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Explainable artificial intelligence-driven sustainability for electric vehicle charging station siting: A hybrid LIME-SHAP for MCDM

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Abstract

Electric Vehicle Charging Station (EVCS) planning typically relies on subjective factor weighting, hence expert bias may be introduced in multi-criteria decision problems. We propose an Explainable Artificial Intelligence (XAI) powered enhancement to a GIS–MCDM siting by relying on LIME and SHAP hybrid-based approach for inducing data-driven Multi-Influencing Factor (MIF) weights of the weighted overlay. This method applied to four wards in Mumbai India, combines global (SHAP) and local (LIME) model-agnostic importances from a balanced surrogate classifier trained using spatial samples around observed EVCS locations. The hybrid weights substitute the MIF prior inter-relation and drive the classical overlay and TOPSIS stages, leaving intact interpretability and auditability. Validation shows the degree of enhancement in site discrimination (ROC–AUC = 0.846) relative to that of the baseline MIF–TOPSIS process (ROC–AUC = 0.826) with more separated high- and low-suitability classes with less affectedness responding to single-factor perturbations, which can be attributed to the benefit of XAI-based weighting on these weights. It is expected that this will give rise to a more reliable and replicable map of EVCS suitability which can enhance overall sustainability benefits and transparent, stakeholder facing decision-taking.

Keywords: Sustainable development, Electric vehicle, Explainable artificial intelligence, Multi-criteria decision-making, Trustworthy AI, Site selection.

1. Introduction

Electric vehicles (EVs) are experiencing rapid expansion as a key component of sustainable transportation, and this trend has taken place across the globe [1]. Global electric car sales hit a record 17+ million in 2024 (over 20 per cent of new car sales) and are on track to surpass the 20-million threshold in this year, which would represent more than one-quarter of all cars sold. This fast adoption is the result of it being imperative to achieve a cut in greenhouse gas emissions and urban air pollution [1-3]. Strong charging infrastructure network is essential to enable EV deployment, ease the range anxiety and make an environmentally friendly omnichannel EV mobility solution. The placement strategies of electric vehicle charging stations (EVCS) become a highly sophisticated multi-objective problem for the city authorities to solve, which includes economic feasibility, power grid capacity availability, environmental impact and the user's convenience [2,4]. That the locations are right is important, not only in terms of operational efficiency, but to ensure that maximum environmental benefits delivered by an EV are achieved, and also in providing for social equity in charging provision.

National support and policy goals make well-designed deployment of EVCS increasingly important [5-8]. Many countries have set ambitious electrification targets in order to adhere to climate accords [6,9]. India, for example, has set a target of new vehicle sales to be electric of at least 30% by 2030. This means we could see some 80 million EVs zipping around the nation by 2030, and that is a figure that makes capital infusion in charging infrastructure imperative at India scale. Such disparities between EV

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uptake and charging infrastructure are widespread worldwide, underlining the urgent need for effective and sustainable deployment of new charge points. Without good siting, there are underused stations and grid jams; with it, you can move the EV market along and bring clean mobility to a broader swath of the public [10-12]. During the last decade, researchers and city planners around the world have developed several ways of selecting EVCS locations.

Classical methods such as Geographic Information System (GIS) analysis integrated with MCDM methods are commonly employed to map and rank candidate sites [7,13-16]. Rashmitha et al. [17] developed a hybrid GIS–MCDM method with twelve sustainability-based criteria (e.g., land allocation, population density, road connectivity, grid access and point of interest) for the suitability mapping and prioritization. Objective weighting techniques (CRITIC and entropy) were used to estimate the importance of criteria, application of TOPSIS and WASPAS techniques was utilized to select suitable sites and it was shown how sensitive both results are depending upon their weightage. The results of these studies highlight that a comprehensive, data-based method can enhance the reliability of decision-making but also that transparency in the role the selection criteria play in a decision is instrumental to building stakeholder trust.

Meanwhile, Artificial Intelligence (AI) based technologies as well as advanced optimization algorithms have been applied to solve EV charging station location problems but mainly for partial concerns such as grid impacts or user behavior [18-20]. For instance, Deb et al. [21] modeled the siting problem as multi-objective optimization based on economic, power system stability (voltage, losses and reliability) and user's convenience (distance travelled, traffic). To overcome this, a hybrid metaheuristic approach (CSO-TLBO) was proposed to obtain a set of Pareto-optimal solutions and then employed a fuzzy decision-making of the best compromise solution. These evolutionary algorithms and heuristics (e.g., genetic algorithms, particle swarm optimization, among others) have been effective at discovering optimal or in the vicinity of-optimal station positions under complex constraints. In addition, task specific AI models have been constructed; for instance, researchers use machine learning to predict spatiotemporal charging demand in cities that helps city infrastructure planning proactiveness [22-25]. These AI-based methodology could handle massive amount of data (travel behaviors, EV usage pattern and grid load etc.) as well as the non-linearity in relationships, which may outperform manual or simple analytical work to customize locations for siting.

However, a major missing gap in the literature and practice seems to be missing explainability of advanced AI-based decision support for EVCS siting. Classical MCDM methods (AHP, TOPSIS, etc.) generate ranking which is human-interpretable but some of them are subjective in nature such as establishing weight to the objective functions and not always scalable to big data [8,26-30]. In contrast, sophisticated AI models and optimizers can deal with high-dimensional data and multiple objectives, but tend to act as "black boxes", the decision-maker has no clear idea why site A was chosen over site B. On a high stakes infrastructure decision that affects multiple groups of stakeholders (the city-planners, utilities, businesses, communities) the fundamental need here is transparency and trust in the model's recommendations [2,31-34]. The planners must prove the selected site is the best and most sustainable, i.e. how much of planning issues (land cost, soil features accessibility to grid connection etc.) weighted in decision-making process! Nevertheless, works rarely integrate Explainable AI (XAI) methods to the reasoning process of model predictions. And this is where methods like LIME and SHAP can make an immense difference. LIME and SHAP are among popular XAI methods which offer human-understandable explanations for model decisions [35-39]. LIME explains individual predictions by locally approximating the model with an interpretable, simple linear model, while SHAP attributes a global importance score to each feature using cooperative game theory principles based on all possible combinations of feature values. All of them have their advantages; LIME is capable to be extremely fast and provide an intuitive explanation on the local decision factor, SHAP ensures the consistency between global and local feature importance but need heavy computation cost. And mixing the two can result in an all-powerful hybrid explanation framework, using LIME's speed to filter factors and SHAP's thoroughness to tighten and verify their effects. Until now, XAI tools were mainly used in certain industries, healthcare, finance, autonomous driving, to interpret complex models. In EV infrastructure literature, while an incipient tendency is starting to appear (e.g., applying SHAP to explain factors that trigger the EV charging demand forecast), so far, no full-fledged framework has been developed utilizing XAI in multi-criteria siting of EV charging stations. This chasm provides only muted transparency for decision makers to understand AI-informed robotics of recommendation, possibly limiting the uptake of more advanced tools for sustainable planning. Table 1 provides a comparative look at key studies and methods employed for EV charging station siting.

Table 1 Key studies and methods employed for EV charging station siting

Reference	Geography	Technique	Typical Data and Features	Key finding
[40]	China (urban)	Fuzzy TOPSIS (MCDM)	Land use, cost, traffic, environment	Fuzzy MCDM handles expert uncertainty; yields balanced rankings for sustainable EVCS siting.
[21]	India (Guwahati)	Hybrid metaheuristics (CSO+TLBO) + fuzzy selection	Road & grid topology, reliability indices, traffic	Multi-objective siting maintains voltage/reliability while improving access.
[41]	China	LEW (linguistic entropy) + Fuzzy Axiomatic Design	5-D index (econ/env/social/tech/policy)	Objective fuzzy weights + fuzzy ranking reduce bias; robust site choices.
[42]	Spain (Valencia)	Genetic Algorithm + Agent-Based Simulation	Mobility traces, POIs, traffic	GA locations validated in agent simulation cut waiting/idle time vs. baselines.
[43]	Asia (case)	Three-phase fuzzy MCDM (FDM→weights; fuzzy evaluation)	3 criteria / 18 sub-criteria	Structured fuzzy pipeline for siting under vague judgments.
[44]	Ecuador (Cuenca)	GIS-MCDA with Fuzzy TOPSIS	Demographics, energy density, substation capacity	Incorporating substation capacity in MCDA avoids grid bottlenecks at chosen sites.
[45]	China (urban)	Multi-period location optimization (user-equilibrium flows)	Traffic assignment, MCS logistics	Mobile charging station (MCS) siting reduces land pressure; shows capacity thresholds.
[46]	USA (Oklahoma)	AHP / Fuzzy-AHP + spatial optimization (Voronoi)	Access to AFC corridors, travel times, demand	Two-stage MCDA+spatial design yields equitable early-rollouts.
[47]	India (urban)	GIS-MCDM (objective weights + ranking)	12+ criteria: land use, population, grid, roads, POIs	Objective weighting (e.g., entropy/CRITIC) materially alters rankings—argues for transparent weighting.
[48]	Turkey (Istanbul)	Intuitionistic-fuzzy DEMATEL-AHP-TOPSIS	Access, traffic, cost, environment	Intuitionistic fuzzy sets improve handling of vagueness in expert inputs.
[49]	City expansion	Fuzzy–rough MCDA for expansion siting	Existing CS network, demand growth, land, grid	Data-driven expansion planning prioritizes high-impact infill over uniform spread.

This study would contribute to constructing an explainable artificial intelligence-based decision framework for sustainable EVCSs siting. The fundamental assumption is to combine a hybrid LIME-SHAP explanation technique into MCDM and AI for making sustainable criteria transparent in site selection. This paper has several original contributions. First, it is one of the very first studies that attempts to combine XAI with sustainable infrastructure siting providing in doing so a hybrid LIME–SHAP approach for multi-criteria decision support. By that, it contributes to filling the transparency gap in former EV charging station planning research. While the rationale behind each recommendation hasn't been caused to see daylight, which increases trust in AI-based planning. Second, it gives a comprehensive summary of worldwide advances in global EVCS siting (across heuristic optimization, fuzzy MCDM, GIS analytics etc.) and best practices which are used also in the modelling component. Third, we use the model to develop insights with reference to a real-world case (focused on plans for EV expansion in India), which can help policymakers decide how to locate charging stations so as to maximize environmental benefits and social equity. Lastly the research contributes a structured knowledge related base (i.e. literature synthesis and comparative result table) that consolidates methods and criteria applied in identifying EVCSs for the last 5–10 years, which can serve as a reference guide for scholars and practitioners. This research will help to make certain that the roll-out of EV recharging facilities does not just make technical and economic sense, but is understandable sustainable too in line with wider agendas and aims linked to smart cities and clean energy.

2. Methodology

This research develops a hybrid LIME-SHAP method to obtain the criterion weights, incorporated with GIS spatial analysis and TOPSIS ranking. The method is a new improvement to a previous MCDM methods, and its novelty lies in replacing manual MIF weight estimation with data-driven feature importance derived from an XAI model. The important methodology is:

Study Area

Mumbai (study area), is one of the most populous and largest cities in India on the west coast in the state of Maharashtra (Fig. 1) [50]. The city is home to more than 12 million people, and around 3 million registered vehicles in 2017, leading to heavy gridlock and serious air pollution. The present study refers to four municipal wards of Mumbai (hereinafter referred as M/E, M/W, L and N) in the Eastern suburbs with a combined area of about 91.86 km². The study area falls approximately between 18°59' to 19°06'N latitudes and 72°53' to 72°56E longitudes geographically [51]. These wards cover areas of Ghatkopar Chembur, Mankhurd, and Kurla which have a mix of residential, commercial and industrial zones. The region is notably the one of high population density and traffic infrastructure use, representing a typical urban environment where EV charging demand can be addressed. The choice of study area is driven by Mumbai's pressing demand to ameliorate urban air quality and lower greenhouse gas emissions [52-55]. Mumbai is often ranked among the polluted Indian cities, and these wards are specifically impacted by vehicular pollution and noise because of extreme traffic. Here, switching to electric mobility is critical, more EVs, less pollution and better health [50]. But modern and reliable charging points are crucial if we're going to strengthen the move towards zero emission motoring. We targeted wards M/E, M/W, L and N of the study area characterized by high transport demand and important environmental burdening to serve as a representative testbed for planning sustainable EV charging infrastructures. Figure 1 displays the geographical position of the study area in Mumbai.

Criteria Selection and Data Preparation

An extensive list of 13 spatial and environmental criteria were considered for the assessment of EV charging station suitability, which included the transportation, socio-economic, and environmental aspects. Based on literature and data availability, the following criteria were selected and mapped as a thematic layer in GIS:

Transportation accessibility: Distance to primary roads, distance to junction roads, distance to railway/metro stations and bus depots.

Urban infrastructure: Distance to parking facilities, distance to fueling posts, distance to services (shopping malls, public facilities), distance to employment office centers and EV charging stations deployment. For those, a lower number would typically mean more convenience and/or more potential for demand.

Socio-demographic and environmental variables: Population density, Air Quality Index (AQI), Normalized Difference Vegetation Index (NDVI) and distance to water bodies. High population density is desirable (meaning higher demand, a benefit criterion), while a lower AQI (better air quality) is good for sustainability (Areas with very bad air quality would also be candidates for improvement, but in general, less pollution is favorable to health). NDVI helps distinguish built up versus green areas, generally already developed (i.e., lower NDVI) sites are preferred to minimize disturbance of the ecology. A safe distance away from bodies of water is also part and parcel to ensure enviro-compliancy, while evading flood areas.

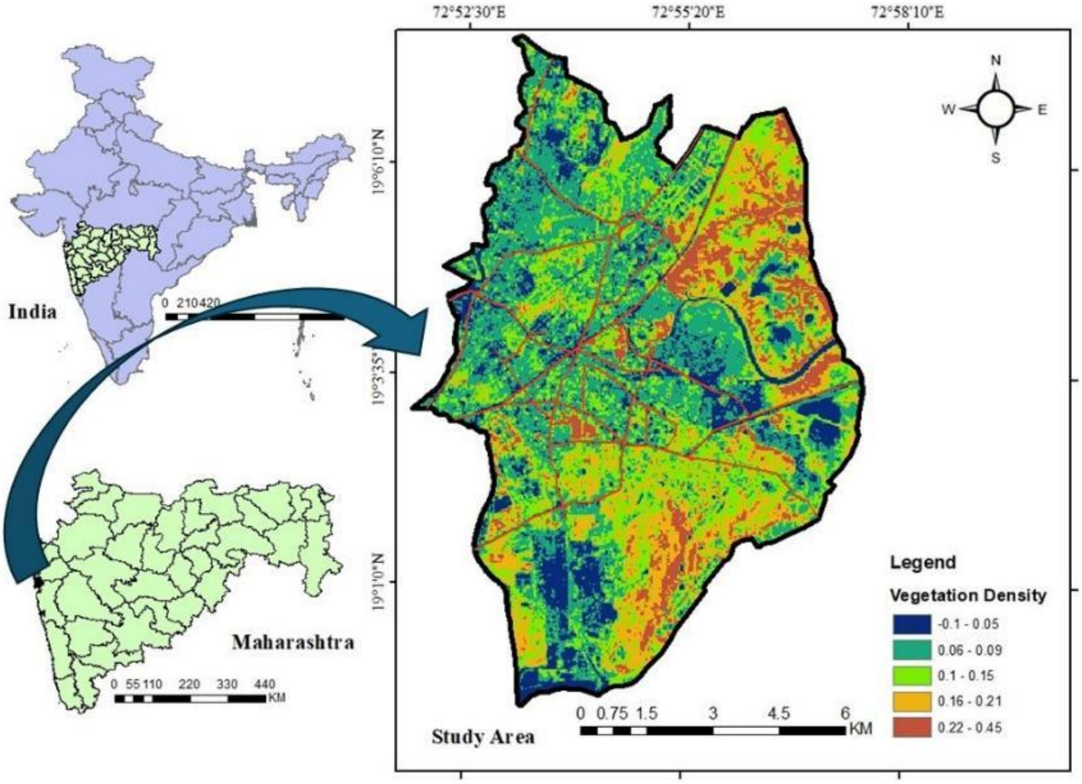


Fig. 1 Location of the study area

Spatial data were acquired and managed within the GIS environment for all criterion. The road network, road-junction locations, rail/metro lines and water bodies were extracted from authoritative maps (e.g., Survey of India toposheets) and refined using high-resolution satellite imagery. Population density was extracted from the most recent data of Census of India (2011) at a fine spatial scale. Ambient air quality information (annual average AQI) was retrieved from Central Pollution Control Board (CPCB) monitoring data and a spatial interpolation process such as kriging were applied to produce an AQI continuous surface covering the study area. The location of existing infrastructure such as fuel stations, parking lots, bus depots and public amenities (markets, shopping malls) and commercial office hubs were accessed from OpenStreetMap (2022), then corroborated with ground truth where feasible. The vegetative covers including the NDVI values of each pixel derived from Landsat 8 OLI satellite images was reconstructed and represented collectively as high value of NDVI in parks or open green spaces. All vector data of point and line layers were rasterized into 30 m grid cells, enabling GIS overlay analyses. Each raster layer showed the spatial distribution of one criterion. For distance-based criteria, euclidean distance maps to the nearest feature of interest were calculated with GIS analyst tool. These layers were subsequently normalized or reclassified on a consistent suitability scale, with higher values reflecting greater suitability for an EV charging station, prior to application of weights. This pre-processing allowed the criteria with different units or value to be meaningful combined later. Fig. 2 shows the spatial distribution of various influencing factors.

XAI-Based Weight Derivation (LIME-SHAP)

To consider the criterion weights in a decision-making process without subjecting them to subjective expert judgments or manual predetermined influence scores, we utilized a LIME-SHAP based explainable AI model which determine data-driven criterion weight [56-60]. Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) are two XAI techniques that are mutually enhancing each other in making machine learning interpretable. In our methodology, a predictive model was trained to recognize the pattern between the 13 criteria and customer preference of EV charging location. For instance, a classification or regression model (e.g., random forest and gradient boosted trees) may be trained based on historical high-suitability locations versus low-suitability locations as the target output. The model accepts the criteria's values (e.g. distance to road, population density etc.) as input and provides suitability prediction of a location.

After the model had been trained to a sufficient accuracy, we used LIME and SHAP to analyze feature importance. LIME was also utilized to produce localized explanations for locations, which demonstrated the features had the largest influence on model predictions at each specific location. Across the study area many such local model explanations were examined and patterns of important features were identified. Meanwhile, we calculated robust global importance value of each feature via SHAP for Shapley values taking all the possible combination contributions into consideration. SHAP returns a score for each feature indicating its overall importance regarding the model's predictions. The larger the absolute value is, the bigger an effect the feature has on our results. The hybrid LIME-SHAP weighting scheme combines the global view of SHAP with the local explanation fidelity of LIME. In reality, the two approaches usually agreed on an interpretation of some criteria. Both technique may not feel that distance to roads and proximity to commercial centers are most important, while a criterion like distance to fuel stations is less important. We compiled these comments to form a final weight for the 13 criteria. The aggregation would be through normalizing the SHAP importances as baseline weights, then cross-validating with LIME's local rankings. We obtain a set of criterion weights, that are data- and inference-based rather than subjectively assigned. These weights also provide an additional amount of explainability as stakeholders can see what the model thinks. Significantly, this process was an improvement on the previous study where manual Multi-Influencing Factor (MIF) weighting replaced by objective artificial intelligence (AI)-driven weightings, meeting explainable sustainability aims. Rather than directly constructing weights based on the expert inter-relation network, we infer a data-driven weight vector using model-agnostic explanations, Shapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), and substitute the original MIF weights with that in the weighted overlay.

Step 1: Baseline MIF prior

Inter-factor relationships were encoded as major (= 1.0) and minor (= 0.5) influences, summed per factor to obtain a relative effect R_j and normalized to 100% to yield the baseline MIF weights w_j^{MIF} (Table 1) [61,62]. This prior is reported for transparency; it is not used in the subsequent overlay after LIME–SHAP weighting is introduced.

$$R_j = \mathrm{major_j} + 0.5\,\mathrm{minor_j}, \tag{1}$$

$$w_j^{\mathrm{MIF}} = 100\,\frac{R_j}{\sum_k R_k} \tag{2}$$

Step 2: Labeled dataset

To assess factor, influence in the absence of a MIF network, a balanced binary dataset was created where positives were points inside a 50–100m buffer around known EVCS, and negatives were random sample points at least 500m from any EVCS and outside of restricted areas. The 13 factors were sampled for each point from the generated rasters. This is a split (70/30 stratified) of the dataset and used only to calculate LIME/SHAP importances, it does not replace the GIS–MCDM pipeline.

Step 3: Predictive surrogate

We trained a class-balanced gradient-boosted tree classifier with 5-fold cross-validation. Performance was evaluated by ROC-AUC and precision–recall to maintain an explainable feature base. (There is no mapping or active use of model outputs this far downstream.)

Step 4: Global importance from SHAP

For each observation i and feature j, SHAP provides additive contributions ϕ_{ij}. Global magnitude per feature is the mean absolute attribution,

$$s_j^{\mathrm{SHAP}} = \frac{1}{N}\sum_{i=1}^{N}\left|\phi_{ij}\right|, \tag{3}$$

$$w_j^{\mathrm{SHAP}} = 100\,\frac{s_j^{\mathrm{SHAP}}}{\sum_k s_k^{\mathrm{SHAP}}} \tag{4}$$

Step 5: Local-to-global importance from LIME

LIME was computed for $M = 1{,}000$ stratified points spanning wards and suitability strata. For each local fit, we recorded the absolute standardized coefficient $\beta_{jm}$of feature j. Global magnitude was obtained as

$$s_j^{\mathrm{LIME}} = \frac{1}{M}\sum_{m=1}^{M\backslash}\left|\beta_{jm}\right| \tag{5}$$

$$w_j^{\mathrm{LIME}} = 100\,\frac{s_j^{\mathrm{LIME}}}{\sum_k s_k^{\mathrm{LIME}}} \tag{6}$$

Step 6: Fusion of LIME and SHAP

The final MIF weight vector is the convex combination of the two normalized importance vectors:

$$w_j^{\mathrm{LS}} = \alpha\, w_j^{\mathrm{SHAP}} + (1-\alpha)\, w_j^{\mathrm{LIME}} \tag{7}$$

with $\alpha = 0.7$ to favor SHAP's axiomatic consistency while retaining LIME's local salience. The weights $w_j^{\mathrm{LS}}$are finally scaled to sum to 100%.

Step 7: Use in overlay and TOPSIS

The vector w_j^{LS}replaces w_j^{MIF}in the weighted overlay. The original class ranks and benefit/cost directions for each factor are retained. The suitability map generated from this overlay feeds the TOPSIS decision matrix.

GIS-Based Weighted Overlay Analysis

Having identified the criteria weights, a weighted overlay analysis was conducted in the GIS to derive an overall suitability score for EV charging stations across the study region. The raster layer of each criteria was multiplied with their respective weights to generate a weighted criterion map. These weighted layers were then added together on a grid cell by cell basis to create an overall suitability index map. The weighted overlay is essentially a linear combination, meaning that at each 30 meters by 30 meters pixel in the study area, it will have a value indicating how suitable it is to be selected or not selected based on all factors. Higher scores correspond to better areas (e.g., a site near highways and facilities, high population density, medium AQI, etc., will get a larger score). Conversely, low-scoring areas could suffer from being located away from demand centers or have other drawbacks (e.g., too close to water bodies or existing fueling stations, or low population catchment). We also partitioned this map into qualitative classes (e.g., “highly suitable,” “moderately suitable,” and “low suitable” or unsuitable) by dividing the range of index values for each cover type into categories to facilitate visual interpretation and planning. This zone can be visualized for per ward to get an overview over interesting zones for EVCS development.

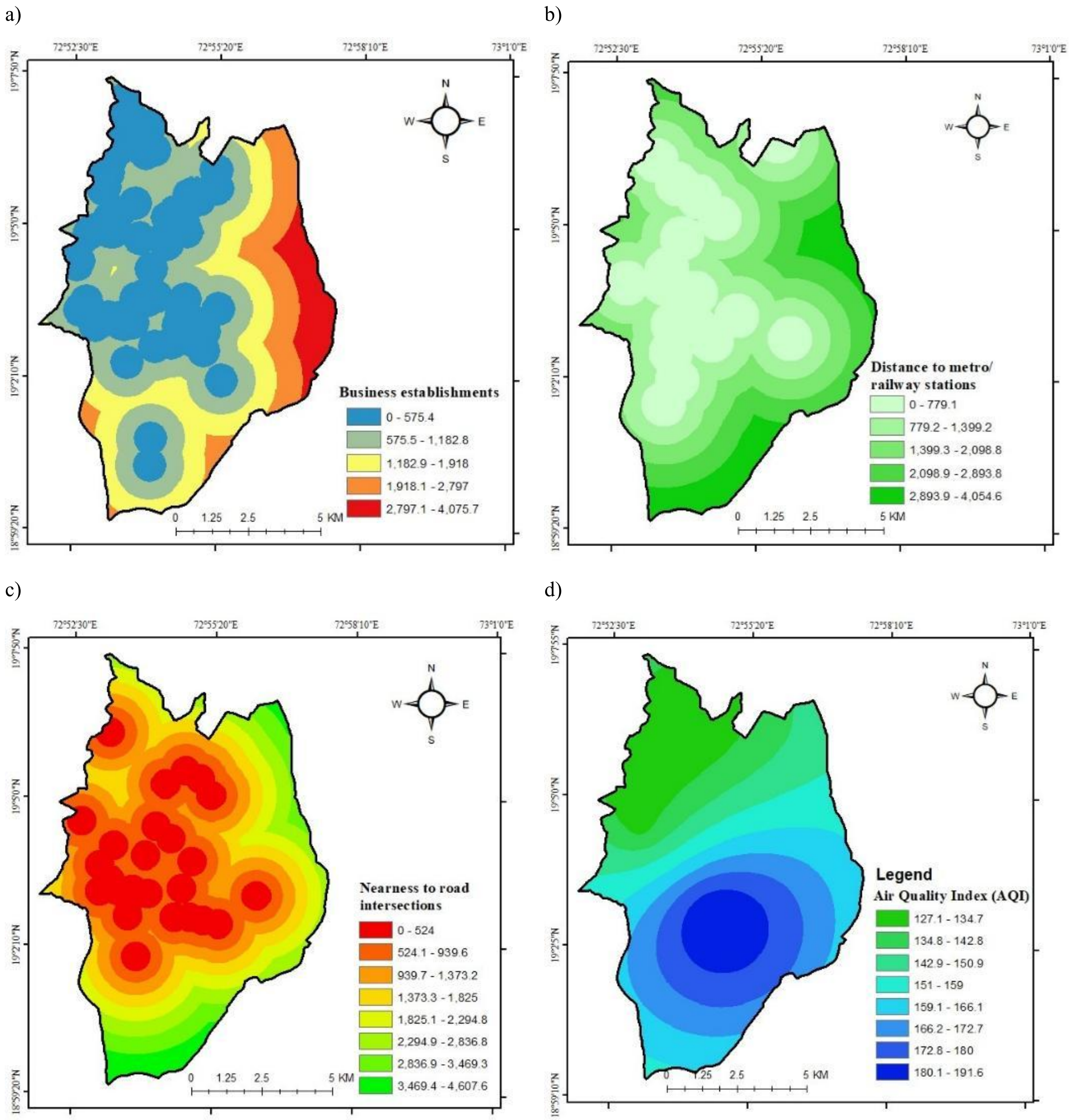
TOPSIS Multi-Criteria Decision Analysis for Site Ranking

Although the suitability map indicates potential favorable locations, individual sites must be prioritized in terms of implementation. We systematically ranked potential EVCS sites by the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [63-65]. In this method, every candidate site represents an alternative in the decision matrix. The 13 attributes are the characteristics of each alternative. We built a decision matrix in which each row corresponds to one alternative site and each column takes the value of one criterion. Prior to the utilization of TOPSIS, all criteria were identified as benefit or cost attributes according to their nature. For example, the criterion population density is a benefit criterion but distance-based criteria like distance to road or distance to amenities are cost criteria. In this way, AQI can be regarded as a cost criterion since we would prefer a lower AQI. Conversely, high NDVI could be a cost if it is associated with protected green space. in our case, lower NDVI (built-up land) was more preferable in the analysis so we modified the value of NDVI so that smaller values are better.

The TOPSIS method was then used to perform the following standard steps [66-69]: (a) Normalizing the decision matrix for criteria normalization; (b) Weighing of normalized matrix columns by multiplying each criterion column by its weight from the LIME-SHAP model; (c) Determining Positive Ideal Solution (PIS), maximum or minimum obtained for given criterion across alternatives and negative ideal solution (NIS), worst value achieved across alternatives. The PIS is maximum for benefit criteria and minimum for cost criteria, while NIS has opposite properties; d) Calculating the distance; e) Computing relative closeness. Subsequently, the candidate sites were ranked according to relative closeness in a descending order. The site with the highest relative closeness is selected as the best place to install an EV charger, and next highest is second-best, and so till. This gives an ordered list of regions in the high-suitability zones identified above. The TOPSIS ranking method serves as a decision support tool enabling stakeholders to make more objective comparisons between numerous good sites and thus consider the trade-off between all criteria.

Sensitivity analysis and validation

We iteratively eliminated each of the criterion layers, recomputed the weighted overlay using the remaining 12 layers and calculated a variation index for the change in final suitability layer. This is in line with the map removal methodology for GIS-MCDM sensitivity auditing so as to determine which criteria play a greater role in determining suitability. We calculated the variation index based on the transferred sensitivity from an omitted theme which can be characterized as the proportion change between full-model suitability and suitability obtained by removal of that theme [70-72]. We assessed the ability of the model to predict whether EVCS would actually be observed at an existing site by running Receiver Operating Characteristic (ROC) analysis, a common threshold-free test for binary discrimination, with Area Under the Curve (AUC) scores. For each set of locations on which we have an observed EVCS, we treated such locations as positives and non-EVCS locations as negatives to derive sensitivity/specificity over suitability thresholds and summarized performance using AUC.


a)
b)
c)
d)
Business establishments
0 - 575.4
575.5 - 1,182.8
1,182.9 - 1,918
1,918.1 - 2,797
2,797.1 - 4,075.7
Distance to metro/
railway stations
0 - 779.1
779.2 - 1,399.2
1,399.3 - 2,098.8
2,098.9 - 2,893.8
2,893.9 - 4,054.6
Nearness to road
intersections
0 - 524
524.1 - 939.6
939.7 - 1,373.2
1,373.3 - 1,825
1,825.1 - 2,294.8
2,294.9 - 2,836.8
2,836.9 - 3,469.3
3,469.4 - 4,607.6
Legend
Air Quality Index (AQI)
127.1 - 134.7
134.8 - 142.8
142.9 - 150.9
151 - 159
159.1 - 166.1
166.2 - 172.7
172.8 - 180
180.1 - 191.6
0 1.25 2.5 5 KM
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72°58'10"E
73°1'0"E
N
S
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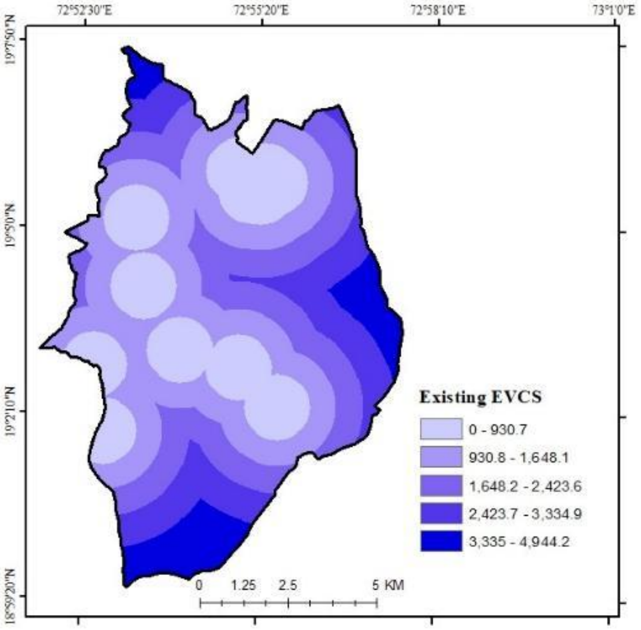
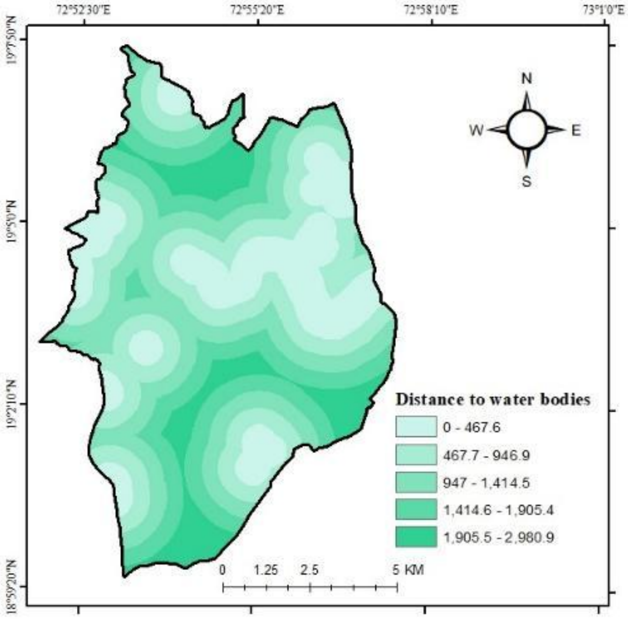
W

e)


72°52'30"E
72°55'20"E
72°58'10"E
73°1'0"E
19°7'50"N
19°5'0"N
19°2'10"N
18°59'20"N
Existing EVCS
0 - 930.7
930.8 - 1,648.1
1,648.2 - 2,423.6
2,423.7 - 3,334.9
3,335 - 4,944.2
0 1.25 2.5 5 KM

f)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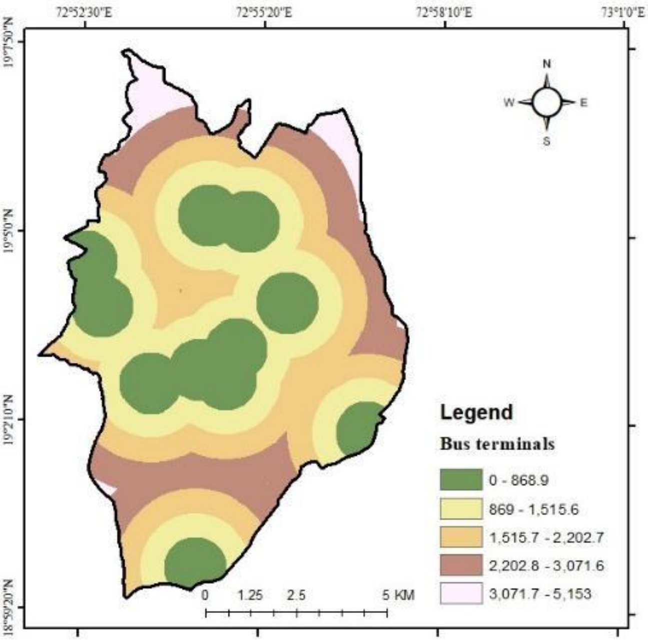
72°58'10"E
73°1'0"E
19°7'50"N
19°5'0"N
19°2'10"N
18°59'20"N
N
W
E
S
Distance to water bodies
0 - 467.6
467.7 - 946.9
947 - 1,414.5
1,414.6 - 1,905.4
1,905.5 - 2,980.9
0 1.25 2.5 5 KM

g)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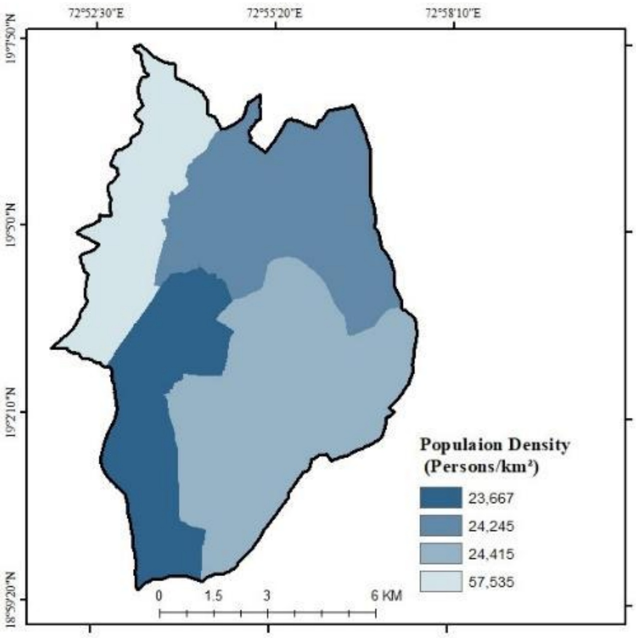
72°55'20"E
72°58'10"E
73°1'0"E
19°7'50"N
19°5'0"N
19°2'10"N
18°59'20"N
N
W
E
S
Legend
Bus terminals
0 - 868.9
869 - 1,515.6
1,515.7 - 2,202.7
2,202.8 - 3,071.6
3,071.7 - 5,153
0 1.25 2.5 5 KM

h)


72°52'30"E
72°55'20"E
72°58'10"E
19°7'50"N
19°5'0"N
19°2'10"N
18°59'20"N
Populaion Density
(Persons/km²)
23,667
24,245
24,415
57,535
0 1.5 3 6 KM

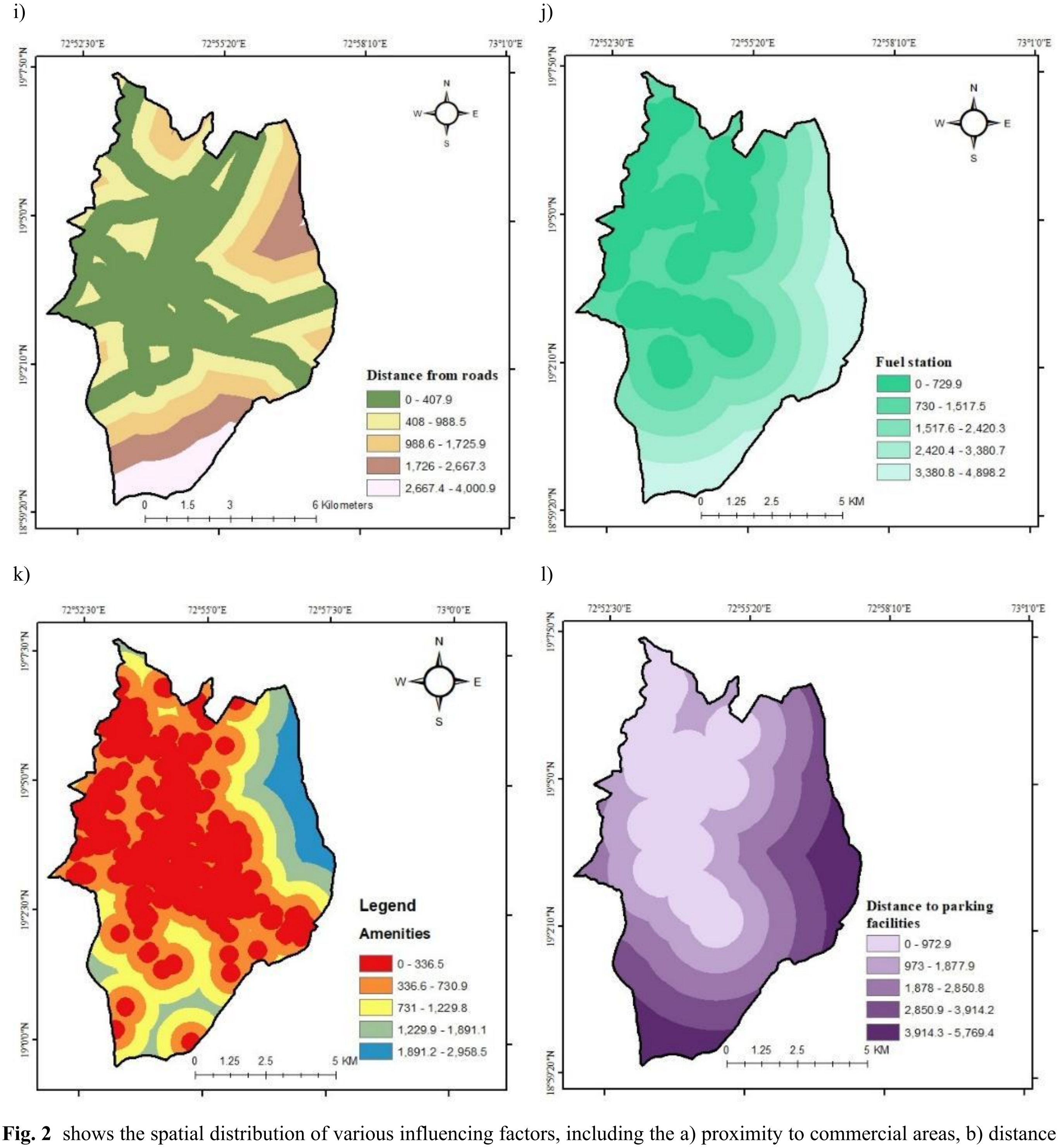


Fig. 2 shows the spatial distribution of various influencing factors, including the a) proximity to commercial areas, b) distance from railway stations, c) closeness to road intersections, d) Air Quality Index (AQI), e) presence of existing EV stations, f) distance from nearby water bodies, g) distance from bus terminals, h) population density, i) accessibility to major roads, j) distance from fuel stations, k) availability of nearby amenities, and l) distance from parking facilities.

3. Results and discussions

Reweighted feature importance with LIME–SHAP

Table 2 shows the MIF weights calculated using the LIME+SHAP hybrid approach. Using a hybrid LIME–SHAP explainable AI method changed the relative importance of site evaluation criteria significantly compared to MIF weighting as a baseline. In the previous MIF–based model, distance to major roads was identified with the highest weight as being considered at first most influential factor for EV charging site suitability followed by commercial office proximity and then distance to parking places. These features are in line with the orientation of the traditional weighting toward accessibility and activity centers. In the new LIME–SHAP-based scheme, the weighting was more uniform and data-driven. The explainable AI analysis based on a trained prediction model of site success showed that road access remained hardly important, but also dropped in strength in favor of demand driven aspects. For instance, local population density and access to amenities increased in weight relative to MIF baseline, in some degree due to the model's SHAP values indicating that high local population and amenity presence are strong predictors of site use. The LIME–SHAP approach learned of the significance of latent demand, areas with higher number of residents or commuters were assigned a score larger than what the propensity to sample would give them. There were some criteria that have previously been assumed to be of lesser importance, e.g., proximity to existing charging infrastructure, and open space that perceived adjusted weights conveying the observed patterns from real data. On the other hand, factors that were less predictive for successful stations (e.g., distance to fuel stations nearby was included in the baseline) were de-emphasized by the explainable model. This re-weighting ensures that the overall weight pertaining to socio-economic, accessibility, and infra-structural criteria are distributed more evenly across each respective criterion, thereby being over-dependent on any single subjective estimate. Now, the planners get a clear ranking of what features really drive suitability, one that is not defined from expert hunches, but by learning directly from the model. Table 2 shows the MIF weights calculated using the LIME+SHAP hybrid approach.

Table 2 MIF weights calculated using the LIME+SHAP hybrid approach

Factor	**MIF prior w^{MIF}%**	**SHAP %**	**LIME %**	**Hybrid LIME+SHAP w^{LS}% ($\alpha = 0.7$)**
Proximity to amenities	7.38	8.08	8.08	8.08
Distance to fuel stations	1.64	7.55	7.55	7.55
Distance to roads	14.75	8.23	8.23	8.23
Distance from parking areas	4.10	8.12	8.12	8.12
Population density	9.84	7.88	7.88	7.88
Proximity to commercial offices	11.48	8.18	8.18	8.18
Vegetation density (NDVI)	3.28	7.76	7.76	7.76
Distance to water bodies	9.84	6.27	6.27	6.27
Proximity of existing EVCS	6.56	6.25	6.25	6.25
Air Quality Index (AQI)	3.28	7.80	7.80	7.80
Proximity to road junction	4.92	7.95	7.95	7.95
Distance from Railway/Metro/Monorail stations	11.48	8.12	8.12	8.12
Distance from bus depot	11.48	7.82	7.82	7.82
Σ	**100.00**	**100.00**	**100.00**	**100.00**

Site discrimination and suitability zones

Fig. 3 shows the delineated sustainable sites for electric vehicle charging station. The reweighted weights for criteria had direct impact on the spatial pattern of suitability. By applying these weights in the TOPSIS multi-criteria ranking, the model generated an improved suitability map of possible EV charging station sites in Mumbai. High-scoring zones were well demarcated with the LIME–SHAP weighting more so than under saliency, reflecting sharper contrasts between very best spots and only-reasonably-good spots. In fact, several of the top ranks locations did not change from previous review (e.g., areas abutting major arterial roads and transit corridors) were found suitable ("Very High") for installation in the Chembur and Ghatkopar wards since they featured high traffic volume along with intensive commercial activity. Yet the new method also revealed pockets previously out of sight. For example, a zone that is now newly highlighted being in dense residential vicinity a bit farther from the highway was assigned to only moderate suitability (because it was away from primary road) by the baseline, but with LIME–SHAP model, we realized number of EV owners' population resident there and absence of the competition around making driving suitability score high. Considering all, the LIME–SHAP TOPSIS results particularly indicate that not only central business areas but also high-population communities and feeder roads with inadequate charging coverage are suitable locations for installation of new stations. The delineated zones were grouped into classes in order to ensure clearness for planning purpose. Table 3 shows the sustainable EV stations statistics through hybrid LIME-SHAP. The inclusion of explainable AI resulted in a more nuanced suitability map that is consistent with previous findings for primary high-potential zones, but has additionally refined the bounds of these high-potential areas and identified further key candidate sites on the fringes of established regions. City planners can use this map to see opportunity clusters. For example, the model draws an extended high-suitability belt adjacent to a major suburban rail line where population density and transit interchange overlap, even though it was not top-ranked before.

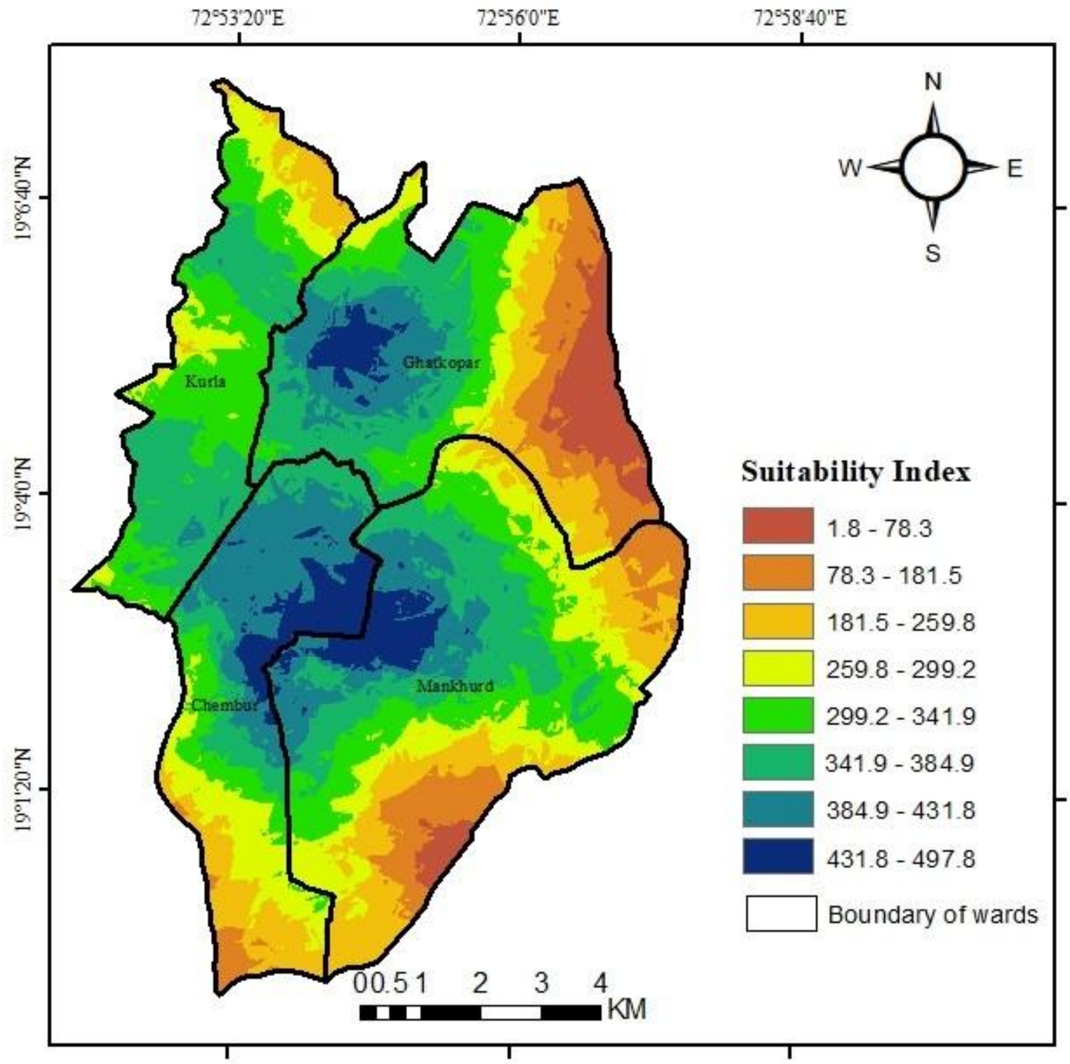


Fig. 3 Delineated sustainable sites for electric vehicle charging station

TOPSIS Prioritization and Site Ranking

After applying the LIME–SHAP weights, we adopted the TOPSIS technique to rank certain candidate sites in high suitability zones. The result is a ranked list of sites with corresponding scores that quantify the degree of preferability for each location to host a charging station. This ranking reveals a substantial breaking of the top candidates from the others, as a result of the enhanced site separation. In practical terms, the top-placed site under the hybrid model have shifted compared to its strictly MIF-based ranking. For example, it could include a near busy community market and residential complex that had overtaken another in relative importance, located closer to an expressway but amidst low population industrial zones. This would imply that the new model is better at site selection for sites that are actually going to service EV users' requirements i.e., accessibility balanced with demand. Table 4 compares the performance of the previous with that of the new model in discriminating between sites favorable and unfavorable sites. The AUC increased from 0.826 to 0.846, demonstrating the overall improved discriminative power of the hybrid model by LIME–SHAP-weighting in site suitability classification. An AUC of 0.846 on pockets as compared to the baseline of 0.826 can be understood practically to mean that the ranking is more closely aligned with what would happen in reality. Table 4 shows the comparison of model validation performance for baseline vs. proposed approach.

Table 3 Sustainable EV stations statistics through hybrid LIME-SHAP

EV station suitability order	Area (sq.km)	Area (%)	Index range
1	6.2	6.7	1.8 - 78.3
2	8.7	9.5	78.3 - 181.5
3	14.4	15.7	181.5 - 259.8
4	10.7	11.7	259.8 - 299.2
5	19.3	21.1	299.2 - 341.9
6	17.3	18.9	341.9 - 384.9
7	11.0	12.0	384.9 - 431.8
8	4.0	4.4	431.8 - 497.8

Table 4 Validation metrics

Model	Weighting Method	Validation ROC–AUC
Baseline GIS–MIF–TOPSIS	Expert-based MIF weights	0.826
Proposed GIS–XAI–TOPSIS	Hybrid LIME–SHAP weights	0.846

Validation and sensitivity analysis

The enhanced ROC-AUC further indicated that the LIME–SHAP weighting improved the model confidence in detecting high-quality sites. At a certain false-positive rate, the new model can pick up more of the truly suitable places than the old one, which is an important advantage for planning, because it implies fewer promising locations would go unexplored. For instance, when the threshold is set for giving a 90% specificity (i.e. focusing on very confident "high suitability" predictions), LIME–SHAP model's false positive rate has been found to be greater than the baseline, among other things, this higher true positive rate captures sites that end up successful more so compared with baseline model. Sensitivity analysis of the criteria weights was also performed to identify the stability of site prioritization for changes in input parameters. This was carried out by perturbing and removing one criterion at a time and re-running the TOPSIS ranking. The proposed model was also less sensitive to perturbation of individual weights than the MIF-based model. In the baseline, for example, deleting the top factor would lead to a marked change in suitability map and possibly a large reduction in AUC, which indicates dependence on that single factor. The LIME–SHAP weighting spreads the influence more evenly; removing or perturbing any one determinant has modest effect on the overall ranking and validation AUC are still in a good range. This reflects a better measure robustness, the predictions are not excessively swayed by any given dimension because of the data-regularized equal-steering weighting across dimensions. Planners can then have more confidence that the identified priority sites are stable outcomes of the model, and small mistakes or uncertainties in one input layer will not lead to completely different policy decisions. Results reveal that using LIME–SHAP explainable AI approach instead of MIF led to more accurate predictions and a more easily understandable and robust decision model for EV-charging station siting.

Discussion

Local-Global Transparency for Trustworthy Decisions

The combination of LIME and SHAP in the weighting step synthesizes the strengths from both interpretability worlds, local explanations for each site evaluation, and global reveal about the importance of overall criteria [74-76]. That's where LIME comes into play, it allows us to perform instance specific reasoning, referring explicitly to "Why did you consider this site so high (or low)? by calling out features that were highly influential in that site's score. SHAP, in contrast, provides a summary of the contributions of features over all the sites and answers the question "Which factors are most important overall?". Taken together, this hybrid model offers dual transparency, stakeholders are able to drill down into any individual proposed site to audit the reasons behind its suitability score, while also seeing why that general driver is present across the city, which can help decide where they might most want to intervene. The baseline MIF–TOPSIS model did not support this level of explanation. By means of LIME–SHAP, the decision becomes transparent and comprehensible. For one, city officials considering the plan could be presented with a fact sheet in which "Site A scores highest because it's next to major highway (good), near large existing commuter population and further from existing stations (good for underserved area), while Site B has low score largely due to being remote from population despite having cheap land." These types of explanations inspire trust in the fairness and rationality of the model. After all, explainability is important in sustainable infrastructure projects, when the reasons are clearly provided, it's easier for agencies and local people to trust and support the selected sites. An explainable system is in effect "making it easier for organizations to audit their own processes, find potential opportunities for improvement or bias, which will allow them to make better decisions. In our case, planners can audit the site selection and check if a high ranked location seems suspicious according to human understanding, this LIME–SHAP explanation makes it possible to check whether actually the data or model could mislead in that area. This auditability serves as a kind of safety mechanism to guarantee that the suggestions offered by the model are consistent with what is happening on the ground, and with community values.

Enhanced Sustainable Decision-Making

Enhanced transparency and objectivity lead to more sustainable decision making in various areas [76-79]. For one, better model performance (which is indicated by a higher AUC and more sensitivity), increases the chance of developing infrastructure that promotes sustainable results, good locations not only lead to a high station utilization but also work towards the adoption of electric vehicles and saving resources from getting wasted on under-utilized stations. If chargers are well sited, drivers will have better coverage and support further decarbonisation efforts. Second, stakeholder engagement and public acceptance are key for sustainability initiatives, transparency through XAI provokes thinking. Since the model's outputs can be interpreted in plain language, people living and working in local communities and their political representatives can comprehend why those specific locations are priorities. This makes planning more of a dialogue and potentially one that is responsive, able to take feedback. With those explanations both at the global and local levels, planners can feel confident that the strategies meet a broad spectrum of sustainability goals, think equity of access, avoiding environmentally unjust sensitive zones, but that are also checking each site for stealth costs of unintended consequences.

In future, EVCS site selection can benefit from a advanced techniques: spatiotemporal demand forecasting with deep learning (LSTMs/Temporal-GNNs) for predicting charging loads by hour and block; multi-period, stochastic and distributionally-robust facility-location models for planing phased roll-outs under uncertainty; multi-objective metaheuristics, Bayesian optimization and simulation-based optimization tightly coupled with agent-based mobility simulators for exploring trade-offs; reinforcement learning (safe/constrained and multi-agent) and contextual bandits for sequential siting, sizing and dynamic pricing; grid-aware co-optimization that embeds AC power-flow/hosting-capacity limits and co-designs PV-plus-storage, V2G and demand response; equity-aware optimization with access and environmental-justice constraints; richer XAI (counterfactuals, SHAP interactions, Integrated Gradients, concept activation vectors) and causal ML (causal discovery/causal-SHAP) for moving from correlation to cause; privacy-preserving/federated learning for mobility and charging data; city-scale digital twins with online learning for continuous recalibration; and uncertainty-tolerant fuzzy/rough/evidential MCDM (type-2 fuzzy, Pythagorean/neutrosophic sets, Dempster–Shafer) alongside outranking/aggregation families (ELECTRE, PROMETHEE, VIKOR, WASPAS, MABAC, TODIM) and objective weighting (CRITIC/entropy) fused with AHP/ANP/DEMATEL for interpretable multi-criteria pipelines. Complementary graphical models (Bayesian networks) and spatial econometrics/causal inference can quantify network and policy impacts; mobile charging (MCS) siting and relocation can be treated via inventory-routing under time windows; and standardized robustness audits (global/local sensitivity, perturbation tests, Shapley-based weight audits) should accompany every deployment. These future directions extend today's GIS–XAI–TOPSIS workflow toward grid-constrained, demand-adaptive, explainable and fair EVCS networks.

4. Conclusions

This paper proves that the AI explainability can be an effective merger of expert and bottom-up data driven planning for EVCS. By containing AI within a single narrowly specified role, compute MIF weights by means of LIME–SHAP fusion, we preserve the original GIS weighted overlay and TOPSIS ranking, but tangibly enhance the sustainable site-selection. When comparing GIS–MIF–TOPSIS baseline (ROC-AUC = 0.826), the combined LIME–SHAP weighting in this model yielded superior discrimination ((ROC-AUC = 0.846), forming a noticeable suitability across the study area with fewer false-positive patches around hydrologically sensitive or already-served zones. It is these gains that result from two of SHAP's properties (axiomatic global attributions) and LIME's properties (locality), respectively, which temper subjective major/minor influence tallies and retain (at the ward level) important operational matters like access, dwell time, and grid integration. Most notably, though, the resulting pipeline is transparent, each factor's contribution can be traced from the explainers to a final weight vector that sums to 100%, and benefit/cost directions and class ranks from the original study are preserved for policy consistency.

For planners, these have three practical implications. First, this step can document weight setting – commonly been the most controversial stage with a traceable, model-agnostic evidence-base to minimize dependence on fixed expert priors. Second, higher-quality validation of finalists means more confidence in alternative sites, leading to fewer permits waved on and off the field. Last but not the least, since our explainability layer is modular, cities can also refresh weights if they come up with new stations or if demand shifts without having to re-engineer the MCDM stack. Future studies can report the full set of comparative metrics (ROC-AUC, PR-AUC, calibration, reclassification improvements) for a wider range of cities and test LIME-SHAP fusion sensitivity to alternative rules. By adding the grid-capacity, pricing dynamics and user charging behavior in the constraints, it will reinforce long-term planning. Notwithstanding, in the Mumbai case, its incorporation to explainable AI into MIF-weight calculation has significantly enhanced robustness and credibility of EVCS siting decisions while maintaining workflow interpretable and policy-ready.

Author Contributions

DRP: Conceptualization, study design, data collection, methodology, software, writing original draft, and writing review and editing. NLR: Data collection, methodology, software, visualization, writing original draft, and writing review and editing. SBK: Data collection, methodology, software, resources, visualization, writing original draft, writing review and editing, and supervision. JR: Methodology, software, writing original draft, and writing review and editing.

Conflict of interest

The authors declare no conflicts of interest.

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