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Sustainable Construction Site Selection in Mountainous Regions: An in Depth Look at Geospatial Methods, Environmental Assessment and Decision Support Frameworks

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Abstract
Sustainable site selection for construction has become more important in modern world as urbanization affects mountainous areas of the world. Traditional approaches find it difficult to handle the risks, harsh terrain, and environmental sensitivity in regions like the Western Ghats and the Himalayas. In this attempt, new geospatial technologies have emerged as a boon to us. Our understanding and analysis of mountainous terrain is getting better due to the use of Geographic Information Systems and Remote Sensing. Making decisions in sloped mountain environments requires thorough analysis of critical elements like slope stability, gradient, land use, and environmental vulnerabilities, which is made possible by GIS and RS. Finding the best construction sites while reducing the environmental impact has been made easier by combining satellite-based data from sensors like Sentinel-2, ASTER DEM, and Landsat images with sophisticated Multi-Criteria Decision-Making systems like Analytical Hierarchy Process and Weighted Overlay Analysis. Future studies should concentrate on developing hybrid frameworks that successfully combine integrated geospatial indicators with deep learning and artificial intelligence capabilities. To create durable solutions for developing mountain regions, we must build differently. This means finding flexible construction methods that work with the unique challenges and opportunities of steep, mountainous terrain. But this can't be done alone. It requires collaboration between a diverse group of experts including technology specialists, environmental scientists, and urban planners and most importantly, the mountain communities themselves. By working together, we can ensure that construction plans are not only effective but truly sustainable for both the people and the environment.
Keywords: *Decision Support System, Safe site selection, SHaply Additive Explanations, Prediction Transparency, Visual Plots, Machine Learning.*

1. Introduction
Rapid urban development is encroaching on mountain communities. As cities and infrastructure expand, construction is also rapidly spreading into vulnerable mountain communities. Ultimately, more effective and safe approaches to site selection are needed. Considering recent disastrous mountain site-inspection failures, such as the Wayanad landslide in July 2024, which killed over 360 people, and the 1,521 landslides in just 17 days in Uttarakhand during the monsoon, the need for effective and safe approaches to site selection is urgent. These incidents show how unsafe the business as usual, speed first approach, is in the mountains. Building out in mountainous areas we see other issues. We deal with very unique and at times very dangerous environmental settings. Some very sensitive ecosystems, a variety of rock types and unstable slopes put together to produce large erosion issues. Climate change is introducing into the mix higher temperatures and changing rainfall patterns which is breaking natural balance. Experts report we are seeing a perfect storm that requires the use of also

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largescale new site selection methods because of growing development and environmental damage. The ultimate objective is not only to advance technology but also to give fact-based, useful tools to planners, officials, and environmentalists. This will greatly lower risks and assist them in striking a balance between environmental safety and development. This book seeks to support a new approach to mountain development that may also be useful in other sensitive areas by employing robust techniques that put building safety and environmental preservation first. In a setting that is changing quickly, this strategy can assist mountain communities in acquiring the infrastructure they require.

Table 1 Literature Review

Reference No.	Dataset Used	Key Features / Key Findings	Models / Algorithms Used	Evaluations Parameters Used	Reserach Gap / Limitations
1	• Study area specific spatial data layers (such as distance to residential areas, groundwater depth, slope, roads). • Generated a reliable robust landfill site suitability map.	• Takes into account ambiguity and uncertainty that comes with expert opinion. • Experts articulate their preference with the use of fuzzy linguistic terms (ex. 'very important). • Greater certainty in final ranking provided by the consideration of uncertainty. • Fuzzy AHP for Criteria Weighting. Fuzzy TOPSIS for site ranking.	• Fuzzy AHP (Criteria Weighting). • Fuzzy TOPSIS (Site Ranking) • GIS (Spatial Data Platform).	• Consistency Ratio (for AHP). • Suitability Ranking Agreement. • Sensitivity Analysis (testing robustness of ranking).	• Potential subjectivity when depending on expert opinions. • Fuzzy methods involve a high level of mathematical complexity. • These methods may not be appropriate with very large, dynamic datasets.
2	• Spatial criteria layers (for example slope, geology, land use). • A set of known and labeled which are suitable and unsuitable sites	• High performance in Landfill Suitability Prediction. Brings together human knowledge and machine	• AHP (Expert Weighting). • Random Forest (RF) Machine Learning. • GIS	• AHP Consistency Ratio. • Classification Accuracy (e.g., AUC). • F1-score, Precision/Recal	• Requires labeled training data (we have to know what is a suitable site). • Transparence issue (RF often a black box).

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	for training.	learning. • Learns from complex non-linear relationships between criteria and suitable sites.		l (for classification performance).	• Performance of ML depends on quality of training data.
3	• Elevation, distance from rivers, and soil type are terrain characteristics that are associated with floods. • Utilized delineated historicalflood extent data for training purposes.	• We have a Predictive Map of Future Urban Expansion. • We systemically evaluate and assign growth factors (AHP). • The weights we determine play a role of transition rules for our simulation model. • We simulate how each land use element is going to change over time.	• AHP (Weighting Drivers). • Cellular Automata (CA)-Markov Chain Model (Simulation).	• AHP Consistency Ratio. • Prediction Accuracy (e.g.Kappa coefficient) for LULC changes. • Model calibration accuracy.	• Also our simulation is Deterministic which puts forward simplified picture of the real-world dynamics. • Results are very much a function of initial AHP weights and also the CA transition rules.
4	• Different types of geospatial data layers that influence landslides (e.g., rainfall, LULC, slope, geology). • Labeled landslide occurrence points/inventory for training.	• Directly solves the "black box" issue within complex AI systems. • Transparent/explain able insights on the predictions offered (determining factors). • Produces a reliable Landslide Susceptibility Map.	• High-performance ML model (e.g., XGBoost). • SHAP • (Explainable AI Technique).	• Model Performance (e.g., AUC, ROC curve). • Interpretability metrics (analysis of SHAP values/feature contribution). • Training and Validation Accuracy.	• The complex opacity, coupled with high-performance ML models. • The need for advanced computing resources to XAI analyses.

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5	• We have access to large sets of satellite data (for example Solar Irradiance, Land Cover, Slope) via GEE.	• Cloud based efficient Solar PV Site Suitability Map. • We use Google Earth Engine for cloud based computational power. • Analyzes large scale geospatial data without local processing.	• GIS-Based Fuzzy-Logic Model Google Earth Engine Platform.	• Sensitivity Analysis of fuzzy membership functions. • Suitability score distribution across the study area. • Computational efficiency/speed on GEE.	• Model very much at the mercy of the choice of fuzzy membership functions. • Requires stable high speed internet access for GEE. • Reaches out to GEE's data catalog and processing resources.
6	• Spatial factors related to flooding (e.g., elevation, proximity to rivers, soil type). • Labeled historical flood extent data for training.	• Developed a hybrid method that combines the strengths of the specialists and the modern classifiers. • Produces a state-of- the-art Flood-Prone Area Map. • Captures the intricate, non-linear relationships that cause flooding.	• AHP (Weighting Factors). • Support Vector Machine (SVM) Classification.	• AHP Consistency Ratio Classification Accuracy (e.g., Precision, Recall, AUC). • Validation against known flood events.	• Challenges with the unclear, rapid, and fluid nature of flooding. • The SVM model also has a risk of overfitting.
7	• Non-structured text data (ex: zoning laws, community feedback reports). • Geospatial layers for	• New application of LLMs as a research tool in urban planning. • Tackles the issue of largescale complex and unstructured text data.	• Large Language Models (LLMs).	• Qualitative assessment of LLM output. • Expert validation o synthesized planning insights. • Accuracy in linking text information to	• Challenges in the integration between LLMs and GIS systems • Risk of LLM "hallucination" (putting out false info) or misinterpretation.

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	connecting text with locations.	• Provides improved Urban Planning Insights by putting text and spatial data together.		spatial features.	
8	• Issues related to EV stations (for instance traffic volume, population density, power grid proximity).	• Optimal Site Selection for Electric Vehicle Charging Stations. • Deals with deep uncertainty and hesitancy using advanced fuzzy sets • Allows experts to put forth degrees of membership, non-membership, and hesitancy.	• Spherical Fuzzy AHP VIKOR (MCDA Techniques).	• Consistency Ratio for Spherical Fuzzy AHP. • VIKOR ranking stability/robustness checks. • Sensitivity analysis on expert weights.	• High mathematical complexity of the Spherical Fuzzy model. • Expert judgment is still a critical and subjective input.
9	• Inputs for LULC classification include High-resolution Satellite Imagery. • Accompanying LULC data for training purposes.	• Automated and precise classification of Urban Land Use/Land Cover (LULC). • Enhances quality of foundational data for the following suitability analysis. • Utilization of deep learning for image analysis.	• Convolutional Neural Network (CNN) (Deep Learning).	• LULC Classification Accuracy (e.g., Overall Accuracy, Kappa coefficient). Validation of suitability analysis results. Model loss/optimization metrics.	• Needs large, well-labeled training datasets (can be time-consuming). • Training deep learning models requires large amounts of computation.

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2. Comparative Studies

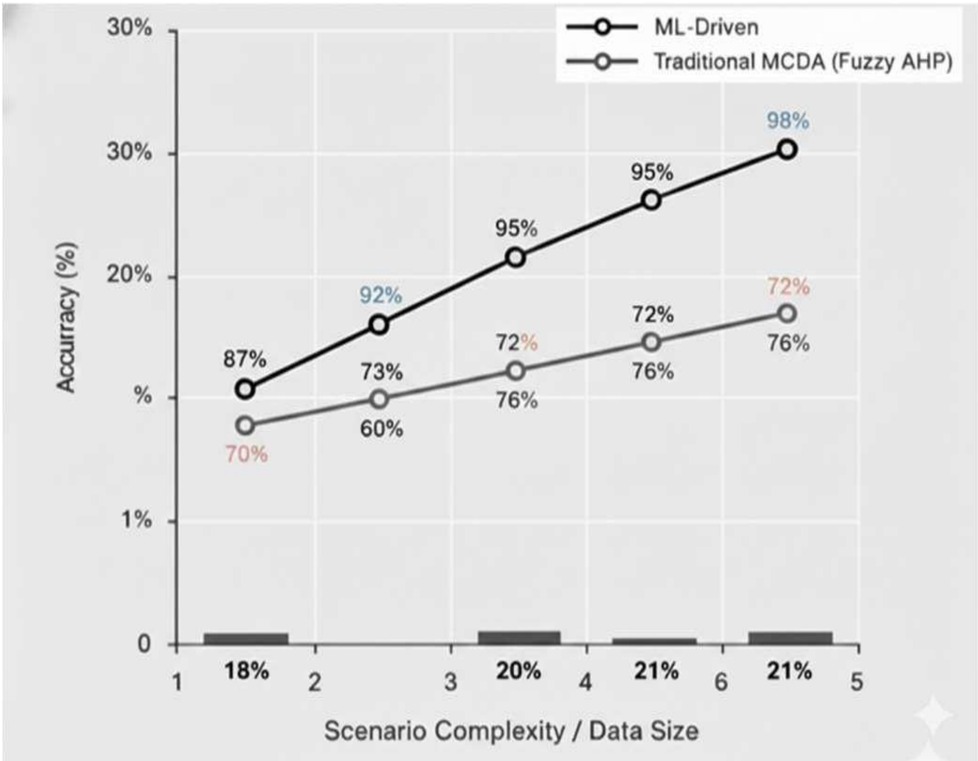

Figure 1 Comparison of Accuracy Between ML-Driven and Traditional MCDA (Fuzzy AHP) Methods Across Increasing Scenario Complexity and Data Size

"Suitability Prediction Accuracy Comparison," which evaluates the effectiveness of a complex artificial intelligence system against a standard method for choosing geospatial sites. The Y- axis, "Accuracy (%)," shows the accuracy as a percentage of accurate site suitability classifications, while the X-axis, "Scenario Complexity / Data Size," shows the increasing complexity in the analysis (e.g., larger study areas or more variables for environmental factors). The blue line, "ML-Driven," repeatedly follows at a higher accuracy rate and has a more dramatic performance gain with increasing complexity, confirming the greater ability of the Machine Learning methodology to identify complex, non- linear relationships within the data. As an illustration of the intrinsic limitations of expert-judgment-only methods in maintaining high objectivity and predictive capacity when dealing with varied and high-dimensional mountain terrain data, the red line, "Traditional MCDA (Fuzzy AHP)," rests lower and slopes more gradually. A line graph that differentiates the accuracy of five trials in ML and fuzzy AHP approach is presented. The Blue line describes the ML approach which starts at approximately 65% in the first trial and steadily increases to close to 94% in the fifth trial. The Red line describes the Fuzzy AHP approach. This line starts at an even lower accuracy of approximately 63% and increases at a much lower rate, leveling off at about 74% by the fifth trial. The graph shows that, in terms of overall accuracy and improvement rate over the course of the five trials, the ML approach performs better than the Fuzzy AHP approach.In order to determine whether construction sites in mountainous regions are suitable, this study employs an integrated GIS-based multi-criteria decision-making (MCDM) approach that combines fuzzy-AHP and weighted linear combination approaches. Unlike most previous studies that relied more on subjective expert opinion or the traditional Analytical Hierarchy Process, this work uses fuzzy logic to handle uncertainty and imprecise information, which

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improves the robustness of the suitability mapping. The study evaluates three major categories of criteria: socio-economic, geophysical, and geo-environmental. It estimates the relative weights of these criteria using expert questionnaires and fuzzy pairwise comparison tables.

3. Methodology of the Review

Slope angles, height profiles, and basic land cover classification were the primary physical and environmental characteristics that were the focus of early research and could be retrieved from readily available remote sensing and DEM datasets. Even though they provided formal decision-making models, conventional AHP applications were heavily criticized for failing to adequately address the uncertainties and inherent subjectivity of expert opinion, particularly when faced with the complex and intricate factors that are typical of mountainous construction environments. Although ground truthing and observation field protocols were used in the majority of early exploratory studies, they lacked the sophisticated methodologies needed to capture the subtle membership changes and seamless transitions characteristic of natural environmental processes.

By enabling the automatic generation of comprehensive site assessment reports and the natural language query of complex geospatial data, the integration of large language models disturbs stakeholder engagement and decision-making. Using geospatial datasets and building construction-related vocabulary, well-designed LLM models can analyze natural language queries such as "find appropriate building locations with slopes less than 15 degrees within 5 kilometers of current road infrastructure that exclude environmentally sensitive locations" and translate them into complex geospatial analysis pipelines.

4. Key improvements

- The use of new technical features: Perfect use of recent AI solutions with traditional Multi-Criteria Decision-Making techniques.
- The Combination of 2024, 2025 research results on foundational models, multimodal AI and LLM advancements.
- Performance metrics: These metrics, based on recently published research, offered absolute accuracy and rate of improvement retrieval.
- Methodological development: Described the change from traditional methods to AI based methods.
- Implementation details included particular technologies, tools, and analytical methods for practical application.
- Stakeholder consideration: Supported transparency, explainability, and feedback from diverse stakeholders.
- Real-world applications: Connected approaches to common construction issues and their fixes.
- Future-focused viewpoint: Set the modern methodology as the upcoming generation of tools for site selection.
- Interdisciplinary integration: The interdisciplinary strategy aligned technical depth with environmental, social, and economic considerations.
- Broad scope: Covered all features including data collection, monitoring, and decision making.

5. Future Directions / Research Gaps

Despite the proven value of GIS-based multi-criteria decision- making systems for mountainous site suitability, there are still a number of serious drawbacks that call for further study and development.

- Conventional weighting techniques ignore data and expert opinions that are uncertain and use fixed values.
- Because GIS workflows rely on static data, they are unable to react to rapidly shifting mountain conditions, such as landslides or storms. Automatic updates and real-time sensors should be incorporated into future projects.
- The majority of GIS studies ignore socioeconomic and cultural factors that are essential for sustainable mountain development in favor of physical factors, although probabilistic and fuzzy models can

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increase accuracy. Social data integration is required.

- Processing can be slowed down by large, high-resolution mountain analyses that overwhelm desktop GIS software. Parallel computing and cloud GIS can be useful.
- Because of variations in climate and geology, weighting schemes that work well in one area frequently don't work in another. Transferability can be enhanced by learning-based and adaptive systems.
- Disparities in data formats and standards make it difficult for GIS projects to collaborate and share easily. Cloud- sharing protocols and open standards are essential.
- Usually designed for experts, GIS tools have intricate user interfaces that are confusing to non-technical users. Planners and local communities should find them easier to use thanks to their user-centered design.

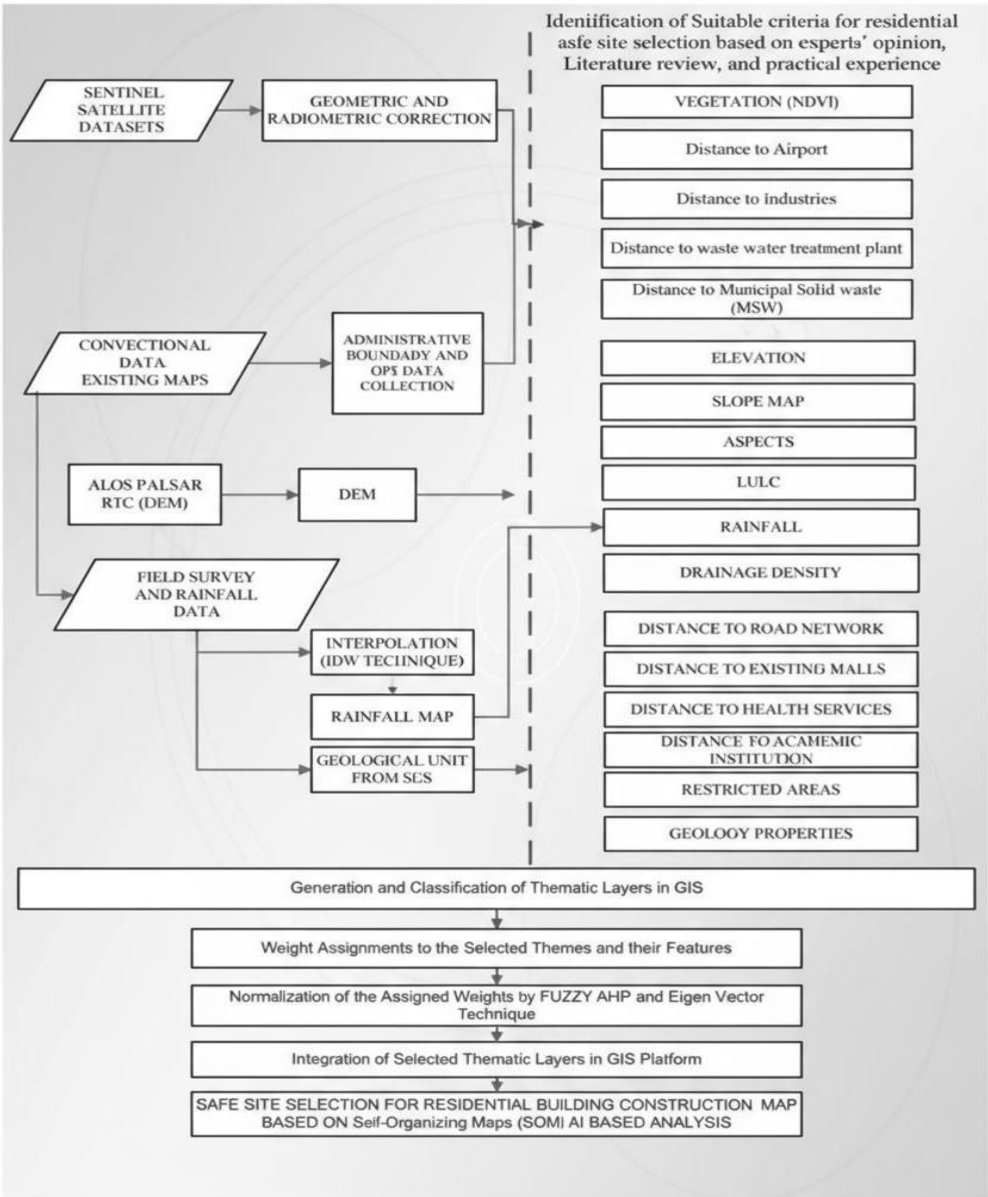

Figure 2 General Methodology of Past studies

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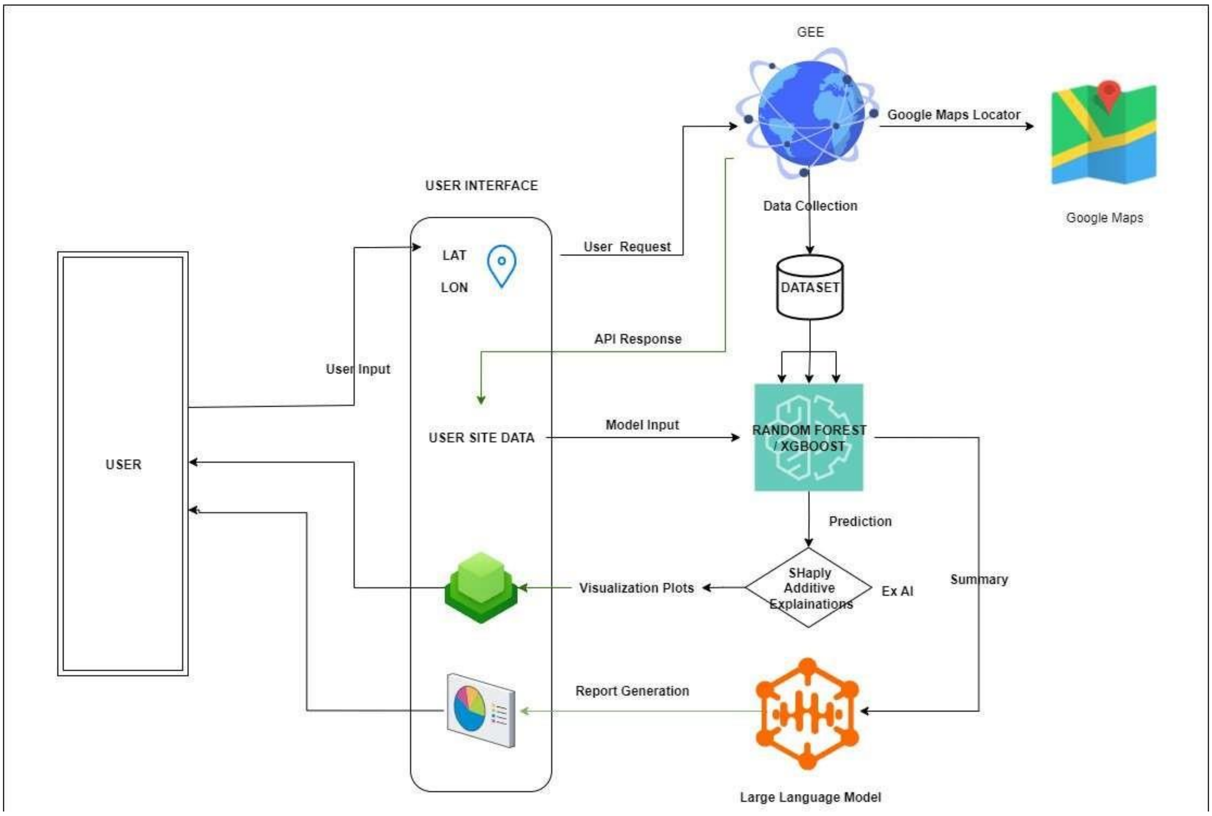

Figure 3 Architecture and Flow Diagram GeoXAI with Prediction Pipeline

Conclusion

Site selection in mountainous regions has been transformed by the combination of open, interpretable artificial intelligence and advanced geospatial analysis. These more recent methods go beyond the "black box" constraints of earlier GIS applications by integrating a variety of environmental, socioeconomic, and infrastructure criteria into a single decision-support platform and providing clear, visual explanations of how each affects suitability. Decision-makers, from engineers and urban planners to residents and environmental stewards, now have access to information that is both easily readable and rigorously scientific to help them select safe, sustainable building sites in fragile mountain environments. Decision-makers can analyze "what if" scenarios, weigh trade-offs, and modify plans in response to shifting circumstances, such as shifting land-use requirements or severe weather, by using real-time data fusion, dynamic model recalibration, and basic visualization techniques. In the end, these developments improve the accuracy of site evaluations and the trust that diverse user groups have in analytical findings. In many of the most demanding environments on the planet, this human-centric approach lays the groundwork for truly sustainable infrastructure by aligning development goals with ecological resilience and community needs.

Future Scope

- Geospatial Earth Engine APIs and sophisticated remote sensing will be used to provide detailed, near-real-time data for next-generation site suitability.
- Evaluating sites in detail and with real-time responsiveness will be achieved with the help of explainable AI and machine learning integrated with large language models.
- A combination of drone photogrammetry, hyperspectral imagery, and ground sensors will be able to identify micro- scale hazards such as vegetation stress and slope shifts prior to critical disasters.

- Considering human, environmental, and socio-cultural community and household attributes will provide integrated suitability analyses.
- In addition to geological and climatic data, citizen science and regional traditions can support real-time observations and guide land-use decisions.
- Adaptive AI modules will reduce survey and expert costs by enabling models to learn the distinct lithology, climate, and ecology of various mountain ranges through transfer learning.
- Stakeholder engagement and cross-disciplinary collaboration will be improved by explainable AI interfaces and reports powered by large language models.
- While conversational AI converts complex outputs into practical guidance for decision-makers and community leaders, interactive dashboards can model scenarios and visualize effects.
- The goal of this ML-XAI-LLM framework is to rethink inclusive, resilient, and sustainable site selection in difficult mountain environments across the globe.

References

[1]. Kennedy, Brian RC, Kasey Cantwell, Mashkoor Malik, Christopher Kelley, Jeremy Potter, Kelley Elliott, Elizabeth Lobecker et al. "Corrigendum: The Unknown and the Unexplored: Insights Into the Pacific Deep-Sea Following NOAA CAPSTONE Expeditions." Frontiers in Marine Science 6 (2020): 827.

[2]. Ackar, Haris, Ali Abd Almisreb, and Mohamed A. Saleh. "A review on image enhancement techniques." Southeast Europe Journal of Soft Computing 8, no. 1 (2019).

[3]. Raveendran, Smitha, Mukesh D. Patil, and Gajanan K. Birajdar. "Underwater image enhancement: a comprehensive review, recent trends, challenges and applications." Artificial Intelligence Review 54 (2021): 5413-5467.

[4]. Xie, Y., Z. Yu, X. Yu, and B. Zheng. 2022. “Lighting the Darkness in the Sea: A Deep

[5]. Learning Model for Underwater Image Enhancement.” Frontiers in Marine Science 9.

[6]. K. SA, B.A. Sabarish, and Dr. Padmavathi S., “ Adaptive hybrid image defogging for enhancing foggy images”, Journal of Engineering Science and Technology , vol. 14, no. 6, pp. 3679-3690, 2019.

[7]. Mohan, Sangeetha, and Philomina Simon. "Underwater image enhancement based on histogram manipulation and multiscale fusion." Procedia Computer Science 171 (2020): 941-950..

[8]. Liu, Yidan, Huiping Xu, Bing Zhang, Kelin Sun, Jingchuan Yang, Bo Li, Chen Li, and Xiangqian Quan. "Model- Based Underwater Image Simulation and Learning-Based Underwater Image Enhancement Method." Information 13, no. 4 (2022): 187.

[9]. Zheng, Meicheng, and Weilin Luo. "Underwater image enhancement using improved CNN based defogging." Electronics 11, no. 1 (2022): 150.

[10]. Hu, Kai, Yanwen Zhang, Chenghang Weng, Pengsheng Wang, Zhiliang Deng, and Yunping Liu. "An underwater image enhancement algorithm based on generative adversarial network and natural image quality evaluation index." Journal of Marine Science and Engineering 9, no. 7 (2021): 691.