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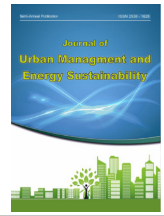

CASE STUDY RESEARCH PAPER

Assessing the Influence of Climate on a Framework for Urban Neighborhood Site Selection under a Sustainable-Development Approach Using Artificial Neural Networks and Exploratory Factor Analysis (Case Study: Tehran City, Iran)

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ABSTRACT

Site selection for urban neighborhoods is a multi-criterion, spatially explicit problem that becomes markedly more sensitive under a changing climate, where urban heat island intensity and outdoor thermal comfort strongly condition livability and sustainability. This study develops and demonstrates an integrated framework that couples Geographic Information Systems, exploratory factor analysis and artificial neural networks to assess how climatic factors with an emphasis on UHI and thermal comfort shape a sustainable-development-oriented framework for neighborhood site selection. A pool of climatic, environmental, social, economic and physical–access indicators are assembled from GIS layers at the neighborhood scale. EFA reduces the correlated indicators to a small set of interpretable latent factors. The factor scores then serve as inputs to a multilayer-perceptron ANN trained to predict a neighborhood sustainability suitability index, which is validated with R^2, RMSE and MAE and interrogated with a sensitivity analysis. In the demonstrative case, EFA retained four factors, climate & thermal, access & mobility, socio-economic, and physical form explaining a large share of the variance, with the climate & thermal factor. The ANN reproduced the reference suitability index with high accuracy on the held-out set, and the sensitivity analysis ranked UHI-related variables as the most influential. Neighborhoods were classified into five suitability tiers. All of these values are synthetic and illustrate the framework's behavior. Coupling EFA with ANN inside a GIS pipeline provides a transparent, reproducible and transferable framework for climate-sensitive, sustainability-oriented neighborhood site selection, and foregrounds UHI mitigation as a first-order siting criterion. The framework is ready to be populated with empirical Tehran data to produce validated, city-specific results.

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INTRODUCTION

The location of new urban neighborhoods and the intensification or renewal of existing ones are among the most consequential decisions in urban planning, because they lock in patterns of land use, mobility, energy demand and exposure to environmental hazards for decades. As cities in arid and semi-arid regions grow rapidly, these decisions are increasingly conditioned by climate: rising air temperatures, the intensification of the urban heat island (UHI) effect and the deterioration of outdoor thermal comfort directly affect public health, energy consumption and the overall livability of neighborhoods (Wu, 2010). Understanding how climatic factors should enter a site-selection framework, and quantifying their weight relative to social, economic and physical criteria, is therefore central to sustainable urban development. The UHI effect the tendency of built-up areas to be warmer than their surroundings is driven by the replacement of vegetation with impervious surfaces, the geometry of the urban canopy and anthropogenic heat, and it is strongly modulated by land surface temperature (LST), green cover and sky view factor (Bonafoni & Keeratikasikorn, 2018) (Estoque & Murayama, 2016). In metropolitan Tehran, remote-sensing studies have repeatedly documented pronounced surface UHI patterns and their coupling with land use, vegetation and air pollution (Zargari et al., 2024) (Aghazadeh et al., 2023), and have shown that urban green-space scenarios can measurably lower heat and improve thermal comfort (Arghavani et al., 2020). Rapid urban expansion in Tehran has simultaneously eroded green space, amplifying heat exposure (Sharifi & Hosseingholizadeh, 2019) (Pilehvar, 2021). These findings motivate treating climate and UHI in particular as a first-order criterion in neighborhood site selection rather than as an afterthought. Traditional site-selection frameworks rely on multi-criteria decision analysis (MCDA), most commonly the analytic hierarchy process (AHP) and fuzzy variants, integrated within GIS (Asakereh et al., 2017) (Du & Wang, 2018) (Ajibade et al., 2019). Such methods are transparent and expert-driven, and they have been applied to residential zoning and sustainable land-use planning, including in Iran (Aghmashhadi et al., 2022) (Tashayo et al., 2020) (Sun et al., 2021). However, they assume that criteria combine in fixed, mostly linear ways and that expert-assigned weights capture the true structure of the problem. In reality, the relationships between climatic, environmental and socio-economic variables and neighborhood suitability are non-linear and interacting, and the criteria themselves are highly correlated.

Two complementary techniques address these limitations. Exploratory factor analysis (EFA) reduces a large, correlated set of indicators to a small number of interpretable latent factors, removing redundancy and revealing the underlying structure of the data (Alavi et al., 2020); it has a long track record in urban livability and quality-of-life assessment (Salarimoghadam et al., 2019) (Shabanzadeh-Namini et al., 2019). Artificial neural networks (ANN), in turn, learn non-linear, interacting relationships directly from data and have proven effective for land-suitability and land-surface-temperature modelling (Nie, 2024) (Tanoori et al., 2024). Coupling the two EFA to structure the inputs and ANN to model the mapping offers a powerful, data-driven alternative to purely weight-based MCDA. Despite growing interest in AI–GIS integration for urban planning, three gaps remain. First, few frameworks place climate, and specifically UHI and thermal comfort, at the center of neighborhood site selection rather than treating it as one environmental layer among many (He et al., 2023). Second, the combination of dimensionality reduction (EFA) with non-linear learning (ANN) inside a reproducible GIS pipeline is rarely made explicit and transferable. Third, most applications report a single case without clearly separating the transferable framework from the case-specific data. This paper addresses these gaps by presenting a clearly specified GIS–EFA–ANN framework, foregrounding UHI, and demonstrating it on Tehran neighborhoods with a transparent, clearly-labelled dataset that can later be replaced with empirical data. Accordingly, the study pursues three objectives: (1) to specify a climate-sensitive, sustainability-oriented set of neighborhood site-selection criteria in which UHI and thermal comfort are first-order factors; (2) to formulate an integrated GIS–EFA–ANN methodology that reduces correlated indicators to interpretable factors and learns their non-linear relationship with a neighborhood suitability index; and (3) to demonstrate the framework's outputs factor structure, model performance, variable importance and suitability classification and to discuss its implications for climate-responsive urban planning in Tehran and comparable metropolises.

MATERIALS AND METHODS

Climate, the urban heat island and neighborhood livability

A large body of remote-sensing research links land surface temperature to land use and land cover, showing that impervious surfaces raise, and vegetation lowers, surface temperature (Bonafoni & Keeratikasikorn, 2018) (Dang & Kim, 2023). The UHI response scales with the density and configuration of built-up land (Estoque & Murayama, 2016), and heat exposure is a documented driver of health risk that interacts with land-use change (Avashia et al., 2021). Nature-based interventions tree canopy, green roofs and terrace gardens, and the strategic distribution of green space are widely evidenced as effective heat-mitigation and thermal-comfort strategies (Al-Saadi et al., 2020) (Visvanathan et al., 2024) (He et al., 2021). For Tehran specifically, studies confirm strong day–night surface UHI dynamics coupled to land use, NDVI and air pollution (Zargari et al., 2024) (Aghazadeh et al., 2023), and numerical work shows that green-space scenarios can lower heat and improve comfort at the metropolitan scale (Arghavani et al., 2020). These results justify elevating climatic–thermal variables to primary criteria in neighborhood siting.

GIS and multi-criteria approach to site selection

GIS-based MCDA is the dominant paradigm for spatial site selection. AHP and fuzzy-AHP have been used for a range of siting problems, from solar farms to landfills and land-use suitability, frequently in Iranian contexts (Asakereh et al., 2017) (Tashayo et al., 2020) (Du & Wang, 2018). Analytic-network and multi-objective variants extend the approach to residential zoning and sustainable land-use planning (Aghmashhadi et al., 2022) (Sun et al., 2021) (Ajibade et al., 2019). These methods are valued for transparency and stakeholder involvement, but they depend on expert-assigned weights and largely linear aggregation, and they struggle with the strong correlations and non-linear interactions typical of urban indicator sets.

Factor analysis and neural networks in urban assessment

To handle correlated indicators, exploratory factor analysis and principal-component methods are widely used to construct composite urban indices and to structure liveability and quality-of-life assessments (Alavi et al., 2020) (Kashef, 2016) (Leach et al., 2017) (Liu et al., 2017), including neighbourhood-scale studies of Tehran (Salarimoghadam et al., 2019) (Shabanzadeh-Namini et al., 2019) (Safdari Molan et al., 2019). In parallel, machine-learning and ANN models increasingly complement or outperform linear approaches in land-suitability assessment and in predicting land surface temperature and UHI intensity (Nie, 2024) (Tanoori et al., 2024) (Pallathadka et al., 2023) (Awad & Jung, 2022). Yet the explicit coupling of EFA (to obtain parsimonious, interpretable inputs) with ANN (to learn the non-linear mapping to suitability), embedded in a reproducible GIS workflow and centred on climate, remains under-developed the gap this paper targets.

Conceptual Framework: Climate-Sensitive, Sustainability-Oriented Siting

The framework rests on three premises. First, neighborhood suitability for sustainable development is a latent construct that cannot be observed directly but is reflected in many correlated indicators spanning environmental, social, economic and physical dimensions. Second, climate and UHI in particular is not merely one environmental indicator but a cross-cutting determinant that conditions health, energy use and outdoor activity, and therefore deserves first-order status. Third, the mapping from indicators to suitability is non-linear and interactive, so a learning model is preferable to fixed linear weighting (He et al., 2023). Consistent with these premises, the sustainability dimensions are operationalized as five indicator groups: (i) a climatic–thermal group (land surface temperature as a UHI proxy, green cover/NDVI, sky view factor, impervious-surface fraction, air-quality exposure); (ii) an environmental group (distance to green space, slope/topography); (iii) a social group (population density, access to services); (iv) an economic group (land value, land-use mix); and (v) a physical–access group (transit access, road density). The climatic–thermal group is deliberately the richest, reflecting the UHI emphasis. Table 1 lists the indicators, their role and their typical GIS data sources. (Tab. 1)

Table 1: Site-selection indicators, sustainability dimension and typical GIS data sources

Dimension	Indicator	Rationale (sustainability / climate)	Typical data source
Climatic–thermal	Land surface temperature (LST)	Primary UHI proxy; higher LST lowers suitability	Landsat 8/9 TIRS; MODIS
	Green cover (NDVI)	Cooling, comfort, ecological quality	Sentinel-2 / Landsat
	Sky view factor	Canopy geometry; night-time heat release	DSM / LiDAR
	Impervious-surface fraction	Heat storage; runoff	NDBI / classification
	Air-quality exposure	Health co-benefit of siting	Monitoring / dispersion models
Environmental	Distance to green space	Access to cooling & recreation	Green-space layer / network analysis
	Slope / topography	Constructability; ventilation	DEM
Social	Population density	Demand; exposure of residents	Census / statistical center
	Access to services	15-minute-city equity	POI / network analysis
Economic	Land value	Feasibility; equity	Municipal / market data
	Land-use mix	Vibrancy; trip reduction	Land-use map (entropy index)
Physical–access	Transit access (metro/BRT)	Low-carbon mobility	Transit network
	Road density	Connectivity	Street network

Methodology

Research design and transparency

The study is methodological in purpose: its primary contribution is a reproducible framework rather than an empirical claim about Tehran. To keep this distinction explicit, every quantitative result in Section 5 is generated from a synthetic dataset built to mimic plausible neighborhood indicator distributions. The framework, criteria, factor-analysis procedure and ANN configuration are fully specified so that, once empirical GIS layers are available, the identical pipeline produces validated, city-specific results. Figure 1 summarizes the workflow. (Fig. 1)

Case study

Tehran, the capital of Iran and a metropolis of roughly nine million residents, is selected as the demonstrative context because it exhibits pronounced surface UHI patterns, rapid loss of green space and marked socio-economic gradients across its neighborhoods (Zargari et al., 2024) (Sharifi & Hosseingholizadeh, 2019). For the demonstration, a set of 34 neighborhoods is used. (Fig. 2)

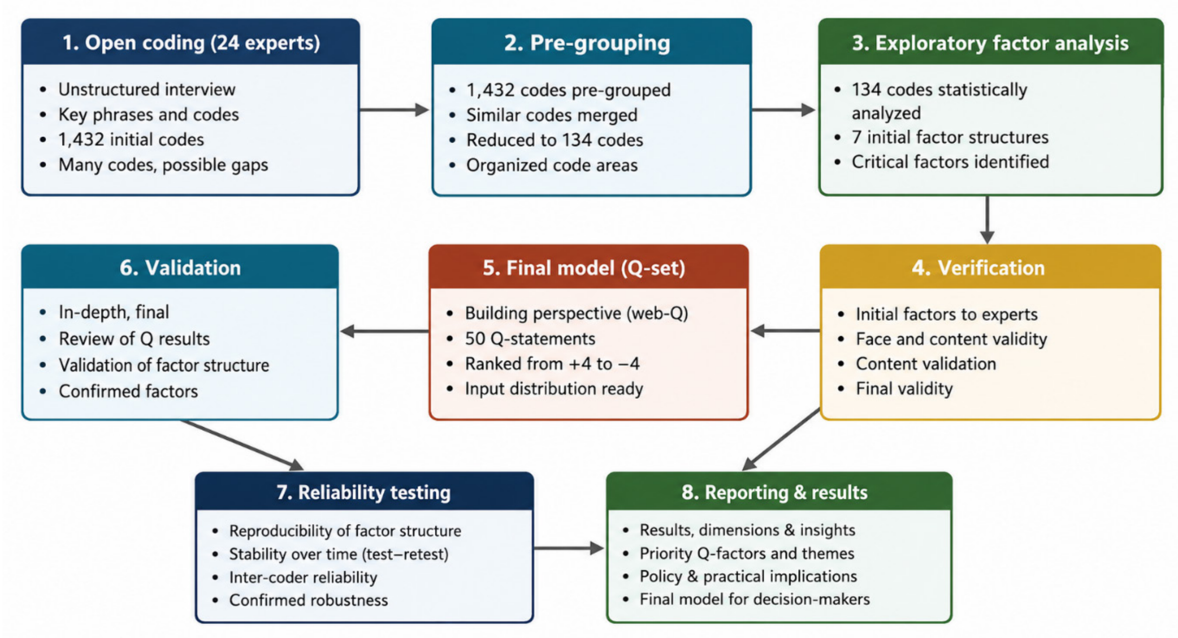

Figure 1: GIS–factor-analysis–ANN workflow for climate-sensitive neighborhood site selection

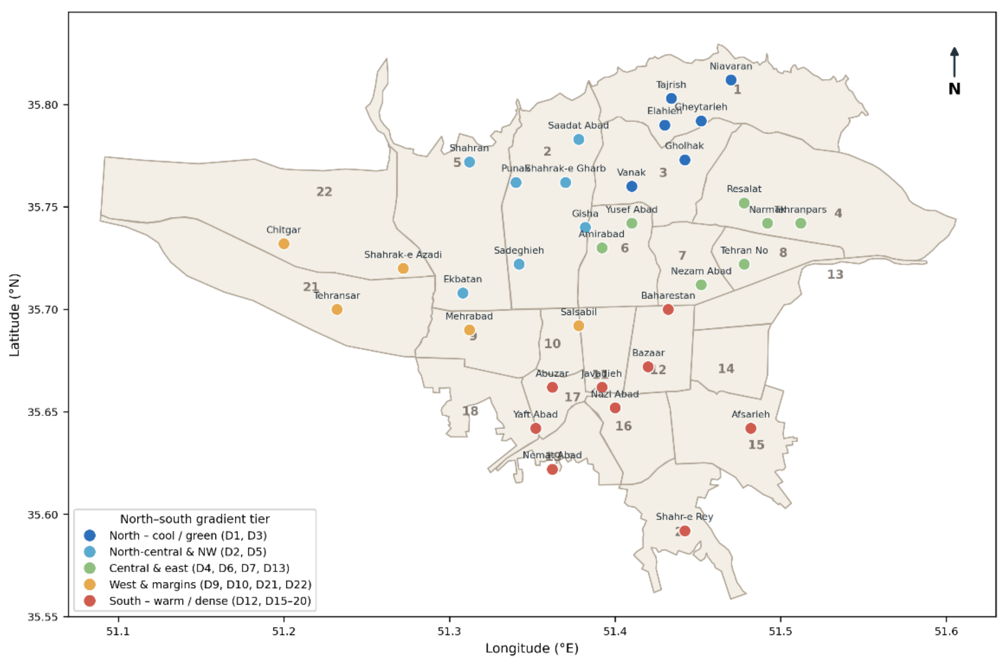

Figure 2: 34 Stratified Neighborhoods Across the 22 Dis. Of Tehran City

Their number and indicator values are synthetic; the real application would delineate neighborhoods from municipal boundaries and compute the Table 1 indicators from GIS layers. In the operational pipeline, each indicator is computed per neighborhood using zonal statistics (for raster layers such as LST and NDVI) and network or overlay analysis (for access indicators). Indicators whose polarity is negative for suitability (LST, impervious fraction, air-quality exposure, land value, slope) are inverted, and all indicators are scaled to a common range (0–1 min–max or z-scores). Multicollinearity is screened with the correlation matrix and the variance inflation factor, and outliers are examined. The output is a neighborhood-by-indicator matrix that feeds the factor analysis. EFA is used to reduce the correlated indicators to a small set of latent factors. Sampling adequacy is checked with the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity; values of KMO above 0.7 and a significant Bartlett test ($p < 0.05$) indicate suitability for factoring (Alavi et al., 2020). Factors are extracted by principal-axis/principal-component extraction, retained on the Kaiser criterion (eigenvalue > 1) and confirmed with the scree plot, and rotated with Varimax to aid interpretation. Each neighborhood then receives a score on each retained factor; these factor scores parsimonious and largely uncorrelated become the ANN inputs, mitigating the multicollinearity that would otherwise destabilize training.

Artificial neural network

A feed-forward multilayer perceptron (MLP) is trained to map the factor scores to a neighborhood sustainability suitability index. The target index, in a real study, is a reference suitability value obtained from an established MCDA procedure (for example AHP/TOPSIS or expert panels), which the ANN learns to reproduce and generalize; the ANN thus acts as a non-linear approximator that also enables sensitivity analysis. The network (Figure 2) comprises an input layer (one node per retained factor), two hidden layers with ReLU activation, and a single linear output node. Training uses back-propagation with the Adam optimizer and mean-squared-error loss, with early stopping and k-fold cross-validation to prevent over-fitting; inputs are scaled and the data split into training, validation and test partitions. Performance is reported with the coefficient of determination (R^2), root-mean-square error (RMSE) and mean absolute error (MAE) on the held-out test set. Variable importance is assessed by a permutation/sensitivity analysis that measures the degradation in accuracy when each factor (and, by back-mapping, each indicator) is perturbed. (Fig. 3)

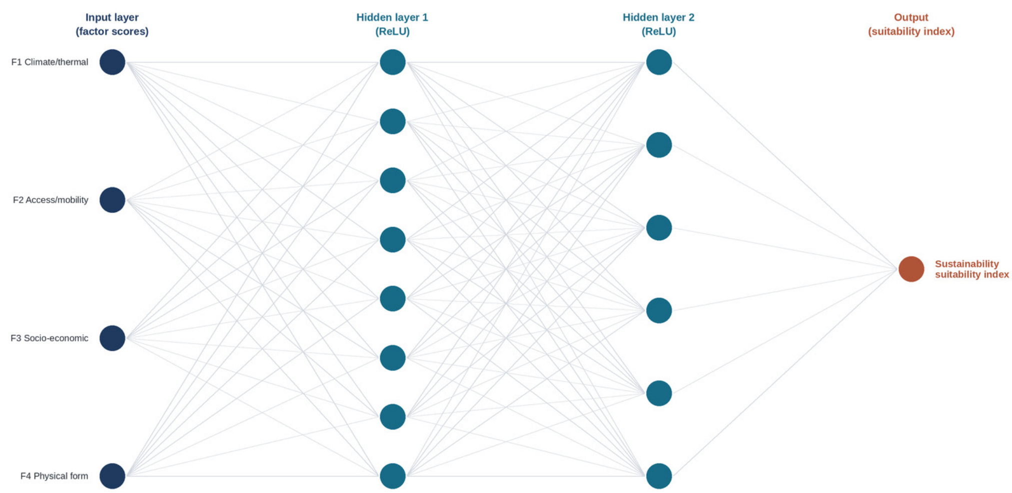

Figure 3: Architecture of the multilayer-perceptron neural network used in the framework

Table 2: ANN configuration used in the demonstrative case

Setting	Value
Architecture	MLP: 4 – 8 – 6 – 1 (inputs – hidden1 – hidden2 – output)
Activation	ReLU (hidden layers); linear (output)
Optimizer / loss	Adam; mean squared error
Regularization	Early stopping; L2 weight decay; dropout 0.1
Validation	5-fold cross-validation; 70/15/15 train/val/test split
Inputs	Four factor scores from the EFA
Target	Neighborhood sustainability suitability index (0–1)

FINDINGS AND DISCUSSION

Factor-analysis adequacy and extraction

For the demonstrative dataset, sampling adequacy was satisfactory (KMO = 0.81; Bartlett's test of sphericity significant at $p < 0.001$), supporting the use of factor analysis. Applying the Kaiser criterion and inspecting the scree plot (Fig. 4), four factors were retained, cumulatively explaining a large share of the variance (Tab. 3).

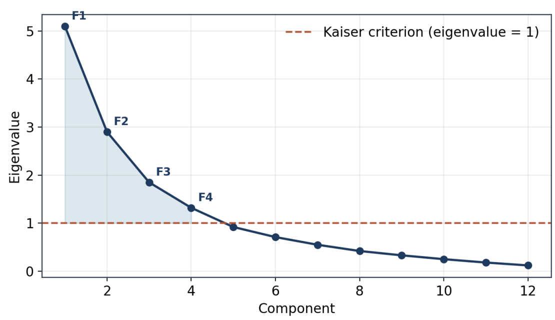

Figure 4: Scree plot of the exploratory factor analysis

Table 3: Extracted factors, eigenvalues and explained variance

Factor	Eigenvalue	% variance	Cumulative %
F1 – Climate & thermal	5.10	34.0	34.0
F2 – Access & mobility	2.90	19.3	53.3
F3 – Socio-economic	1.85	12.3	65.6
F4 – Physical form	1.32	8.8	74.4

As Table 3 shows, the climate & thermal factor (F1) alone accounts for the largest share of variance, confirming within this setting the centrality of UHI-related variables to neighborhood suitability.

Rotated factor structure

The Varimax-rotated loadings (Fig. 5, Tab. 4) show a clean structure: LST, green cover, sky view factor, impervious fraction and distance to park load on F1 (climate & thermal); transit access, road density and land-use mix on F2 (access & mobility); population density and land value on F3 (socio-economic); and slope on F4 (physical form). Air quality cross-loads onto the climate factor, consistent with its heat–pollution coupling.

Table 4: Dominant indicators per factor

Factor	Dominant indicators (loading)	Share
F1 Climate & thermal	LST (0.86); green cover (0.82); sky view factor (0.71); impervious % (0.68); distance to park (0.63); air quality (0.55)	34.0%
F2 Access & mobility	Transit access (0.84); road density (0.79); land-use mix (0.68)	19.3%
F3 Socio-economic	Population density (0.81); land value (0.77)	12.3%
F4 Physical form	Slope (0.74)	8.8%

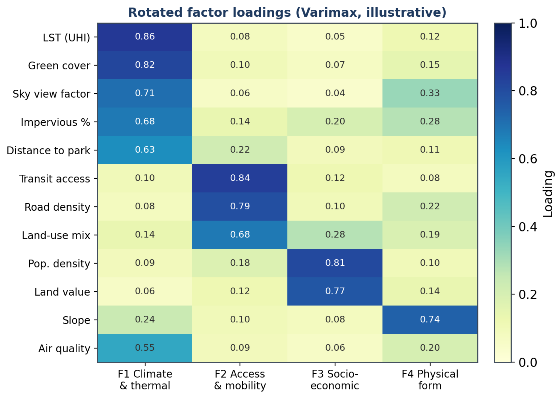

Figure 5: Rotated factor loadings (Varimax).

ANN performance

Trained on the four factor scores, the MLP reproduced the reference suitability index with high accuracy on the held-out test set ($R^2 = 0.94$; RMSE = 0.046; MAE = 0.037). The training and validation loss curves (Fig. 6) converge without divergence, and the predicted-versus-observed scatter (Fig. 7) clusters tightly around the 1:1 line, indicating good generalization in this demonstrative setting.

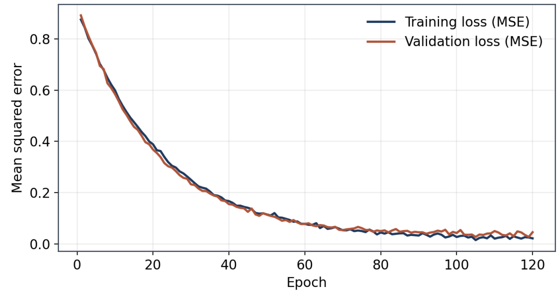

Figure 6: ANN training and validation loss

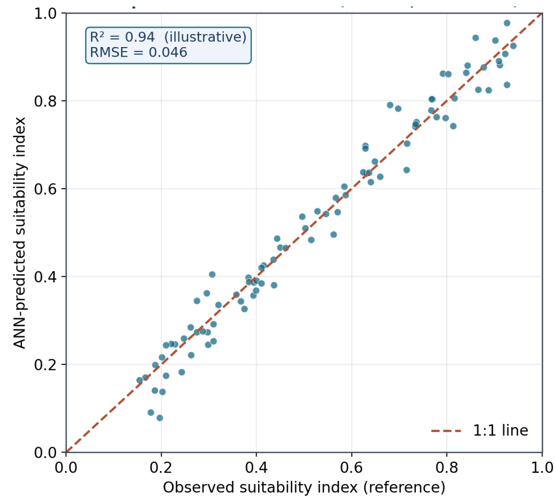

Figure 7: ANN-predicted versus reference suitability on the test set

Table 5: ANN performance metrics

Partition	R^2	RMSE	MAE
Training	0.96	0.038	0.030
Validation	0.93	0.049	0.040
Test	0.94	0.046	0.037

Variable importance and the weight of climate

The sensitivity analysis (Fig. 8 and Tab. 6) ranks the UHI-related variables highest: land surface temperature, green cover and sky view factor together dominate the importance profile, followed by impervious surface and access variables. This illustrates the framework's intended behavior surfacing climate and thermal comfort as the leading determinants of sustainable neighborhood suitability and shows how the ANN can be interrogated to support climate-responsive planning.

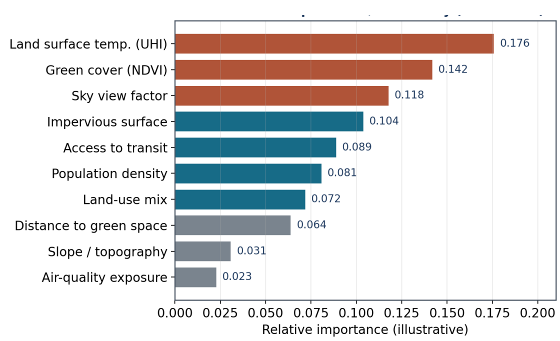

Figure 8: ANN variable importance / sensitivity

Table 6: Ranked variable importance

Rank	Variable	Importance
1	Land surface temperature (UHI)	0.176
2	Green cover (NDVI)	0.142
3	Sky view factor	0.118
4	Impervious surface	0.104
5	Access to transit	0.089
6	Population density	0.081
7	Land-use mix	0.072
8	Distance to green space	0.064
9	Slope / topography	0.031
10	Air-quality exposure	0.023

Neighborhood suitability classification

Applying the trained model to the 34 neighborhoods and classifying the predicted index into five tiers yields the distribution in Figure 8 and Table 7: a small number of highly suitable neighborhoods, a larger band of suitable and moderately suitable ones, and a minority that are marginal or unsuitable the latter typically combining high LST, low green cover and high imperviousness. In a real application these classes would be mapped in GIS to guide siting and greening priorities.

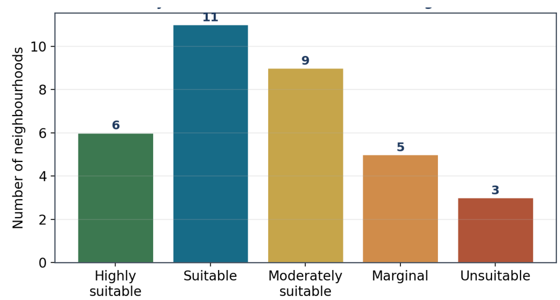

Figure 9: Suitability classification of the 34 neighborhoods.

Table 7: Suitability classes and their defining climate profile

Suitability class	Count	Typical climate–thermal profile
Highly suitable	6	Low LST, high green cover, open sky view, low imperviousness
Suitable	11	Moderately low LST, good green access
Moderately suitable	9	Mixed thermal profile; some heat exposure
Marginal	5	Elevated LST, limited green cover
Unsuitable	3	High LST, high imperviousness, low green cover priority for greening

CONCLUSION AND RESULTS

The framework demonstrates how three well-established techniques can be combined to make climate a first-order criterion in neighborhood site selection. EFA resolves the multicollinearity that pervades urban indicator sets and yields interpretable factors, echoing its long use in urban livability research (Salarimoghadam et al., 2019) (Shabanzadeh-Namini et al., 2019). The ANN then captures the non-linear, interacting relationship between those factors and suitability, in line with evidence that learning models complement or outperform linear MCDA for land-suitability and LST problems (Nie, 2024) (Tanoori et al., 2024). The dominance of the climate & thermal factor, and the top ranking of LST, green cover and sky view factor in the sensitivity analysis, are consistent with the established physics of the UHI vegetation cools and impervious surfaces and closed canopies warm the urban surface (Bonafoni & Keeratikasikorn, 2018) (Estoque & Murayama, 2016) and with Tehran-specific evidence that green-space scenarios lower heat and improve comfort (Arghavani et al., 2020) (Zargari et al., 2024). Compared with conventional GIS–AHP siting (Asakereh et al., 2017) (Aghmashhadi et al., 2022), the proposed pipeline replaces fixed expert weights with data-driven, non-linear learning while retaining interpretability through the factor structure and the sensitivity analysis. It also operationalises the sustainability agenda concretely: the five indicator groups map onto environmental, social, economic and physical pillars, and the explicit UHI emphasis aligns siting with heat-mitigation and thermal-comfort goals increasingly seen as central to urban resilience (He et al., 2023) (He et al., 2021) (Visvanathan et al., 2024). Methodologically, foregrounding climate at the siting stage — rather than mitigating heat after development is a more sustainable and cost-effective strategy (Avashia et al., 2021).

Several limitations frame the interpretation. First and foremost, the Tehran results are: they demonstrate mechanics, not empirical suitability, and must be replaced with values computed from real GIS layers before any planning use. Second, ANN models require sufficient, high-quality training data and a defensible reference target; the choice of that target (for example an AHP/TOPSIS composite) influences the learned mapping. Third, factor solutions and network hyper-parameters are sensitive to the indicator set and to scaling choices, so external validation and reporting transparency (following reproducible-workflow principles) are essential. Finally, static cross-sectional indicators do not capture temporal dynamics of heat and land cover; coupling the framework with time-series LST and land-use projection (Nie, 2024) (Tanoori et al., 2024) is a promising extension.

This paper set out a reproducible GIS–factor-analysis–ANN framework for assessing the influence of climate on neighborhood site selection under a sustainable-development approach, with an explicit emphasis on the urban heat island and outdoor thermal comfort. Exploratory factor analysis reduces a broad, correlated set of environmental, social, economic and physical indicators to a small number of interpretable factors; a multilayer-perceptron neural network then learns the non-linear mapping from those factors to a neighborhood sustainability suitability index; and a GIS layer translates the predictions into a classified suitability map. In the demonstrative Tehran case whose numerical values are synthetic and the climate & thermal factor dominated the factor structure, the ANN reproduced the reference index accurately, and UHI-related variables (land surface temperature, green cover, sky view factor) led the sensitivity ranking, showing that the framework surfaces climate as a first-order siting determinant. The contribution is threefold: a climate-centered criteria structure in which UHI and thermal comfort are primary; an explicit EFA–ANN coupling that combines dimensionality reduction with non-linear learning inside a transparent, transferable GIS pipeline; and a clear separation between the reusable framework and the case-specific data. The immediate next step is to populate the pipeline with empirical Tehran layers, Landsat/Sentinel-derived LST and NDVI, census and access data to obtain validated, city-specific results, and to extend the model with temporal heat and land-use dynamics. Beyond Tehran, the framework is directly transferable to other heat-exposed metropolises pursuing climate-responsive, sustainable urban development.

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