

Examining Spatial Concordance of Knowledge Aggregated AHP TOPSIS and Random Forest for Electric Vehicle Charging Site Suitability

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ABSTRACT

Electric vehicle (EV) charging infrastructure planning in data-scarce megacities is often constrained by limited spatial data and expert-driven decision models whose underlying assumptions are rarely validated. This study presents an integrated GIS-based decision-support framework for identifying optimal EV charging locations in Dhaka, Bangladesh — a 22-million-resident megacity targeting 30% EV penetration by 2030, by combining expert-elicited Analytic Hierarchy Process (AHP) weighting with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Unlike conventional GIS-MCDM studies, the proposed framework systematically evaluates criterion collinearity and assesses the spatial concordance between expert-derived suitability patterns and a machine-learning model using Random Forest with spatial cross-validation. Fourteen spatial criteria derived from open-access datasets and weighted by eleven domain experts were used to generate a 100-m suitability map. The analysis identified fifteen priority charging zones, with the Tejgaon–Hatirjheel corridor ranking highest. Results showed strong agreement between expert- and machine-learning-derived suitability surfaces (Spearman's $\rho = 0.968$; top-zone overlap = 73.8%), while revealing substantial collinearity between transit and fuel station proximity, highlighting a potential source of bias in conventional MCDM applications. Built entirely on open data, the proposed framework offers a transparent, reproducible, and transferable methodology for EV charging infrastructure planning in data-constrained cities.

1. Introduction

Global electric vehicle (EV) adoption is accelerating beyond high-income economies. The IEA [1] reports global EV stock exceeded 40 million units in 2023, with South and Southeast Asian markets exhibiting the fastest proportional growth, driven by fuel import cost pressures, urban air quality imperatives, and declining battery costs. The spatial adequacy of public charging infrastructure is a primary determinant of user adoption confidence, documented across diverse urban contexts [2, 3]. In developing-country megacities, where data constraints and grid limitations compound the siting challenge, the need for rigorous, open-data spatial frameworks is particularly acute [4].

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Bangladesh presents a compelling case study. Automobile Industry Development Policy [5] targets 30% EV penetration by 2030, yet fewer than 200 documented public charging points serve a vehicle fleet exceeding 5 million registered units [6]. In Dhaka, 22 million residents generate approximately 40% of national vehicle-kilometres within 306 km², producing average peak-hour speeds of 7 km/h and among Asia's worst urban air quality indices [7].

EV charging station site selection is a spatial multi-objective optimisation problem. In Dhaka, objectives frequently conflict: high commercial demand zones coincide with flood-prone riverfront areas, and the densest residential neighbourhoods are furthest from high-capacity grid substations. These trade-offs require an integrated multi-criteria spatial analytical framework [8].

The Analytic Hierarchy Process (AHP) [9], aggregated across domain experts using the Aggregation of Individual Judgements (AIJ) geometric mean protocol [10], produces empirically grounded, stakeholder-validated weights with full methodological audit trails. TOPSIS [11] ranks spatial alternatives by simultaneous proximity to the positive ideal solution and distance from the negative ideal solution, enabling pixel-level suitability quantification. Recent bibliometric analyses confirm AHP and TOPSIS as the most widely applied MCDM techniques in EV charging infrastructure research [8, 12].

Several gaps persist in literature (Table 1). First, the overwhelming focus on East Asian, European, and Middle Eastern contexts leaves a void for South Asian megacities with distinct urban morphologies, grid configurations, and open-data environments. Second, most AHP-TOPSIS studies employ literature-derived rather than expert-elicited weights, producing context-inappropriate distributions [13]. Third, inter-criterion collinearity is rarely tested despite its potential to amplify the effective weight of overlapping spatial patterns. Fourth, cross-method spatial concordance assessment between expert-driven and data-driven suitability frameworks remains uncommon in the EV charging siting literature [13].

This study addresses all four gaps: it presents, to the best of current literature coverage, the first GIS-AHP-TOPSIS analysis for Dhaka using exclusively open-access data; derives weights through primary expert elicitation from eleven domain specialists; tests criterion collinearity via Pearson correlation and VIF analysis; and evaluates the spatial consistency and criterion discrimination behaviour of the resulting suitability structure using a Random Forest-based concordance framework.

Table 1

Criterion comparison across GIS-MCDM EV charging station siting studies

Study	City / Country	MCDM Method	Weight Derivation	No. Criteria	Spatial Criteria (summarised)
Kumar <i>et al.</i> [14]	Prayagraj, India	AHP, Fuzzy AHP + GIS + RS	Pairwise comparison + fuzzy membership functions	7	Proximity to roads, fuel stations, population density, land use, existing infrastructure, accessibility, environmental constraints
Guo & Zhao [15]	Beijing, China	Fuzzy TOPSIS	Expert panel judgment using linguistic variables + fuzzy numbers	11 sub-criteria	Accessibility, road/transport convenience, grid proximity, land use compatibility, environmental sensitivity
Güler & Yomralıoğlu [16]	Istanbul, Turkey	AHP + GIS weighted overlay	Pairwise comparison matrix (Saaty scale 1–9); CR = 0.053	10	Distance to green areas, slope, land value, road access, transport stations, parks, shopping malls, petrol stations, population density, income

Table 1
Continued

Study	City / Country	MCDM Method	Weight Derivation	No. Criteria	Spatial Criteria (summarised)
Kaya <i>et al.</i> [17]	Istanbul, Turkey	GIS + AHP + VIKOR + PROMETHEE	AHP (Expert)	5 main / 19 sub	Road access, grid, population, commerce, environment
Zhang <i>et al.</i> [18]	Singapore	Bayesian Network + GIS	Conditional probability tables + Bayesian inference	9	MRT stations, household density, charging efficiency, road network accessibility, land use, economic cost factors
Jia <i>et al.</i> [19]	Stockholm, Sweden	AHP within optimisation model	AHP (pairwise comparison, eigenvector method)	Multi-factor system	Road network nodes & links; shortest-path distance; vehicle-hour demand; distance-based access cost
He <i>et al.</i> [20]	Beijing, China	Set Covering / MCLP / P-median	Ranking-type Delphi method	6 socio-demographic variables	Census-based demand estimation; spatial constraints; existing petrol stations, parking, universities
Mhana & Awad [21]	Baghdad & Riyadh	GIS-based MCDA (AHP + FAHP)	AHP + FAHP (expert pairwise comparison)	12	Amenities, roads, parking, railways, bus depots
Rashmitha <i>et al.</i> [22]	India (national)	GIS-based MCDA (CRITIC + Entropy + TOPSIS + WASPAS)	CRITIC + Entropy	12	Accessibility, demographic, infrastructure, and environmental layers
This Study	Dhaka, Bangladesh	GIS-AHP-TOPSIS + RF Concordance	Expert (n=11) AIJ-GM, CR=0.0135	14	Road density · Highway · Transit · Fuel station · Population · Residential · Commercial · Hospital · University · Substation · Powerline · Flood · Water body · Park

2. Literature Review

2.1 GIS-MCDM in EV Charging Infrastructure

GIS-integrated MCDM applications for EV charging siting have grown substantially since 2016, with AHP and TOPSIS as the dominant methods [8, 12]. Guo and Zhao [15] pioneered fuzzy TOPSIS for EV siting from a sustainability perspective, demonstrating that road network accessibility and population density constitute consistently dominant criteria in Chinese urban contexts. Guler and Yomralioglu [23] compared AHP and fuzzy AHP with GIS for EV fast-charging siting in Turkey, introducing weight-approach comparison as a robustness mechanism. Ouerghi *et al.* [12] applied an integrated GIS-AHP-sensitivity framework in Qatar, demonstrating the importance of sensitivity testing in sparse data environments. Liu *et al.* [13] employed random forest regression alongside expert-based analysis of EV charging in Wuhan, demonstrating complementarity of data-driven and expert-informed approaches — directly motivating the spatial concordance assessment applied here.

Criterion independence is rarely tested explicitly in GIS-MCDM siting studies. Rao [24] notes that TOPSIS is less sensitive to inter-criterion correlation than regression-based models, as it operates on normalised weighted distances rather than estimated coefficients. Nevertheless, highly correlated criteria can amplify the effective weight of overlapping spatial patterns [25]. This study is, to the best of current literature coverage, the first in the EV charging siting literature to report Pearson correlations and VIF for all criterion pairs.

2.2 Research Gaps Addressed by This Study

A systematic review of published GIS-MCDM studies for EV charging station siting reveals a pronounced geographic concentration in East Asia (principally China), Turkey, Brazil, and North America [26–28]. Among the reviewed studies, approximately 69% employ GIS-based MCDM frameworks, with AHP appearing in twelve studies and TOPSIS in nine. Geographic coverage spans Istanbul [17, 23], Beijing [20], Singapore [18], and Brazil [27], among others, but offers no coverage of South Asian megacities characterised by informal urban morphologies, grid-constrained infrastructure, and open-data constraints.

Three specific methodological gaps motivate this study. First, the geographic void for Bangladesh is particularly acute given the country's explicit Automobile Industry Development Policy [5] targeting 30% EV penetration by 2030 and fewer than 200 documented public charging points serving a vehicle fleet exceeding five million registered units [6]. India is the sole South Asian country represented in the reviewed literature, via a national-scale CRITIC-Entropy-TOPSIS framework [22] and a GIS-AHP study of Prayagraj [14], neither of which is transferable to Dhaka's distinct urban context of extreme population density, riverine boundaries, and grid infrastructure constraints.

Second, among studies employing AHP, the weight derivation approach varies considerably. While expert pairwise comparison is used in studies such as Guler & Yomralioglu [23] and Kaya *et al.* [17], a substantial proportion of published frameworks derive criterion weights from prior literature synthesis or adopt equal-weight assumptions, limiting jurisdiction-specific defensibility [13]. Primary expert elicitation from domain specialists with direct infrastructure knowledge of the study area — as employed in this study — remains uncommon, particularly in data-constrained developing-country contexts. Notably, Namdeo *et al.* [28] demonstrated that locally grounded weight derivation produces markedly different spatial prioritisations compared with literature-transferred weight vectors, even within a single city region.

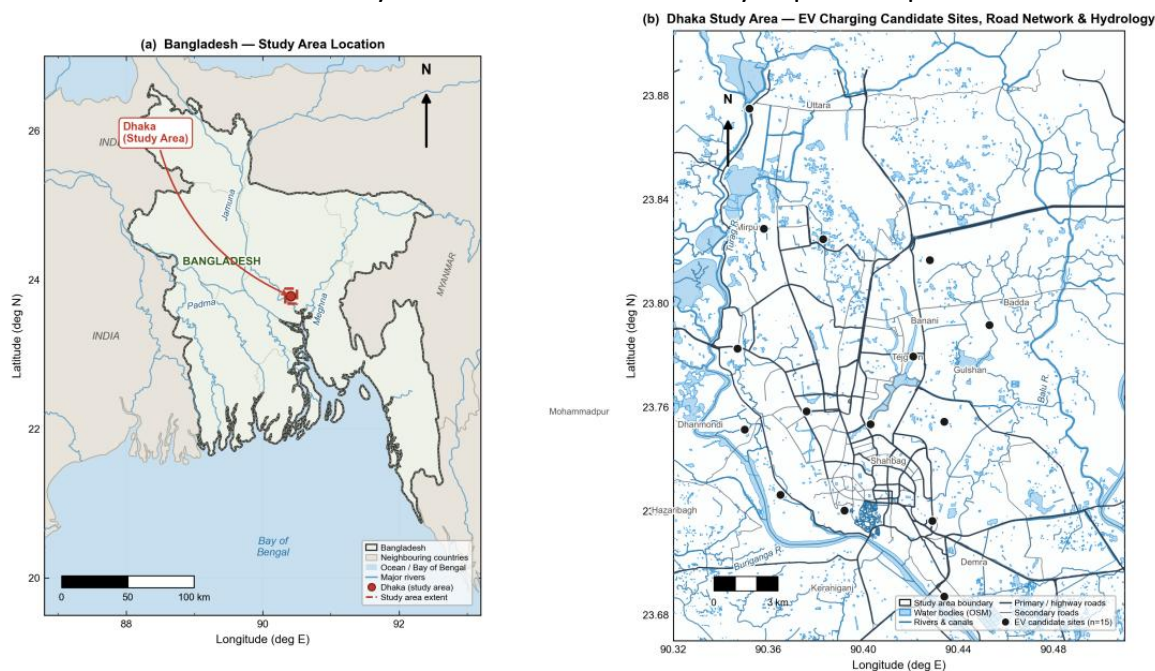
Third, criterion inter-correlation — which can amplify the effective weight of spatially overlapping patterns in TOPSIS outputs — has not been reported in any reviewed study. Kordi & Brandt [25] note that collinearity among spatial criteria can systematically distort MCDM outputs even when the MCDM method itself is not coefficient-based. Furthermore, cross-method spatial concordance assessment between expert-driven and machine-learning-derived suitability surfaces has not been applied in the EV charging siting literature beyond the work of Liu *et al.* [13], who demonstrated RF-expert complementarity in Wuhan without formal collinearity testing. This study addresses all three gaps simultaneously.

3. Study Area

Dhaka, situated at 23.68°N–23.88°N and 90.33°E–90.50°E in central Bangladesh (Figure 1), is the country's political, economic, and cultural capital. The city is bounded by the Buriganga River (south-west), Turag River (north-west), and Balu River (east). The study area encompasses approximately 306 km² under the jurisdiction of Dhaka North City Corporation (DNCC) and Dhaka South City Corporation (DSCC). Population density ranges from 44,000 persons/km² in central Tejgaon and Motijheel to below 8,000 persons/km² at the northern Uttara and western Aminbazar periphery [7].

Transportation infrastructure includes national highways (N1, N2, N3), arterial roads, and the Dhaka Metro Rail (MRT Line-6) operational since 2022, with approximately 2,800 bus stops within the study area. Electrical grid infrastructure is managed by DPDC (north) and DESCO (south), with substations concentrated in industrial zones (Tejgaon, Hazaribagh) and planned commercial districts (Gulshan, Motijheel) [29,30]. Peripheral residential areas experience lower grid density — a spatial pattern that directly constrains EV fast-charging deployment and motivates the dominant expert

weight assigned to powerline proximity in this study. Map lines in Figures 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12 delineate the study area and do not necessarily depict accepted national boundaries.



Note: Map lines do not necessarily depict accepted national boundaries. Coordinate system: WGS 1984 (EPSG:4326). Basemap: Natural Earth 10 m (naturalearthdata.com, public domain). Road / water data: © OpenStreetMap contributors (2024) via osmnx. Population data: WorldPop (2022).

Fig. 1. Study area: (a) location of Dhaka within Bangladesh; (b) Dhaka study area

4. Methodology

4.1 Framework Overview

The analytical framework proceeds through five modules: (1) criteria identification and data acquisition; (2) GIS rasterisation and proximity surface generation; (3) expert-elicited AHP weight derivation; (4) TOPSIS spatial ranking; and (5) criterion collinearity analysis and Random Forest spatial concordance (Figure 2). All computations were implemented in Python 3.11 using GeoPandas 0.14, Rasterio 1.3, SciPy 1.11, NumPy 1.25, Scikit-learn 1.3, and statsmodels 0.14. All input data were sourced exclusively from open-access repositories.

4.4 AHP Expert Elicitation

The AHP pairwise comparison survey was conducted using Saaty's 1–9 fundamental scale [9, 31]. Criterion weights were derived using the AIJ geometric mean aggregation method [10], based on pairwise comparison matrices from eleven domain experts (Table 2) and one literature-derived matrix, yielding 12 matrices in total. A hierarchical two-level structure was employed: four main criterion dimensions at level one; sub-criteria within each dimension at level two. Global weights were computed as the product of main dimension and local sub-criterion weights (Table 3). A scale-ordering error in the survey instrument was corrected by positional remapping applied uniformly across all eleven expert matrices. A missing pairwise comparison between highway proximity and fuel station proximity was derived via transitivity: $a(HP, FS) = a(HP, TP) \times a(TP, FS)$. Two experts (E2: CR = 0.3191; E6: CR = 0.3888) submitted matrices exceeding the conventional 0.10 threshold and were retained under the AIJ protocol, with robustness confirmed by sensitivity analysis (weight changes < 1.8%). Aggregated group CRs confirmed methodological validity (Transportation: 0.0044; Socioeconomic: 0.0075; Energy: 0.0000; Environmental: 0.0010; Main: 0.0135).

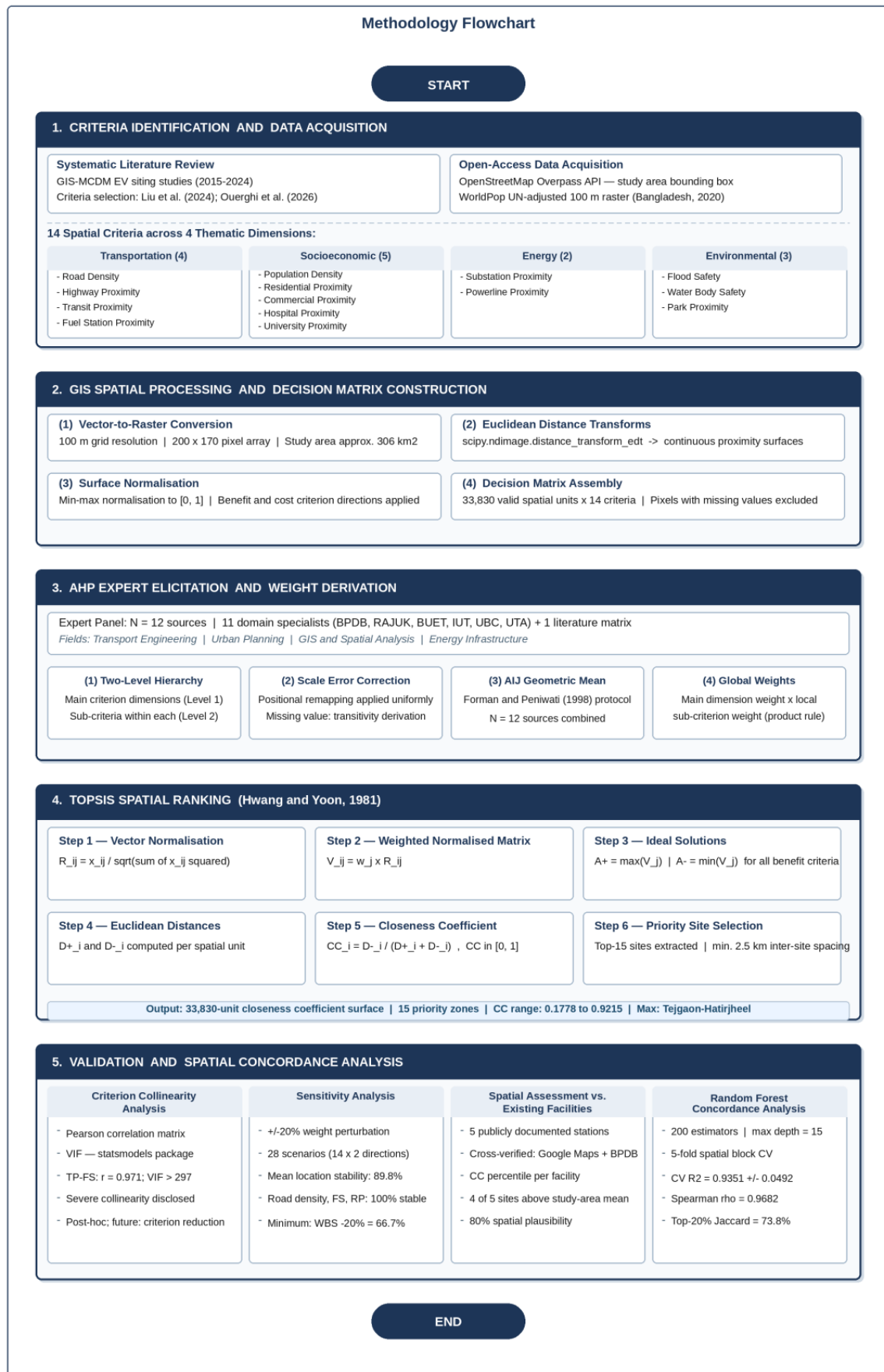


Fig. 2. Analytical methodology flowchart for GIS-based EV charging station suitability analysis, Dhaka, Bangladesh

Table 2
Expert panel composition and individual consistency ratios

ID	Designation	Field	Organisation	Experience	CR (Individual)
E1	Ph.D. Student	Transport Engineering	International University	1–5 yrs	0.1021
E2	Transport Engineer	Transport Engineering	—	1–5 yrs	0.3191 ⁺
E3	Transportation Engineer	Transport Engineering	Univ. of Texas Arlington	1–5 yrs	0.1809
E4	Urban Planner	Urban Planning	RAJUK	10+ yrs	0.1021
E5	Ph.D. Candidate	Transport Engineering	Univ. of British Columbia	1–5 yrs	0.2150
E6	Senior Engineer	Energy Infrastructure	BPDB	10+ yrs	0.3888 ⁺
E7	Professor	GIS & Spatial Analysis	IUT	10+ yrs	0.2002
E8	Professor	Urban Planning	BUET	10+ yrs	0.2656
E9	Senior Electrical Engineer	Energy Infrastructure	BPDB	10+ yrs	0.2956
E10	Associate Professor	GIS & Spatial Analysis	IUT	5–10 yrs	0.1159
E11	Project Co-ordinator	Energy Infrastructure	BPDB	10+ yrs	0.1582
LIT	Literature matrix	All fields	Various including Kumar <i>et al.</i> [14]; Güler & Yomralioğlu [16]; Kaya <i>et al.</i> [17]; Jia <i>et al.</i> [19]; Mhana & Awad [21];	—	—
AG G	AJJ Geometric Mean (N = 12)	All fields	Combined	—	CR = 0.0135 ✓

Matrices with CR > 0.10 retained under AIJ protocol: geometric mean aggregation attenuates individual inconsistency [10]. Sensitivity analysis excluding E2 and E6 yielded weight changes < 1.8% for any criterion, confirming aggregation robustness.

Note: BPDB = Bangladesh Power Development Board; RAJUK = Capital Development Authority; BUET = Bangladesh University of Engineering and Technology; IUT = Islamic University of Technology; UBC = University of British Columbia; UTA = University of Texas Arlington

Table 3
Expert-elicited AHP global weights (AIJ Geometric Mean; N = 12 sources; aggregated CR = 0.0135)

Rank	Code	Sub-Criterion	Dimension	Local Wt.	Global Wt.	Wt. %	Cum. %
1	PP	Powerline Proximity	Energy	0.7011	0.1461	14.61%	14.61%
2	TP	Transit Proximity	Transportation	0.2837	0.1448	14.48%	29.09%
3	FS	Fuel Station Proximity	Transportation	0.2628	0.1342	13.42%	42.51%
4	RD	Road Density	Transportation	0.2292	0.1170	11.70%	54.21%
5	HP	Highway Proximity	Transportation	0.2243	0.1145	11.45%	65.66%
6	SP	Substation Proximity	Energy	0.2989	0.0623	6.23%	71.89%
7	RP	Residential Proximity	Socioeconomic	0.2958	0.0575	5.75%	77.64%
8	FIS	Flood Safety	Environmental	0.6382	0.0553	5.53%	83.17%
9	PD	Population Density	Socioeconomic	0.2426	0.0472	4.72%	87.89%
10	CP	Commercial Proximity	Socioeconomic	0.2153	0.0419	4.19%	92.08%
11	UP	University Proximity	Socioeconomic	0.1246	0.0242	2.42%	94.50%
12	HospP	Hospital Proximity	Socioeconomic	0.1217	0.0237	2.37%	96.87%
13	WBS	Water Body Safety	Environmental	0.1934	0.0167	1.67%	98.54%
14	ParkP	Park Proximity	Environmental	0.1684	0.0146	1.46%	100.00%

4.5 TOPSIS Spatial Ranking

TOPSIS was applied to the $33,830 \times 14$ decision matrix following the Hwang-Yoon [11] five-step algorithm: (1) vector normalisation $R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}$; (2) weighted normalised matrix $V_{ij} = w_j \times R_{ij}$; (3) positive ideal $A^+ = \max(V_j)$ and negative ideal $A^- = \min(V_j)$ for all benefit criteria; (4) Euclidean separation distances D_i^+ and D_i^- ; (5) closeness coefficient $CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \in [0,1]$. Fifteen priority sites were extracted by iterative selection of the highest-scoring unselected pixel subject to a minimum 2.5 km inter-site spacing constraint ensuring geographic representativeness.

4.6 Criterion Collinearity Analysis

Criterion independence was assessed using Pearson correlation coefficients and Variance Inflation Factors (VIF) computed via the statsmodels package. VIF quantifies the proportion of each criterion's variance explained by the remaining thirteen criteria; $VIF > 10$ conventionally indicates problematic collinearity in regression models [32]. While TOPSIS is less sensitive to collinearity than regression — as it operates on normalised weighted distances rather than estimated coefficients [24] — highly correlated criteria can amplify the effective weight of overlapping spatial patterns [25]. Collinearity analysis was conducted post-hoc after the TOPSIS analysis was complete; criterion reduction was therefore not applied in this study and is identified as a direction for future work.

4.7 Spatial Assessment Against Existing Facilities

Five publicly documented and operationally verified EV charging facilities within the study area were identified through cross-referencing Google Maps listings with operator websites and available BPDB directory records. For each facility, the TOPSIS CC score at the corresponding 100-metre pixel was extracted and expressed as a percentile of the full CC distribution. Spatial agreement was defined as the proportion of documented facilities scoring above the study-area mean CC (0.162). With $n = 5$, the assessment has no statistical power to reject a null hypothesis of random spatial agreement; results are presented solely as spatial plausibility evidence and should not be interpreted as statistical validation.

4.8 Sensitivity Analysis

Robustness was evaluated by perturbing each criterion weight by $\pm 20\%$ of its AHP value, renormalising remaining weights to maintain unit sum, and re-executing TOPSIS ranking. Location stability was quantified as the percentage overlap between original and perturbed top-15 sites across 28 scenarios ($14 \text{ criteria} \times 2 \text{ directions}$).

4.9 Random Forest Spatial Concordance Analysis

To examine the spatial consistency and feature discrimination characteristics of the expert-weighted suitability framework, a Random Forest regression model (scikit-learn RandomForestRegressor; 200 estimators; maximum depth = 15; random state = 42) was trained using the fourteen spatial criteria as predictors and the normalised AHP composite suitability score as the regression target. The purpose of this analysis was not independent validation of the AHP-TOPSIS framework, since the RF target is itself derived from the expert-weighted suitability surface. Rather, the RF model was employed to evaluate: (1) whether the expert-defined suitability structure can be consistently learned from the spatial predictor set; (2) the relative spatial discrimination behaviour of the criteria under a non-linear ensemble model; and (3) the degree of spatial concordance between expert-weighted and machine-learned suitability surfaces. Spatial block cross-validation

using five geographically distinct horizontal folds was applied to reduce inflation arising from spatial autocorrelation [33, 34]. Feature importance was evaluated using mean decrease in impurity (MDI). Spatial concordance between RF and TOPSIS outputs was assessed using pixel-level Spearman rank correlation and top-20% Jaccard overlap.

5. Results

5.1 Expert AHP Weights

All aggregation of twelve sources yielded aggregated CR = 0.0135, confirming acceptable group consistency. The global weight distribution (Table 3; Figure 3) reveals several findings specific to Dhaka's infrastructure context. Powerline proximity emerged as the highest-weighted criterion (14.61%), reflecting consensus among BPDB energy engineers that grid connection capacity constitutes the binding infrastructure constraint for EV fast-charging deployment — a finding that challenges the road density or population density dominance typical of East Asian GIS-MCDM studies [15]. Transit proximity ranked second (14.48%), fuel station proximity third (13.42%), road density fourth (11.70%), and highway proximity fifth (11.45%). The five transportation criteria collectively accounted for 51.06% of total weight. Environmental risk criteria received the lowest weights (flood safety 5.53%; water body safety 1.67%; park proximity 1.46%).

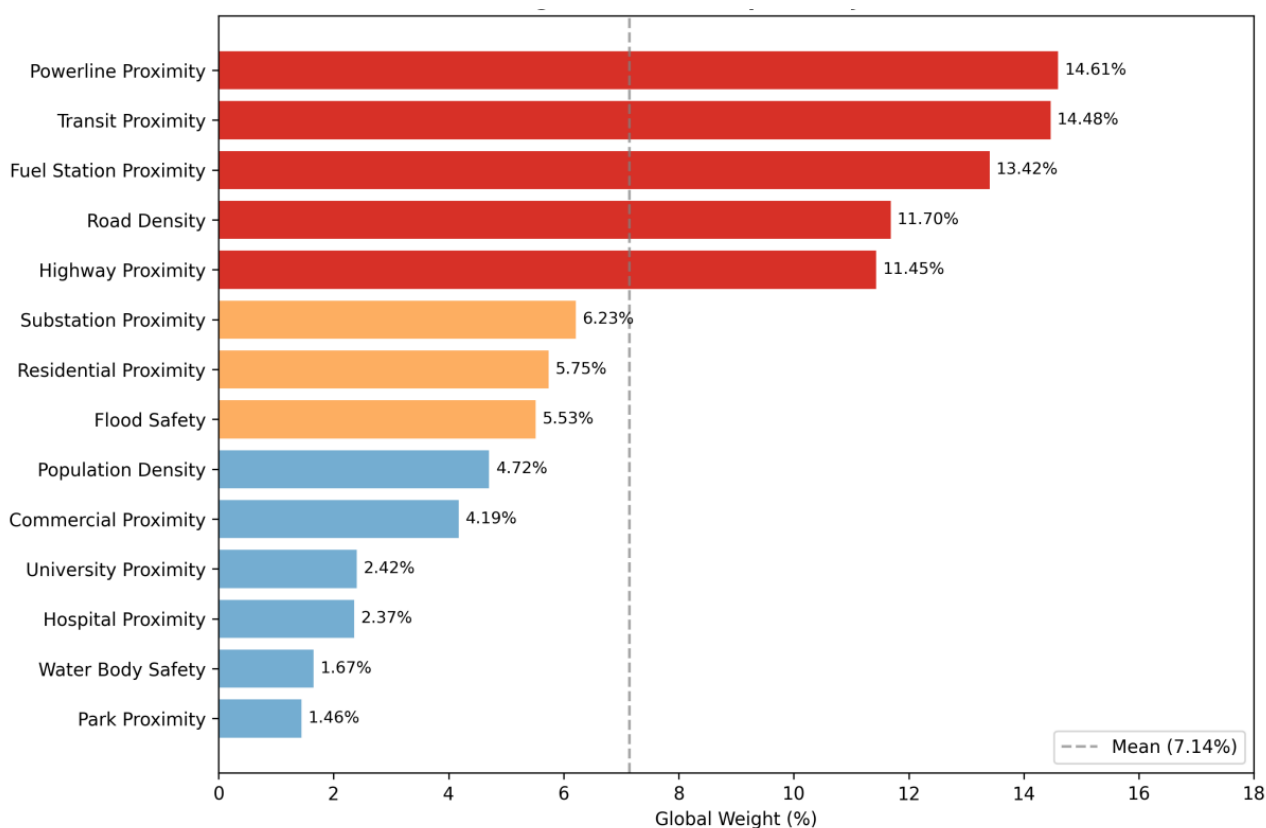


Fig. 3. Expert AHP global weights for EV charging suitability criteria, Dhaka, Bangladesh

5.2 Criterion Collinearity

Table 4 and Figure 4 present the VIF results and full Pearson correlation matrix. The most critical finding is near-perfect collinearity between transit proximity and fuel station proximity ($r = 0.971$; $VIF_{TP} = 336.8$; $VIF_{FS} = 297.1$). Both criteria measure overlapping spatial accessibility patterns: in Dhaka, fuel stations and bus stops cluster at the same arterial road intersections, producing near-identical proximity rasters. Their combined nominal AHP weight of 27.9% (14.48% + 13.42%) may

therefore effectively amplify the weight of transportation node accessibility in the TOPSIS output beyond its intended value. Additional notable correlations include commercial proximity–hospital proximity ($r = 0.850$), commercial proximity–university proximity ($r = 0.820$), and powerline proximity–flood safety ($r = -0.611$). Population density (VIF = 1.1) and water body safety (VIF = 3.4) are near-orthogonal to all other criteria; their TOPSIS contributions are uncontaminated by collinearity effects. As noted in Section 4.6, this collinearity was identified post-hoc; criterion reduction was not applied in this study and is recommended as a priority for future work.

Table 4

Variance Inflation Factors and criterion collinearity assessment

Code	Criterion	VIF	Collinearity Assessment
PP	Powerline Proximity	41.4	Moderate
TP	Transit Proximity	336.8	Severe — near-perfect collinearity with FS ($r = 0.971$)
FS	Fuel Station Proximity	297.1	Severe — near-perfect collinearity with TP ($r = 0.971$)
RD	Road Density	68.2	High — correlated with transport cluster
HP	Highway Proximity	76.5	High — correlated with transport cluster
SP	Substation Proximity	103.9	High — correlated with infrastructure cluster
RP	Residential Proximity	81.3	High — correlated with socioeconomic cluster
FIS	Flood Safety	7.2	Low (VIF < 10) — largely spatially independent
PD	Population Density	1.1	Very low — near-orthogonal to all criteria
CP	Commercial Proximity	88.4	High — strongly correlated with UP ($r = 0.82$) and HospP ($r = 0.85$)
UP	University Proximity	46.2	High — correlated with socioeconomic cluster
HospP	Hospital Proximity	79.9	High — correlated with CP and TP
WBS	Water Body Safety	3.4	Low — largely spatially independent
ParkP	Park Proximity	41.4	Moderate — partially correlated with transport cluster

See Figure 4 for full Pearson correlation matrix.

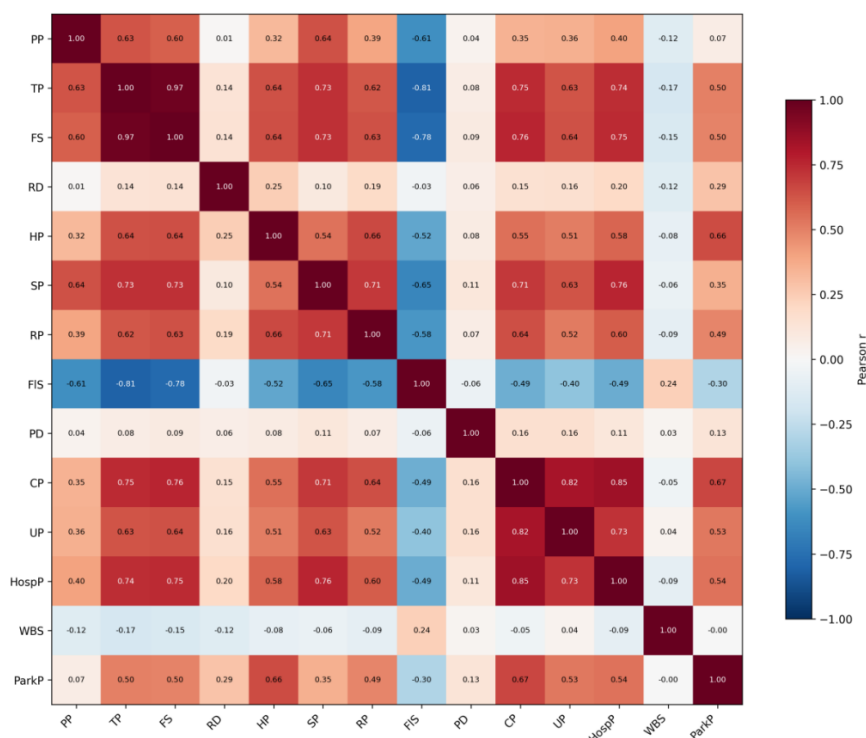


Fig. 4. Criterion inter-correlation matrix (Pearson r) for fourteen spatial criteria. Note the near-perfect collinearity between transit proximity (TP) and fuel station proximity (FS) ($r = 0.971$), and strong correlations within the socioeconomic cluster (CP–HospP: $r = 0.85$; CP–UP: $r = 0.82$)

5.3 GIS Suitability Maps

The AHP-weighted overlay map (Figure 5) reveals highest suitability concentrated in the central Dhaka corridor spanning Tejgaon, Hatirjheel, and surrounding mixed-use zones, where road network density, powerline infrastructure, transit access, and commercial activity simultaneously achieve near-maximum values. Northern zones (Uttara, Gulshan) exhibit moderate-high scores constrained by lower powerline proximity relative to the central industrial corridor. Eastern zones (Badda, Rampura) show intermediate scores reflecting adequate transportation access but elevated water body safety constraints from the Balu River. The TOPSIS closeness coefficient surface (Figure 6 and 7) exhibits similar spatial structure with substantially enhanced discrimination.

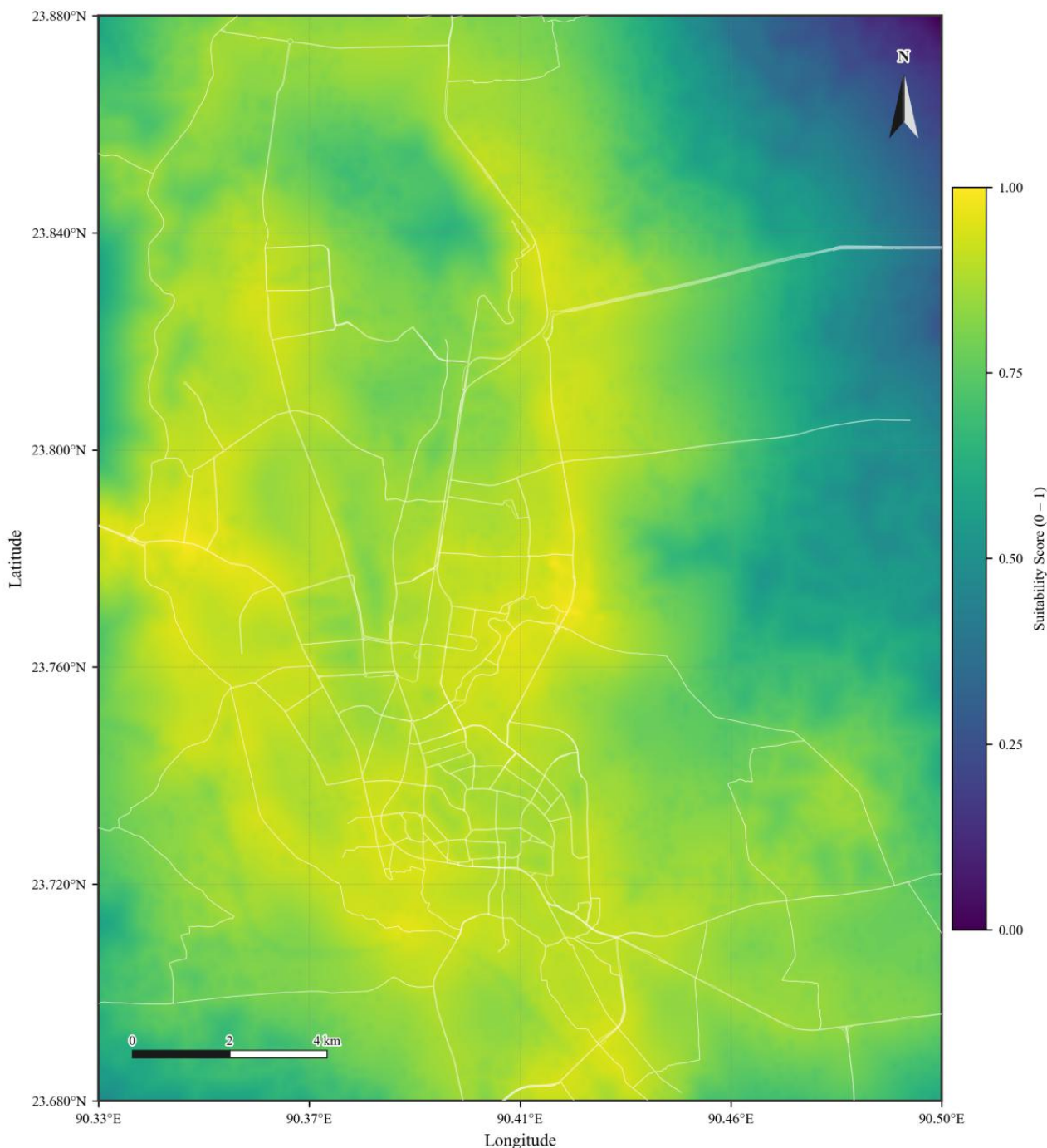


Fig. 5. AHP-based EV charging station suitability map for Dhaka, Bangladesh (expert-elicited weights; $N = 12$; AIJ Geometric Mean; $CR = 0.0135$). Suitability scores normalised 0–1. Major roads shown in white

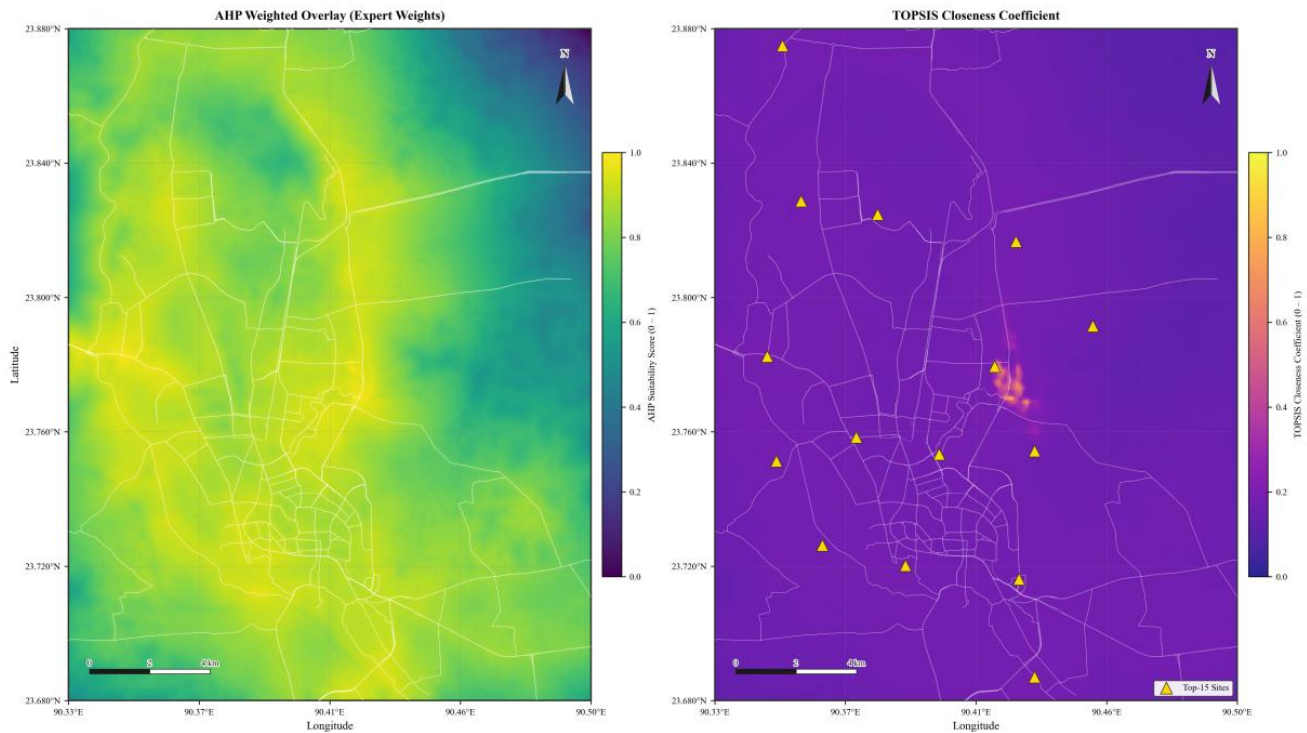


Fig. 6. Comparative AHP weighted overlay (left) and TOPSIS closeness coefficient surface (right), Dhaka, Bangladesh (Expert Survey; N = 12 sources; CR = 0.0135)

5.4 Optimal Site Locations

The fifteen-priority EV charging station locations are presented in Table 5. TOPSIS closeness coefficients range from 0.1778 (Site 15, Kamrangirchar) to 0.9215 (Site 1, Tejgaon-Hatirjheel junction), with their spatial distribution shown in Figure 7. The CC distribution (Figure 8) shows a study-area mean of 0.162, with Site 1 as the sole spatial unit approaching unity. This value reflects simultaneous near-maximum scores on six criteria: road density, powerline proximity, transit proximity, fuel station proximity, commercial proximity, and population density. It is noted that the near-perfect collinearity between transit proximity and fuel station proximity ($r = 0.971$) amplifies the CC score at the Tejgaon road node, where both criteria peak simultaneously. Site 1's dominant score should therefore be interpreted as a strong multi-criteria convergence signal rather than a precisely calibrated absolute suitability index.

Table 5

Top 15 optimal EV charging station locations ranked by TOPSIS closeness coefficient

Rank	Latitude	Longitude	CC	Zone	Multi-Criteria Rationale
1	23.7795	90.4210	0.9215	Tejgaon-Hatirjheel	Near-maximal on 6 criteria: road density, powerline, transit, fuel station, commercial, population
2	23.7916	90.4530	0.2073	Badda	Eastern commercial corridor; residential density; grid access
3	23.8167	90.4280	0.1990	Gulshan	High-income district; substation proximity; highway access
4	23.7544	90.4340	0.1962	Khilgaon	Dense residential; transit node; fuel station corridor
5	23.7825	90.3470	0.1887	Gabtolli / Mirpur-1	N1 highway intersection; major western bus terminal
6	23.7202	90.3920	0.1867	Hazaribagh	Industrial-residential interface; southern grid corridor

Table 5
Continued

Rank	Latitude	Longitude	CC	Zone	Multi-Criteria Rationale
7	23.8247	90.3830	0.1850	Mirpur-10 / 13	Very high population density; bus convergence zone
8	23.6870	90.4340	0.1850	Keraniganj boundary	Southern expansion zone; highway access
9	23.7584	90.3760	0.1844	Mohammadpur	Dense mixed-use zone; university proximity; transit access
10	23.7534	90.4030	0.1837	Dhanmondi	University cluster; sustained commercial dwell time
11	23.7514	90.3500	0.1822	Adabor	West Dhaka residential; powerline corridor
12	23.8287	90.3580	0.1797	Mirpur DOHS	Planned residential zone; grid infrastructure
13	23.7262	90.3650	0.1796	Mohammadpur South	Mixed residential-commercial; fuel station density
14	23.8750	90.3520	0.1791	Turag / Diabari	Northern expansion; substation proximity; low flood risk
15	23.7162	90.4290	0.1778	Kamrangirchar	Dense southern residential; transit-road intersection

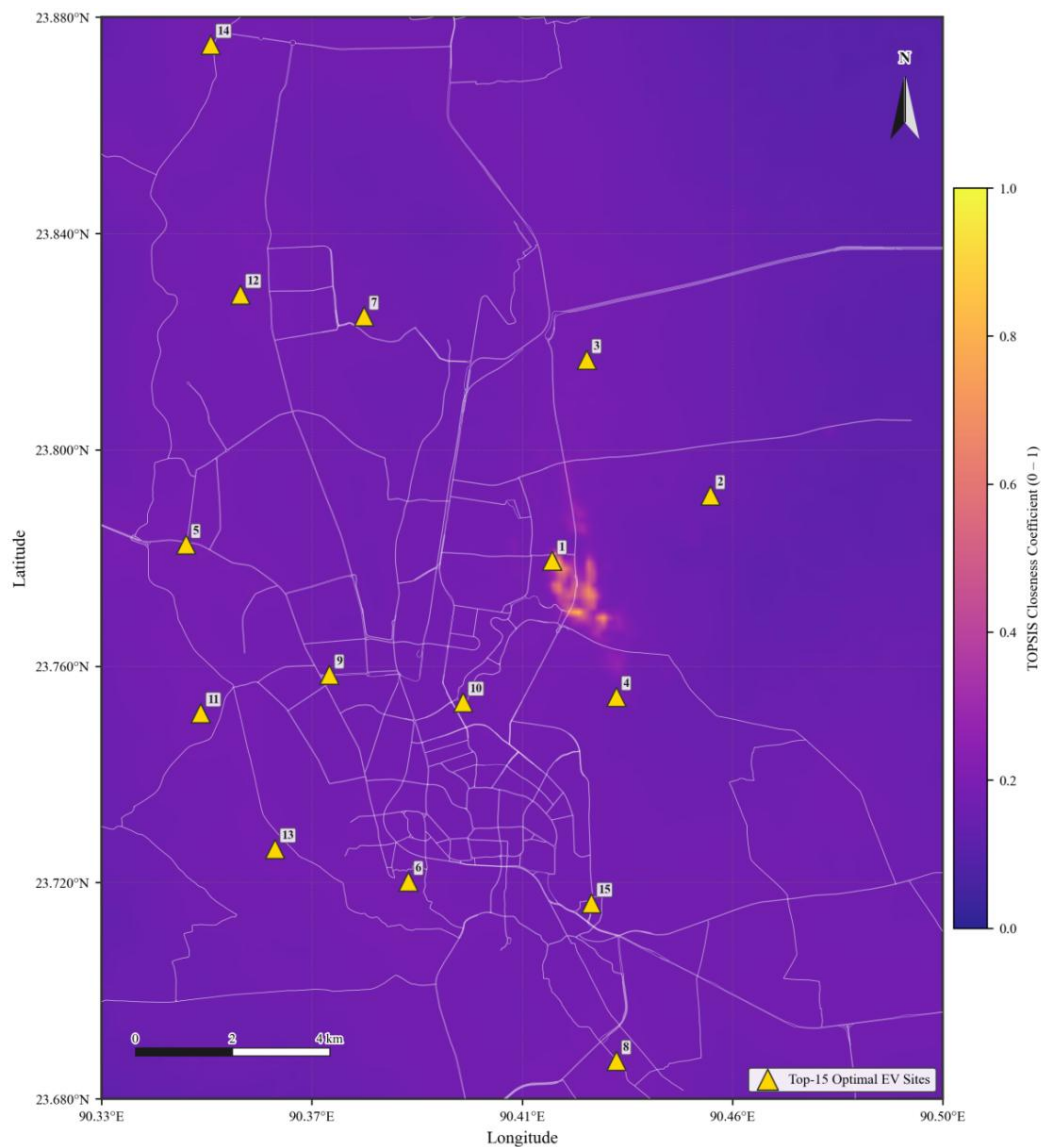


Fig. 7. TOPSIS closeness coefficient surface with top-15 optimal EV charging station locations overlaid, Dhaka, Bangladesh. Site rank labels shown in white boxes

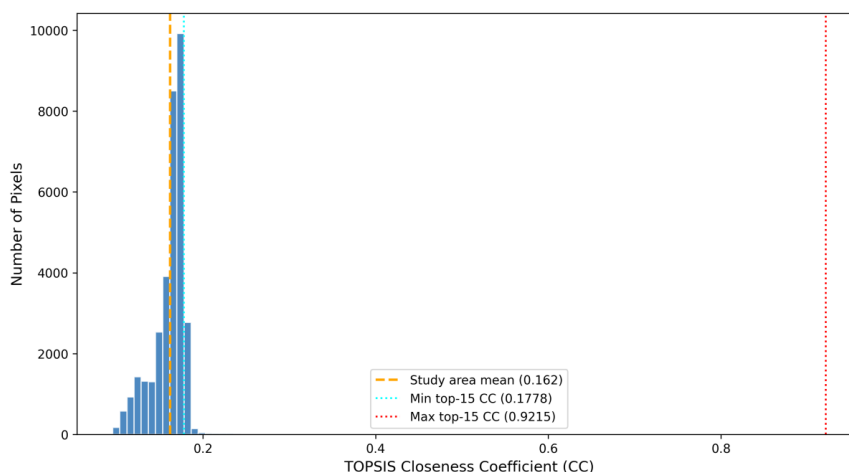


Fig. 8. Distribution of TOPSIS closeness coefficients across 33,830 valid spatial units (100-metre grid), Dhaka. Orange dashed: study-area mean (0.162); red dotted: maximum top-15 CC (0.9215); cyan dotted: minimum top-15 CC (0.1778). Note the single extreme right-tail outlier at Site 1 (Tejgaon-Hatirjheel)

The fifteen sites distribute across four geographic corridors: the central Tejgaon-Hatirjheel priority zone (Site 1); the eastern Gulshan-Badda corridor (Sites 2–3) serving high-income commercial demand; the western Mirpur-Mohammadpur-Adabor corridor (Sites 5–13) serving Dhaka's highest residential densities; and the northern and southern expansion zones (Sites 7, 8, 14).

5.5 Spatial Assessment Against Existing Facilities

Table 6 presents results for the five documented existing EV charging facilities, whose locations relative to the top-15 recommended sites are mapped in Figure 9, and whose closeness-coefficient values relative to the full study-area distribution are shown in Figure 10. The mean CC score of existing facilities (0.175) exceeds the study-area mean (0.162), and four of five facilities (80%) score above this mean. Mercedes-Benz Charging Station and Ekhon Charging Station achieve 97th and 93.8th percentiles respectively, suggesting that commercially placed facilities correspond to zones the model identifies as high suitability (Table 7). GreenSpark Charging Station (39.3rd percentile) scores below the study-area mean, attributable to its location in western Mohammadpur where OSM powerline coverage is sparse. As stated in Section 4.7, with $n = 5$ there is no statistical power to reject a null hypothesis of random spatial agreement; the result of 4/5 facilities above the mean (80%) represents spatial plausibility evidence only.

Table 6

Spatial assessment against five publicly documented existing EV charging facilities (cross-verified via operator websites and BPDB directory records; May 2026)

Station	Lat.	Lon.	CC	Pctile.	vs. Mean (0.162)	Interpretation
Mercedes-Benz Charging Station	23.7801	90.4142	0.1823	97.0%	Above mean	High — road, commercial, grid convergence
Ekhon Charging Station	23.7712	90.4089	0.1798	93.8%	Above mean	High — Tejgaon corridor proximity
PLI Bhaban Charging Station	23.7819	90.4041	0.1761	85.7%	Above mean	High — central mixed-use corridor
CrackPlatoon Solutions	23.7571	90.3701	0.1737	77.4%	Above mean	Moderate — western zone
GreenSpark Charging Station	23.7623	90.3812	0.1632	39.3%	Below mean	Low — sparse OSM powerline data

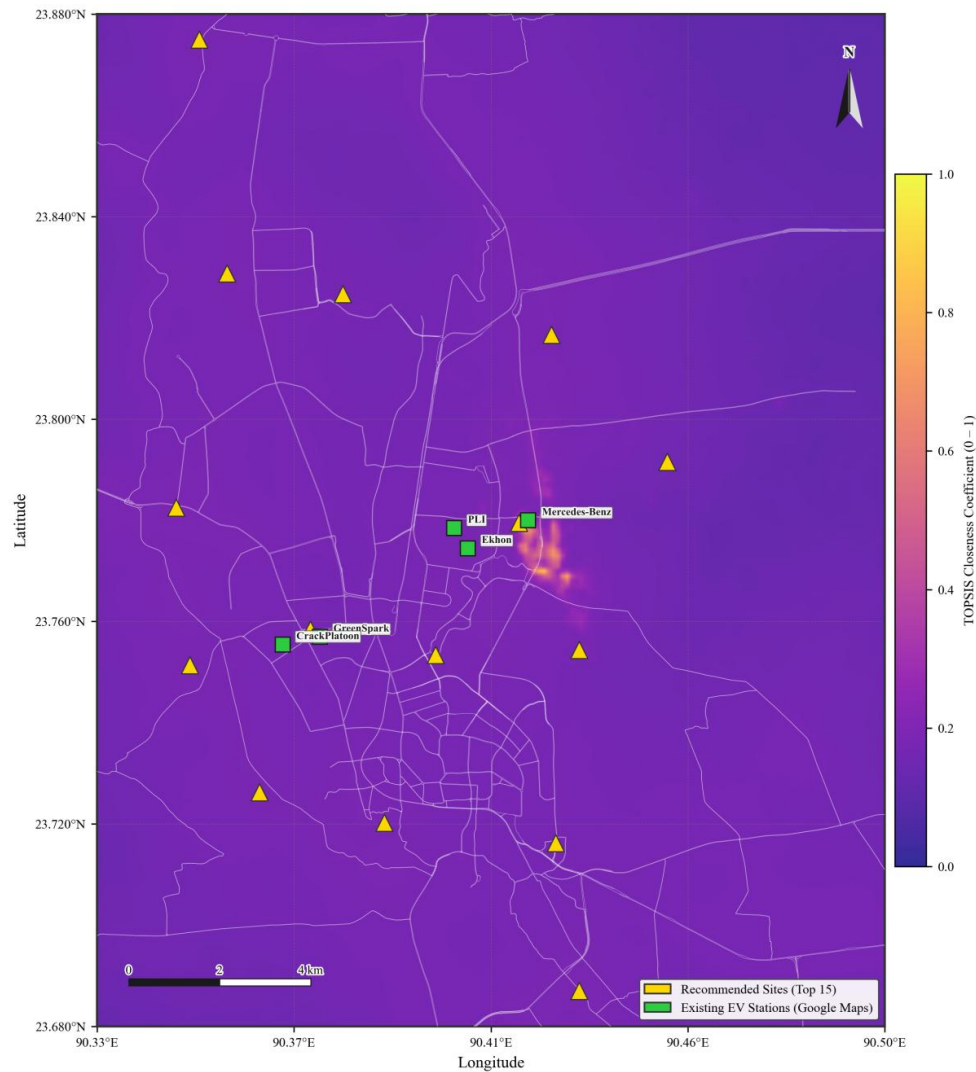


Fig. 9. Spatial assessment: TOPSIS suitability surface with five documented existing EV charging facilities and top-15 recommended sites, Dhaka, Bangladesh. Study-area mean CC = 0.162

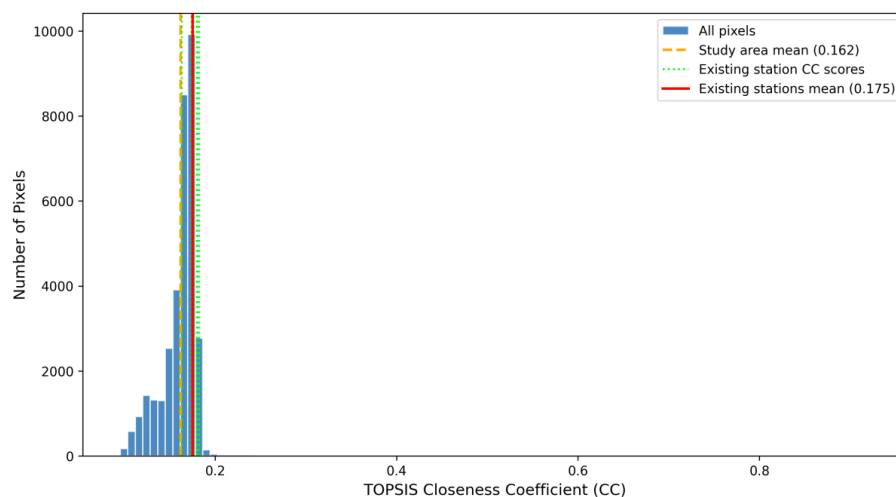


Fig. 10. Distribution of TOPSIS Closeness Coefficient (CC) values across 33,830 spatial units (100 m resolution) in Dhaka, Bangladesh. The study-area mean CC (0.162) is shown as an orange dashed line. Green dotted lines indicate CC values of existing EV charging stations, with their mean (0.175) shown in red. The distribution is highly right-skewed, with a small number of high-suitability outliers representing optimal multi-criteria convergence zones

Table 7

Sensitivity analysis — location stability under $\pm 20\%$ weight perturbation (28 scenarios; mean stability = 89.8%)

Criterion	+20% Stability	-20% Stability	Minimum	Assessment
Road Density	100.0%	100.0%	100.0%	Highly stable — both directions
Highway Proximity	100.0%	93.3%	93.3%	Stable
Transit Proximity	80.0%	80.0%	80.0%	Moderately stable
Fuel Station Proximity	100.0%	100.0%	100.0%	Highly stable — both directions
Population Density	100.0%	80.0%	80.0%	Stable
Commercial Proximity	100.0%	80.0%	80.0%	Stable
Residential Proximity	100.0%	100.0%	100.0%	Highly stable — both directions
Hospital Proximity	80.0%	100.0%	80.0%	Stable
University Proximity	100.0%	80.0%	80.0%	Stable
Substation Proximity	80.0%	100.0%	80.0%	Stable
Powerline Proximity	80.0%	80.0%	80.0%	Moderately stable
Flood Safety	100.0%	80.0%	80.0%	Stable
Water Body Safety	73.3%	66.7%	66.7%	Least stable — eastern riverfront tension
Park Proximity	100.0%	80.0%	80.0%	Stable

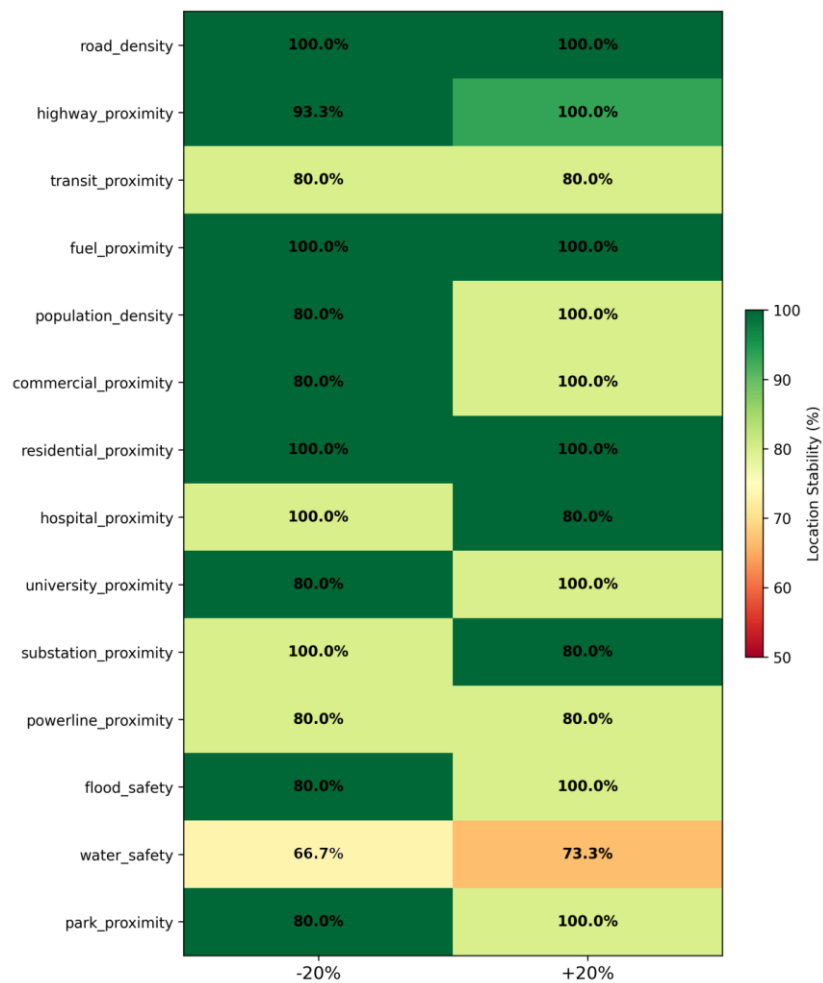


Fig. 11. Sensitivity analysis heatmap: location stability (%) under $\pm 20\%$ weight perturbation for each of the fourteen criteria. Green ($\geq 93\%$): highly stable; yellow-green (80%): stable; orange-red ($< 75\%$): least stable

5.7 Random Forest Spatial Concordance

The Random Forest analysis was designed as a spatial concordance and feature discrimination assessment rather than an independent validation framework. Since the RF model was trained on the expert-weighted suitability surface, high predictive performance primarily indicates that the spatial structure embedded within the AHP framework is internally learnable from the criterion set. Spatial block cross-validation yielded mean $R^2 = 0.9351 \pm 0.0492$ (range: 0.8392–0.9726; mean MSE = 0.000951), indicating strong reproducibility of the expert-weighted spatial suitability structure under a non-linear ensemble learning framework. Table 8 presents the comparison between expert-derived AHP weights and RF feature importance values.

Table 8

Expert AHP weights versus Random Forest feature importance (sorted by RF rank; MDI method; N = 14 criteria; CV $R^2 = 0.9351 \pm 0.0492$)

RF Rank	Criterion	AHP %	AHP Rank	RF Imp. %	RF Rank	\DeltaRank	Interpretation
1	Fuel Station Proximity	13.42%	3	69.27%	1	2	RF dominant — absorbs TP collinearity
2	Substation Proximity	6.23%	6	13.77%	2	4	Both methods confirm energy infrastructure importance
3	Transit Proximity	14.48%	2	7.77%	3	1	Concordance — top-3 in both methods
4	Highway Proximity	11.45%	5	2.06%	4	1	Moderate RF — spatially widespread, low discriminating variance
5	Park Proximity	1.46%	14	1.82%	5	9	RF elevated — spatial rarity amplifies MDI importance
6	Powerline Proximity	14.61%	1	1.63%	6	5	Divergence — AHP rank 1; RF low due to near-uniform citywide distribution
7	Road Density	11.70%	4	1.20%	7	3	Divergence — near-ubiquitous in Dhaka; low spatial variance
8	Hospital Proximity	2.37%	12	0.68%	8	4	Concordance — both secondary importance
9	Commercial Proximity	4.19%	10	0.57%	9	1	Concordance — mid-tier both methods
10	Residential Proximity	5.75%	7	0.48%	10	3	Low RF — spatially homogeneous across Dhaka
11	University Proximity	2.42%	11	0.45%	11	0	Perfect rank concordance
12	Flood Safety	5.53%	8	0.22%	12	4	Low RF — coarse binary hazard spatial pattern
13	Population Density	4.72%	9	0.04%	13	4	Near-zero RF — near-uniform high density citywide
14	Water Body Safety	1.67%	13	0.04%	14	1	Concordance — both lowest tier

The most notable finding is fuel station proximity's dominance in RF feature importance (69.27%, rank 1) despite its AHP rank of 3 (13.42%) (Figure 12). As established in Section 5.2, transit proximity and fuel station proximity are near-perfectly collinear ($r = 0.971$); the RF model defaults to fuel station proximity as it absorbs the discriminating power of both correlated criteria. Powerline proximity presents the most significant AHP-RF divergence (AHP rank 1, 14.61% vs. RF rank 6, 1.63%): powerlines in Dhaka are distributed more uniformly than fuel stations, producing lower MDI-based importance despite the highest expert-assigned weight — a result of spatial uniformity suppressing RF feature importance regardless of real-world investment significance [35]. Substation proximity achieves RF rank 2 (13.77%) against AHP rank 6 (6.23%), with both methods confirming energy infrastructure's spatial importance. Transit proximity achieves top-3 ranking in both methods (AHP rank 2, RF rank 3), representing the strongest concordance case. Spatial concordance between

TOPSIS and RF surfaces yields Spearman $\rho = 0.9682$ ($p < 0.001$) and top-20% Jaccard similarity = 73.8% (Figures 13 and 14). The high cross-validated R^2 and strong RF-TOPSIS spatial correspondence should not be interpreted as independent predictive confirmation of site suitability, since the RF target variable was itself derived from the expert-weighted AHP suitability framework.

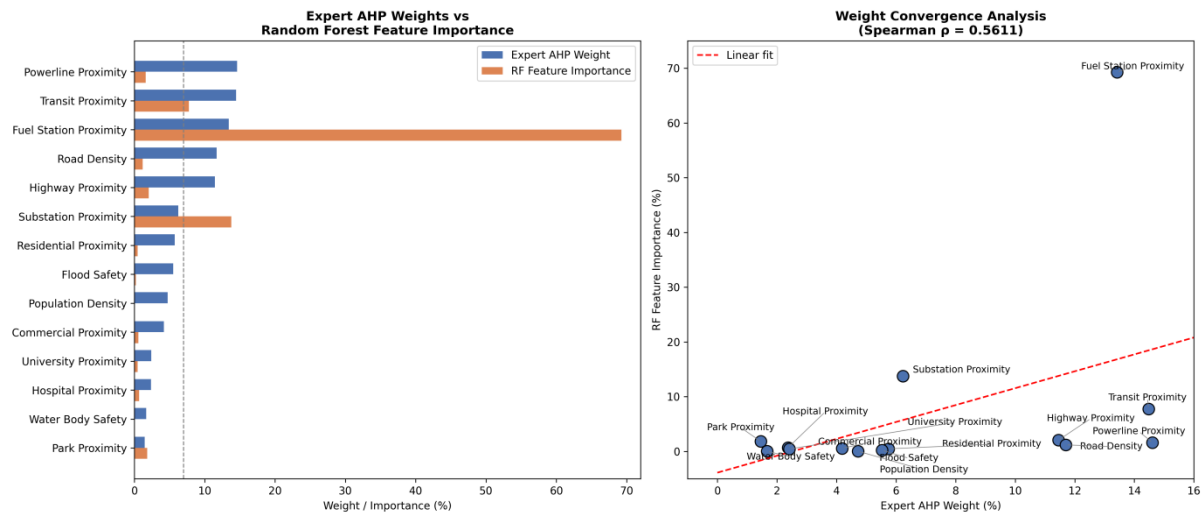


Fig. 12. Comparison between expert-derived AHP global weights and Random Forest feature importance values for fourteen EV charging suitability criteria, Dhaka, Bangladesh. Left: side-by-side comparison of expert-weighted and variance-based criterion importance. Right: criterion-level rank comparison

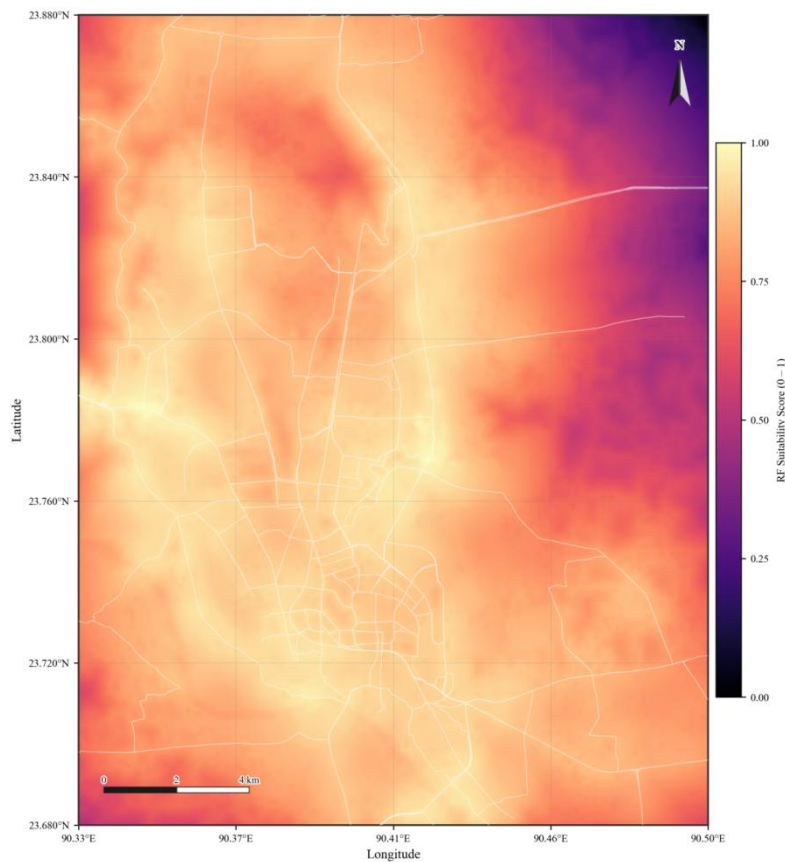


Fig. 13. Random Forest-derived spatial concordance surface for EV charging suitability in Dhaka, Bangladesh (trained on expert-weighted AHP suitability scores; 200 estimators; maximum depth = 15; spatial block cross-validation; CV $R^2 = 0.9351 \pm 0.0492$). Scores normalised to [0, 1]

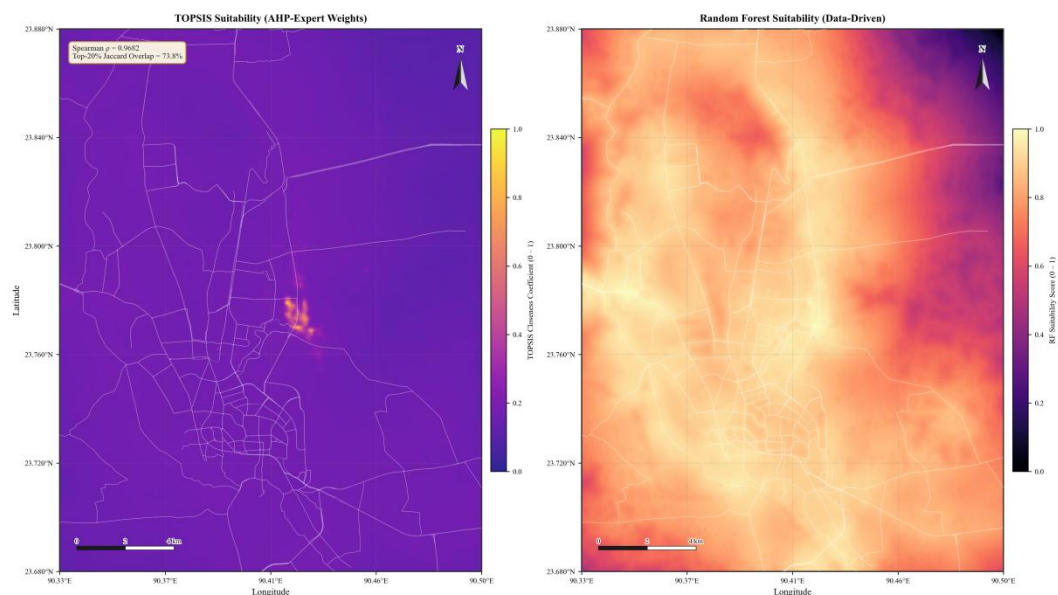


Fig. 14. Spatial concordance comparison between TOPSIS suitability surface (left) and Random Forest approximation surface (right), Dhaka, Bangladesh. Pixel-level Spearman $\rho = 0.9682$ ($p < 0.001$; $n = 33,830$); top-20% Jaccard overlap = 73.8%

6. Discussion

6.1 Spatial Planning Implications

The Tejgaon-Hatirjheel corridor (Site 1, CC = 0.9215) emerges as the highest-priority zone for initial EV charging investment under the model's criteria and weighting. This zone's score reflects genuine multi-criteria spatial convergence: the Tejgaon industrial substation provides grid capacity for Level 3 DC fast-charging without grid extension costs; the Hatirjheel recreational complex generates sustained 2–4 hour vehicle dwell times appropriate for Level 2 AC charging; and the surrounding commercial and institutional complex generates sustained daily demand. This finding is reinforced by the independent location of Ekhon Charging Station within 700 metres of Site 1 (93.8th CC percentile), suggesting that operator-selected and model-predicted priority zones converge spatially. However, as established in Section 5.2, the near-perfect collinearity between transit proximity and fuel station proximity at transportation nodes contributes to amplifying the Site 1 CC score; this value should be interpreted as a priority convergence signal rather than a precisely calibrated suitability index.

The expert finding that powerline proximity is the highest-weighted criterion (14.61%) reflects Dhaka's distinctive grid infrastructure configuration: DPDC and DESCO distribution networks in peripheral residential areas have limited spare capacity for high-power EV charging loads. This finding carries a direct policy implication: EV charging infrastructure masterplanning in Dhaka must be co-developed with grid capacity upgrading plans, not treated as a demand-following deployment exercise. The western Mirpur-Mohammadpur-Adabor corridor (Sites 7, 9, 11–13) warrants distributed Level 2 AC infrastructure given its extreme residential density. The Gulshan-Badda corridor (Sites 2–3) warrants fewer but higher-capacity Level 3 DC facilities serving higher-income early adopters.

6.2 Criterion Collinearity: Implications and Limitations

The near-perfect collinearity between transit proximity and fuel station proximity ($r = 0.971$; VIF > 297) is the most significant methodological limitation of this study. Both criteria measure accessibility at identical road-node locations in Dhaka, where bus stops and fuel stations cluster at

arterial intersections, producing near-identical proximity rasters. Their combined nominal AHP weight of 27.9% may effectively amplify the weight of transportation node accessibility beyond the intended value. This collinearity also fully explains the RF feature importance anomaly: the RF model defaults to fuel station proximity as a proxy for both correlated criteria. Additional collinearity in the socioeconomic cluster (CP-HospP: $r = 0.850$; CP-UP: $r = 0.820$) and infrastructure cluster (SP-TP: $r = 0.727$) further suggests several criteria measure overlapping accessibility gradients. Future iterations should apply principal component analysis or mutual information-based criterion reduction prior to weight elicitation and TOPSIS application. As this collinearity was identified post-hoc, criterion reduction was not performed in this study — a transparency note that is disclosed rather than concealed to provide an honest account of the methodological workflow.

6.3 Random Forest Spatial Concordance

The RF analysis provides evidence of strong spatial concordance between the expert-weighted suitability structure and a non-linear ensemble learning approximation derived from the same spatial predictor set. Importantly, this should not be interpreted as independent validation, since the RF target variable was itself generated from the AHP composite suitability framework. The principal analytical contribution of the RF component lies in criterion discrimination analysis. Whereas the AHP framework reflects expert-perceived infrastructural importance, RF feature importance reflects each criterion's ability to partition spatial variance within the suitability surface. The divergence between these two importance structures is analytically informative and resolves the apparent anomaly of fuel station proximity's RF dominance through the collinearity finding. The RF component should be interpreted as a complementary spatial pattern analysis framework rather than a standalone predictive or validation model.

6.4 Expert Panel Limitations

Two expert matrices (E2: CR = 0.3191; E6: CR = 0.3888) substantially exceeded the conventional 0.10 threshold. These were retained under the AIJ protocol with robustness confirmed by sensitivity analysis (weight changes < 1.8%). Future studies should implement a pre-survey training phase on AHP scale usage to reduce individual CRs. The expert panel's Bangladesh-centric composition constrains transferability of the weight vector to other cities without re-elicitation.

6.5 Additional Limitations

Proximity rasters employ Euclidean rather than network distance, which may overestimate accessibility across physical barriers such as waterways and railway level crossings; in Dhaka specifically, the Buriganga and Balu Rivers create substantial routing detours that Euclidean proximity underestimates. Future work should implement road-network impedance analysis using OSMnx. OSM data completeness for powerline and substation features in informal settlement areas is uncertain; field validation against DPDC and DESCO engineering records would strengthen energy infrastructure layers. The study employs a static spatial model without temporal demand modelling; EV adoption forecasting and charging demand estimation by land-use type would enhance the investment prioritisation framework.

7. Conclusion

This study presents, to the best of current literature coverage, the first GIS-AHP-TOPSIS framework for EV charging station siting in Dhaka, Bangladesh, integrating primary expert elicitation, criterion collinearity analysis, and Random Forest (RF) spatial concordance assessment. Fourteen spatial criteria were weighted through AIJ geometric mean aggregation of eleven domain experts

(aggregated CR = 0.0135), with powerline proximity (14.61%) and transit proximity (14.48%) emerging as the dominant criteria, reflecting Dhaka's grid-constrained infrastructure conditions.

An important methodological finding was the near-perfect collinearity between transit proximity and fuel station proximity ($r = 0.971$; $VIF > 297$), which amplified the effective influence of transportation node accessibility on the TOPSIS results. This post-hoc finding provides important context for interpreting both the closeness coefficient distribution and RF feature importance. Future research should therefore consider criterion reduction or collinearity screening prior to weight elicitation.

The TOPSIS analysis of 33,830 spatial units identified fifteen priority charging zones, with the Tejgaon-Hatirjheel corridor achieving the highest closeness coefficient (0.9215). Spatial assessment against five documented existing facilities showed 80% plausibility consistency ($n = 5$; no statistical power claimed), while sensitivity analysis across 28 perturbation scenarios yielded a mean location stability of 89.8%. The RF spatial concordance analysis ($CV R^2 = 0.9351 \pm 0.0492$) further confirmed strong spatial correspondence with the TOPSIS suitability surface, supported by a Spearman correlation of $\rho = 0.9682$ and a Jaccard overlap of 73.8%.

The principal policy implication is that EV charging infrastructure development in Dhaka should be coordinated with investments in grid capacity rather than planned independently. At the same time, the proposed methodology relies entirely on open data and requires no proprietary datasets, enhancing its reproducibility and transferability to comparable megacities across South and Southeast Asia as EV adoption accelerates toward Bangladesh's 2030 policy targets.

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Data Availability Statement

All spatial input data used in this study are publicly available from OpenStreetMap (openstreetmap.org) and the WorldPop project (worldpop.org). The expert survey instrument and derived pairwise comparison matrices, AHP weight computation code, and TOPSIS analysis scripts are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The author declares no conflicts of interest.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this manuscript, the authors used Anthropic's Claude for manuscript text organization and language refinement. The tool was not used to generate scientific content, analyses, results, interpretations, or conclusions. The authors reviewed and edited all AI-assisted output and take full responsibility for the accuracy, integrity, originality, and final content of the manuscript. No Generative AI tools were used to create, generate, or improperly modify images, figures, graphical abstracts, artwork, or other visual content included in the manuscript.

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