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Research paper

WHO HAS ACCESS TO GREEN RELIEF? A COST-DISTANCE EQUITY INDEX FOR GREEN INFRASTRUCTURE PLANNING IN NIŠ

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Abstract

The ecosystem services of Urban green infrastructure (UGS) are well-documented, however conventional accessibility measures like Euclidean buffers and arbitrarily weighted composite indices poorly capture real pedestrian access or defensible priority-setting. This study develops a network-based cost-distance equity index for green infrastructure in the urban core of Niš, Serbia, using a 100 m analysis grid. Walking-time costs to local, district, and city parks were derived via GRASS r.cost, transformed through negative exponential decay functions calibrated wiht planning standars, and combined into a non-compensatory composite deficit score. Bivariate Local Indicators of Spatial Association (LISA), tested across three spatial weight specifications, identified statistically robust priority clusters overlapping deficit with four age-vulnerable population subgroups. In total, 6,134 grid cells are examined. Of these, 917 cells, or 15.0%, fall into robust Tier 1 priority zones. These zones hold about 57 to 59% of the vulnerable population for each subgroup. That is a large share, even though the zones cover only 15% of the study area. The resulting three-tier classification, together with descriptive attributes for each cluster, gives a ranked set of planning outputs that can be used for decission making procecss. This approach avoids arbitrary weights at each step, and keeps the same logic from the decay calibration, through the deficit index build, cluster robustness test. Thus it offers a transparent, reproducible framwork that other mid-sized cities with comparable open data availability could adapt to their own green infrastructure planning processes.

Key words: *Green infrastructure accessibility, Cost-distance analysis, Spatial equity, Bivariate LISA, Decision making, Urban planning*

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1. INTRODUCTION

UGS are essential to Urban Green Infrastructure (UGI), facilitating the creation of a network of linked green and semi-green habitats that enhance urban ecosystem services [1]. With the rapid pace of global urbanization, it is essential to implement strategic planning and prioritize investments in urban green spaces, especially parks, to optimize environmental and social advantages amid constrained municipal resources [2]. Emphasizing UGS necessitates a harmonious integration of environmental sustainability, social equality, economic efficiency, and ecological connectedness [3,4]. Certain types of UGS offer more advantages than their counterparts. Expansive and intricate green areas, particularly parks, offer vital ecological benefits and community roles [5].

Parks are the most efficient and versatile urban green spaces, providing vast, uninterrupted areas for a variety of ecological functions and human endeavors. Multifunctional parks represent a more sustainable alternative to traditional gray infrastructure, since green infrastructure offers enhanced management flexibility and long-term adaptation [1].

Many studies, also confirms a significant effect on park proximity to our health. The effects seem to shift based on how big the green spaces are, how well they are kept, and whether people can access them fairly. A study of [6,7] found that people near larger and better equipped parks have more physical activity, and better mental well-being. Similar study in Brazil [8] reported that green space nearness and how suitable the spaces are can lower psychological distress. Liu et al. in Guangzhou in 2025 described two linked pathways. Visits to green space help explain how high city density harms mental health. At the same time, how much green space is available changes the strength of that harm, which means it can lessen the impact [9]. Overall, parks appear to support both physical and mental well-being only when they come with enough size, good quality, and fair access for residents.

Serbian legislation and policy frameworks emphasize the advancement of parks and urban green spaces, as well as sustainable urban development. The 2019 Serbian Sustainable Urban Development Strategy, together with the 2021 Action Plan, aims to create resilient and sustainable urban environments. Insufficient human, organizational, and financial resources, together with inadequate training for urban planning stakeholders, persist as institutional constraints. National strategic objectives and local development agendas frequently diverge due to reliance on experiential knowledge and ad hoc criteria, rather than systematic assessment of urban green spaces, encompassing parks and ecosystem services [10].

These problems are likewise evident in the urban environment of Niš, the third-largest city in Serbia. Research indicates that hardly 30% of the residents in Niš have access to parks over 1.5 hectares within an 800-meter proximity [11]. A simiilar study found that 36.7% of urban areas are within a 15-minute walk to parks, with 62.6% in any park, rising to 62.6% for larger district and city parks [12]. Reduced distance criteria (e.g., 400 meters) reveal considerable underserved regions, necessitating tailored planning. These results indicate that intentional park planning and spatial allocation enhance ecological standards and equity.

Building on previous findings this study deepen the accessibility analysis focusing on vulnerable groups that can be more at risk: those under 5, those under 15, those 65 and older, and those 70 and older. These groups tend to get more health value from nearby green areas. At the same time, they move around on their own less often. Because of that, they react more to the walking time cutoffs that are studied here than the overall public does. For this reason, it makes more sense to use a risk measure that fits each subgroup. A single combined vulnerability value would be less useful for planning. The study is organized around a single overarching research question:

Which zones of the Niš urban core exhibit statistically significant spatial overlap between high cost-distance deficit in access to hierarchically distributed parks and high concentrations of age-vulnerable population? Correspondingly, the specific objectives were to: (1) quantify green-space accessibility by park type (city, district, and local) using a cost-distance approach; (2) derive a single per-cell accessibility deficit measure from park-type-specific planning standards; (3) identify statistically significant spatial clusters of overlapping accessibility deficit and vulnerable-population concentration.

2. MATERIALS AND METHODS

The analysis was conducted for the urban core of Niš, using a regular 100 m grid as the unit of analysis, covering 6,134 cells within the defined urban boundary. All spatial layers were processed in EPSG:32634 (UTM zone 34N), a projected, metric coordinate reference system, ensuring that grid cell dimensions and network distances were measured accurately in metres.

2.1. Park inventory and type definitions

The anlysis focuses Niš urban core and cnsiders local, district, and city parks (Figrue 1), as defined by UN Habitat [13]. Regional and peri-urban parks were eliminated. In practice, these parks sit in catchments that are wider and less walk-oriented. Comparing walking time, most homes in the area would reach a regional park on walking cost beyond threshold for the city park. That limit is 12.0 minutes. It is set as the upper bound for the biggest park group kept in the study. On the other extreme pocket parks are also excluded. The reason is definitional. Many items labeled as “pocket parks” in Niš cadastral data and in OpenStreetMap are actually paved squares or plazas. They usually bring only a small set of ecosystem services. Keeping the pocket parks would mix real green infrastructure with places that do not give walkable “green relief.” That is what this index is meant to measure. It would weaken the deficit logic used in the composite score.

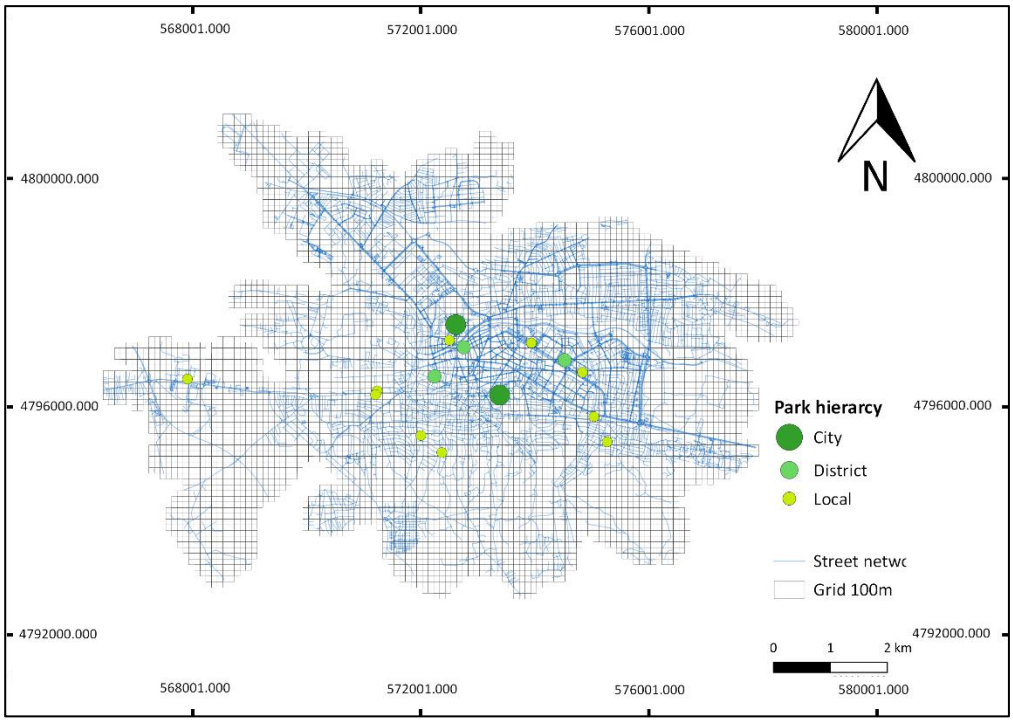


Figure 1. Study area

2.2. Population data, street network and data coverage

Population data are derived form WorldPop (2026) [14] for four age-vulnerable subgroups: 1) children under 5, children under 15, residents 65 and older, and residents 70 and older. Each subgroup raster was aggregated to the 100 m analysis grid by zonal summation, giving four population fields per cell.

The pedestrian street network was derived from OpenStreetMap data for the study's urban extent. Data set is filtered by the highway attribute to retain only segments relevant to pedestrian movement. The network was subsequently prepared for topological consistency in QGIS through a standardised sequence of operations: geometry validation, conversion of multi-part to single-part features, node snapping within a 1 m tolerance, and explicit line-splitting at every intersection. Thus, the full network connectivity is ensured to enable correct functioning of network-analysis algorithms. Grid cells that lack buildings or buildings with a valid cost-distance value to one or more park types, were excluded from the deficit calculation rather than assigned an imputed value. This approach was preferred over imputation because it avoids introducing artificial accessibility values into locations where no residential exposure exists.

2.3. Access thresholds and distance decay

Access thresholds for each park type were derived from UN Habitat [13] service-radius planning recomendation: local parks (300–400 m), district parks (400–600 m), and city parks (800–1,000 m). They are converted to walking-time equivalents using the

midpoint of each radius range and an assumed walking speed of 4.5 km/h. This resulted in thresholds of 4.67, 6.67, and 12.0 minutes for local, neighbourhood, and city-wide parks, respectively.

Raw walking time was turned into an accessibility score from 0 to 1. The rule used a negative exponential decay function (1) that was calibrated for each park type. The score equal 0.5 exactly at the relevant trashold (2). The score of 1 relate to minimal walking cost, while the score approaching 0 indicate progressively poorer accesibility with increased walking time.

$$score = e^{-\lambda \cdot \mathrm{gcost}} \tag{1}$$

$$\lambda = \frac{\ln(2)}{threshold} \tag{2}$$

2.4. Composite accessibility deficit

The three specific accessibility scores were combined into a single composite accessibility deficit per cell using the geometric mean:

$$deficit = 1 - \sqrt[3]{score_{local} \cdot score_{district} \cdot score_{city}} \tag{3}$$

The geometric mean penalizes cells scoring poorly on any single tier more than a simple average, following standard composite-index construction practices, such as the post-2010 revision of the Human Development Index [15,16]. Data-sparse cells without a valid score for any of the three park categories were assigned a missing composite deficit value instead of an imputed score to prevent overstating accessibility or deficit.

2.5. Bivariate spatial cluster analysis (LISA) and priority tier classification

Local Moran's I statistic, were computed using GeoDa [17,18]. Rook contiguity, queen contiguity, and k-nearest-neighbor weights (k = 8) were used to test cluster classification sensitivity to neighborhood definition. Using 999 conditional permutations and a significance criterion of $p < 0.05$, Bivariate Local Moran's I was calculated for each of the four population subgroups against the composite deficit under three weight specifications. Twelve cluster classifications per cell were classified using the standard LISA typology. The main outcome was high-high clusters, cells with high accessibility deficit surrounded by high vulnerable-population concentration.

A robust High-High cluster was only identified for each population subgroup if it was significant under all three weight requirements at once. Cells that were significant under at least one weight specification but not all were labeled as partially robust. The number of population subgroups for which each cell had a resilient High-High cluster was used to construct a priority count (0–4). Tier 1 (priority count ≥ 1: robust High-High cluster for vulnerable subgroup), Tier 2 (priority count = 0 but partially robust for subgroup under weight specification: flagged for field verification), or Tier 3 (no significant High-High classification for any subgroup) were assigned to cells.

2. RESULTS

The study used 6,134 grid cells. For 3,114 of them, 50.8%, the buildings in that cell did not have a valid cost-distance value that covered all three park types. Because of that, these cells were left out of the deficit composite. That left 3,020 cells for the main analysis. The coverage was rather binary, not a gradual split. Out of 3,021 cells that had at least one building with a valid cost value for at least one park type, 3,020 had valid values for all three park types at the same time. Only one cell had a valid value for exactly one park type. Overall, this suggests that the key factor is whether a cell has any building that connects to the street network at all. It is less about having different levels of connection for each park type. The missing data is not spattialy random. Cells with no buildings mostly cover parks, water, and undeveloped land. The high exclusion rate fits the mixed land use in Niš. The final set of 3,020 cells covers most of the city's built residential area. Figure 2 shows the continuous composite deficit surface genrated before cluster classification.

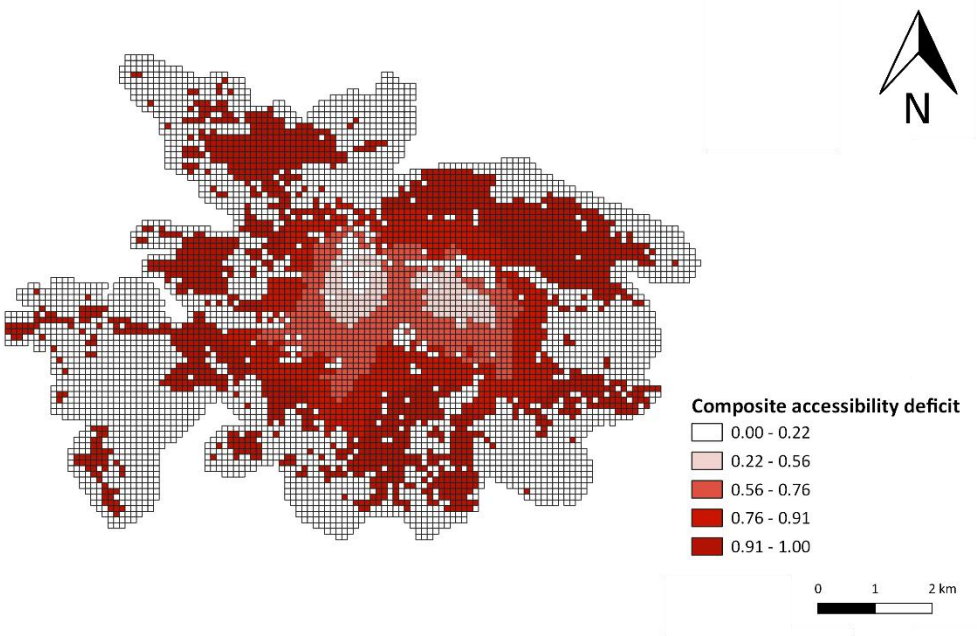


Figure 2. Composite accessibility deficit across the 100 m analysis grid

Out of 6,134 grid cells, 917 of them (15.0%), were classified as Tier 1. These cells showed a strong High-High bivariate LISA relationship between the composite accessibility deficit and at least one vulnerable group. This result held up under all three spatial weight choices. Next, 212 cells (3.5%) fell into Tier 2. They had a significant High-High relationship under at least one weight choice. These are marked for extra field checks. They are not meant for immediate investment priority. The last group, Tier 3, was 5,005 cells (81.6%). Tire 3 shuld not be treated as „well served." Tier 3 includes cells with low deficit. It also includes cells left out of the LISA test because building level accessibility data was missing. Rsults of the Indivudal LISA test is shown in Figure 3.

Distribution of how many people under each vulnerable group falls under each tire is shows in Table 2. Despite comprising only 15.0% of grid cells, Tier 1 clusters are home to 57–59% of the city's population in every vulnerable subgroup (57.4% of children under 5; 57.2% of children under 15; 58.5% of residents 65+; 59.1% of residents 70+). Looking at Tier 1 and Tier 2 together, about 18.4% of grid cells cover most of the vulnerable population. This uneven concentration bolsters the equity justification for tiered prioritization: the accessibility shortfall in Niš is not uniformly spread throughout the vulnerable demographic but is significantly concentrated within a limited, geographically defined segment of the urban center. Total population reported in Table 2 are the sum of WorldPop-modelled subgroup estimates across the 6,134-cell analysis grid (and should not be compared directly to official census or municipal registry population figures for the full administrative territory of Niš, which extends considerably beyond the study area.

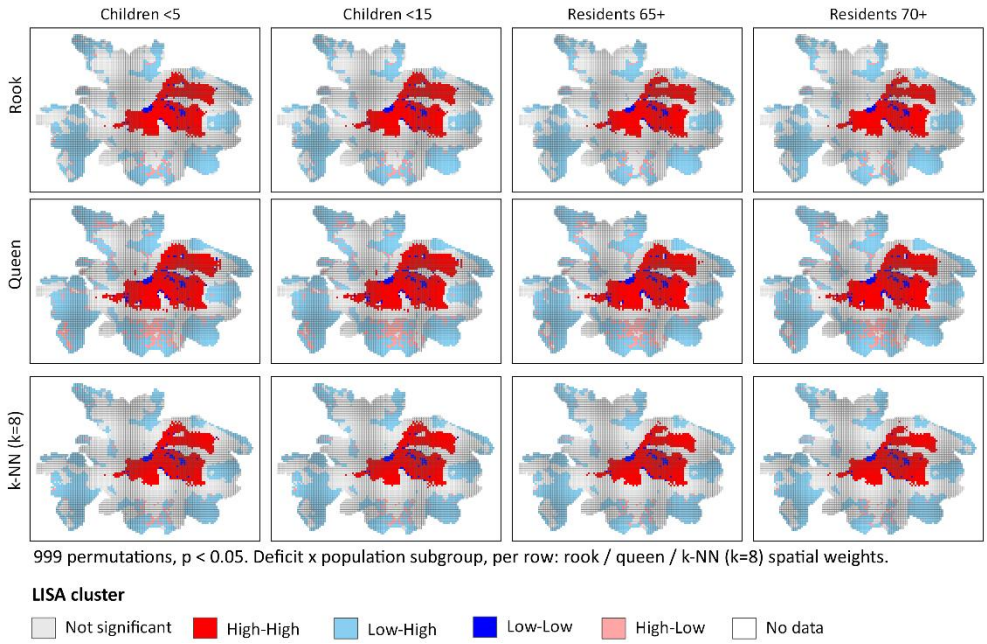


Figure 3. Bivariate LISA cluster maps: composite deficit × vulnerable population subgroups

Table 1. Distribution of grid cells by priority tier

Tier	Definition	n	% of total
Tier 1	Robust High-High for ≥1 subgroup (all 3 weight matrices)	917	15.0%
Tier 2	Partially robust High-High (1–2 of 3 weight matrices)	212	3.5%
Tier 3	No significant High-High clustering	5,005	81.6%

Table 2. Vulnerable-population totals by priority tier and demographic subgroup

Tier	n cells	Under 5 (%)	Under 15 (%)	65+ (%)	70+ (%)
Tier 1	917	6,104 (57.4%)	19,087 (57.2%)	27,294 (58.5%)	19,250 (59.1%)
Tier 2	212	737 (6.9%)	2,320 (7.0%)	3,188 (6.8%)	2,204 (6.8%)
Tier 3	5,005	3,793 (35.7%)	11,956 (35.8%)	16,191 (34.7%)	11,136 (34.2%)

In order to illustrate results following text describes typical cells from each tire (Figure 4). Cell 5259 illustrates a typical Tier 1 case. A composite accessibility deficit of 0.98 (near the upper value of the index) coincides with a substantial resident population across all four vulnerable subgroups (4.4 children under 5, 14.1 children under 15, 17.3 residents aged 65 and over, and 12.0 residents aged 70 and over) and was classified High-High for every subgroup under all three weight specifications (priority count = 4). Such cells constitute the strongest candidates for new green infrastructure investment.

Cell 2259 illustrates the Tier 2 category and the practical value of the weight-matrix sensitivity check: with a deficit of 0.73 and a comparable resident population (4.7 children under 5, 14.7 children under 15, 21.1 residents 65+), the cell was classified High-High for the under-5 and under-15 subgroups under rook and queen contiguity, but not under k-nearest-neighbour weights. This divergence illustrates why such cells are treated as candidates for field verification rather than automatically included in, or excluded from, the priority list.

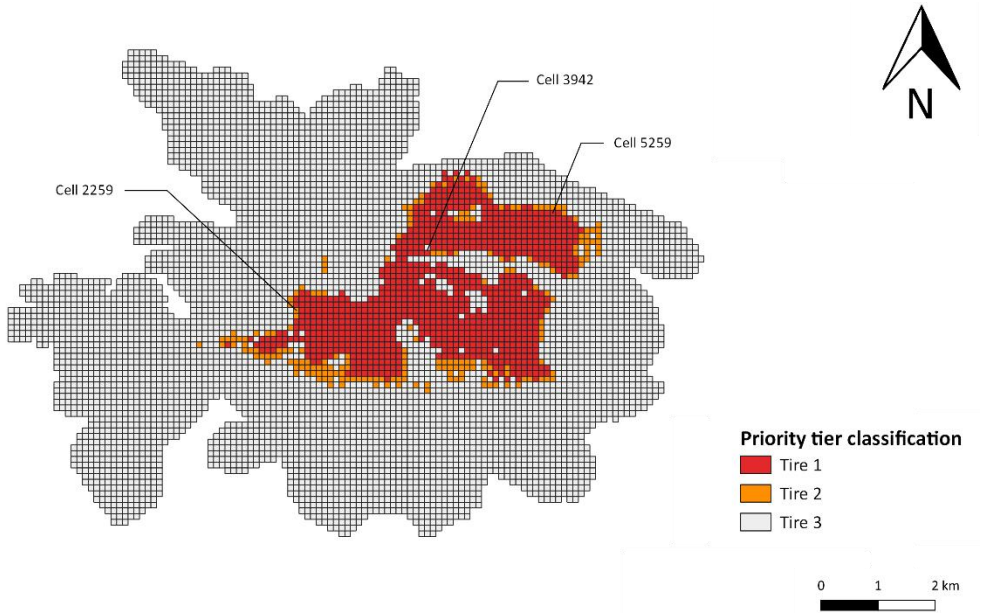


Figure 4. Final priority tier classification for green infrastructure investment in the Niš urban core

Cell 3942 illustrates a typical Tier 3 case: despite a substantial resident population (10.1 children under 5, 32.0 children under 15, 39.5 residents 65+), the cell recorded a composite deficit of 0.00 — indicating that all three park types were within their respective planning-standard walking-time thresholds — and consequently showed no significant High-High clustering for any subgroup. This example demonstrates that Tier 3 is not synonymous with "high vulnerable population", but rather reflects adequate measured accessibility regardless of population size.

4. CONCLUDING REMARKS

The results from the composite deficit work and the bivariate LISA show clear priority areas. In these spots, weak access to parks lines up with higher numbers of residents who are more at risk by age. The findings are strong enough to treat as reliable, and the locations match across the analysis.

To turn the results as an decision making imput for planning, the study uses a three level map. Tier 1 is the highest priority. Tier 2 is only partly robust. Tier 3 is not a priority. This setup gives a simple order for action. It avoids the need for planners to read a smooth deficit surface that is harder to explain.

The population results in Table 2 support the equity argument. Tier 1 covers just 15.0% of the grid. Even so, it holds about 57 to 59% of the city's vulnerable residents in every demographic group tested. When Tier 2 is added, the coverage rises to 18.4% of the city. At the same time, it brings in about 64 to 66% of vulnerable people. However, Tier 2 cells are a bit different. They were not labeled as strong priorities. Still, they should be checked with more field work before they are fully ruled out. The reason is that the result can shift when the spatial weights change.

This pattern is not small or random. It shows that in Niš, the access gap in the main urban area falls hardest on the residents who have the least ability to cope with it using their own mobility. So the case points to targeting resources in specific places, not spreading them evenly across the whole city.This section should be read with the note from Section 2.2 about data coverage. In short, about half of the grid was left out of the deficit numbers. The reason was that there were no buildings with usable network links there. This gap shows up mainly in non-residential land uses, like parks, water areas, and institutional sites. It is not just a random data issue. So the population concentration that study report is best seen as a low estimate of how much unfair exposure may exist. It should not be treated as a full city-wide measure.

Study also built a repeatable accessibility index for green infrastructure in the Niš city core. The index uses a network perspective on accessibility. It combines cost-distance modelling, decay cutoffs taken from planning standards, and a deficit method that does not allow trade offs. Then it utilize bivariate spatial cluster tests, checking the results with extra robustness using three different spatial weight setups. The output is a three-level priority map.

For planners, this gives a spatially precise starting point: 1) a ranked set of priority clusters, where each cluster comes with a reported deficit size, a count of vulnerable people, and a note on how solid the result is, and 2) an equity reason to focus limited funds on these spots in the next budget round. The same logic can guide the next update to the city’s plan for green infrastructure planning processes.

ACKNOWLEDGMENT

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