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Geospatial Clustering and Proximity of Campus Landscape Features in Semi-Arid Nigeria

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ABSTRACT

Aims: Campus landscapes influence comfort, safety, and use, yet spatial-statistical assessments of how trees, seating, lighting, and circulation features are distributed remain scarce for Nigerian higher-education institutions. This study characterized the spatial distribution, clustering, and proximity relationships of landscape features at Sa'adatu Rimi College of Education, Kano State, Nigeria.

Materials & Methods: A complete GPS-based inventory of trees, streetlights, seating facilities, and linear circulation features was analyzed in an integrated applied geospatial assessment combining Average Nearest Neighbor (ANN) analysis, quartic Kernel Density Estimation (KDE; bandwidth = 81 m), DBSCAN clustering (ε = 45 m; minPts = 3), and nearest-feature Euclidean proximity analysis in ArcGIS 10.4 and Python (scikit-learn v1.2.0).

Findings: Trees (594; 1,024 trees.km^{-2}) were significantly clustered (R = 0.855, z = −6.762, p < 0.001) and far outnumbered streetlights (55 km^{-2}) and seats (53 km^{-2}). DBSCAN separated a northern academic-core cluster from a southern boundary belt, consistent with the KDE surface (complementary descriptions of the same points rather than independent validation). At the same time, the central open ground and eastern sector had low tree density. Seats lay a mean of 9 m from the nearest tree, 34 m from the nearest circulation route, and 51 m from the nearest streetlight.

Conclusion: Landscape features are spatially concentrated rather than evenly distributed, with seating close to trees but comparatively distant from streetlights. Because GPS uncertainty is ±5–10 m and only Euclidean distance was measured, the results describe spatial proximity rather than verified shading, illumination, or access; they nonetheless provide a spatial baseline from which preliminary, zone-specific planning implications for planting, lighting, and seating are drawn for field verification.

Keywords: Campus Landscape; Cluster Analysis; DBSCAN; Geospatial Analysis; Kernel Density Estimation; Proximity Analysis.

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Introduction

University campuses function as micro-urban environments in which the configuration of trees, pathways, seating, and lighting shapes thermal comfort, restoration, and social interaction [1]. Academic green spaces serve social, regenerative, ecological, educational, and scientific functions [1], and campus soils under trees and shrubs show greater carbon-sink potential than lawns, making campuses candidate urban living labs [2]. The distribution of these amenities is increasingly examined as a planning concern: a remote-sensing assessment of 2,556 Chinese universities found pronounced greenspace inequality, with students having the lowest per-capita access [3], and mapping at the University of British Columbia identified campus zones with less than 2% greenspace coverage [4].

Point-pattern methods allow such distributions to be described objectively. ANN compares the observed mean nearest-neighbor distance with that expected under complete spatial randomness [5] and has been applied to urban green spaces [6], campus trees [7], and campus facilities [8]. Mukasyaf reported clustered tree patterns (nearest neighbor ratios of 0.52 and 0.56) on two campuses of Universitas Muhammadiyah Surakarta [7], while Nyong found strongly clustered lecture halls at the University of Calabar, Nigeria (Rn = 0.01; z = −4.49) [8]. KDE converts points into a continuous density surface that delineates concentrations and sparse areas [9]; Atara et al. used KDE heatmaps to map species concentration along the Academic Oval of the University of the Philippines Diliman [10]. DBSCAN identifies clusters of arbitrary shape without a pre-specified number of clusters and labels isolated points as noise [11]; it has been used for crowd detection on a smart campus [12] and outperformed K-Means and agglomerative clustering on geospatial data [13]. Proximity analysis complements these by measuring distances between complementary elements such as seats, trees, lights, and routes, which matters because street greenery improves outdoor thermal comfort [14] and the provision and management of open-space facilities shape how such spaces are used [15].

Evidence from Nigeria remains limited and largely descriptive or single-method. Aseyan found greenspace use in six private universities in Southwest Nigeria to be mostly passive, with social and design factors as the main determinants [16]; Ahmed et al. offered a qualitative reading of walkability in a North Central Nigerian university [17]; Idowu et al. appraised the condition of hard and soft landscape elements at the Federal College of Education, Kontagora [18]; and Nyong applied ANN alone to lecture halls [8]. Combined approaches exist elsewhere, notably Mukasyaf's integration of ANN, KDE, and hotspot analysis for campus trees in Indonesia [7], but we are not aware of a Nigerian campus study that jointly analyses trees, seating, lighting, and circulation using point-pattern, density, clustering, and proximity methods. The contribution of this study is therefore applied rather than methodological. ANN, KDE, DBSCAN, and proximity analysis are established techniques; their value here lies in combining them within one applied geospatial assessment of a complete feature inventory for an under-studied college campus in semi-arid northern Nigeria. The objectives were to (1) characterize the spatial distribution of major landscape features; (2) describe tree concentration using global (ANN), continuous (KDE), and discrete (DBSCAN) descriptors; and (3) quantify the proximity of seating facilities

to trees, streetlights, and circulation routes, interpreting these patterns by campus zone to support site-specific planning.

Materials & Methods

Study Area

Sa'adatu Rimi College of Education lies within the Kano metropolis, Northwestern Nigeria, at latitude 11°55'08" N and longitude 8°33'06"E, and is about 469 m above sea level. The campus occupies approximately 64 hectares along Zaria Road, bordered by Gidan-Fiat to the north, a residential layout to the south-east and the Eastern bypass to the east (Figure 1). The climate is tropical wet and dry (Köppen Aw), with a wet season from May to September and a dry season from October to April; temperatures range from about 11 °C during the Harmattan to 40 °C between mid-March and mid-May [19], creating a strong demand for shade near outdoor seating. Kano metropolis had a 2006 census population of 2,826,307 [20] and continues to grow rapidly, intensifying pressure on institutional land and facilities [21].

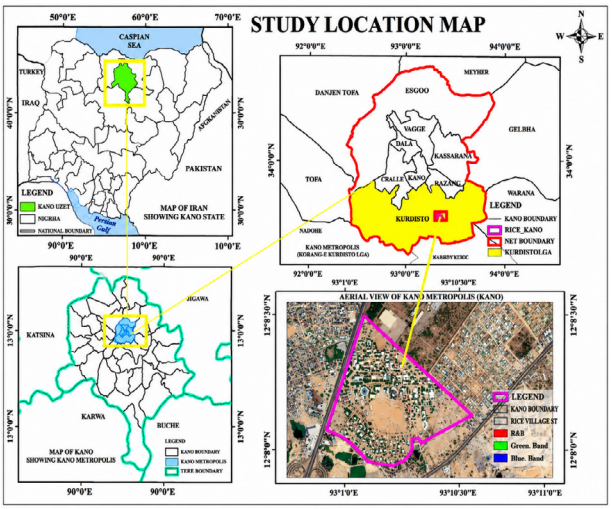


Figure 1) Location of the study area: (a) Nigeria, showing Kano State; (b) Kano State, showing Kano Metropolis; (c) Kano Metropolis, showing Kumbotso Local Government Area (LGA); and (d) satellite image (true-colour RGB composite) of the Sa'adatu Rimi College of Education campus, Kano, Nigeria, with the campus boundary.

Data Collection

A systematic walk-over survey inventoried every tree, streetlight, and seating facility on the campus, giving complete coverage rather than a sample. Point features were recorded with a handheld GPS receiver with a stated positional accuracy of ±5–10 m. Linear features (tarred and untarred roads, interlocking pavements, drainage channels, and pedestrian circulation routes) were digitized, and their lengths were computed in GIS. All data were projected to WGS 84 / UTM Zone 32N (EPSG:32632), so all distances are planar Euclidean distances in meters. Feature density (D) was computed as count, or length for linear features, per unit area (A) using Eq. (1):

$$D = \frac{N}{A} \qquad \text{Eq. (1)}$$

Descriptive statistics were computed in SPSS v26.0; ANN, KDE, and proximity analyses in ArcGIS 10.4; and DBSCAN in Python (scikit-learn v1.2.0).

Average Nearest Neighbor Analysis

ANN [5] tested whether the 594 trees deviate from complete spatial randomness. The nearest neighbor ratio (R) is the observed mean distance between each tree and its nearest neighbor divided by the expected mean distance for a random pattern of the same intensity as given in Eq. (2):

$$R = \frac{\bar{D}_O}{\bar{D}_E}, \quad \bar{D}_O = \frac{\sum_{i=1}^{n} d_i}{n}, \quad \bar{D}_E = \frac{0.5}{\sqrt{\frac{n}{A}}} \qquad \text{Eq. (2)}$$

where d_i is the distance from tree i to its nearest neighbor, and n is the number of trees. A is the study-area extent (the ArcGIS default minimum enclosing rectangle of the points, 0.66 km^2 for the 594 trees, as implied

Table 1) Number or length and density of the landscape features inventoried within the Sa'adatu Rimi College of Education campus, Kano, Nigeria (campus area = 0.58 km^2; densities in units.km^{-2} for point features and km.km^{-2} for linear features**).**

Landscape Features	Total Units / Length	Density (units.km^{-2} for points; km.km^{-2} for lines; total area = 0.58 km^2)
Trees	594	1024
Streetlights	32	55
Seating Facilities	31	53
Untarred Roads	2.8	4.8
Tarred Roads	1.2	2.1
Interlocking Pavements	1.1	1.9
Drainage	3.0	5.2
Pedestrian Circulation Routes	4.7	8.1

by the expected mean distance in Figure 3; this differs from the 0.58 km^2 campus boundary used for the densities in Table 1). Significance was assessed with Eq. (3):

$$z = \frac{\bar{D}_O - \bar{D}_E}{SE}, \quad SE = \frac{0.26136}{\sqrt{\frac{n^2}{A}}} \qquad \text{Eq. (3)}$$

R < 1 with a significant negative z indicates clustering; R ≈ 1 indicates randomness; and R > 1 indicates dispersion.

Kernel Density Estimation

A continuous tree-density surface was produced with the quartic kernel implemented in ArcGIS [9] using Eq. (4):

$$f(x) = \frac{1}{r^2}\sum_{d_i<r}\frac{3}{\pi}\left[1-\left(\frac{d_i}{r}\right)^2\right]^2 \qquad \text{Eq. (4)}$$

where d_i is the distance from location x to tree i and r is the bandwidth (search radius). The bandwidth was obtained with the ArcGIS default procedure, a spatial variant of Silverman's rule of thumb that minimizes estimation error under a normal reference distribution [9] with the help of Eq. (5):

$$r = 0.9 \times \min\left(SD, \sqrt{\frac{1}{\ln 2}} \times D_m\right) \times n^{-0.2} \qquad \text{Eq. (5)}$$

where SD is the standard distance, and D_m is the median distance of points from their mean center. Output density is expressed in trees.km^{-2}. For the 594 trees, this procedure gave a bandwidth (search radius) of r = 81 m, and the surface was computed with an output cell size of 3.7 m.

DBSCAN Clustering

DBSCAN [11] was applied to the projected tree coordinates. For a point p, its ε-neighbourhood is calculated using Eq. (6):

$$N_\varepsilon(p) = \{q \in D \mid dist(p, q) \le \varepsilon\} \qquad \text{Eq. (6)}$$

A point is a core point when $|N_\varepsilon(p)| \ge$ minPts, a border point when it lies within ε of a core point without being core itself, and noise (label −1) otherwise. minPts was fixed at 3; ε was selected at the elbow of the sorted k-distance plot with k = minPts = 3, giving ε = 45 m, and Euclidean distance on UTM coordinates was used as the metric. Each

tree was then classified as a core, border, or noise point, and the counts and proportions of each class are reported to allow the analysis to be reproduced.

Proximity Analysis

For each of the 31 seating facilities, the distance to the nearest tree, streetlight, and pedestrian circulation route (point-to-line shortest distance) was computed with the ArcGIS Near tool:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \qquad \text{Eq. (7)}$$

The mean, minimum, maximum, and standard deviation were summarised for each pair. These values are GIS-derived positional distances; they are interpreted as spatial proximity only, not as measured shading, illumination, or walking access.

Rationale for Method Combination

ANN provides a global inferential test of clustering, KDE shows where density varies continuously, and DBSCAN partitions the same points into discrete clusters and outliers. Because all three use the same point dataset, agreement among them is treated as a convergent, complementary description of the pattern rather than independent validation.

Findings

Spatial Distribution and Inventory of Landscape Features

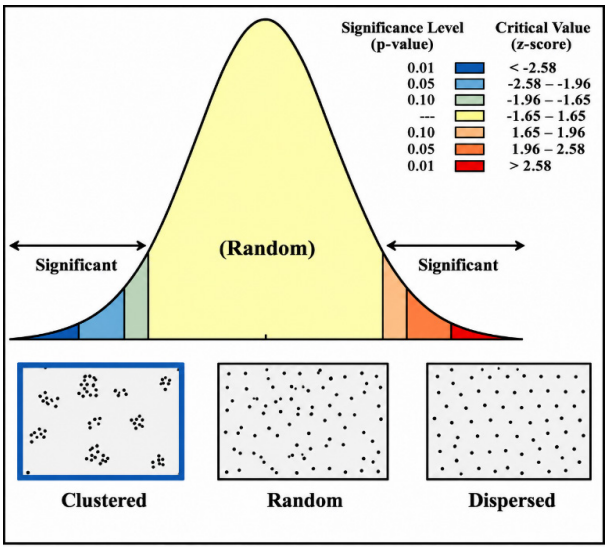
Trees are the most widespread element, occupying the northern academic core, the main east–west corridor and a belt along the southern and south-western boundary (Figure 2). Seating and streetlights are confined to the northern academic core and the east–west corridor, while the large central open ground and the eastern sector contain few features. The 594 trees give a density of 1,024 trees.km^{-2}, far exceeding streetlights (55 km^{-2}) and seats (53 km^{-2}) (Table 1). Among linear features, pedestrian circulation routes are the longest (4.7 km), followed by drainage (3.0 km) and untarred roads (2.8 km); untarred roads are more than twice as long as tarred roads (1.2 km).



Figure 2) Spatial distribution of the landscape features inventoried by GPS survey within the Sa'adatu Rimi College of Education campus (0.58 km^2), Kano, Nigeria: trees (n = 594), streetlights (n = 32) and seating facilities (n = 31), with untarred and tarred roads, interlocking pavements, drainage channels, pedestrian circulation routes and the campus boundary.

Spatial Distribution Pattern of Trees

ANN indicates significant clustering of trees ($R = 0.855$; $z = -6.762$; $p < 0.001$): the observed mean nearest-neighbor distance (14.24 m) is smaller than the random expectation (16.66 m) (Figure 3). Under complete spatial randomness, a nearest-neighbor ratio this low would be expected in fewer than 0.1% of realizations ($p < 0.001$). ANN establishes clustering but not its cause; the pattern is consistent with concentrated landscape development around particular functional areas such as building surrounds, the main corridor, and the boundary.



Observed Mean Distance:	14.24 m
Expected Mean Distance:	16.66 m
Nearest Neighbor Ratio:	0.854970
z-score:	-6.762112
p-value:	0.000000

Figure 3) Average Nearest Neighbour (ANN) analysis of the 594 trees within the Sa'adatu Rimi College of Education campus, Kano, Nigeria. The normal curve shows the critical z-score ranges (dimensionless) and significance levels (p-value) for clustered, random and dispersed patterns; the observed z-score (−6.762) falls in the clustered tail ($p < 0.001$). The table gives the observed and expected mean nearest-neighbour distances (m), the nearest neighbour ratio (R), the z-score and the p-value.

Density-Based Clusters and Density Surface

DBSCAN identified two tree clusters and a small number of noise points (Figure 4). With ε = 45 m and minPts = 3, 582 trees (98.0%) were classified as core points, 9 (1.5%) as border points, and 3 (0.5%) as noise; Cluster 0 contains 382 trees and Cluster 1 contains 209 trees. Cluster 0 covers the northern academic core and the east–west corridor, where buildings, seats, and streetlights are concentrated. Cluster 1 forms a dense belt along the southern and south-western boundary that contains no seating or lighting. The noise points are isolated trees in the eastern sector. The KDE surface (Figure 5; bandwidth r = 81 m) peaks at about 3,730 trees.km^{-2} in the northwestern academic core and in the south-western boundary belt, and falls to near zero over the central open ground and the eastern and south-eastern sector. The high-density areas of the KDE surface coincide with the two DBSCAN clusters; because both methods are applied to the same tree coordinates, this agreement complements the description of the pattern rather than validating it independently.

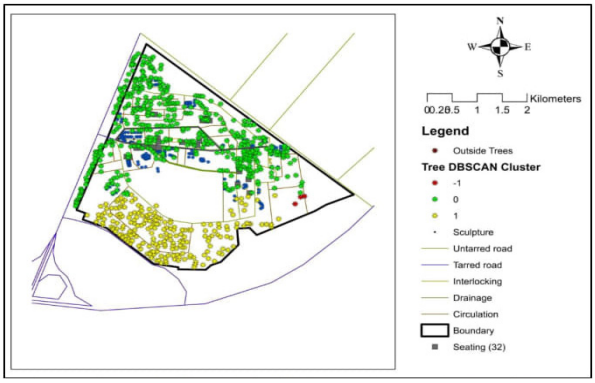


Figure 4) Tree clusters identified by DBSCAN (ε = 45 m; minPts = 3) within the Sa'adatu Rimi College of Education campus, Kano, Nigeria: Cluster 0 (n = 382; northern academic core and east–west corridor), Cluster 1 (n = 209; southern and south-western boundary belt) and noise points (−1; n = 3; eastern sector), shown with seating facilities, circulation features and the campus boundary.

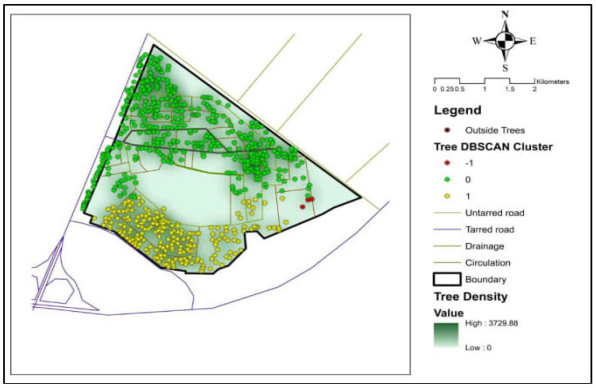


Figure 5) Tree density surface (trees.km^{-2}) estimated by quartic Kernel Density Estimation (bandwidth r = 81 m; cell size 3.7 m) within the Sa'adatu Rimi College of Education campus, Kano, Nigeria, overlaid with the DBSCAN tree clusters (0, 1 and noise −1); density ranges from 0 to about 3,730 trees.km^{-2}.

Table 2) Descriptive statistics of the Euclidean distances (m) from each seating facility (n = 31) to the nearest tree, streetlight and pedestrian circulation route within the Sa'adatu Rimi College of Education campus, Kano, Nigeria.

Distance of Seat to Nearest Landscape Feature (m)		Statistics			
S/N	Features	Average	Minimum	Maximum	Standard Deviation
1	Trees	9	0	22	4
2	Streetlights	51	12	148	35
3	Circulation routes	34	4	79	21

Proximity of Seating to Circulation, Lighting and Trees

Seats lie a mean of 34 m from the nearest circulation route (range 4–79 m; SD 21 m) (Table 2; Figure 6); seven seats, mainly in the eastern part of the academic core, are more than 43 m from a route. The mean distance to the nearest streetlight is 51 m (range 12–148 m; SD 35 m) (Figure 7): 15 seats are within 35 m of a streetlight, whereas five are more than 82 m away. Seats are closest to trees, with a mean distance of 9 m (range 0–22 m; SD 4 m), and 29 of the 31 seats lie within 14 m of a tree (Figure 8). Because the GPS error (±5–10 m) is of the same order as the seat–tree distances, a 0 m value indicates that a seat and a tree coincide within positional tolerance, not that they occupy the same location; the larger seat–circulation and seat–streetlight distances exceed this uncertainty.

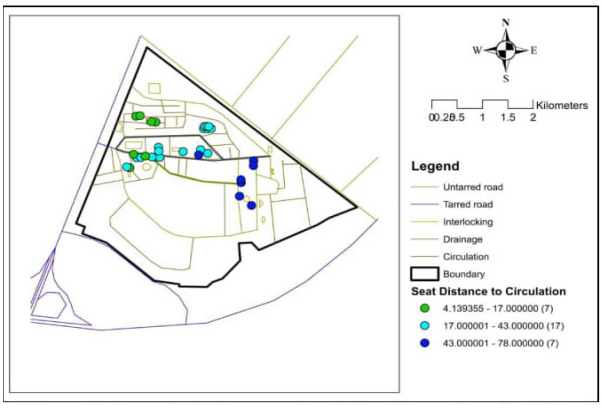


Figure 6) Euclidean distance (m) from each of the 31 seating facilities to the nearest pedestrian circulation route within the Sa'adatu Rimi College of Education campus, Kano, Nigeria, in three classes (number of seats in brackets); seven seats, mainly in the eastern part of the academic core, lie more than 43 m from a route.

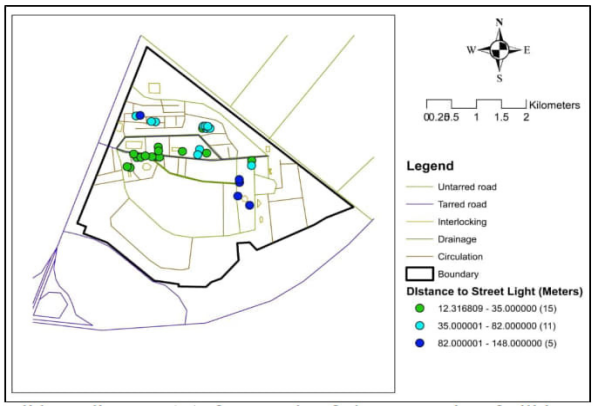


Figure 7) Euclidean distance (m) from each of the 31 seating facilities to the nearest streetlight within the Sa'adatu Rimi College of Education campus, Kano, Nigeria, in three classes (number of seats in brackets); five seats lie more than 82 m from a streetlight.

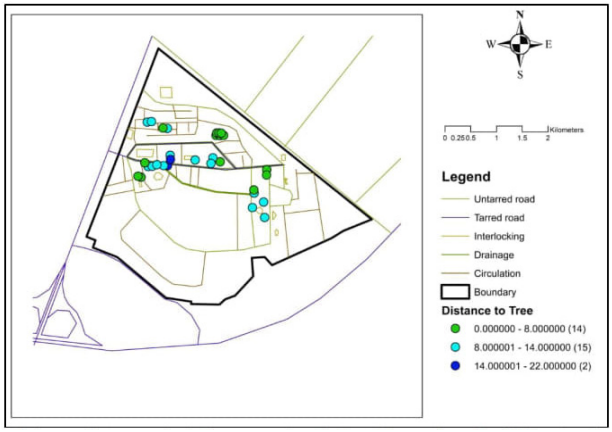


Figure 8) Euclidean distance (m) from each of the 31 seating facilities to the nearest tree within the Sa'adatu Rimi College of Education campus, Kano, Nigeria, in three classes (number of seats in brackets); 29 of the 31 seats lie within 14 m of a tree.

Discussion

The results describe a campus in which landscape features are concentrated in a few zones. The northern academic core

has the highest tree density, the largest DBSCAN cluster, and all seating. The close seat–tree distances there suggest that seats have generally been placed near tree canopy, which matters in a climate where maxima reach 40 °C [19] and street greenery measurably improves outdoor thermal comfort [14]. Distance alone, however, does not establish shading: canopy size, orientation, and seasonal leaf cover were not measured, and most seat–tree distances fall within GPS uncertainty.

Along the east–west corridor, seats are comparatively distant from streetlights (mean 51 m, five seats beyond 82 m), indicating that lighting and seating have not been coordinated. This proximity gap may limit evening use, since facility provision and management influence how open spaces are used [15]. However, illuminance was not measured, and the effect on safety or use remains to be confirmed. The southern boundary belt presents a contrasting pattern: dense tree cover (DBSCAN cluster 1) with no seating, lighting, or circulation, suggesting a buffer function rather than a social space. The central open ground and the eastern sector have the lowest tree density, isolated noise trees and no amenities, and therefore appear to be the clearest candidates for new planting where current land use allows.

Compared with other campus studies, the tree pattern here is significantly but moderately clustered ($R = 0.855$), less so than the 0.52–0.56 reported by Mukasyaf [7] and far less than Nyong's lecture-hall pattern ($Rn = 0.01$) [8]. The concentration of trees along main corridors resembles the KDE pattern along the Academic Oval of UP Diliman [10]. Studies in China and Canada documented unequal campus greenspace provision with explicit per-capita or coverage metrics [3,4]; the present study shows uneven distribution but does not measure equity among user groups. The amenity concentration in the academic core also aligns with Nigerian evidence that design and siting shape the use of campus green spaces [16,18]. More broadly, the findings fit the use of GIS-based spatial statistics to translate inventories into zoning decisions [22,23], and the persistence of clustered patterns noted in hotspot studies [24] implies that uneven distribution is unlikely to correct itself without deliberate intervention.

Positional uncertainty affects the methods differently. Random GPS error tends to blur point patterns toward randomness, so the ANN clustering result is likely conservative. Individual trees near the ε threshold could switch between core, border, and noise labels. However, the two DBSCAN clusters are separated by the treeless central ground over a distance far larger than the GPS error, so the two-cluster structure is unlikely to be an artifact. The agreement among ANN, KDE, and DBSCAN is convergent evidence of concentration, not independent validation.

Limitations of the Study

Several limitations define the scope of this paper. First, the handheld GPS accuracy (±5–10 m) limits the interpretation of short distances; a differential or RTK resurvey was beyond the scope of this study. Second, only Euclidean distance was measured; canopy shading, illuminance, network walking distance, and user perception were not assessed, so the results indicate spatial proximity rather than functional integration, comfort, safety, or accessibility. Third, no explicit equity or accessibility metric (e.g., per-capita provision or service-area coverage by user group) was computed. Fourth, the sensitivity of the KDE surface

to bandwidth and of DBSCAN to ε (only the single bandwidth and ε reported above were tested), and the statistical association between feature densities across zones, were not analyzed and are left to future work. Fifth, ANN results depend on the study-area definition and are subject to edge effects. Sixth, the mechanisms behind the clustering could not be tested because historical planting and management records were unavailable. Finally, the study covers one campus at a time and excludes topography and other secondary data that can refine spatial analyses [25]. Future work could combine very-high-resolution satellite or UAV imagery for canopy delineation [26,27], class-level landscape metrics of canopy patches and fragmentation [28], comparison of alternative density or interpolation surfaces [29], lux measurements, network analysis and user surveys.

Preliminary Planning Implications

The following implications are drawn from the density and proximity patterns and are preliminary. Lighting adequacy, path condition, canopy shade, and user demand were not measured, so each implication should be confirmed by a field audit before implementation. In the northern academic core and east–west corridor, seats more than 35 m from a streetlight, particularly the five beyond 82 m, are priority locations for an illuminance survey to establish whether additional (for example, solar-powered) lighting is needed. Seats more than 43 m from a circulation route, mainly in the eastern part of the core, could be checked for informal desire lines to decide whether a short paved link or relocation is warranted. In the central open ground and the eastern sector, low tree density suggests scope for planting indigenous drought-tolerant trees along edges and paths, provided this does not conflict with the current use of the open ground. In the southern boundary belt, the existing tree cover could be evaluated as potential usable space, for example with a footpath and seating, once canopy shade and security have been assessed. Periodic GIS audits using higher-accuracy positioning, canopy and illuminance measurements, and consultation with students and staff should be used to test these implications before investment.

Conclusion

This integrated applied geospatial assessment shows that landscape features at Sa'adatu Rimi College of Education are spatially concentrated rather than evenly distributed. Trees are significantly clustered ($R = 0.855$, $z = -6.762$, $p < 0.001$) in two main zones, the northern academic core and the southern boundary belt. At the same time, the central open ground and eastern sector are sparsely planted. Tree density (1,024 trees.km^{-2}) far exceeds that of streetlights (55 km^{-2}) and seats (53 km^{-2}). Seats lie close to trees (mean 9 m) and moderately close to circulation routes (34 m) but farther from streetlights (51 m). Within the stated limits of GPS accuracy and distance-only measures, these patterns provide a spatially explicit baseline for campus landscape planning in Nigerian tertiary institutions. ANN, KDE, and DBSCAN offer convergent but complementary descriptions of the same tree pattern, not independent validation, and the planning implications drawn from them are preliminary.

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Authors' Contributions: D SULEIMAN

conceived and designed the study, developed the research methodology, coordinated the field data collection, conducted the geospatial and statistical analyses, interpreted the results, and prepared the original manuscript; **I HASSAN** contributed to the research design, field data collection, spatial data processing, interpretation of findings, and critical review of the manuscript; **A YUSUF** contributed to field data collection, geospatial data management and analysis, interpretation of results, and critical revision of the manuscript, and **M IDRIS** contributed to data analysis and interpretation, methodological review, and critical revision of the manuscript for intellectual content. **All Authors** reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work, ensuring that questions related to the accuracy and integrity of the research are appropriately investigated and resolved.

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AI Use Declaration: The authors confirm that generative artificial intelligence tools were not used to generate the research data, perform the geospatial analyses, interpret the findings, or develop the scientific conclusions. Any AI-assisted language editing, where applicable, was limited to improving grammar, clarity, and readability, and the authors retain full responsibility for the accuracy, originality, and integrity of the manuscript.

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