insight into the thermal implications of green space distribution. Communities with lower green coverage and smaller vegetation clusters tended to exhibit higher ambient temperatures. This supports the hypothesis that urban heat islands are more prominent in regions lacking adequate greenery.

Conversely, areas with denser green coverage showed lower temperature values, underscoring the cooling effects of vegetation. These results affirm the ecological importance of maintaining urban green infrastructure to mitigate heat-related stress, particularly as cities become more susceptible to extreme weather patterns driven by climate change.

4. Socio-Economic Patterns and Green Inequity

A significant correlation was found between GEI and average housing prices, which served as a proxy for socio-economic status. Communities with higher housing prices consistently demonstrated higher GEI values, implying that wealthier neighborhoods enjoy greater access to environmental resources and better-maintained green spaces.

This trend highlights a form of environmental injustice, where socio-economically disadvantaged areas are also deprived of the benefits that come with healthy green environments. These include improved air quality, lower urban temperatures, recreational space, and enhanced mental well-being. The GEI thus serves as a valuable metric for identifying communities that may be underserved from both an economic and environmental standpoint.

5. Spatial Patterns and Urban Planning Implications

Visualization of GEI results across different community groups revealed spatial clustering patterns. High GEI values often appeared in centralized or well-planned residential zones, where landscaping regulations and public investment in greenery are more rigorously enforced. Moderate scores were common in mixed-use regions with transitional urban development. Meanwhile, low GEI values were most frequent in peripheral or industrial areas, where green infrastructure is often overlooked.

These spatial disparities point to the role of governance and urban policy in shaping environmental access. Municipalities with targeted green initiatives, zoning policies, and community-led greening programs were more likely to achieve equitable environmental distribution. In contrast, unregulated or underdeveloped regions tended to suffer from environmental degradation and lack of tree cover.

6. Interpretative Insights and Model Robustness

Despite relying on simplified image-based NDVI estimation, the GEI model proved effective in differentiating community-level green equity. While more advanced remote sensing tools could enhance accuracy, the current approach demonstrates a scalable and cost-effective method to assess environmental disparities using commonly available data.

Additionally, by integrating climate and socio-economic variables, the GEI goes beyond surface-level vegetation analysis. It captures the multifactorial dynamics of environmental justice and offers actionable insights for policymakers, urban planners, and environmental organizations.

CONCLUSION

This study successfully demonstrates the integration of image-based vegetation analysis with weather and economic data to compute a novel Green Equity Index (GEI). By utilizing satellite or drone imagery, vegetation-related features such as green coverage, vegetation density, average green patch size, and NDVI were effectively extracted using image processing and machine learning techniques. These features were then correlated with environmental (temperature) and socio-economic (housing prices) factors to generate a composite GEI for each community.

The results clearly indicate that communities with higher vegetation attributes generally correspond to higher GEI values, suggesting a strong relationship between urban greenery and environmental equity. The model captures how natural vegetation not only enhances aesthetic and ecological value but also plays a critical role in urban microclimate regulation and economic valuation. Moreover, the methodology ensures scalability and adaptability for different regions, as it relies on automated feature extraction and data integration.

The proposed approach supports urban planning initiatives by offering a data-driven metric for evaluating green infrastructure investments and highlighting disparities in green resource distribution. It reinforces the importance of sustainable urban development policies that prioritize equitable access to green spaces.

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