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ANALYTIC HIERARCHY PROCESS VS. MACHINE LEARNING: MAPPING SCHOOL SUITABILITY IN BATNA CITY, ALGERIA WITH SPATIAL ANALYSIS

Abstract: The present study considers the suitability of sites for elementary schools in Batna, Algeria. The Analytic Hierarchy Process (AHP) method is compared to the three machine learning (ML) models, namely Random Forest (RF), Gradient Tree Boosting (GTB) and Classification and Regression Trees (CART). Spatial analysis techniques based on Geographic Information System (GIS) such as K-Nearest Neighbors (KNN), Moran's I, inverse distance weighting (IDW) and Buffer Analysis were conducted prior to comparison to detect principal deficiencies and showed that 44.6 % of the 83 schools are located in 52% of the residential sectors. Peripheral gaps were also highlighted Nearest Neighbors Ratio (NNR = 0.69, Moran'I = 0.32, $p < 0.001$). AHP prioritized population density: 51.99%, while RF with an Area Under the Curve (AUC = 0.75) emphasized environmental limitations (slope, river spacing), differing from GTB (AUC = 0.65) and CART (AUC = 0.61). The combined suitability maps showed complementarity and guide planners to effectively address Batna's educational inequalities.

Keywords: school site selection, analytic hierarchy process, machine learning, GIS spatial analysis, suitability mapping, Batna (Algeria)

Introduction

The task of selecting optimal school locations is a multifaceted issue that has direct impacts on educational accessibility, social equity, and urban sustainability (WCED, 1987;

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UNESCO, 2016; Siagian & Revida, 2021). An inefficient distribution of schools may lead to longer travel times, overcrowding, and unequal educational access, especially in rapidly urbanizing sectors (Moreno-Monroy et al., 2018; Al-Sabbagh, 2022; Sharma & Patil, 2022). Quantitative decision-support methods, AHP and ML, have been introduced to address these issues in optimizing school site selection (Huang et al., 2023; Huu Duy et al., 2024, Villalba et al., 2024).

AHP (Saaty, 1980) is a Multi-Criteria Decision-Making (MCDM) method that permits decision-makers to prioritize potential school sites by assigning weights to different components through pairwise comparisons (Saaty, 1990; Taleai et al., 2021; Abdollahi et al., 2024). This strategy is widely used in urban planning, infrastructure improvement, and site suitability, because it combines quantitative and qualitative components (Samad et al., 2012; Yang et al., 2017; Ramadan et al., 2022). AHP is useful in cases where expert knowledge is critical, such as adjusting population density, road accessibility, and environmental constraints (Rekha et al., 2020; Murad et al., 2020; Abdullah et al., 2023). Though it follows a well-organized process, it is more likely to be subjective, as weight assignments depend on stakeholders' judgment, which can vary among decision-makers and introduce potential biases (Hwang & Yoon, 1981; Dridi et al., 2015; Deruyter et al., 2013).

ML models have demonstrated high performance in predicting site suitability by leveraging large geographical datasets to optimize decisions (Zhang et al., 2022; Meena et al., 2023; Han et al., 2023; Srivastava & Saxena, 2023; Huu Duy et al., 2024). Some ML algorithms have been widely used in urban planning, transportation, and environmental risk assessment (Huang et al., 2024; Luo et al., 2024; AlQuhtani, 2023). Unlike AHP, the ML models do not require predetermined weights or complex spatial models determined from historical data (Breiman, 2001; Chen and Guestrin, 2016). However, a principal challenge for ML methods is their black-box nature, which means that even if they are superior in predictions, they do not have transparent decisions like AHP, which makes the interpretation more complicated for urban planners (Zangana et al., 2024).

Among the ML approaches, RF, GTB, and CART stand out for their applicability to spatial decision-making tasks like school site selection. RF, an ensemble method, leverages multiple decision trees to enhance predictive accuracy and robustness, making it effective for handling complex spatial datasets (Breiman, 2001). GTB, a boosting technique, iteratively improves predictions by minimizing errors, excelling at capturing nonlinear relationships in urban planning contexts (Friedman, 2001). CART, a simpler decision tree algorithm, offers high interpretability by recursively partitioning data based on key features, providing a transparent alternative for suitability analysis (Breiman et al., 1984). These models, with their distinct strengths, have been increasingly adopted in geospatial studies, offering data-driven insights to complement traditional methods (Huu Duy et al., 2024; Huang et al., 2024).

The research presented here addresses this gap by first employing spatial analysis techniques including KNN, Moran's I, IDW, and buffer analysis to assess the existing distribution of primary schools, followed by applying AHP and three ML models: RF, GTB, and CART to evaluate school location suitability in Batna, Algeria, a city marked by rapid urban growth and uneven educational infrastructure distribution (Abdelhalim, 2022; Dridi et al., 2015).

Materials and Methods

Study Area

This study examines Batna city's primary schools in northeastern Algeria (35.5558° N, 6.1748° E), spanning 61.96 km² including non-residential sectors (Figure 1). Batna's 14 urban sectors exhibit uneven development, with central urban sectors overcrowded with facilities and peripheral urban sectors underserved (Abdelhalim, 2022; Dridi et al., 2015; Bendib, 2022), particularly in educational infrastructure (Table 1).

Table 1. Batna City sectors

Sector name	Sector code	Primary schools/sector
Araar	14	**1**
Bouakal	3	**14**
Bouzourane	6	**8**
City center	1	**5**
Hamla	14	**3**
Chouhada	7	**6**
Kechida	13	**8**
Parc àFourage	5	**10**
Quartiers Anciens	2	**11**
Route de Tazoult	8	**3**
ZHUN1	9	**5**
ZHUN2	10	**10**
Industeial zone	11	**0**
Military zone	12	**1**

Population density varies widely, as detailed in Table 2. This spatial disparity drives the analysis of primary school distribution to improve accessibility.

Table 2. Population Density and Area Coverage of Batna City Sectors

Sector Type	Density Range (inhabitants/ha)	Area (ha)	Percentage of City Area
Low-Density	0–74.47	4893	78.97%
Medium-Density	74.47–106.72	849	13.70%
High-Density	106.72–372.25	454	7.33%

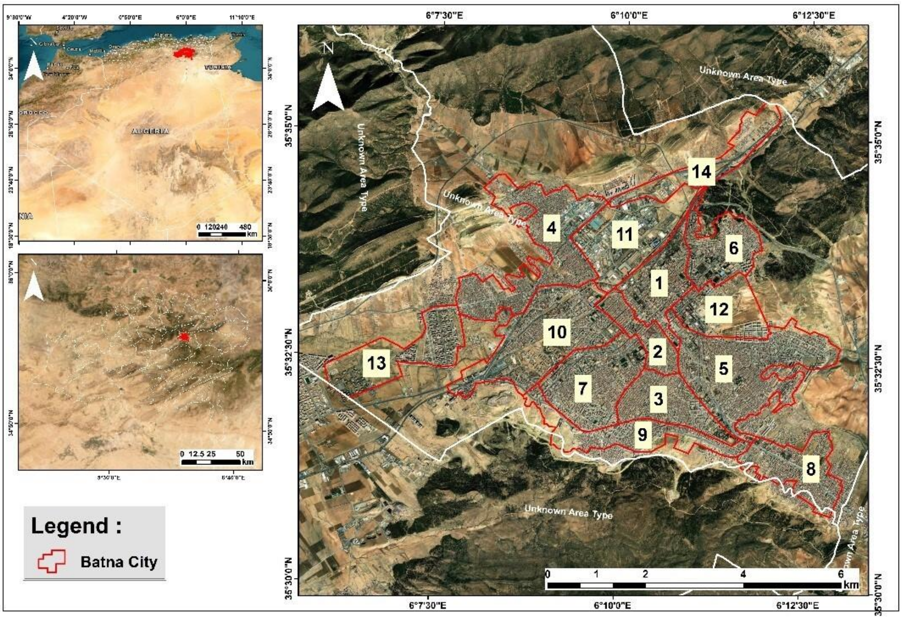

Fig.1. Map of Batna City study area showing sectors and population density

Data Collection

This study combines data records from several sources and mapped primary schools in Batna. Geographical coordinates of 83 primary schools in 14 urban sectors (e.g., Bouakal, City Center) were obtained from local education authorities. Population data, low (0-74.47 inhabitants/ha), moderate (74.47–106.72 inhabitants/ha), and high (106.72–372.25 inhabitants/ha) classes from the Batna urban planning document (Dridi et al., 2015). City land use data covered by residential, industrial, and military zones was drawn from the city's GIS database. All data records were placed for UTM Zone 32N projections and processed for spatial analysis in ArcGIS. Table 3 lists the data types, sources, and descriptions.

Table 3. Data Types and Sources for Spatial Analysis in Batna

Data Type	Source	Description
School Locations	Local Educational Authorities	Coordinates of 83 primary schools
Population Density	Urban Planning Records	Density classes per sector
Urban Land Use	GIS Database	Residential, industrial, military zones

Spatial Analysis Techniques

This study employs four GIS-based spatial analysis techniques, KNN, Moran's I, IDW, and Buffer Analysis within ArcGIS to map the distribution and accessibility of primary schools in Batna, Algeria, and to identify spatial inequities critical to school site suitability mapping. KNN assesses school clustering by calculating the Nearest Neighbor Ratio (NNR), where NNR < 1 indicates clustering and NNR ≈ 1 suggests randomness, informing urban planning decisions about facility distribution (Clark & Evans, 1954). Moran's I measures spatial autocorrelation to detect significant clustering patterns, providing insights into the spatial structure of educational infrastructure. IDW, alongside ordinary kriging, interpolates school density to visualize areas with high or low coverage relative to population density, highlighting underserved zones. Buffer Analysis maps 500-meter radius zones around schools, per Ministry of Education standards, to evaluate accessibility and identify coverage gaps, particularly in peripheral urban sectors. These methods collectively address the study's objective of detecting spatial deficiencies in school distribution, guiding the application of AHP and ML models for optimized site selection.

$$NNR = \frac{\overline{R}_{obs}}{\overline{R}_{exp}} \tag{1}$$

$\overline{R}_{obs} = \frac{1}{n}\sum_{i=1}^{n} r_i$ average distance to the nearest neighbor for each point.
$\overline{R}_{exp}$= expected mean distance in a random pattern $= \frac{1}{2\sqrt{\frac{n}{A}}}$ or a Poisson process in area A),
n = number of schools.
A = study area.
Second, Moran's I statistic measured spatial autocorrelation of school locations, with positive values signaling clustering; it is computed as:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{2}$$

Where n is the number of schools, w_{ij} is the spatial weight between locations i and j and x_i, x_j are school presence values, with $\bar{x}$ as their mean.

Third, ordinary kriging and IDW interpolated school density across Batna. Kriging uses variogram analysis to weight data constrained by $\sum \lambda_i = 1$ while IDW applies:

$$Z(u) = \frac{\sum_i Z_i / d_i^2}{\sum_i 1/d_i^2} \tag{3}$$

where $Z(u)$ estimates density at point $(u), (Z_i)$ is the known value at point i, and (d_i) is distance $with\ (p = 2)$.

Fourth, buffer zones of 500-meter radius, per Ministry of Education standards, were drawn around schools to evaluate coverage:

$$B_\mathrm{i} = \left\{(x, y) \middle| \sqrt{((x - x_\mathrm{i})^2 + (y - y_\mathrm{i})^2)} \leq 500m\right\} \tag{4}$$

B_i = buffer zone for school i,
(x_i, y_i) = coordinates of school i,
500 m = radius per Ministry of Education standards,
(x, y) = any point within 500 meters of school i.

A Venn diagram (Figure 2) illustrates the interconnections among these techniques applied to assess Batna's school patterns.

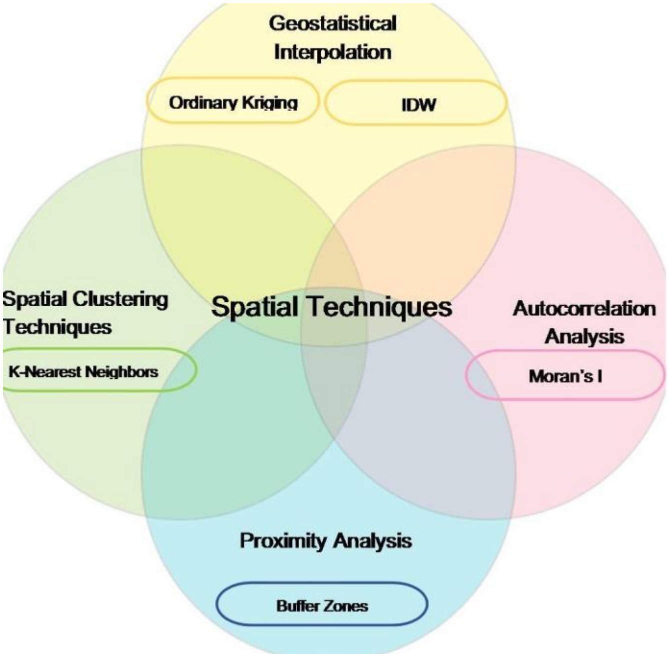

Fig. 2. Venn diagram of spatial analysis techniques

AHP and ML Framework

The present work employs AHP and ML to assess optimal school locations in Batna, Algeria, enabling a comparative evaluation of their effectiveness. AHP relies on expert judgment, while ML leverages data-driven predictions, both tailored to Batna's spatial challenges, such as population density disparities (Zangana et al., 2024). Their application and comparison are outlined below and visualized in Figure 3.

AHP, developed by Saaty (1980), prioritizes school site criteria in this case: population density, road network accessibility, river proximity, and topographic slope using pairwise comparisons based on expert input and local guidelines (Saaty, 1990). This standalone method generates weighted suitability scores, offering a transparent evaluation of qualitative and quantitative factors, independent of ML techniques.

ML Techniques

Three supervised ML methods — RF, GTB, and CART — predict site suitability from spatial data e.g., population density, road access (Breiman, 2001; Friedman, 2001). Unlike AHP, these models learn patterns without predefined weights. RF and GTB use ensemble decision trees for robust predictions, while CART offers a simpler tree-based approach. Hierarchical clustering preprocesses data to group similar criteria, improving ML efficiency (Hastie et al., 2009).

Random Forest (RF)

An ensemble learning method that builds multiple decision trees and aggregates their outputs, known for robustness and accuracy in classification tasks (Breiman, 2001). RF for suitability mapping starts with bootstrap sampling, using random subsets with replacement. Decision trees are constructed with splits based on Gini impurity, defined as:

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2 \quad (5)$$

where p_i is the proportion of class i in a node and C is the number of classes.

Predictions are aggregated via majority vote or averaging, minimizing variance. Feature importance, such as slope in Batna, is calculated as the average decrease in impurity across trees. Out-of-Bag (OOB) error, estimated as OOB $= \frac{1}{N}\sum_{i=1}^{N} L\left(y_i, \widehat{y_i^{\mathrm{OOB}}}\right)$ where L is the loss function and $\widehat{y_i^{\mathrm{OOB}}}$ is the OOB prediction for sample i , validates the model. Performance is evaluated using AUC (Breiman, 2001).

Gradient Tree Boosting (GTB)

A boosting algorithm that enhances prediction accuracy by sequentially building decision trees to correct previous errors, effectively capturing nonlinear relationships in Batna's suitability mapping to classify sites (Friedman, 2001). GTB minimizes a loss function, such as log-loss for classification,

$$L(y,p) = -\sum_{i=1}^{N} [yilog(pi) + (1 - yi)log(1 - pi)] \quad (6)$$

using gradient descent to update predictions as $p_i^{(m)} = p_i^{(m-1)} - \eta \frac{\partial L}{\partial p_i^{(m-1)}}$

where η is the learning rate and m is the iteration.

Each tree splits nodes using Gini impurity, $G = \sum_{i=1}^{C} pi(1 - pi)$.

Predictions are aggregated by weighted voting. GTB evaluates performance with metrics like AUC.

Classification and Regression Trees (CART)

A simple yet powerful decision tree algorithm that classifies sites in Batna's suitability mapping with high interpretability and efficiency (Breiman et al., 1984; Hastie et al., 2009). CART builds a single tree by recursively splitting nodes based on Gini impurity for classification:

$$G = \sum i = 1Cpi(1 - pi) \quad (7)$$

selecting the feature and threshold that minimize impurity. The final prediction at each leaf is the majority class

$$\hat{y} = \mathrm{argmax}_i (p_i) \quad (8)$$

CART's performance is evaluated using AUC.

Application and Comparison

AHP and ML methods were applied independently to Batna's dataset, as shown in Figure 3. AHP produced a suitability map from expert-weighted criteria, while RF, GTB, and CART generated separate predictions from data patterns. Their results were compared based on accuracy, interpretability, and alignment with urban planning goals, with findings detailed in results section.

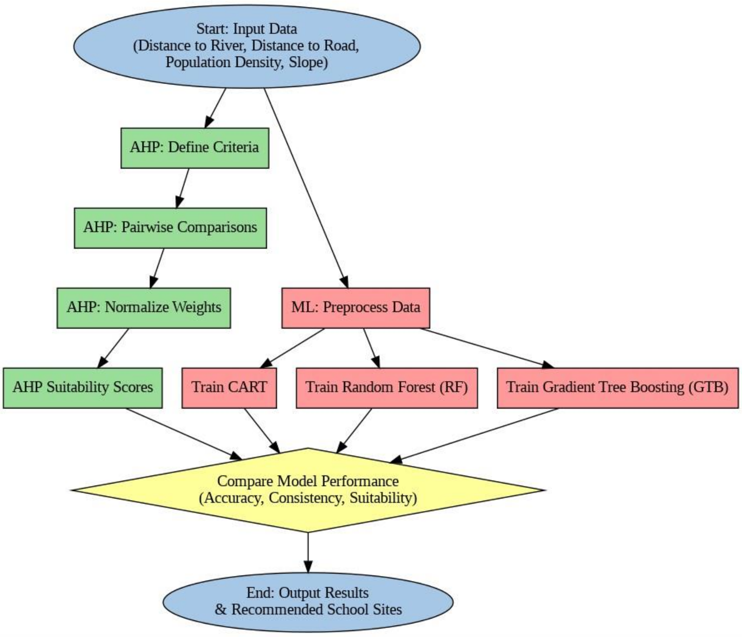

Fig. 3. Framework for AHP and ML comparison

Software and Tools

Spatial analyses and multicriteria decision-making for this study were conducted using ArcGIS (version 10.8) for spatial analysis, modeling, and mapping in Batna (ESRI, 2020). The Spatial Statistics toolbox performed KNN, Moran's I, ordinary kriging, IDW, and buffer zone analysis, as detailed above, while also mapping sectors and visualizing population density. AHP was implemented using ArcGIS's multicriteria decision-making tools to weight criteria via pairwise comparisons, as described and applied. ML models CART, RF, and GTB were executed on Google Earth Engine (GEE), with hierarchical clustering applied to preprocess criteria within GEE. Data preprocessing, including georeferencing to UTM Zone 32N, was managed within ArcGIS. Table 4 summarizes the tools and their roles.

Table 4. Software and Tools Used in the Study

Tool/Library	**Version**	**Purpose**
ArcGIS	10.8	Spatial analysis (KNN, Moran's I, kriging, IDW, buffer zones), mapping
ArcGIS Toolboxes	-	Spatial Statistics (KNN, Moran's I, kriging, IDW, buffer zones); Spatial Analyst (AHP weighting,
Google Earth engine	-	ML model execution (CART, RF, GTB), hierarchical clustering

Results and Discussion

This section presents the findings from the application of GIS-based spatial analysis techniques and the comparison of AHP and ML methods to evaluate the distribution of primary schools in Batna, Algeria, and their implications for urban planning and educational policy.

Spatial Analysis Techniques

Spatial analysis of Batna's 83 primary schools across 14 sectors revealed significant clustering and uneven distribution patterns. The KNN method (Figure 4a) produced a NNR of 0.69 (z-score = 5.54, $p < 0.001$), indicating strong clustering, while Moran's I (Figure 4b) yielded a value of 0.32 (z-score = 5.32, $p < 0.001$), confirming positive spatial autocorrelation. These results highlight a clear concentration of schools in central sectors like Bouakal (14 schools) and Parc à Fourage (10 schools), particularly in the city's core and oldest neighborhoods where population density is higher . Conversely, peripheral sectors such as Araar (1 school), Road of Tazoult, and Hamla exhibit significantly lower school density, suggesting a gradient that decreases outward from the city center.

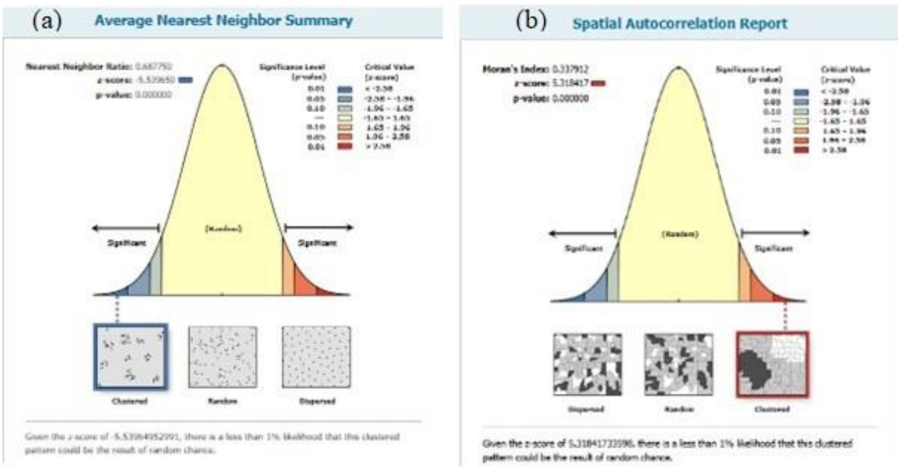

Fig. 4. Spatial analysis results for primary schools in Batna, showing (a) nearest neighbor analysis (KNN) (b) Moran's I

Kriging and IDW interpolations, using population density to estimate student distribution (Figure 5a), mapped school density across Batna (Figure 5b), with kriging yielding a smoother distribution and IDW a sharper one, confirming high school density in central sectors and sparse coverage in peripheral sectors, with some dispersion elsewhere. Per Ministry of Education standards, primary schools require a protected area within a 500 m radius, representing students' walking distance. Buffer analysis revealed extensive overlap of these 500 m zones around Batna's 83 schools in densely populated central sectors (e.g., 106.72–372.25 inhabitants/ha), but significant gaps persist in peripheral and non-residential sectors, such as military and industrial zones (e.g., Industrial Zone: 0 schools) (Figure 5c). Additionally, a circle with a 3,180 m radius, centered in the city, encompasses 37 schools (44.6% of the total) (Figure 5d), covering 31.7 km^{2}approximately 52% of Batna's urban sectors of 61.96 km^2 (Hersous et al., 2023). This central clustering aligns with observed patterns, though school distribution within this circle shows no clear pattern, leaving 55.4% of schools and 48% of the urban area underserved. These findings highlight accessibility inequities in Batna, consistent with urban planning challenges (Zangana et al., 2024).

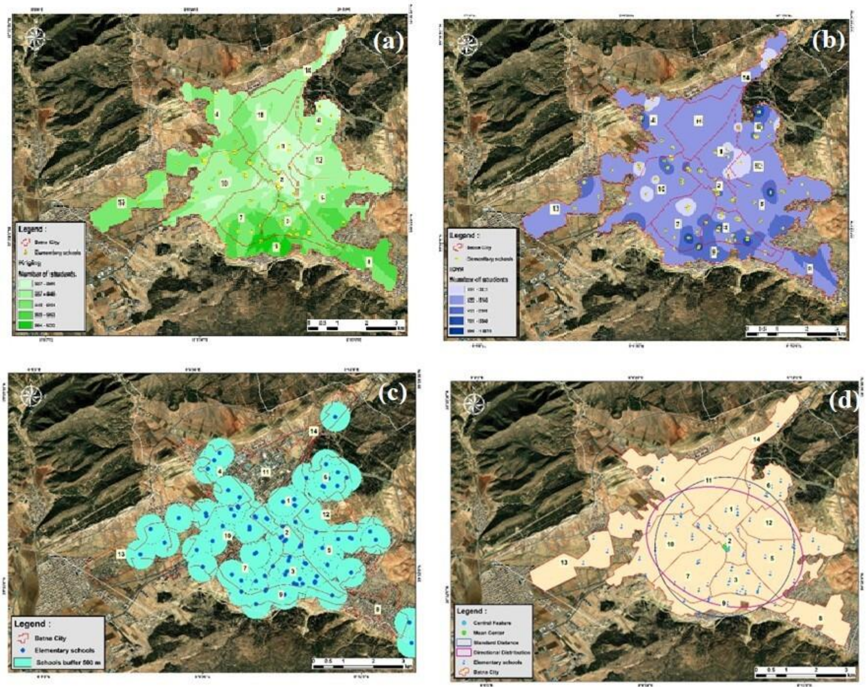

Fig. 5. Spatial analysis of primary schools in Batna, showing (a) ordinary kriging interpolation of student distribution based on population density, (b) IDW of school density, (c) buffer zones (500 m radius), (d) geographical distribution with a 3,180 m radius circle.

AHP Results

AHP assessed school site suitability in Batna using four factors: population density (weight: 51.99%), road network (26.82%), river network (14.09%), and topographic slope (7.09%). Population density led due to accessibility priorities, followed by road connectivity, with river proximity limiting flood-risk zones and slope having minor influence. The Consistency Ratio (CR) of 0.068 (< 0.1) validated the weights' reliability. Thematic maps (Figure 6) display each factor's spatial pattern, with suitability scores ranging from 1 (least suitable, red) to 9 (most suitable, green), guiding suitability toward central, connected sectors (e.g., Bouakal, Parc à Fourage) with high population density and road access (green zones) over peripheral or flood-prone sectors (e.g., near rivers in Araar) with low suitability (red zones).

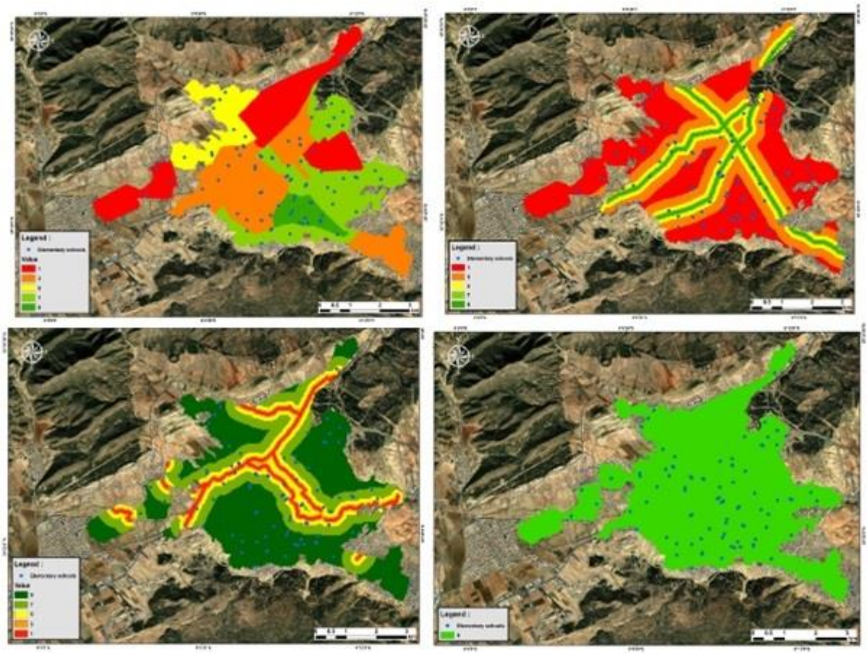

Fig. 6. AHP thematic maps for school site suitability in Batna, showing (a) population density, (b) road network, (c) river network, and (d) topographic slope

Machine Learning Results

ML models RF, GTB, and CART were implemented on GEE to analyze factor importance for school site suitability in Batna. Hierarchical clustering was applied to preprocess the spatial criteria, grouping similar factors such as population density and road distance, though its direct impact on feature importance rankings was not explicitly evaluated. RF prioritized slope and river distance (environmental constraints), GTB emphasized river distance while balancing slope, population density, and road distance, and CART favored river and road distance, downplaying slope (Figure 7). Receiver Operating Characteristic (ROC) analysis showed RF led with an AUC of 0.75, GTB scored 0.65, and CART trailed at 0.61, indicating RF's superior predictive accuracy.

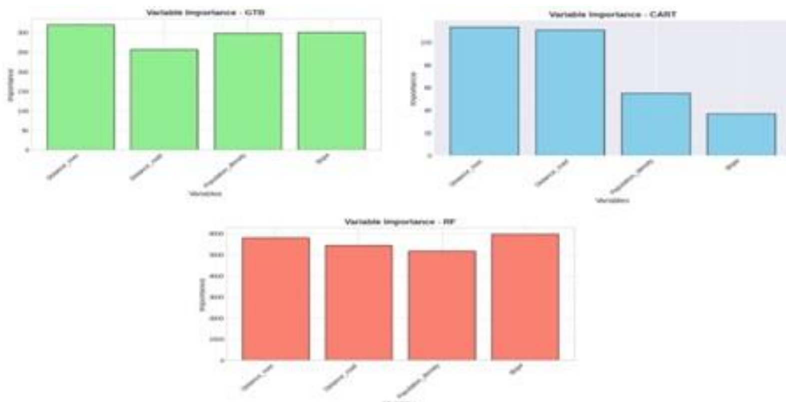

Fig. 7. Variable importance for ML models in school site suitability analysis in Batna, generated using Google Earth Engine (GEE)

ML-derived maps, generated using GEE, emphasize environmental factors over AHP's accessibility focus, highlighting distinct spatial priorities (Figure 8). These results underscore RF's data-driven strength and set up a comparative lens with AHP's expert-driven approach. RF's emphasis on environmental constraints aligns with Batna's peripheral gaps, where steep slopes and rivers limit viable sites, while AHP's focus on population density and roads matches central clustering trends. RF's higher AUC suggests data patterns may capture nuances expert weighting overlooks, though GTB and CART's lower scores indicate model sensitivity to factor selection. This divergence environmental vs. accessibility suggests complementary strengths, pending integrated mapping.

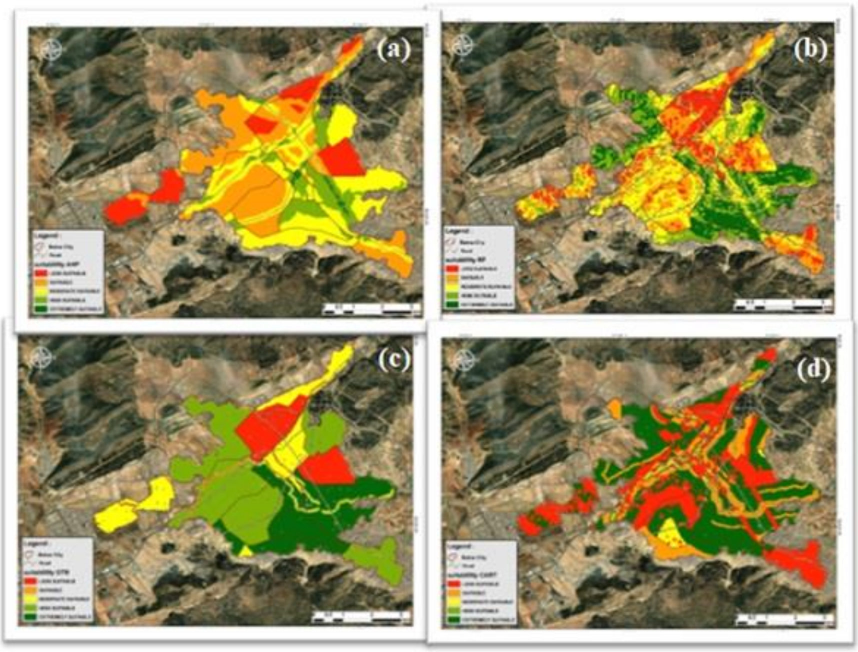

Fig. 8. Suitability maps for school site selection in Batna, comparing (a) AHP, (b) Random Forest (RF), (c) Gradient Tree Boosting (GTB), and (d) Classification and Regression Trees (CART).

Conclusion

This study evaluated primary school site suitability in Batna, Algeria, using GIS-based spatial analysis, AHP, and ML models (RF, GTB, and CART) executed on GEE. Spatial analysis revealed significant clustering (NNR = 0.69, Moran's I = 0.32, $p < 0.001$), with 44.6% of 83 schools concentrated in 52% of the urban sectors, leaving peripheral urban sectors underserved. AHP prioritized accessibility (population density: 51.99%, road network: 26.82%) with a reliable Consistency Ratio (CR) of 0.068, favoring central, connected sites. ML, led by RF (AUC = 0.75), emphasized environmental constraints (slope, river proximity), outperforming GTB (AUC = 0.65) and CART (AUC = 0.61), and highlighted peripheral limitations. Comparative suitability mapping (Figure 8) showed overlapping optimal urban sectors but divergent priorities—AHP for accessibility, ML for terrain—offering complementary insights. These findings validate RF's predictive edge and AHP's structured utility, providing planners a dual lens to address Batna's educational inequities efficiently and sustainably. Future studies could explore integrating socioeconomic indicators or simulating population growth to enhance site selection models, while policymakers may leverage these findings to prioritize equitable school distribution in Batna's underserved urban sectors.

Conflicts of Interest: The authors declare no conflict of interest.

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