GEO-EYE

REVIEW ARTICLE

Bridging Analytic Hierarchy Process (AHP) and GeoAI: Innovations in Geographical Decision-Making and Spatial Planning

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Abstract

The Analytic Hierarchy Process (AHP) is a prominent multi-criteria decision-making (MCDM) approach that enables systematic evaluation of complex problems by structuring criteria hierarchically and applying pairwise comparisons. In geographical contexts, AHP facilitates informed spatial decision-making by integrating diverse factors such as topography, land use, accessibility, environmental sensitivity, and socio-economic attributes. This review examines the theoretical foundations of AHP and its practical applications in urban planning, environmental management, tourism development, and resource allocation. Particular attention is given to recent innovations that bridge AHP with GeoAI, including integration with Geographic Information Systems (GIS), incorporation of fuzzy logic to manage uncertainty, artificial intelligence–enhanced decision support, and the Analytic Network Process (ANP) for addressing interdependencies among criteria. The study highlights that combining AHP with GeoAI not only enhances analytical rigor but also enables dynamic, scalable, and real-time spatial planning solutions. The review concludes that hybrid AHP–GeoAI frameworks represent a promising frontier for advancing precision and efficiency in geographical decision-making.

Keywords: Analytic Hierarchy Process, GeoAI, Spatial decision-making, GIS integration, fuzzy AHP, Multi-criteria evaluation, Urban and environmental planning

OPEN ACCESS
Received: 01-09-2025
Accepted: 22-12-2025
Published: 28-12-2025

Citation: Gadakh BL, Jaybhaye RG. Bridging Analytic Hierarchy Process (AHP) and GeoAI: Innovations in Geographical Decision-Making and Spatial Planning. 2025; 14(2):70-77. https://doi.org/10.53989/bu.ge.v14.i2.25.22

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Funding: None

Competing Interests: None

Published By Bangalore University, Bengaluru, Karnataka

ISSN
Print: 2347-4246
Electronic: xxxx-xxxx

1 Introduction

The growing complexity of spatial challenges in geography demands robust and adaptable decision-making frameworks [8, 9]. The Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty (1977, 1980, 1988, 1995), stands out as one of the most widely recognized multi-criteria decision-making (MCDM) techniques. AHP provides a structured approach to decompose complex problems into hierarchical levels, enabling systematic evaluation and ranking of alternatives based on both qualitative judgments and quantitative data [2, 7]. By assigning weights to criteria through pairwise comparisons, AHP accommodates incomplete or inconsistent inputs while generating overall scores and consistency measures [3, 11].

Geographical decision-making is inherently multifaceted, as it involves the interplay of diverse natural, social, and economic factors [1, 6]. Geographers frequently face tasks such as evaluating land-use alternatives, assessing environmental risks, prioritizing resource allocation, or planning urban expansion—all requiring consideration of multiple, sometimes conflicting, criteria [8, 9]. For instance, identifying suitable land for urban development entails balancing topography, soil quality, transportation access, population density, and ecological sensitivity [3, 11]. Similarly, environmental management requires harmonizing conservation objectives with hazard mitigation and socio-economic development goals [2, 7].

Traditional single-criterion models are insufficient for addressing such multidimensional complexity, as they often prioritize one factor at the expense of others [8, 10]. Multi-criteria decision analysis (MCDA) approaches, particularly AHP, have thus gained prominence in geography and related disciplines. AHP enables decision-makers to structure problems hierarchically, decomposing them into a goal, criteria, sub-criteria, and alternatives. Through pairwise comparisons, priority weights are derived that integrate expert knowledge and quantitative data [9]. The inclusion of a consistency ratio (CR) ensures logical coherence in judgments, enhancing reliability [11]. This structured yet flexible methodology aligns well with geospatial reasoning, where qualitative assessments (e.g., cultural values, community priorities) and quantitative measures (e.g., slope gradients, rainfall intensity, economic costs) must be combined for informed decision-making [1, 7].

Over the past four decades, AHP has become central to geographical analysis, underpinning research in urban and regional planning, environmental management, tourism development, and natural resource evaluation [2, 8]. Its integration with Geographic Information Systems (GIS) further strengthens its applicability by providing spatial data handling and visualization capabilities [6, 7]. Recent methodological innovations—including fuzzy AHP, Analytic Network Process (ANP), and AI-assisted frameworks—address limitations of subjectivity, uncertainty, and interdependent criteria, enhancing the method's analytical power [3, 10].

This review synthesizes the conceptual foundations and methodological strengths of AHP, highlights its applications in geographical research, examines its limitations, and explores emerging trends—particularly the integration with GeoAI—that expand its potential for dynamic, data-driven spatial decision-making [2, 9]. By situating AHP within the evolving landscape of spatial analysis, this paper underscores its enduring relevance as a cornerstone methodology in geographical problem-solving.

2 Methodology

The methodological framework for integrating the Analytic Hierarchy Process (AHP) with GeoAI involves a systematic multi-step approach, combining the strengths of multi-criteria decision-making (MCDM) with spatial data analysis and artificial intelligence techniques. This hybrid approach is designed to enhance accuracy, objectivity, and scalability in geographical decision-making and spatial planning.

2.1 Problem Definition and Hierarchical Structuring

The first step involves clearly defining the spatial problem and identifying objectives, criteria, sub-criteria, and alternative solutions. In AHP, the problem is decomposed hierarchically, where the goal occupies the top level, followed by criteria and sub-criteria at intermediate levels, and alternatives at the lowest level [8, 10]. For example, in urban land-use planning, criteria may include environmental sensitivity, accessibility, socio-economic potential, and topographical constraints. Sub-criteria under environmental sensitivity may include soil type, slope, and flood susceptibility.

2.2 Criteria Weighting Using AHP

Once the hierarchy is established, pairwise comparisons are conducted to assess the relative importance of criteria and sub-criteria. Expert judgment, stakeholder input, and quantitative data are combined to generate priority weights. The consistency of judgments is evaluated using the Consistency Ratio (CR), ensuring logical reliability in the decision-making process [3, 11]. This step allows the decision-maker to capture both subjective preferences and objective measures, a crucial requirement for spatial decision-making where factors are often interdependent.

2.3 Spatial Data Integration with GIS

Geographic Information Systems (GIS) serve as a critical platform for spatial data management, visualization, and analysis. Criteria and sub-criteria are represented as spatial layers, which are standardized, weighted, and combined to generate suitability or priority maps [6, 7]. For instance, slope maps, land-use/land-cover data, transportation networks, and population density maps can be integrated to evaluate the suitability of land for urban expansion.

2.4 Incorporation of GeoAI Techniques

GeoAI methods, including machine learning, neural networks, and spatial predictive modeling, enhance the analytical power of traditional AHP by enabling dynamic, large-scale, and real-time spatial analysis. GeoAI can be applied to refine weights, model interdependencies, detect patterns in high-dimensional spatial datasets, and reduce subjectivity in expert judgments [1, 5]. Fuzzy logic can also be incorporated to handle uncertainty and vagueness in criteria evaluation, resulting in a more robust decision-making framework [3].

2.5 Decision Synthesis and Mapping

The final stage involves synthesizing weighted criteria using AHP-GeoAI integration to generate composite spatial suitability maps, prioritize alternatives, and support decision-making. Sensitivity analysis is performed to test the stability of results under varying weight scenarios [8, 9]. These outputs provide planners and policymakers with evidence-based, visually intuitive tools for spatial planning, resource allocation, and environmental management.

2.6 Validation and Feedback

Validation of results is conducted by comparing model outputs with observed spatial patterns, historical data, or stakeholder assessments. Iterative refinement ensures that the integrated AHP-GeoAI framework remains adaptive and responsive to evolving spatial dynamics [2, 5].

This methodology demonstrates how AHP and GeoAI can be combined to create a powerful hybrid framework for complex geographical decision-making, enabling planners to evaluate multiple criteria simultaneously, account for uncertainty, and leverage large-scale spatial datasets efficiently.

3 Applications of AHP in Geography

The Analytic Hierarchy Process (AHP) has been widely adopted in geographical research due to its capacity to integrate multiple criteria, combine qualitative and quantitative data, and support structured decision-making. Its applications span urban planning, environmental management, tourism development, natural resource allocation, and hazard assessment.

3.1 Urban and Regional Planning

AHP is extensively used for urban and regional planning, particularly in land-use suitability analysis, site selection, and infrastructure development. By evaluating multiple spatial factors such as topography, accessibility, land use, and population density, AHP helps planners rank alternative locations for urban expansion, industrial zones, or transportation networks [2, 7]. Integration with GIS allows spatial visualization of suitability maps, supporting evidence-based policy decisions [6].

3.2 Environmental Management and Conservation

Environmental planning often requires balancing ecological protection with socio-economic development. AHP assists in assessing the suitability of areas for conservation, identifying environmentally sensitive zones, and prioritizing sites for natural resource management. For example, AHP has been applied in watershed management, forest conservation, and habitat suitability analysis by weighing criteria such as slope, soil type, vegetation cover, and human impact [3, 8].

3.3 Disaster Risk Assessment and Hazard Mapping

AHP facilitates the evaluation of hazard-prone areas by integrating multiple risk factors. In flood, landslide, and seismic vulnerability mapping, AHP is used to rank regions based on hazard intensity, exposure, and socio-economic vulnerability. Coupled with GIS, this approach enables the creation of hazard maps that inform disaster management and mitigation strategies [2, 9].

3.4 Tourism and Cultural Site Planning

In tourism geography, AHP helps identify optimal sites for tourism development by considering accessibility, aesthetic appeal, cultural significance, infrastructure, and environmental sensitivity. This method allows planners to prioritize areas for investment while minimizing ecological and social impacts [8, 9].

3.5 Natural Resource Management

AHP is applied to prioritize locations for resource extraction, agriculture, and renewable energy development. For instance, criteria such as soil fertility, water availability, slope, and climatic conditions can be weighed to identify suitable areas for crop cultivation, solar or wind energy projects, and mining operations [3, 5].

3.6 Integration with GeoAI for Enhanced Applications

Recent advancements in GeoAI, including machine learning and spatial predictive modeling, have expanded the potential of AHP in geography. By integrating AHP with GeoAI, planners can handle large spatial datasets, model interdependencies among criteria, and support dynamic, real-time decision-making. This hybrid approach is particularly effective in urban growth simulation, smart city planning, and environmental monitoring, where traditional methods alone may fall short [1, 5].

Overall, the versatility of AHP in geography stems from its structured, transparent, and adaptable methodology, which allows decision-makers to incorporate expert judgment, stakeholder preferences, and quantitative spatial data simultaneously.

4 Role of GeoAI in Spatial Analysis

Geospatial Artificial Intelligence (GeoAI) represents a transformative approach in spatial analysis, integrating artificial intelligence (AI), machine learning, and advanced computational techniques with geographic information systems (GIS) to analyze complex spatial phenomena [1, 5]. Unlike traditional GIS methods that primarily rely on static data and rule-based models, GeoAI can process large-scale, heterogeneous spatial datasets, identify patterns, and generate predictive insights for decision-making in real time.

4.1 Enhancing Data Processing and Pattern Recognition

GeoAI leverages machine learning algorithms, including deep learning and neural networks, to detect spatial patterns and relationships that may not be apparent through conventional analysis. For instance, it can identify urban growth trends, land-use changes, or environmental degradation by analyzing satellite imagery, sensor networks, and crowdsourced geographic data [5, 12]. This capability allows planners and researchers to uncover complex spatial interactions and correlations efficiently.

4.2 Predictive Modeling and Scenario Analysis

One of the key strengths of GeoAI is its predictive capability. By integrating spatial and temporal datasets, GeoAI models can forecast land-use transformations, urban expansion, or environmental hazards, providing decision-makers with scenario-based insights for proactive planning [1, 4]. These predictive models support strategic interventions in urban planning, resource allocation, and disaster management, enabling adaptive and evidence-based policies.

4.3 Integration with Multi-Criteria Decision-Making

GeoAI enhances traditional multi-criteria decision-making frameworks, such as AHP, by automating weight estimation, reducing subjectivity, and capturing interdependencies among criteria [3, 5]. For example, in land suitability analysis, GeoAI can refine the relative importance of factors such as slope, accessibility, population density, and ecological sensitivity based on spatial patterns extracted from data, thereby improving the accuracy and reliability of decision outcomes.

4.4 Real-Time and Dynamic Spatial Analysis

The integration of GeoAI with real-time data streams from IoT devices, remote sensing platforms, and social media feeds allows for dynamic spatial analysis [1, 5]. This capability is particularly valuable for disaster monitoring, smart city management, and environmental surveillance, where timely information is critical for effective interventions.

4.5 Visualization and Decision Support

GeoAI facilitates advanced visualization of spatial patterns and decision scenarios through interactive maps, 3D modeling, and geospatial dashboards. By combining AI-driven analytics with GIS visualization, planners and policymakers can interpret complex spatial relationships intuitively, communicate insights effectively, and make informed decisions in multi-stakeholder environments [4, 12].

In summary, GeoAI serves as a powerful tool in spatial analysis by enhancing pattern recognition, predictive modeling, real-time monitoring, and decision support. When integrated with AHP, GeoAI not only strengthens multi-criteria evaluation but also enables dynamic, data-driven, and scalable solutions for complex geographical problems.

5 Integration of AHP and GeoAI

The integration of the Analytic Hierarchy Process (AHP) with Geospatial Artificial Intelligence (GeoAI) represents a significant advancement in geographical decision-making, combining the structured multi-criteria evaluation of AHP with the predictive, dynamic, and computational capabilities of GeoAI [1, 5]. This hybrid approach enhances the ability to address complex spatial problems that involve large datasets, multiple interdependent criteria, and uncertain or dynamic conditions.

5.1 Framework for Integration

The integration begins with problem structuring using AHP, where the decision objective, criteria, sub-criteria, and alternatives are hierarchically organized [8, 10]. GeoAI is then applied to enhance each stage of AHP:

- **Data Processing:** GeoAI efficiently handles large-scale spatial datasets, including satellite imagery, sensor data, and social media feeds, preparing them for multi-criteria evaluation [5].
- **Criteria Weighting:** Machine learning models can refine AHP weights by analyzing historical data and identifying patterns in spatial relationships, reducing subjectivity in expert judgments [3].
- **Interdependency Modeling:** Complex interrelationships among criteria, which are difficult to quantify manually, can be captured using neural networks or other AI techniques [4].

5.2 Advantages of Integration

Integrating AHP with GeoAI provides several key benefits:

- **Scalability and Speed:** GeoAI allows rapid processing of large spatial datasets, enabling AHP to be applied to regional or national scales efficiently [5].
- **Dynamic and Real-Time Analysis:** Real-time data streams, such as remote sensing updates or IoT sensors, can be incorporated into the AHP framework through GeoAI, supporting adaptive decision-making [1].
- **Improved Accuracy and Reliability:** AI-assisted weight estimation and pattern recognition enhance the robustness of AHP outcomes, especially in situations with high uncertainty or incomplete data [3, 5].
- **Enhanced Visualization:** Integration allows the generation of interactive spatial maps and dashboards, facilitating intuitive interpretation of multi-criteria analysis results for stakeholders and policymakers [12].

5.3 Applications in Geographical Planning

The AHP–GeoAI hybrid framework has been successfully applied in:

- **Urban Planning:** Optimizing land-use allocation, infrastructure placement, and smart city planning [4, 5].
- **Environmental Management:** Prioritizing conservation zones, monitoring ecological risk, and supporting sustainable resource management [3].
- **Disaster Management:** Hazard mapping, vulnerability assessment, and emergency response planning using predictive spatial models [9].

5.4 Future Prospects

The integration of AHP and GeoAI is expected to evolve further with advances in deep learning, cloud computing, and real-time geospatial data acquisition. These developments will enhance decision-making in complex, dynamic environments and support evidence-based planning at multiple scales [1, 5].

6 Critical Evaluation

The integration of the Analytic Hierarchy Process (AHP) with Geospatial Artificial Intelligence (GeoAI) offers significant advantages in addressing complex geographical problems, yet it also presents certain limitations and challenges. A critical evaluation is essential to understand both the strengths and constraints of this hybrid framework.

6.1 Strengths

- **Structured Decision-Making:** AHP provides a transparent and systematic approach to decompose complex spatial problems into hierarchical levels, allowing decision-makers to incorporate multiple criteria, including both qualitative and quantitative factors [8, 10].
- **Enhanced Analytical Power:** The integration with GeoAI enables the handling of large-scale spatial

datasets, detection of complex spatial patterns, and predictive modeling, which traditional AHP alone cannot efficiently achieve [1, 5].

- **Reduction of Subjectivity:** AI-assisted weighting and pattern recognition reduce human bias and increase the reliability of decision outcomes, especially in contexts with incomplete or uncertain data (Huang et al., 2011; Li et al., 2021).
- **Dynamic and Real-Time Applications:** GeoAI facilitates real-time spatial analysis by incorporating streaming data from remote sensing, IoT devices, and social media, supporting timely decision-making in urban planning, disaster management, and environmental monitoring [3, 5].

6.2 Limitations

- **Data Dependency and Quality Issues:** The accuracy of the AHP–GeoAI framework heavily depends on the availability, quality, and resolution of spatial data. Inconsistent or outdated datasets may lead to erroneous conclusions [5, 8].
- **Complexity and Computational Demand:** Integrating AHP with GeoAI requires advanced computational resources and technical expertise, which may limit its applicability in regions with limited infrastructure or human capacity [1, 4].
- **Subjectivity in Initial Structuring:** While AI can refine weights and detect patterns, the initial formulation of criteria, sub-criteria, and hierarchical structure still relies on expert judgment, which can introduce bias [3, 11].
- **Interpretability Challenges:** Highly complex AI models, such as deep neural networks, can produce results that are difficult to interpret, potentially reducing transparency and stakeholder trust [5].

6.3 Opportunities for Improvement

- **Hybridization with Fuzzy Logic and ANP:** Combining AHP–GeoAI with fuzzy logic or the Analytic Network Process (ANP) can better handle uncertainty, interdependencies, and subjective judgments, improving decision reliability [3, 7].
- **User-Friendly Interfaces:** Developing interactive dashboards and GIS-integrated tools can make the hybrid framework more accessible to planners, policymakers, and stakeholders, enhancing usability and adoption [12].
- **Validation and Calibration:** Continuous validation with ground-truth data, historical observations, and stakeholder feedback is necessary to enhance the credibility and accuracy of AHP–GeoAI models [5, 9].

7 Research Gaps and Future Directions

While the integration of the Analytic Hierarchy Process (AHP) with Geospatial Artificial Intelligence (GeoAI) has significantly advanced geographical decision-making, several research gaps and opportunities for future exploration remain. Addressing these gaps can enhance the effectiveness, scalability, and applicability of the hybrid AHP–GeoAI framework.

7.1 Research Gaps

- **Limited Integration of Dynamic Data:** Most existing studies focus on static spatial datasets, while the potential of real-time and high-frequency geospatial data for AHP–GeoAI applications remains underexplored [4, 5]. Dynamic datasets, such as IoT sensors, traffic flows, and social media geotags, could improve adaptive decision-making but require robust methods to handle temporal variability.
- **Handling of Uncertainty and Interdependencies:** Although fuzzy AHP and Analytic Network Process (ANP) have been used to address uncertainty and interdependencies, comprehensive integration with AI-driven approaches is still limited [3, 8]. There is a need for frameworks that systematically combine these approaches to enhance robustness.
- **Scalability Challenges:** Applying AHP–GeoAI to large-scale regional or national planning problems is computationally intensive. Efficient algorithms and cloud-based solutions are required to ensure scalability without compromising accuracy [1, 5].
- **Interpretability and Stakeholder Engagement:** The use of complex AI models can reduce transparency and limit stakeholder understanding of decision outcomes [12]. There is a need for interactive, user-friendly interfaces that improve interpretability and support participatory decision-making.
- **Limited Case Studies Across Diverse Contexts:** Most applications of AHP–GeoAI have focused on urban planning, environmental management, or land-use

suitability. Its potential in other contexts, such as climate adaptation, disaster resilience, and sustainable resource management, remains insufficiently explored [2, 9].

7.2 Future Directions

- **Integration with Big Data and IoT:** Future research should focus on integrating AHP–GeoAI with large-scale, real-time data sources from IoT devices, remote sensing platforms, and crowdsourced data to enable dynamic and adaptive spatial decision-making [1, 5].
- **Hybridization with Advanced AI Techniques:** Incorporating deep learning, reinforcement learning, and probabilistic models can enhance the predictive and analytical capabilities of AHP–GeoAI frameworks, particularly for complex spatial interactions [4].
- **Enhanced Uncertainty Modeling:** Future frameworks should integrate fuzzy logic, stochastic modeling, and ANP to address uncertainties and interdependencies systematically, improving the reliability of spatial decisions [3, 8].
- **Participatory and Decision-Support Tools:** Developing interactive GIS dashboards and visualization platforms can improve stakeholder engagement, interpretability, and transparency, facilitating collaborative decision-making [12].
- **Expanded Applications:** There is a significant opportunity to apply AHP–GeoAI in emerging fields such as climate change adaptation, disaster risk reduction, sustainable agriculture, and energy planning, thereby broadening the practical impact of this hybrid approach [2, 9].

8 Conclusion

The integration of the Analytic Hierarchy Process (AHP) with Geospatial Artificial Intelligence (GeoAI) represents a transformative advancement in geographical decision-making and spatial planning. AHP provides a structured, transparent, and systematic framework for multi-criteria evaluation, allowing decision-makers to incorporate both qualitative judgments and quantitative data. When combined with GeoAI, the framework benefits from enhanced data processing capabilities, predictive modeling, dynamic analysis, and the ability to handle large-scale and complex spatial datasets [1, 5].

This hybrid AHP–GeoAI approach addresses many limitations of traditional decision-making methods, including subjectivity, limited scalability, and difficulty in managing interdependent criteria. It has been successfully applied across urban planning, environmental management, disaster risk assessment, tourism development, and natural resource allocation. Moreover, by leveraging machine learning, deep learning, and real-time spatial data, AHP–GeoAI enables adaptive, evidence-based, and transparent decision-making [3, 4].

Despite its strengths, challenges remain, including data dependency, computational complexity, interpretability of AI models, and the need for stakeholder-friendly interfaces. Future research focusing on real-time integration, uncertainty modeling, participatory decision-support tools, and broader applications in climate adaptation, energy planning, and sustainable resource management will further enhance the utility of this hybrid framework.

In conclusion, AHP–GeoAI integration offers a robust, scalable, and versatile methodology for addressing complex geographical problems. It bridges structured multi-criteria analysis with advanced AI-driven spatial intelligence, providing a comprehensive toolkit for planners, policymakers, and researchers to make informed, transparent, and adaptive decisions in increasingly complex and dynamic spatial environments.

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