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Beyond City-Level Canopy Cover: A Contextualized Tree Equity Score (Tes) Framework for Greening Indian Cities

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Abstract

Urban trees provide critical ecosystem services that enhance thermal comfort, public health, and urban livability. However, tree cover equity—the fair distribution of tree-based benefits across socio-economic groups—remains weakly addressed in Indian urban policy. Existing greening initiatives, such as the Smart Cities Mission and Nagar Van Yojana, primarily emphasize the quantity of green space or carbon sequestration within designated parks, often overlooking neighbourhood-scale disparities in everyday exposure to shade and cooling. This study proposes a contextualized Tree Equity Score (TES) framework for Indian cities by modifying the conventional TES methodology to better reflect local land constraints. Using Bhubaneswar as a case study, the analysis integrates existing tree cover, heat exposure, and socio-economic vulnerability at the ward scale. The conventional TES, which defines canopy targets based on biome classification and building density, identifies only a small number of inequitable wards, largely due to suppressed canopy targets in high-density areas. To address this limitation, the modified framework recalibrates canopy targets using ward-level plantable area derived from land-cover classification, while retaining the original weighting structure for vulnerability and heat exposure. Results show that incorporating plantable area does not uniformly lower equity scores but selectively reveals inequities in dense Old Town wards, environmentally constrained residential areas, and transitional peripheral zones that were masked under the conventional approach. Planned neighbourhoods and forest-adjacent wards remain stable across both frameworks, indicating genuinely favourable greening conditions. The findings demonstrate that canopy target formulation strongly shapes equity diagnostics and that plantable-area-based targets offer a more actionable basis for prioritizing urban greening in land-constrained Indian cities.

Keywords: treecover equity, environmental justice, urban greening, heat mitigation, plantable area

1. Introduction

Rapid urbanization, intensifying urban heat island (UHI) effects, and increasing frequency of heatwaves have brought renewed attention to the role of urban trees in mitigating thermal stress and enhancing urban livability worldwide (Aboelata & Sodoudi, 2020; Guo et al., 2023; He et al., 2024; Salmond et al., 2016). Trees provide localized cooling through shading and evapotranspiration (Yin et al., 2024), improve thermal comfort, and offer co-benefits such as air-quality improvement (Chaudhuri et al., 2022), stormwater regulation (Kansal & Bose, 2025), and psychological well-being (Thapa et al., 2024). However, these benefits are not uniformly distributed within cities, giving rise to growing concerns around tree cover equity and environmental justice (Grant et al., 2022; Locke et al., 2021; Lowry et al., 2012; Nesbitt et al., 2019).

1.1 Need for Equity-oriented Framework in Indian Context

In India, urban greening policies have historically prioritized the quantity of green space rather than its spatial distribution or functional performance. National programmes such as the Smart Cities Mission emphasize parks and recreational open spaces (Turaga et al., 2020), while afforestation initiatives like the Nagar Van Yojana focus on increasing carbon sequestration through tree planting within existing parks and gardens (MoEFCC, 2020). While valuable, these approaches tend to concentrate tree-based benefits within already greener neighbourhoods, overlooking inequities in everyday exposure to shade and cooling across residential areas. Consequently, vulnerable populations living in dense, infrastructure-deficient neighbourhoods remain disproportionately exposed to heat stress.

Achieving equitable and inclusive cities therefore requires an explicit equity-oriented framework for urban greening that goes beyond aggregate tree counts or park provision. The Tree Equity Score (TES), developed by American Forests, represents one such attempt to operationalize tree equity by integrating existing tree canopy, socio-economic vulnerability, and climatic exposure into a single diagnostic index (American Forests, 2025). The TES conceptualizes equity as the gap between existing tree cover and a target canopy goal, weighted by indicators of socio-economic vulnerability and heat exposure.

1.2 Challenges of Applying the Conventional TES Framework in High Density Indian Cities

However, the application of the conventional TES framework to Indian cities presents important challenges. Canopy targets in the TES are derived from broad biome classifications and adjusted for building density, leading to substantially lower target canopy thresholds in high-density urban contexts. In Indian cities, where built-up densities frequently exceed 30% across most wards, this approach severely penalizes canopy goals—often reducing them to as low as 10% (see Figure 1). As a result, many wards appear to meet or exceed target canopy levels despite exhibiting pronounced intra-urban inequities in tree distribution and heat exposure.

Building density (%)	Forest (% canopy)	Grassland (% canopy)	Mediterranean (% canopy)	Desert (% canopy)
<14%	50% [1.25]	30% [1.5]	30% [1.5]	15%
14-22%	40%	30% [1.5]	25% [1.25]	15%
22-30%	30% [0.75]	25% [1.25]	20%	15%
>30%	20% [0.5]	20%	15% [0.75]	15%

*Goals are in percent tree canopy. Adjustment factor in brackets

Figure 1: Canopy goals set by Tree Equity Score Analyzer based on biome type and building density classification. Source: Screen capture from https://www.treeequityscore.org/methodology

1.3 Greening Need vs Greening Capacity

Recent scholarship has highlighted the limitations of canopy-based equity diagnostics that rely on abstract or uniform targets without adequately accounting for local spatial constraints and urban morphology. Nesbitt et al. demonstrate that assessments based solely on existing canopy distribution often obscure inequities in access to vegetation, particularly in dense urban cores where opportunities for additional tree planting are structurally limited (Nesbitt et al., 2019). Similarly, Reidman et al. argue that numeric canopy targets divorced from local land-use, governance, and maintenance contexts may lead to ineffective or unjust greening interventions (Riedman et al., 2022). While these studies stop short of operationalizing equity through an integrated index, they collectively highlight the need to ground tree equity diagnostics in realistic greening potential.

1.4 Aim of the study

Building on this emerging direction, the present study proposes a modified, contextualised TES framework for Indian cities by replacing density-based canopy targets with targets derived from ward-level plantable area. Using Bhubaneswar as a case study, the paper compares results from the conventional and modified TES approaches and evaluates how incorporating land constraints alters city-wide equity metrics as well as spatial greening priorities.

1.5 Study Area and Data Sources

Bhubaneswar (20.2960° N, 85.8246° E), the capital city of Odisha, India, presents an appropriate case for examining contextualized tree equity due to its pronounced contrasts in urban form, planning history, and land availability. Conceived in the post-independence period as a planned administrative capital in 1961, the city was originally designed for a population of approximately 40,000, with generous plot sizes, institutional green spaces, and low building densities. Over subsequent decades, Bhubaneswar has expanded rapidly (Panigrahi & Sharma, 2025) and unevenly, evolving into a complex urban system with varying heat exposure (Dhar et al., 2025) across formally planned neighbourhoods, a dense historic Old Town, environmentally constrained zones, and rapidly urbanizing peripheral outgrowth areas. In 2011, the city accommodated a population of about 7 lakhs (Census of India, 2011b). This growth has been accompanied by substantial spatial variation in land-use patterns, building density, and access to infrastructure and open space. As a result, wards differ markedly in both existing tree cover and realistic capacity for additional greening. Thus, it serves as a suitable case to evaluate how conventional density-adjusted canopy targets perform, and how targets set by plantable area would perform. The analysis integrates multiple openly available datasets tabulated in Table 1.

Table 1: Compilation of data sources used in the study

Variable	Source	Spatial Resolution
Treecover	GEE 1m Global Canopy Height Maps (Meta & WRI, 2023; Tolan et al., 2024)	1m; aggregated to ward level based on height > 3m
Heat exposure	Landsat 8 and 9 TIR (all scenes for May-July 2022) from USGS Explorer (https://earthexplorer.usgs.gov/)	100m; aggregated to ward level using mean
Socio-economic data	Census 2011 (Census 2011a; Census 2011b)	Ward level
Ward boundaries	BhubaneswarOne (https://bhubaneswarone.in/)	Ward level

TES framework computes socio-economic vulnerability on the basis of age, employment, race, income, health burden and language. Health and language data is not available publicly in India. For age, percentage of population younger than 5 years, and, percentage of population older than 60 years were considered. For employment, marginal workers proportion was considered. For race, in India, minority classes are represented by Scheduled Caste and Scheduled Tribe populations. There was no direct indicator for income, thus, we used 7 indicators as a proxy for income data – (i)poor or dilapidated house condition, (ii)household crowding above 5 members, (iii)thatch roofing, (iv)lighting using oil or kerosene, (v)latrine facilities outside premises, (vi) drinking water facilities outside premises, and (vii) households using heat emitting fuel for cooking.

Land-cover classification was performed using cloud-free Sentinel-2 multispectral imagery (10 m spatial resolution) on ArcGIS Pro 3.5 software to delineate built surfaces, vegetation, water bodies, and barren land for the purpose of estimating ward-level plantable area. A supervised maximum likelihood classification (MLC) approach was adopted, informed by visually interpreted training samples derived from high-resolution basemap imagery and field familiarity with the study area. Five land-cover classes were defined: (i)built-up, (ii)barren land, (iii)waterbodies, (iv)dense vegetation and (v)grass or shrubs.

Classification accuracy was evaluated using an independent set of 500 randomly distributed validation points, stratified across land-cover classes. A confusion matrix was generated to compute Producer's Accuracy (PA), User's Accuracy (UA), and Overall Accuracy (OA). Producer's accuracy ranged from 78% to 93%, while user's accuracy ranged from 78% to 99% across classes, indicating strong classification performance. Higher accuracies were observed for built-up and dense vegetation classes, while relatively lower accuracy for water bodies reflects spectral mixing along narrow channels and seasonal variation in water extent. Given the study's objective of identifying plantable versus non-plantable surfaces rather than detailed vegetation typologies, the achieved overall accuracy (87%) and Kappa accuracy (83%) is considered sufficient for further equity analysis. The confusion matrix and accuracy metrics are reported in **Annexure A**.

2. Methodology

The methodology (visually depicted in Figure 2) integrates existing tree cover (EC), and priority score (PS) derived from socio-economic vulnerability and heat exposure, with differing canopy GOAL formulations defined using (i) density-adjusted, biome-based goals in the conventional TES and (ii) plantable-area-based goals in the modified TES.

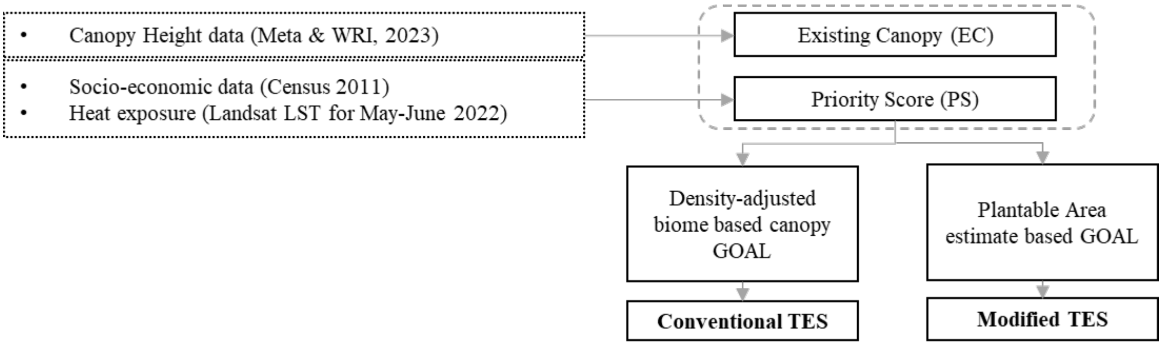

Figure 2: Research framework for conventional and modified Tree Equity Score (TES) computation

2.1 Conventional Tree Equity Score (TES)

The conventional TES was calculated following the American Forests framework, which defines TES as a function of (i) The gap between existing tree cover and a target canopy goal, and (ii) Weighted by socio-economic vulnerability and heat exposure.

2.2 Canopy Target and Canopy Gap Calculation

For each ward, a target tree cover percentage (GOALi) was defined based on the underlying natural biome and subsequently adjusted according to building density, recognizing that higher building densities constrain available planting space.

Existing tree cover (EC_i), was calculated as the proportion of ward land area covered by tree canopy. Although a supervised land-cover classification was developed for estimating plantable area, existing tree cover was derived from the '*High Resolution 1m Global Canopy Height Maps*' available on Google Earth Engine. This choice was made for two reasons. First, the canopy height product explicitly distinguishes trees from low-lying vegetation by allowing extraction using height thresholds (>3 m as per Forest Survey of India guidelines (FSI MoEFCC, 2023)), aligning more closely with the ecological definition of tree canopy used in the Tree Equity Score framework. Second, the dataset is open-access, globally consistent, and independently validated, enhancing transparency and reproducibility across cities.

The canopy gap (GAP_i) was then computed as the difference between the density-adjusted canopy target and existing tree cover:

$$GAP_i = max(0,\ GOAL_i - EC_i) \qquad (1)$$

Consistent with the TES Analyzer methodology, negative gap values—indicating wards where existing canopy exceeded the target—were converted to zero prior to normalization, ensuring that surplus canopy did not contribute additional credit to the equity score. To enable integration with socio-economic vulnerability, the canopy gap was normalized across wards using min–max normalization, where GAPscore$i$ ∈ [0,1]:

$$GAPscore_i = \frac{GAP_i - \min(GAP_i)}{\max(GAP) - \min(GAP)} \qquad (2)$$

2.3 Priority Score Calculation

The Priority Score (PS) captures relative socio-economic and climatic vulnerability and was constructed as an equally weighted additive index of five indicators: age dependency, income vulnerability, heat exposure, employment vulnerability, and racial or social disadvantage.

Each indicator X*ij* (for ward *i* and indicator *j*) was normalized using min–max normalization:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{3}$$

The Priority Score was then computed as the unweighted mean of the normalized indicators:

$$PS_i^{raw} = \frac{1}{5}\sum_{j=1}^{5} X'_{ij} \tag{4}$$

To ensure a non-zero minimum priority weight while preserving relative differences, the score was linearly rescaled to the range [0.1, 1]:

$$PS_i = 0.1 + 0.9 \times PS_i^{raw} \tag{5}$$

2.4 Tree Equity Score Calculation

The final Tree Equity Score was calculated by integrating the normalized canopy gap and the Priority Score using Eq. 6 as follows:

$$TES_i = 100 \times (1 - GAPscore_i \times PS_i) \tag{6}$$

By construction, TES values range from 0 to 100, where lower values indicate greater need for tree planting and protection, and a score of 100 signifies that a ward meets its density-adjusted canopy target given its relative socio-climatic priority.

The methodology by (American Forests, 2025) prescribes the following equation (Eq. 7) to compute the composite TES for city-wide performance, where $TES_{<100}$ is a Tree Equity Score below 100, $N_{TES<100}$ is the number of wards having TES below 100, and E_{100} is a priority index for a Tree Equity Score of 100.

$$Composite\ Score = \frac{\Sigma(TES_{<100}) + (\Sigma E_{100}) \times 100}{N_{TES<100} + \Sigma E_{100}} \tag{7}$$

2.5 Modified TES Based on Plantable Area

In the modified framework, canopy targets were recalibrated using ward-level plantable area, $GOAL^{PA}_i$,defined as land occupied by grass and barren surfaces through the landcover classification. This approach reflects the realistic potential for additional tree planting given physical land constraints (Nyelele & Kroll, 2021). The modified TES was computed using the same weighting structure as the conventional TES, enabling direct comparison between the two approaches:

$$GAP_i^{PA} = max(0,\ GOAL_i^{PA} - EC_i) \tag{8}$$

3. Results and Discussion

3.1 Priority Score Distribution

The Priority Score (PS), derived from unweighted linear addition of normalized socio-economic vulnerability and heat exposure indicators, ranged from 0.24 to 0.7 across wards in Bhubaneswar (see Figure 3). Wards falling in the highest PS classes (0.49–0.70) are concentrated in parts of the northern, central, and selected southern wards, indicating areas where socio-economic sensitivity coincides with elevated land surface temperatures. These wards typically exhibit higher proportions of vulnerable age groups, marginal workers, and lower housing quality, combined with limited adaptive capacity to heat stress.

3.2 Conventional TES Results

Using the conventional TES framework, only 7 wards out of 67 were found to have inequitable treecover (see Figure 4). All other wards had TES of 100, the most equitable scenario. Amongst the 7 wards, Ward 15 had the lowest TES of 88 due to high age and class related vulnerability. Ward 67 (high marginal population), 44 in the south eastern periphery also featured relatively low TES. Ward 52, majorly comprising of the airport with a high amount of tarmac area, is a surface heat hotspot, thus having low TES. Ward 5 has extremely low existing canopy (0.07% of the ward) in major part due to the presence of the Kuakhai River, while Ward 4 has high class related vulnerability combined with relatively low existing canopy (11%).

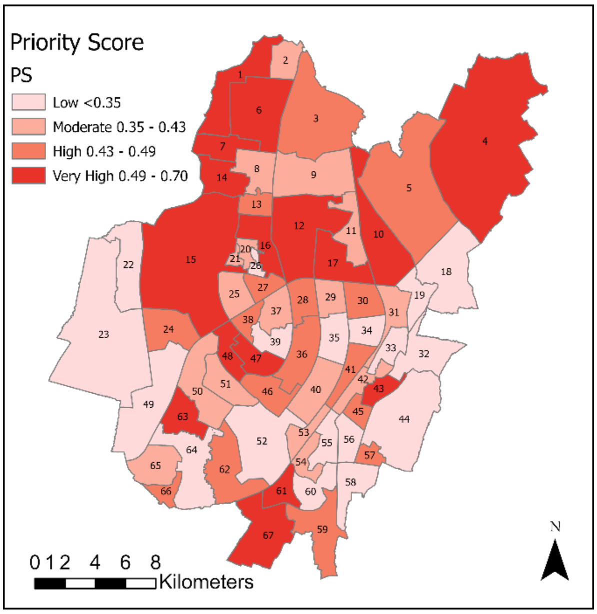

Figure 3: Spatial distribution of Priority Score incorporating socio-economic vulnerability and heat exposure classified into quartiles Labels correspond to ward numbers. Source: Authors

3.3 Modified TES Results

The modified TES resulted in 21 wards having inequitable treecover (TES lesser than 100). Modified TES appears to follow a core-periphery divide in the city (see Figure 4), with recently annexed agricultural villages having a combination of high social vulnerability and lower treecover. The planned wards, most Old Town wards as well as the wards with Reserved Forest (Ward 15) have equitable treecover as per the modified framework.

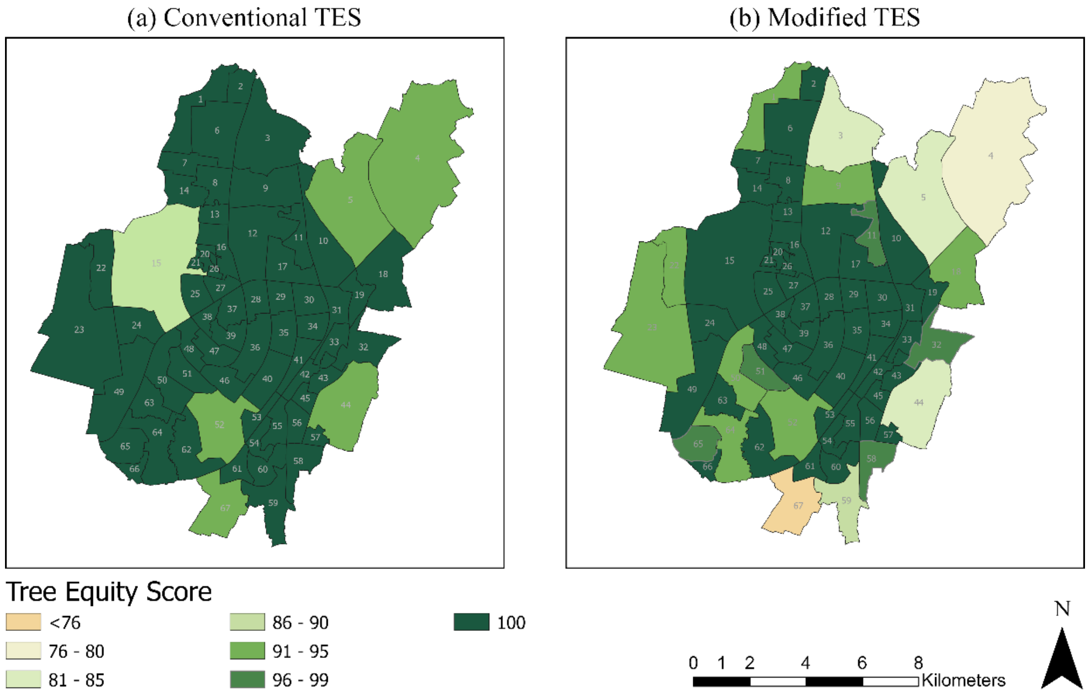

Figure 4: Spatial distribution of tree equity score (TES) based on (a) conventional framework and (b) modified framework. The separate class for TES equivalent to 100 signifies the TES threshold. Sub-100 values were grouped into narrow classes to distinguish marginal from substantial canopy deficits.Wards are labelled by the ward number. Source:Authors

3.4 Comparison Between Conventional and Modified TES Results

The comparison between the conventional Tree Equity Score (TES) and the plantable-area-based TES reveals systematic and policy-relevant patterns across planning typologies and dominant land-use contexts in Bhubaneswar. Composite TES scores reduced from 99 to 97. While city-wide averages suggest relatively high equity under both frameworks, ward-level analysis demonstrates that canopy-target formulation strongly influences how equity is diagnosed spatially (see Figure 5).

3.4.1 Stability of TES in Planned Neighborhoods

Planned wards (e.g., Wards 17, 28–30, 35–36, 40, 46–48) exhibit stability between the two approaches, with ΔTES values of zero. These areas are characterized by regulated layouts, institutional land uses, wider road reserves, and reserved open spaces, which collectively provide sustained capacity for tree planting. The persistence of high TES values after accounting for plantable area indicates that equity outcomes in planned neighbourhoods are not due to suppressed canopy targets but reflect favourable greening conditions.

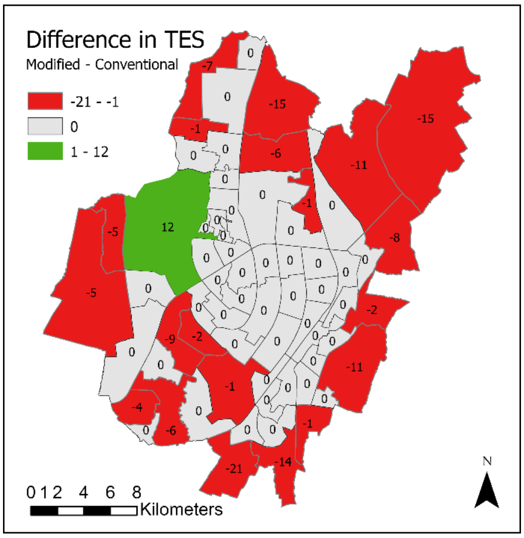

Figure 5: Difference in TES between the modified and the conventional frameworks. Labelling on the wards correspond to the difference value. Source: Authors

3.4.2 Masked inequity in Old Town and Dense Residential Wards

In contrast, selected Old Town wards (e.g. Wards 54, 55, 58, 60, 61, 67, and notably Ward 59, ΔTES = −14) experience pronounced reductions in TES under the modified framework. These wards are defined by compact built form, fine-grained land subdivision, and limited setbacks, which significantly constrain additional tree planting. Under the conventional TES, high density-adjusted canopy targets allow such wards to score as equitable despite limited scope for future greening. Incorporating plantable area exposes these structural constraints, revealing inequities that were previously masked.

3.4.3 Transitional and Peripheral Wards

Outgrowth and agriculturally influenced wards display mixed but policy-relevant responses. While some outgrowth wards show no change, others (e.g., Ward 64, ΔTES = −6; Ward 65, ΔTES = −4) experience moderate declines, reflecting early erosion of greening potential due to incremental urbanisation. The agriculturally dominated Ward 67 exhibits the largest decline (ΔTES = −21), indicating high vulnerability combined with limited tree cover and constrained planting opportunities. These results identify peripheral and transitional areas as emerging zones of concern where proactive greening interventions are critical.

3.4.4 Forest and Park-Dominated Outliers

Ward 15, located adjacent to the Chandaka Reserve Forest, behaves as a positive outlier, with TES increasing under the modified framework (ΔTES = +12). Extensive plantable land and low heat exposure, despite high socio-economic vulnerability, results in substantially higher equity scores. Such wards are analytically distinct from urban residential contexts and should be interpreted separately to avoid skewing aggregate assessments.

3.5 Sensitivity Analysis

Sensitivity analysis was conducted to assess the robustness of the Tree Equity Score (TES) to key methodological choices, including indicator weighting (Scenario A), normalisation scheme (Scenario B), and plantable area definitions and thresholds (Scenario C). Across most tested scenarios, spatial patterns of inequity remained largely stable, with strong correlations ($r > 0.9$) between baseline and alternative TES estimates. Only for rank normalisation scheme, the correlation with the baseline reduced to 0.71. All sensitivity analyses results and their interpretations are recorded in **Annexure B**.

Socio-economic indicators were derived from Census 2011, while tree cover data correspond to approximately 2020, reflecting a common constraint in Indian urban analysis due to the absence of more recent ward-level socio-economic data. To assess the robustness of the Tree Equity Score (TES) to this temporal mismatch, sensitivity analyses were conducted by perturbing the Priority Score by ±15% (Scenario D1 and D2 in Annexure B), simulating plausible shifts in socio-economic vulnerability over time. Results show that while absolute TES values vary modestly, ward-level rankings and typology-level patterns remain highly stable (Pearson's $r > 0.9$). These findings indicate that the key spatial conclusions and policy-relevant prioritisation emerging from the conventional or the contextualised TES framework are robust to reasonable uncertainty in socio-economic inputs arising from methodological variations or temporal misalignment of datasets.

3.6 Implications for Interpreting Tree Equity

The comparison between conventional and plantable-area-based TES frameworks demonstrates that equity diagnostics are highly sensitive to how canopy targets are defined. Density-based penalties embedded in the conventional TES tend to suppress canopy goals in high-density wards, potentially misidentifying equity as achieved even where spatial disparities exist. By contrast, the plantable-area-based approach aligns canopy targets with realistic spatial capacity, improving the interpretability of TES outcomes.

Importantly, the modified TES does not eliminate spatial inequity; rather, it clarifies where greening interventions are both most needed and most feasible. This distinction is particularly critical for Indian cities, where land scarcity and regulatory constraints complicate uniform greening mandates.

The study has the following limitations:

1. Priority score has been derived from available datasets. Health and language data were not publicly available. Race was substituted by Scheduled Caste and Scheduled Tribe population. Employment, defined as unemployment rate was substituted by proportion of population composed of marginal workers. Thus, even the conventional TES score cannot be compared with cities from other countries.
2. For the conventional TES computation, US-based biome and building density adjustment factors are directly used without empirically validating for the Indian context. Development of suitable adjustment factors could be an area of further research.
3. The study focuses on distributive equity and does not address participatory or recognition justice dimensions, which require community-engaged approaches beyond the scope of this analysis.
4. Plantable area are to be treated as best-case scenarios rather than directly implementable planting surface. Due to the absence of parcel-level land ownership and accessibility data, the analysis does not explicitly differentiate between public, semi-public, and private land. estimates do not account for private ownership barriers to tree planting. Private ownership, institutional control, and infrastructure-related constraints may substantially reduce effective plantable area in practice.
5. The high-resolution canopy dataset is from 2020 whereas the socio-economic data is from 2011, as Census 2021 was not carried out. Future work would gain from a more temporally compatible analysis.

4 Conclusion

This study demonstrates the importance of contextualizing tree equity metrics for high-density and spatially heterogeneous Indian cities. While the conventional Tree Equity Score provides a valuable starting point for diagnosing distributive inequities in tree cover, its reliance on biome- and density-adjusted canopy targets suppressed benchmark values in dense urban contexts, potentially masking spatial inequities. By incorporating plantable area into canopy target formulation, the modified TES framework aligns equity assessment more closely with realistic greening capacity.

Applied to Bhubaneswar, the contextualized TES did not uniformly lower equity scores but instead refined its spatial interpretation. Planned neighbourhoods and wards with substantial public or forest land consistently exhibit equitable outcomes, while inequities are selectively revealed in dense Old Town areas, environmentally constrained residential wards, and transitional peripheral zones where planting opportunities are limited or rapidly diminishing. This distinction between greening need and greening feasibility is particularly critical for Indian cities, where land scarcity, regulatory constraints, and informal development complicate uniform greening mandates.

The plantable-area-based TES framework is readily transferable to other Indian and Global South cities characterized by high built densities, informal development patterns, and constrained availability of open land. Because the framework relies on widely available remote-sensing data and census-based socio-economic indicators, it can be replicated across diverse urban contexts with minimal data requirements.

Compared to access-based metrics (e.g., distance to parks or green spaces) and canopy-per-capita indicators, the proposed TES offers a more integrated assessment by explicitly combining heat exposure, socio-economic vulnerability, and greening capacity—accounting for differential exposure to heat stress and the physical feasibility of additional tree planting. Relative to inequality indices such as the Gini coefficient, which summarize distributional imbalance at the city level, the modified TES provides spatially disaggregated diagnostics that identify specific wards experiencing concurrent deficits in tree cover and adaptive capacity.

From a policy perspective, the findings underscore three key implications. First, reliance on density-adjusted canopy targets alone risks overstating equity in compact urban cores. Second, plantable-area-based targets enable planners to distinguish between where trees are most needed and where they can realistically be planted, supporting more defensible and efficient prioritization of interventions. Third, declining equity scores in peripheral and transitional wards highlight the urgency of embedding tree-based infrastructure early in urban expansion processes, before greening opportunities are irreversibly lost.

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