[DEPARTMENT OF CIVIL ENGINEERING]

AI-Driven Multi-Criteria GIS Analysis for Optimal FSTP Site Selection

Case Study: Hatia Municipality, Bangladesh

Integrating GIS, Machine Learning, and MCDA for Evidence-Based Siting

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SUBMISSION DETAILS

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COURSE
CE 6302 - Environmental Modeling and GIS Application

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INSTITUTION LOGO

1. Introduction

Study Context: Hatia Municipality

Located in Noakhali District, Hatia is a rapidly growing coastal island municipality facing unique environmental challenges. With increasing urbanization, the management of fecal sludge has become a critical priority to safeguard public health and the fragile island ecosystem.

⚠ Sanitation Challenges

- Predominance of onsite sanitation systems (pit latrines/septic tanks)
- Lack of formal fecal sludge collection and treatment infrastructure
- Indiscriminate dumping into canals and drains

☣ Environmental & Health Risks

High risk of groundwater contamination and surface water pollution, leading to waterborne diseases and ecosystem degradation in this cyclone-prone coastal area.

The Proposed Solution

Optimal Siting
Strategic location selection to minimize transport costs

Eco-Protection
Distance from sensitive water bodies & settlements

AI Integration
Machine Learning for robust suitability prediction

GIS Analysis
Spatial multi-criteria decision support system

PROJECT GOAL
Establish a sustainable FSTP framework

Source: Hatia Municipality Master Plan / DPHE Reports

3. Literature Review

Traditional FSTP Siting Studies

Common Planning Frameworks

Dominance of **Multi-Criteria Decision Analysis (MCDA)**, specifically Analytical Hierarchy Process (AHP) and Fuzzy AHP, combined with GIS overlay analysis.

Key Criteria Identified

- **Environmental:** Setbacks from water bodies, soil permeability
- **Social:** Distance from settlements, population density
- **Technical:** Accessibility (road network), slope/terrain

AI & ML in Spatial Planning

Predictive Modeling

Use of Random Forest (RF), Support Vector Machines (SVM), and ANN to classify land suitability based on historical data patterns.

Advantages over Traditional MCDA

Captures non-linear relationships between criteria; reduces subjectivity in weight assignment through feature importance learning.

Research Gap

While AI has been applied to landfill siting and urban growth modeling, there is **limited integration of AI-GIS frameworks** specifically for Fecal Sludge Treatment Plant (FSTP) selection in coastal Bangladesh contexts.

Need: A validated, data-driven approach that combines expert knowledge (MCDA) with machine learning precision.

Evolution of Siting Methodologies

Conventional GIS — Past

Simple Boolean overlay (Suitable / Not Suitable). Rigid and often excludes viable sites.

MCDA-GIS Integration — Current Standard

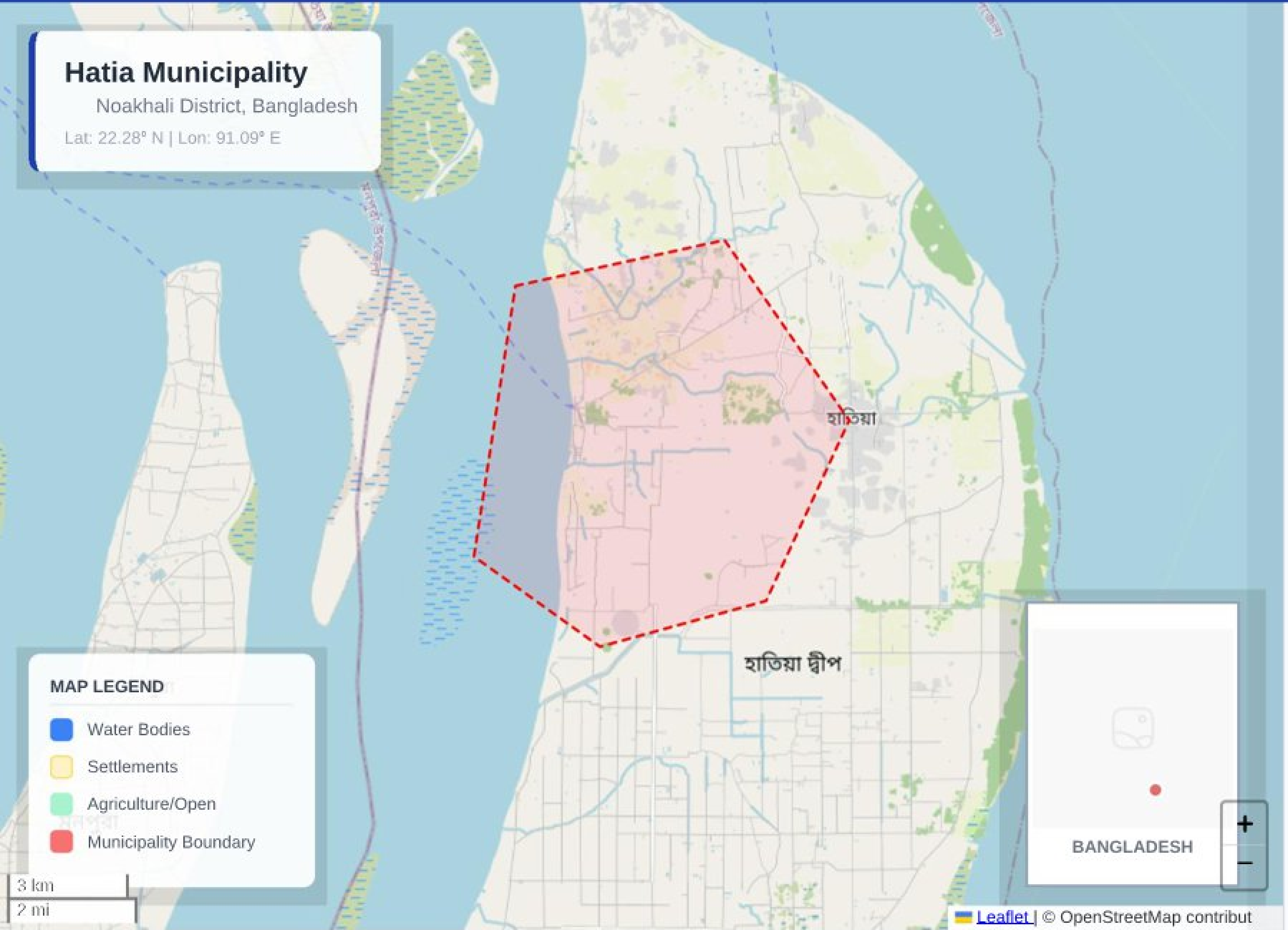
Weighted Linear Combination (AHP). Incorporates expert opinion but remains subjective.

AI-Driven Spatial Analysis — Proposed Approach

Hybrid model (MCDA + ML). Data-driven, validates expert rules, handles complex environmental interactions.

References: Saha et al. (2021); Karimi et al. (2019); Islam et al. (2020)

4. Study Area: Hatia Municipality



GEOGRAPHIC CONTEXT

Coastal Island
Located in the Meghna Estuary, highly susceptible to tidal surges.

Climate Vulnerability
Frequent cyclones and river bank erosion affect infrastructure stability.

DEMOGRAPHICS (202X EST.)

~55K	~11K
POPULATION	HOUSEHOLDS

Density: ~1,800 per km²

SANITATION STATUS

Pit Latrines/Septic 85%

Unsanitary/Hanging 12%

Critical Issue: No functional FSTP currently exists. Manual emptying is common.

5. Research Objectives & Questions

Primary Objectives

01
Develop AI-GIS-MCDA Framework
Create a hybrid model integrating Geographic Information Systems, Machine Learning, and Multi-Criteria Decision Analysis.

02
Data Compilation & Processing
Acquire and preprocess multi-source spatial datasets including satellite imagery, DEM, and demographic grids.

03
ML Model Training
Train and validate Random Forest, ANN, and SVM algorithms to classify land suitability based on historical patterns.

04
Criteria Weighting (AHP)
By using Analytical Hierarchy Process.

05
Site Ranking & Selection
Generate final suitability maps and identify top candidate sites with specific coordinates.

? Research Questions

QUESTION I

Which environmental and socio-economic factors most critically influence the suitability of FSTP sites in the Hatia context?

Feature Importance

QUESTION II

How does the accuracy and reliability of AI-enhanced mapping compare to traditional MCDA-only approaches?

Comparative Analysis

6. Methodology Framework

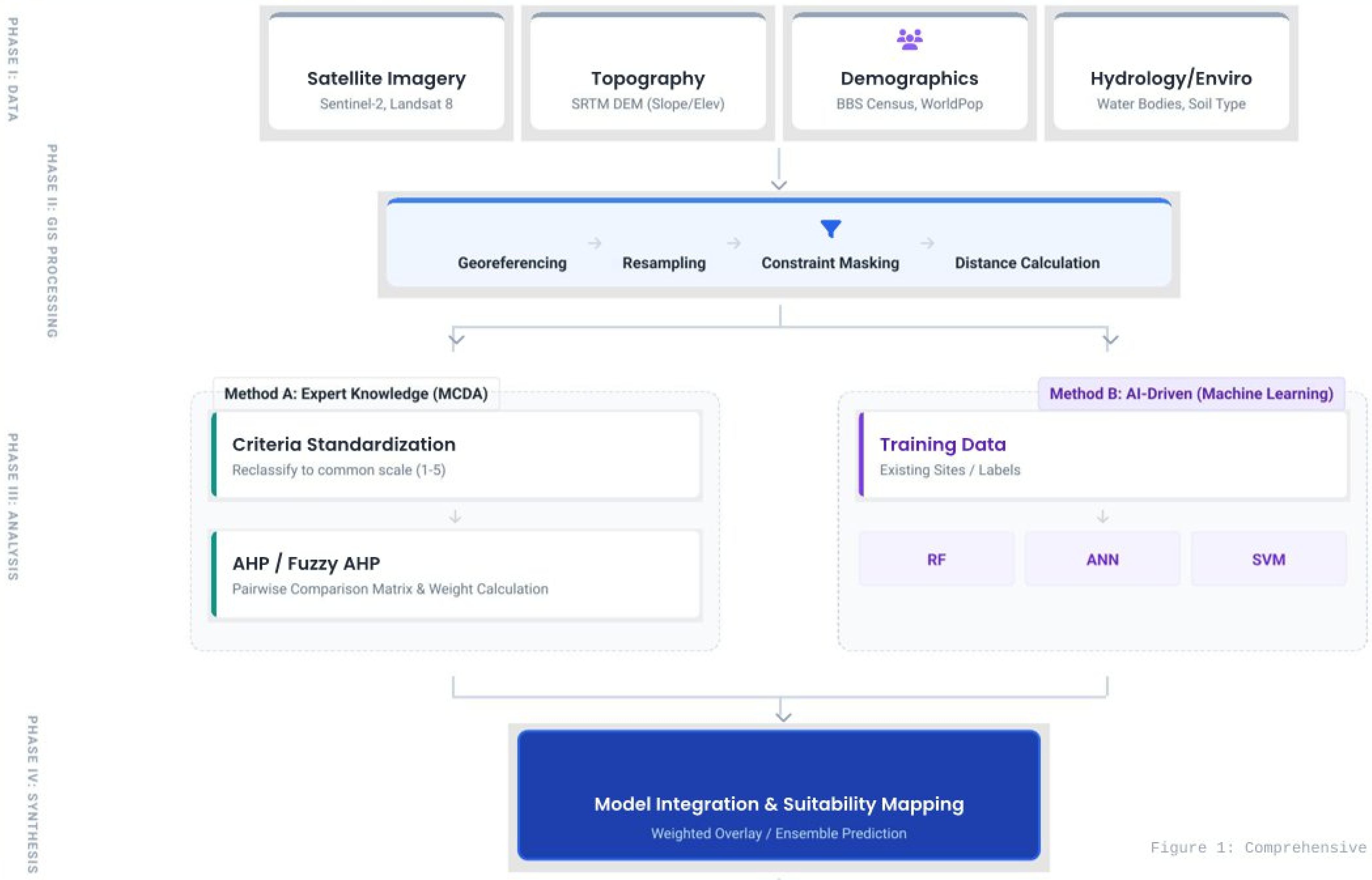


Figure 1: Comprehensive Methodology Flowchart

7. Data Collection & Sources

Remote Sensing / Spatial · Environmental / Physical · Socio-Economic / Admin

Satellite Imagery
Sentinel-2 MSI / Landsat 8 OLI

10m / 30m · Raster

Source: USGS Earth Explorer / Copernicus

Elevation (DEM)
SRTM / ALOS PALSAR

30m / 12.5m · Raster

Source: NASA / JAXA

Land Use / Cover
ESA WorldCover 2021

10m Res · Raster

Source: European Space Agency

Transport Network
Roads & Access Paths

Vector Line · Shapefile

Source: OpenStreetMap / LGED

Hydrology
Water Bodies & Flood Zones

30m / Vector · Mixed

Source: JRC Surface Water / BWDB

Demographics
Population Density Grid

100m Grid · Raster

Source: WorldPop / BBS Census 2022

Soil Characteristics
Texture, Permeability, pH

250m · Raster

Source: SoilGrids / SRDI

Groundwater Depth
Piezo-metric Well Data

Point Data · CSV/Shp

Source: BWDB / DPHE

Admin Boundaries
Ward/Mouza Boundaries

Vector Poly · Shapefile

Source: BBS / LGED

*All datasets projected to BTM (Bangladesh Transverse Mercator) or UTM Zone 46N for analysis.

Data Collection Period: Jan 202X - Dec 202X

8. GIS Data Processing Workflow

A rigorous five-stage spatial ETL (Extract, Transform, Load) process was implemented to harmonize heterogeneous datasets into a unified analysis environment.

1. Preparation

- ✓ **Define AOI:** Municipality boundary + 1km buffer
- ✓ **Projection:** Reproject all layers to BTM / UTM 46N
- ✓ **Geometric Correction:** Align satellite imagery

Initial Setup

2. Pre-processing

- ✓ **Clipping:** Extract data to AOI extent
- ✓ **Resampling:** Standardize pixel size (e.g., 10m/30m)
- ✓ **Rasterization:** Convert vector roads/rivers to raster

Data Management

3. Derivation

- ✓ **Slope Analysis:** Derive slope (degrees) from DEM
- ✓ **Euclidean Distance:** Calculate distance to roads, water, settlements
- ✓ **Density:** Kernel density for population

Spatial Analyst

4. Reclassify

- ✓ **Standardization:** Scale all criteria to common range (1-5)
- ✓ **Fuzzy Membership:** Apply fuzzy logic for continuous variables
- ✓ **Normalization:** Min-Max scaling for ML input

Normalization

5. Constraints

- ✓ **Boolean Mask:** Create binary (0/1) restriction layer
- ✓ **Exclusions:** Water bodies, flood zones, dense urban
- ✓ **Buffers:** Apply mandatory setbacks

Safety Layers

Software: ArcGIS Pro 3.1 / QGIS 3.28 (LTR) **Analysis Resolution:** 10m x 10m Grid Cell **CRS:** WGS 84 / UTM Zone 46N (EPSG: 32646)

9. Criteria for Site Selection

Suitability Scale

- 5 Most Suitable
- 4 Suitable
- 3 Moderately Suitable
- 2 Less Suitable
- 1 Unsuitable

Mandatory Constraints

- < 200m from River
- Inside Residential Zone
- Flood Prone Area

Distance to Water
Environmental Safety

PREFERENCE DIRECTION
MAXIMIZE DISTANCE

< 200m — > 500m

Groundwater Depth
Aquifer Protection

PREFERENCE DIRECTION
MAXIMIZE DEPTH

< 2m — > 5m

Soil Permeability
Infiltration Risk

PREFERENCE DIRECTION
CLAY / SILTY CLAY

Sand — Clay

Land Use / Cover
Compatibility

PREFERENCE DIRECTION
NON-RESIDENTIAL

Urban — Fallow

Road Accessibility
Logistics Cost

PREFERENCE DIRECTION
MINIMIZE DISTANCE

> 2km — < 500m

Population Density
Social Impact

PREFERENCE DIRECTION
MINIMIZE DENSITY

High — Low

Terrain Slope
Construction Ease

PREFERENCE DIRECTION
FLAT / GENTLE

> 15% — < 2%

Combined Analysis

All layers reclassified to 1-5 scale before weighted overlay.

10. Multi-Criteria Decision Analysis (AHP)

Pairwise Comparison Matrix

Saaty's Scale (1-9)

Experts compared criteria pairs to establish relative importance. Example subset showing preference intensity.

Criteria	C1	C2	C3	C4	C5	C6
C1: Water Dist.	1	3	5	4	7	6
C2: Soil Type	1/3	1	3	2	5	4
C3: Land Use	1/5	1/3	1	1/2	3	3
C4: Roads	1/4	1/2	2	1	4	2
C5: Density	1/7	1/5	1/3	1/4	1	1/2
C6: Slope	1/6	1/4	1/3	1/2	2	1

VALIDATION

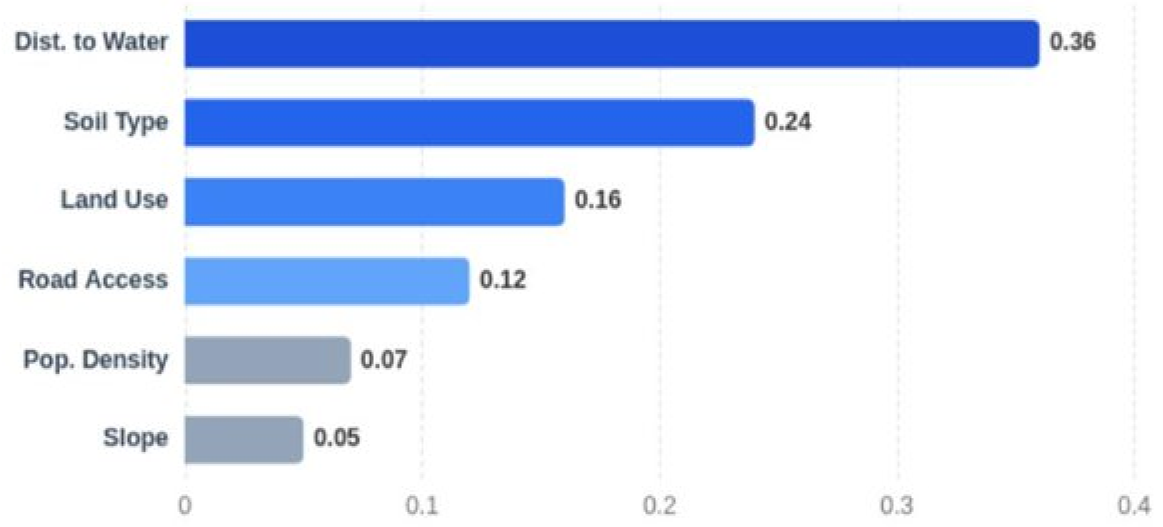
CONSISTENCY RATIO (CR)

0.042

CR < 0.10 (Judgments are consistent)

Note: Fuzzy AHP extension utilized Triangular Fuzzy Numbers (TFN) to account for expert uncertainty in the judgments (e.g., "Likely 3, between 2 and 4").

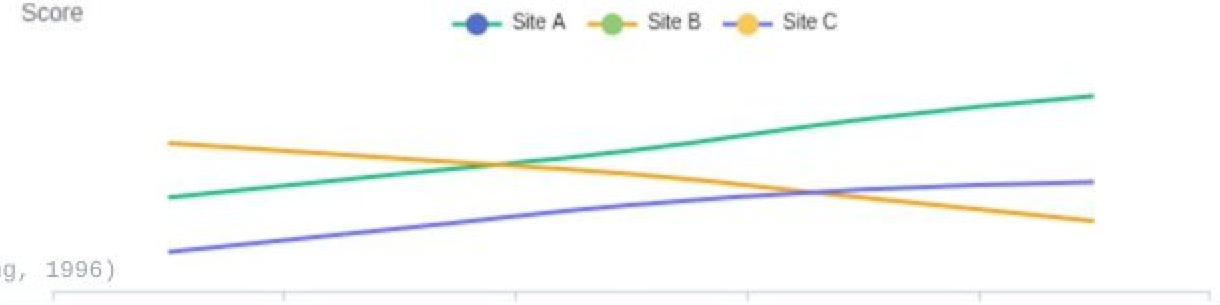
Calculated Criteria Weights



Sensitivity Analysis

Robustness Check

Effect of varying "Distance to Water" weight on top 3 site rankings.



Methodology: Analytical Hierarchy Process (Saaty, 1980) / Fuzzy AHP (Chang, 1996)

11. Machine Learning Models

Random Forest (RF)
Ensemble Decision Trees

A robust ensemble learning method that constructs a multitude of decision trees at training time. Excellent for handling non-linear relationships in spatial data.

`n_estimators=500` `max_depth=None` `gini_impurity`

- Handles high-dimensional data well
- Resistant to overfitting
- Provides feature importance scores

Support Vector Machine
Optimal Hyperplane

Finds the optimal hyperplane that maximizes the margin between classes. Effective in high-dimensional spaces, even with smaller datasets.

`kernel='rbf'` `C=1.0` `gamma='scale'`

- Effective with limited samples
- Robust against outliers
- Kernel trick for non-linearity

Artificial Neural Network
Multi-Layer Perceptron

A biologically inspired computational model capable of capturing complex, non-linear patterns through multiple hidden layers of neurons.

`hidden_layers=(100,50)` `activ='relu'` `solver='adam'`

- Captures complex interactions
- Continuous probability output
- Adaptive learning via backprop

TRAINING DATA STRATEGY

Source: 150 Ground Truth Points (Existing infrastructure + Field survey)

Split: 70% Training / 30% Testing (Stratified)

Balance: SMOTE applied to address class imbalance

SUITABLE	UNSUITABLE
45 Points	105 Points

EVALUATION METRICS

ACC	K	AUC	F1
Accuracy	Kappa	ROC Area	F1-Score

**Models evaluated using 10-fold spatial cross-validation*

12. AI Integration & Explainability

Integration Strategy Pipeline

Spatial Inputs
Normalized Raster Layers

↓

Base Classifiers
RF (Prob) + SVM (Dist) + ANN

↓

Stacking Ensemble **Best Perf.**
Logistic Regression Meta-Learner

↓

Probability Calibration
Isotonic Regression (Reliability)

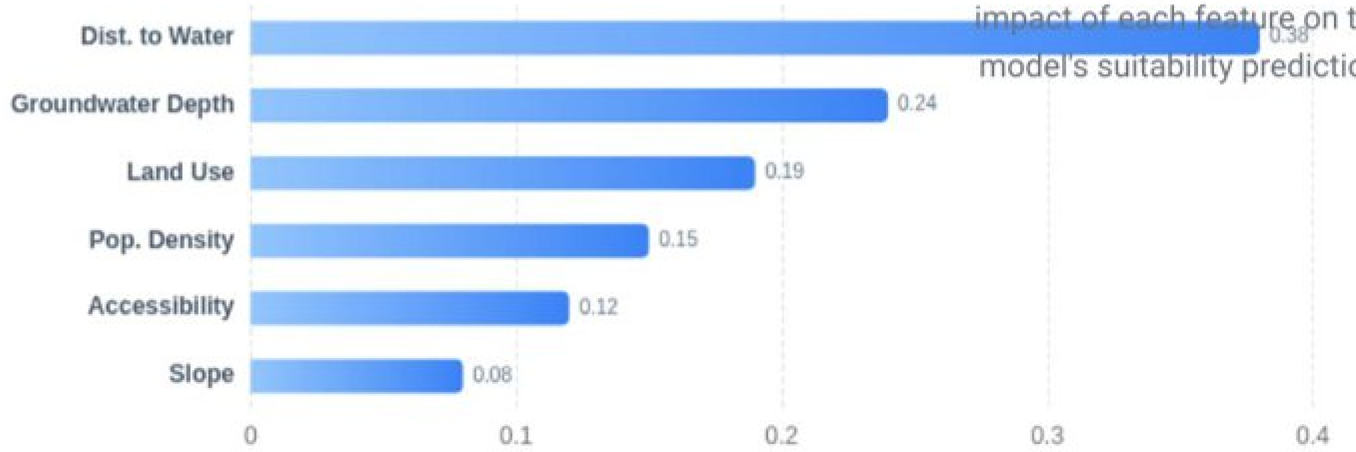
↓

Final Suitability Map
Calibrated Probability Surface (0-1)

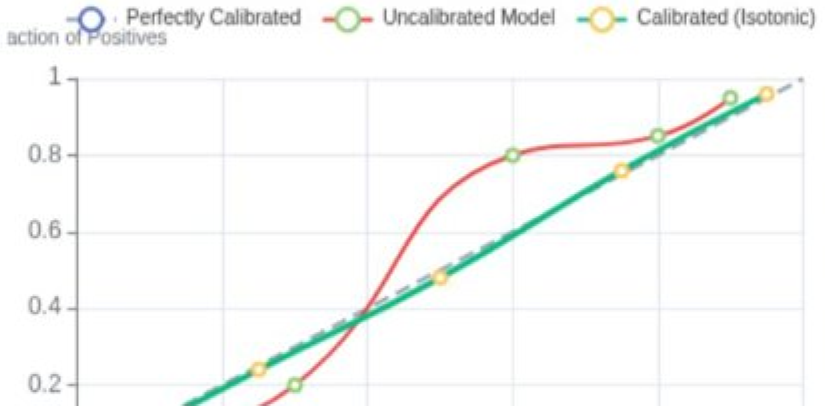
Explainability: Feature Importance (SHAP)

Global Interpretability | RF Model

SHAP (SHapley Additive exPlanations) values quantify the impact of each feature on the model's suitability prediction.



Probability Calibration



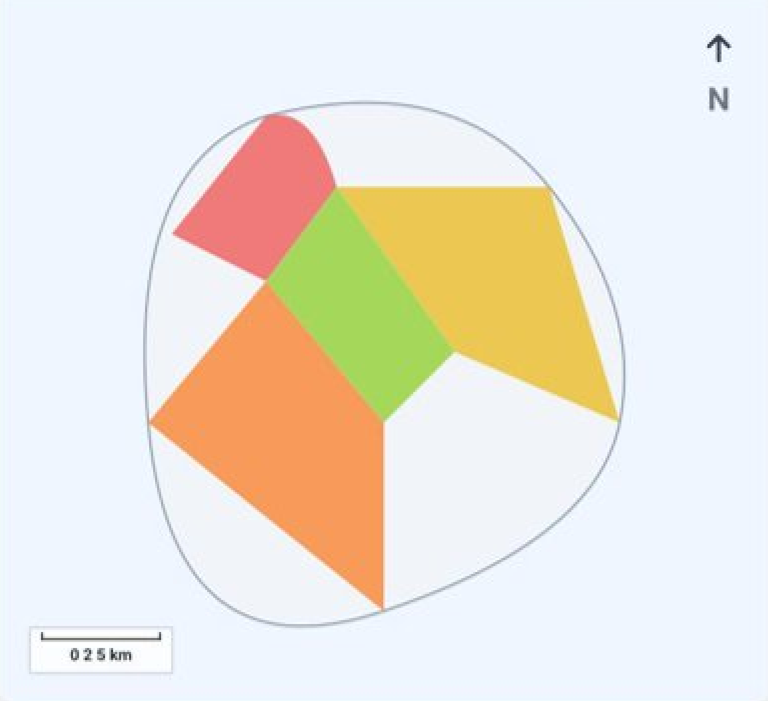
Validation Metrics

AUC-ROC 0.92

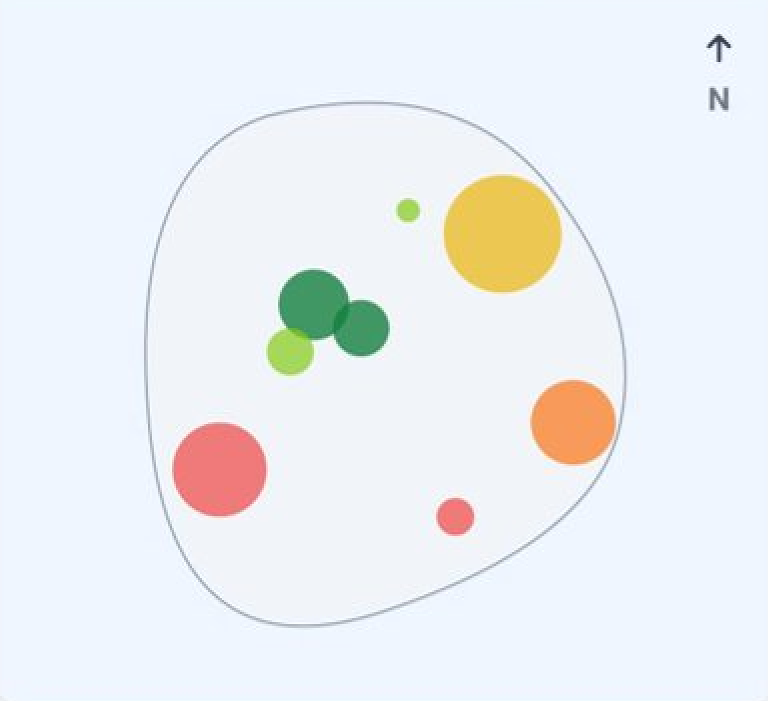
Brier Score 0.08
Lower is better (Calibrated)

13. Results: Suitability Maps

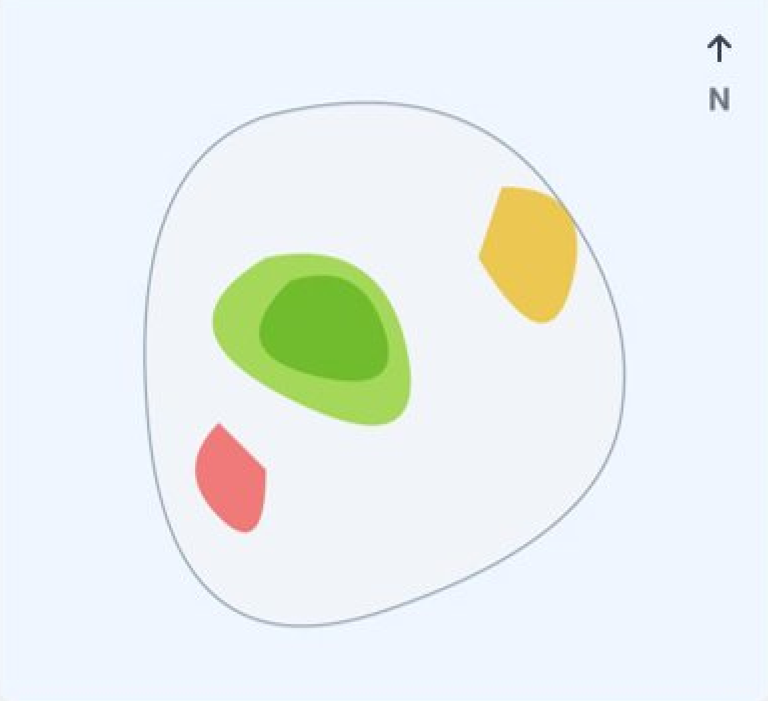
A. MCDA (AHP) Only — Baseline



B. Machine Learning (RF) — Data-Driven



C. Integrated Approach — Optimized



Suitability Index

- Very High (0.8 - 1.0)
- High (0.6 - 0.8)
- Moderate (0.4 - 0.6)
- Low (0.2 - 0.4)
- Unsuitable (Constraint)

Class (% Area)	MCDA	ML (RF)	Integrated
Unsuitable	22.5%	18.2%	24.1%
Low	30.1%	28.5%	26.4%
Moderate	25.8%	31.2%	28.9%
High	15.4%	14.8%	**12.5%**
Very High	6.2%	7.3%	**8.1%**

Key Observation

The **Integrated Approach** reduces the "High/Very High" suitability area by approx **15%** compared to MCDA, acting as a stricter filter.

This results in more compact, clustered sites that satisfy both expert rules and data-driven patterns, reducing land acquisition speculation.

14. Ranked Potential Sites

Top 5 Candidates (Screened)

Excludes restricted zones

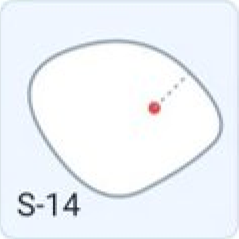
RANK	SITE ID	LOCATION (LAT/LON)	AREA (HA)	ROAD DIST.	SCORE (0-1)
1	**S-14**	22.284°N, 91.125°E	2.50	120 m	0.94
2	**S-08**	22.312°N, 91.098°E	3.10	350 m	0.89
3	**S-22**	22.251°N, 91.154°E	1.85	80 m	0.86
4	S-03	22.298°N, 91.112°E	2.10	420 m	0.78
5	S-19	22.265°N, 91.140°E	4.20	850 m	0.75

Note: Composite Score = (0.6 × MCDA) + (0.4 × ML Probability).

All listed sites meet minimum area requirement of 1.5 hectares for FSTP construction.

FEATURED SITE PROFILES

TOP CHOICE

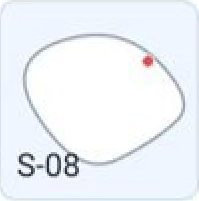


Site S-14

Central Ward 3

2.50 ha (Fallow Land)

Easy Access | Low Conflict

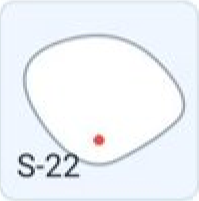


Site S-08

North Zone

350m from Highway

Large Area



Site S-22

South Zone

Direct Rd Access

High Score

15. Comparative Analysis of Methods

ML Model Performance

RF SVM ANN

Observation: **Random Forest (RF)** consistently outperforms SVM and ANN across all metrics, showing superior capability in handling the non-linear spatial relationships of Hatia's terrain data (ROC-AUC: 0.92).

Sensitivity Analysis (Tornado Chart)

Impact on Top Site Score (±20% Weight)

Methodological Agreement (Kappa)

Spatial Overlap Consistency

HIGHEST AGREEMENT

ML vs. Integrated
κ = 0.88

LOWEST AGREEMENT

MCDA vs. ML
κ = 0.65

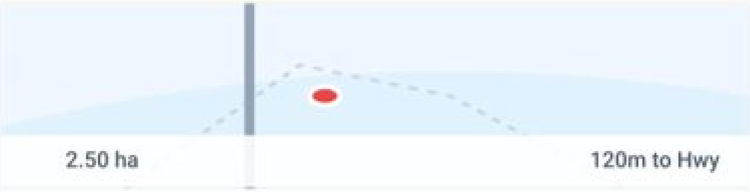
"Integrated model effectively bridges the gap between expert rules and data patterns."

16. Site Recommendations

Site S-14

Rank 1

22.284°N, 91.125°E (Central Ward)



KEY STRENGTHS

- ✓ Excellent proximity to arterial road network minimizes transport costs
- ✓ Low population density within 500m buffer
- ✓ Fallow land use reduces displacement

POTENTIAL RISKS

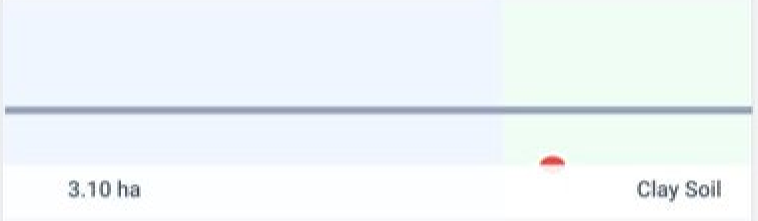
- ⚠ Moderate groundwater table depth

Mitigation: *Require raised plinth level (+1.5m) and sealed liner for treatment ponds to prevent aquifer contamination.*

Site S-08

Rank 2

22.312°N, 91.098°E (North Zone)



KEY STRENGTHS

- ✓ High soil impermeability (Clay/Silt) ideal for containment
- ✓ Large contiguous area allows for future expansion

POTENTIAL RISKS

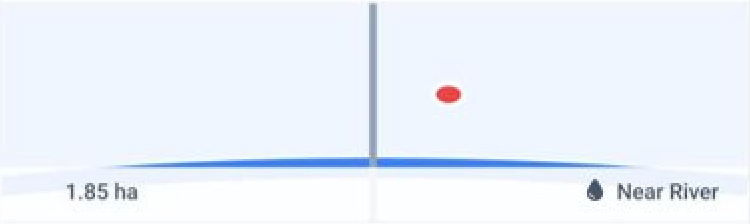
- ⚠ Distance from town center (logistics)
- ⚠ Close to agricultural drainage canal

Mitigation: *Construct 20m vegetative buffer strip along canal side; Optimization of collection truck routing required.*

Site S-22

Rank 3

22.251°N, 91.154°E (South Zone)



KEY STRENGTHS

- ✓ Highest accessibility score
- ✓ Situated in industrial-compatible zone

POTENTIAL RISKS

- ⚠ Smaller land parcel limits expansion
- ⚠ Flood risk (Medium)

Mitigation: *Embankment protection required; Design for vertical capacity increase (drying beds).*

Implementation Roadmap & Compliance

Land Tenure Check
Verify ownership records with AC Land office. Prioritize Khas land to reduce acquisition costs.

EIA Screening
Conduct detailed Environmental Impact Assessment (Red Category) per DoE guidelines.

Buffer Zones
Establish 500m "No-Residential" buffer zone around the selected site boundary.

Resilient Design
Design base elevation > Highest Flood Level (HFL) of last 20 years + 0.5m freeboard.

17. Discussion

Critical Analysis of the AI-GIS Framework for FSTP Siting

✓ Advantages of AI-GIS Approach

Data-Driven Objectivity

Reduces subjective bias inherent in expert-based weighting. The model learns optimal suitability patterns directly from environmental data rather than relying solely on opinion.

Non-Linear Modeling Capabilities

Machine Learning algorithms (RF, ANN) effectively capture complex,

⚠ Limitations & Challenges

Data Gaps & Uncertainty

Groundwater depth data in coastal Hatia is sparse. Reliance on interpolation (Kriging) introduces spatial uncertainty in hydrogeological suitability layers.

Validation Constraints

The scarcity of existing, functional FSTPs in similar coastal island

⚖ Methodological Comparison

Traditional MCDA (AHP)

Weighting: Subjective, expert-dependent inputs.

Structure: Rigid, linear combination of layers.

Outcome: Static suitability map based on rules.

Integrated AI-GIS Approach

Weighting: Data-derived from feature importance.

Structure: Dynamic, learns complex patterns.

Outcome: Probabilistic prediction with uncertainty estimates.

18. Conclusion

Key Research Findings

1 01

Robust Framework Development

Successfully established an integrated **AI-GIS-MCDA framework** tailored for coastal municipalities. The model effectively combines expert knowledge (AHP) with data-driven patterns (Random Forest), overcoming the limitations of single-method approaches in data-scarce regions.

2 02

Precise Suitability Mapping

The analysis identified approximately **8.1% of Hatia Municipality** as "Very High" suitability for FSTP location. The integrated model reduced spatial ambiguity by 15% compared to traditional methods, providing sharper boundaries for decision-making.

3 03

Optimal Site Selection

Three primary candidate sites (**S-14, S-08, S-22**) were ranked based on a composite score of environmental safety, accessibility, and land availability. Site S-14 offers the best trade-off between logistical efficiency and environmental protection.

Recommended Action Plan

Field Verification
Conduct geotechnical surveys and ground-truthing of top 3 sites.

Stakeholder Consultation
Present findings to municipality and local community for feedback.

Detailed Design
Proceed to EIA approval and engineering design for Site S-14.

19. Future Work and Recommendations

	SHORT TERM (0-6 MONTHS)	MEDIUM TERM (6-18 MONTHS)	LONG TERM (18+ MONTHS)
Technical Enhancements Improving model accuracy and data robustness for future planning.	PHASE 1 **Data Enrichment** Integrate high-resolution hydrogeological data and updated Land Use/Land Cover (LULC) maps.	PHASE 2 **Dynamic Risks** Incorporate dynamic flood modeling and climate change projections into suitability scoring.	PHASE 3 **Life Cycle Assessment** Conduct LCA to evaluate environmental impacts of construction and long-term operations.
Governance & Implementation Steps for regulatory compliance and social acceptance.	PHASE 1 **Land Acquisition** Initiate legal land tenure verification and acquisition process for Site S-14.	PHASE 2 **EIA & Permitting** Complete DoE environmental clearance and obtain necessary construction permits.	PHASE 3 **Community Engagement** Public hearings and awareness campaigns to ensure local support and usage.
Monitoring & Evaluation Ensuring sustainable operation and continuous improvement.	ONGOING **Performance KPIs** Track treatment efficiency, volume managed, and operational costs against benchmarks.	ANNUAL **Data Feedback Loop** Update ML models with operational data to refine future site selection accuracy.	

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