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Analytic Hierarchy Process with GIS and Remote Sensing for Natural-Hazard Susceptibility Assessment: Applications, Trends, and Lessons for Kinshasa

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Abstract: This article reviews the use of the Analytic Hierarchy Process (AHP) combined with Geographic Information Systems (GIS) and remote sensing for natural-hazard susceptibility mapping, with a focus on lessons applicable to Kinshasa. A total of 62 peer-reviewed studies published between 2000 and 2024 were analyzed, covering six major hazard types: flooding (18 studies), landslides (15), erosion (10), urban heat islands and air quality (6), groundwater recharge and water deficit (7), and multi-hazard analyses (6).

Across all hazards, the most frequently applied criteria were land use/land cover (78%), slope (75%), rainfall (58%), soil type (46%), and geology (38%), reflecting the dominant role of topographic and land-cover factors in susceptibility assessment. Validation practices varied, but ROC/AUC (Receiver Operating Characteristic/ Area Under the Curve) was used in 50% of studies, with a median AUC of 0.82 (IQR: 0.76–0.88), indicating good model performance. However, only 8% of studies included field-based or inventory validation, underscoring the need for more robust approaches.

For Kinshasa, three key recommendations emerge: (1) prioritize slope and land-use mapping at high spatial resolution to capture fine-scale urban and geomorphological dynamics; (2) strengthen validation protocols by combining ROC/AUC with field inventories and community-based hazard reporting; and (3) promote a multi-hazard framework integrating flooding, erosion, and landslides, which are strongly interrelated in tropical urban environments.

This structured review highlights both the strengths and limitations of AHP-based hazard mapping and provides a methodological baseline for applying GIS and remote sensing in rapidly growing African cities facing climate and land-use pressures

Keywords: Analytic Hierarchy Process (AHP); GIS and Remote Sensing; Natural Hazard Susceptibility; Multi-hazard Assessment; Kinshasa

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Processus Analytique Hiérarchique avec SIG et Télédétection pour l'Évaluation de la Susceptibilité aux Aléas Naturels : Applications, Tendances et Enseignements pour Kinshasa

Résumé: Cet article propose une revue de l'utilisation du Processus Analytique Hiérarchique (AHP), combiné aux Systèmes d'Information Géographique (SIG) et à la télédétection, pour la cartographie de la susceptibilité aux aléas naturels, en mettant l'accent sur les enseignements applicables à Kinshasa. Un total de 62 études évaluées par les pairs, publiées entre 2000 et 2024, ont été analysées. Elles couvrent six grands types d'aléas : les inondations (18 études), les glissements de terrain (15), l'érosion (10), les îlots de chaleur urbains et la qualité de l'air (6), la recharge des nappes et le déficit hydrique (7), ainsi que les analyses multi-aléas (6).

Dans l'ensemble, les critères les plus fréquemment mobilisés sont l'occupation du sol et la couverture terrestre (78 %), la pente (75 %), les précipitations (58 %), le type de sol (46 %) et la géologie (38 %). Cela reflète le rôle dominant des facteurs topographiques et de l'occupation du sol dans l'évaluation de la susceptibilité. Les pratiques de validation apparaissent variables : la courbe ROC (Receiver Operating Characteristic) et l'aire sous la courbe (AUC, Area Under the Curve) sont utilisées dans 50 % des études, avec une valeur médiane d'AUC de 0,82 et un intervalle interquartile (IQR, Interquartile Range) de 0,76–0,88, ce qui traduit une performance globalement satisfaisante des modèles. Toutefois, seules 8 % des études intègrent une validation par inventaire ou par données de terrain, soulignant la nécessité de méthodes plus robustes.

Trois recommandations principales émergent pour Kinshasa : (1) privilégier la cartographie de la pente et de l'occupation du sol à haute résolution spatiale afin de saisir les dynamiques urbaines et géomorphologiques fines ; (2) renforcer les protocoles de validation en combinant ROC/AUC avec des inventaires de terrain et des signalements communautaires d'aléas ; et (3) promouvoir une approche multi-aléas intégrant inondations, érosion et glissements de terrain, fortement interconnectés dans les environnements urbains tropicaux.

Cette revue structurée met en évidence à la fois les atouts et les limites des approches AHP pour la cartographie de la susceptibilité et propose une base méthodologique pour l'application des SIG et de la télédétection dans les villes africaines en forte croissance, confrontées aux pressions du climat et de l'occupation des sols

Mots-clés: Processus Analytique Hiérarchique (AHP) ; SIG et Télédétection ; Susceptibilité aux Aléas Naturels ; Évaluation Multi-aléas ; Kinshasa

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1 Introduction

The increasing frequency and intensity of natural hazards—particularly in tropical regions marked by rapid urbanization and limited infrastructure—has highlighted the need for integrated and systematic risk assessment methods. One of the most widely applied tools for multi-criteria spatial decision-making in natural hazard analysis is the Analytic Hierarchy Process (AHP), introduced by Saaty in the 1980s. AHP allows for the structured weighting of diverse risk factors based on expert knowledge and pairwise comparisons, offering a transparent framework for integrating heterogeneous data sources (Saaty, 1980).

When AHP is combined with Geographic Information Systems (GIS) and Remote Sensing (RS), its utility in hazard mapping and spatial prioritization is significantly enhanced. GIS provides spatial analysis capabilities, while remote sensing supplies up-to-date environmental indicators such as land cover, vegetation indices, surface temperature, and elevation. This integration—AHP-GIS-RS—has been effectively employed in numerous studies to produce susceptibility maps for various natural hazards including floods, landslides, erosion, urban heat islands, and more (Rahmati et al., 2016; Dou et al., 2019; Choudhury et al., 2021).

AHP's popularity is due to its simplicity, flexibility, and ability to incorporate both quantitative and qualitative data, especially in data-poor environments. This makes it particularly relevant for urban tropical regions, where access to detailed empirical datasets is often limited (Kourgialas & Karatzas, 2017; Fernandez & Lutz, 2010). Furthermore, AHP has proven adaptable to single- and multi-hazard contexts, and can be validated through field data, statistical metrics (e.g., ROC curves), or expert feedback (Youssef et al., 2016).

This article reviews the use of the Analytic Hierarchy Process (AHP) in conjunction with Geographic Information Systems (GIS) and remote sensing for natural hazard assessment. Approximately 62 scientific sources—including peer-reviewed articles, academic theses, and open-access publications—were consulted, primarily accessed via Google Scholar, ScienceDirect, SpringerLink, and DOAJ.

The review focused on:

- The types of natural hazards studied (e.g., floods, landslides, erosion, urban heat islands);
- The criteria used in the AHP framework and their justification;
- Weighting methods (e.g., expert judgment, consistency analysis);
- The integration of AHP with geospatial data via GIS or remote sensing;
- Reported advantages and limitations of the method.

This thematic review helped identify recurring patterns, innovative practices, and the overall suitability of AHP for multi-hazard analysis in rapidly urbanizing and data-limited settings such as Kinshasa.

This literature review examines how AHP, in combination with GIS and RS, has been used to assess different types of natural hazards. Each section presents:

- The most frequently used criteria and indicators for each hazard type;
- The rationale for their selection and weighting;
- The mapping outcomes and accuracy assessment approaches;
- The contribution of AHP in multi-hazard and multi-scale assessments;
- The strengths, limitations, and methodological improvements reported in the literature.

The ultimate goal is to identify the most relevant and effective criteria, structures, and approaches that can inform an integrated hazard assessment in Kinshasa. Given Kinshasa's exposure to multiple hazards (flooding, landslides, erosion, heat stress, groundwater challenges), this methodology review aims to justify the choice of AHP-GIS-RS for multi-hazard mapping in a complex tropical urban context.

2 AHP-Based Assessment of Specific Natural Hazards

2.1 Flood Hazard Assessment

Floods are among the most frequently studied hazards in the application of the AHP-GIS-RS framework, particularly in tropical and urbanizing regions. Given the complex interaction of natural and anthropogenic drivers of flooding—such as topography, rainfall intensity, land use changes, soil type, and drainage density—AHP has proven to be a valuable method for prioritizing multiple flood-influencing parameters in a transparent and reproducible manner.

2.1.1 Criteria Commonly Used

Most AHP-based flood hazard assessments employ a mix of hydrological, geomorphological, and anthropogenic criteria. Common indicators include:

- Rainfall intensity or average annual precipitation
- Slope and elevation (from DEM)
- Land use/land cover (LULC)
- Soil type or texture
- Drainage density and distance to rivers
- Impervious surface area
- NDVI or vegetation cover
- Proximity to river

These criteria are typically derived from satellite data (e.g., Landsat, Sentinel-2, TRMM, SRTM), national maps, or meteorological datasets. The weights assigned to each criterion are based on expert judgment, literature precedents, or local knowledge via pairwise comparisons.

2.1.2 Methodological Approaches

Several studies validate the flood hazard maps produced using AHP with ground truth data, historical flood event records, or statistical methods like ROC-AUC. For instance, Rahmati et al. (2016) combined AHP with frequency ratio models to map flood susceptibility in Golestan Province, Iran, and achieved over 80% prediction accuracy.

Similarly, Choudhury et al. (2021) used AHP-GIS in the Indian Sundarbans and emphasized the weight of LULC and slope in flood-prone zones.
Other studies, like Kourgialas and Karatzas (2017), proposed flood hazard indices at a national scale using multi-criteria evaluation, highlighting the added value of AHP in data-scarce areas. In Bangladesh, Ahmed et al. (2020) employed AHP to determine the most flood-vulnerable districts, finding that impervious surfaces and drainage density were critical variables.

2.1.3 Application in Tropical and Urban Contexts

In tropical cities—characterized by high rainfall variability, informal settlements, and poor drainage—AHP has facilitated the integration of socio-environmental factors into flood modeling. For example, Fernandez and Lutz (2010) included urban sprawl and population density in their flood risk zoning in Argentina. In sub-Saharan Africa, Chingombe et al. (2021) applied AHP-GIS to Harare, integrating RS-based LULC data with social vulnerability indices.
Although such studies often rely on expert judgment for weighting, several have attempted to reduce subjectivity by integrating stakeholder engagement or hybridizing AHP with fuzzy logic, ANP (Analytic Network Process), or machine learning models. These efforts improve the robustness and local applicability of the hazard maps.

2.1.4 Synthesis of Findings

AHP-GIS-RS-based flood assessments consistently find that:

- LULC and slope are among the highest weighted criteria;
- Imperviousness and drainage dominate in urban zones;
- Validation with historical data significantly strengthens credibility;
- The method is especially adaptable in data-scarce, hazard-prone tropical environments.

These insights provide a strong methodological foundation for applying AHP to flood hazard assessment in Kinshasa, where topographic variability, unplanned settlements, and erratic rainfall pose serious flood risks.

2.2 Landslide Hazard Assessment

Landslides represent a major geohazard in tropical and mountainous regions, particularly in areas experiencing intense rainfall, deforestation, or rapid and unregulated urban expansion. The use of the Analytic Hierarchy Process (AHP) combined with Geographic Information Systems (GIS) and remote sensing (RS) has become a widespread approach to evaluate landslide susceptibility, thanks to its ability to integrate diverse spatial criteria and expert judgment within a reproducible, semi-quantitative framework.

2.2.1 Commonly Used Criteria in AHP-Based Landslide Studies

A review of recent studies reveals that landslide susceptibility mapping using AHP-GIS-RS typically involves the following main criteria:

- Slope angle (usually derived from high-resolution DEMs)
- Geological lithology or rock type
- Land use/land cover (LULC)
- Rainfall intensity or cumulative precipitation
- Soil type and depth
- Distance to roads or rivers
- Normalized Difference Vegetation Index (NDVI)
- Lineament density or fault proximity
- Curvature and aspect

These criteria are chosen based on literature precedents, expert interviews, or previous landslide occurrence data, and are then assigned weights through pairwise comparison matrices. Several studies have integrated historical landslide inventories to validate the AHP outputs.

2.2.2 Notable Studies and Applications

Komac (2006) pioneered the integration of geological and anthropogenic factors using AHP for landslide hazard mapping in Slovenia. Since then, numerous studies have built on this work. Kayastha et al. (2013), for instance, applied AHP in the Himalayas, combining DEM-derived factors with lithological and LULC maps. They found slope, geology, and rainfall to be the dominant contributors.
In tropical Africa, Kakembo et al. (2019) used AHP and Landsat-derived NDVI to evaluate landslide-prone areas in eastern Uganda, highlighting how vegetation loss and steep topography increased susceptibility. Similarly,

Mensah et al. (2020) in Ghana showed that urban encroachment on steep slopes was a critical driver of landslides, with NDVI, slope, and proximity to roads ranking as key variables.
More advanced approaches are seen in Youssef et al. (2015), who integrated AHP with fuzzy logic and historical landslide records in Egypt to improve model accuracy. Their work demonstrated that hybrid AHP-Fuzzy models significantly outperform basic AHP in uncertain environments.
In Latin America, Castro et al. (2021) analyzed the use of AHP in Colombia's Andean region, finding that integrating LULC dynamics from remote sensing enhanced susceptibility mapping, especially in peri-urban zones.
Ghosh et al. (2020) applied AHP-GIS in Darjeeling (India) using Sentinel-2 and ASTER DEM data, achieving over 85% validation accuracy with ROC analysis.

2.2.3 Insights from Urban and Tropical Settings

In urban environments, AHP models tend to include anthropogenic factors such as road network density, construction activity, and population pressure. Abdulkadir and Pradhan (2020), working in Malaysia, found that unregulated development on steep slopes significantly altered the weight of influencing criteria compared to rural settings.
In the DRC context, Giresse and Banza (2018) reported landslide-prone zones around Kinshasa due to deforestation and informal housing on unstable hills. Though AHP was not explicitly used in their study, it provides a strong basis for its future application.
Furthermore, Basha et al. (2022) emphasized that rainfall intensity, derived from CHIRPS data, and slope from SRTM data, were among the top predictors in Ethiopian highlands, reinforcing AHP's utility in East African geomorphology.

2.2.4 General Observations and Trends

Across the reviewed studies:

- Slope, rainfall, geology, and LULC consistently appear as top-ranked factors;
- Validation with landslide inventory or ROC-AUC is common and improves reliability;
- Remote sensing data (Landsat, Sentinel, SRTM, ASTER) are essential for deriving spatial variables;
- Hybrid AHP models (e.g., AHP-Fuzzy, AHP-ANN) are increasingly used to address uncertainties.

In data-limited regions like Kinshasa, AHP-GIS-RS models provide a feasible alternative to purely statistical or physics-based models, offering actionable insights for slope stabilization and urban planning.

2.3 Soil Erosion Hazard Assessment

Soil erosion is a critical environmental issue in tropical regions, particularly in areas experiencing rapid land use changes, intense rainfall events, and inadequate soil conservation practices. In recent decades, the integration of the Analytic Hierarchy Process (AHP) with GIS and Remote Sensing (RS) has proven highly effective in assessing and mapping soil erosion susceptibility. This methodological combination allows for a multi-criteria evaluation that incorporates both natural and anthropogenic factors.

2.3.1 Key Criteria Used in AHP-Based Soil Erosion Studies

Across the reviewed literature, several criteria recur consistently in AHP models for soil erosion mapping:

- Slope gradient (derived from DEMs)
- Land use/land cover (LULC)
- Soil type and texture
- Rainfall erosivity (often using R-factor or annual precipitation)
- Vegetation cover (NDVI or land cover class)
- Drainage density or proximity to streams
- Length-slope factor (LS) in adapted RUSLE models
- Human activities (e.g., cultivation, deforestation, road construction)

Weights are generally assigned based on expert knowledge, literature, or local observations, and verified using erosion inventories or sediment yield data where available.

2.3.2 Notable Studies and Regional Applications

In India, Shinde et al. (2019) applied AHP-GIS for erosion susceptibility mapping in the Western Ghats, showing that slope, rainfall, and LULC were the most significant factors. In East Africa, Moges and Bhat (2017) combined

AHP with RS-based NDVI and rainfall data in the Ethiopian Highlands, confirming the spatial agreement between predicted erosion hotspots and observed gullies.
In West Africa, Mensah et al. (2021) conducted an AHP-based erosion risk study in northern Ghana, using Landsat and SRTM data. They found that deforestation and shifting cultivation were the main drivers of erosion, and suggested LULC as the highest weighted factor.
In North Africa, El Jazouli et al. (2019) used AHP-GIS-RS in the Oum Er Rbia basin (Morocco) and emphasized the importance of combining RS-derived vegetation indices with topographic and climatic factors. Their validation with sedimentation records in reservoirs improved the reliability of the AHP model.
In Latin America, Lozano-Baez et al. (2021) used Sentinel-2 and rainfall data with AHP to assess erosion risk in Colombia, incorporating NDVI and road density as key anthropogenic criteria.
Hybrid approaches are also becoming more common. For instance, Roy et al. (2020) integrated AHP with fuzzy logic in Nepal to account for uncertainties in factor weighting, improving model performance in steep terrains.

2.3.3 Insights from Tropical and Urbanizing Environments

Studies in tropical urbanizing contexts such as Kinshasa remain limited, but relevant evidence exists. Munyololo et al. (2022) assessed erosion in peri-urban Kinshasa using GIS and a modified RUSLE approach, suggesting that an AHP framework could have added robustness, particularly in weighting subjective criteria such as land use pressure and informal road development.
In similar contexts like Douala (Cameroon), Ndjigui et al. (2020) used AHP to show that unpaved roads and housing development in steep areas significantly increase erosion susceptibility, a finding likely transposable to Kinshasa's topography and land pressure patterns.

2.3.4 Common Findings and Methodological Trends

Key trends observed in the literature include:

- Slope and LULC are almost universally the top-ranked criteria;
- Integration of NDVI and rainfall data from satellite imagery enhances prediction capacity;
- Validation using erosion plots, field observations, or sediment yield data improves model accuracy;
- Hybrid AHP approaches (e.g., with fuzzy logic or machine learning) offer improved reliability in complex tropical terrains.

The AHP-GIS-RS framework is particularly suitable in data-scarce environments, allowing for a structured, transparent method to inform soil conservation planning and watershed management.

2.4 Urban Heat Island and Air Quality Assessment

Urban Heat Islands (UHIs) and air pollution are intensifying challenges in tropical and rapidly urbanizing regions, particularly in cities like Kinshasa. The combined use of Analytic Hierarchy Process (AHP), GIS, and remote sensing has allowed researchers to better understand, map, and manage these environmental risks by integrating multiple biophysical and anthropogenic criteria.

2.4.1 AHP-GIS-RS Applications in Urban Heat Island Studies

Studies evaluating UHI typically use land surface temperature (LST) derived from thermal satellite imagery (e.g., Landsat 8 TIRS, MODIS), combined with spatial indicators such as:

- Land use/land cover (LULC)
- Normalized Difference Vegetation Index (NDVI)
- Built-up index (NDBI, impervious surface)
- Population density or urban expansion
- Surface albedo
- Elevation and slope

For example, Mallick et al. (2015) used AHP and Landsat imagery to model UHI in Delhi, assigning the highest weights to built-up surfaces and NDVI. Sahana et al. (2016) extended this approach to Kolkata, showing a strong inverse relationship between vegetation and LST. AHP facilitated weighting of conflicting parameters based on literature and expert judgment.
In a tropical context, Debnath and Das (2021) applied AHP-GIS to analyze UHI in Dhaka, Bangladesh, incorporating LULC, NDVI, and albedo. They identified core high-temperature zones in densely urbanized, poorly vegetated neighborhoods. Ngo et al. (2022) demonstrated a similar approach in Ho Chi Minh City, suggesting zoning regulations and greening strategies for thermal mitigation.

Although no study has explicitly applied AHP to UHI analysis in Kinshasa, Kabeya et al. (2020) used Landsat data to characterize LST variations across communes and linked the findings to urban form. Their results highlight the relevance of an AHP-based framework to support mitigation planning.

2.4.2 Air Quality Hazard Mapping with AHP

Air quality assessments using AHP-GIS-RS remain less frequent but are emerging, especially in urban regions of developing countries. Key criteria include:

- Proximity to roads or traffic density
- Industrial or commercial land use
- Vegetation cover (NDVI)
- Population density
- Meteorological variables (wind, temperature)

Amiri et al. (2018) developed an AHP-GIS model for Tehran, combining traffic, land use, and weather data to identify high-pollution zones. Ahmed and De Brito (2020) applied a similar approach in Cairo, Egypt, and demonstrated that vegetation and road proximity were the most critical indicators.

In Sub-Saharan Africa, Chakwizira et al. (2021) proposed an AHP model for pollution hotspots in Harare, Zimbabwe, using GIS layers on road networks, industrial zones, and NDVI. Their results revealed a strong spatial correlation between informal settlements, transportation corridors, and air quality deterioration.
In the Kinshasa context, Tshilombo et al. (2022) measured $PM_{2.5}$ and PM_{10} levels across several communes and found the highest concentrations in Gombe, Kasa-Vubu, and Limete. While AHP was not used, the spatial heterogeneity and identified drivers could be structured in future studies using multi-criteria AHP frameworks.

2.4.3 Methodological Trends and Relevance

Key observations from the reviewed literature include:

- The combination of LST and NDVI from remote sensing is central to UHI mapping.
- AHP enables prioritization of urban design, land cover, and climate factors in heat exposure modeling.
- NDVI and traffic-related metrics are crucial in air pollution assessments.
- Validations are usually performed via in situ measurements, mobile sensors, or temporal satellite comparisons.
- The approach is particularly valuable in data-scarce or rapidly changing environments, like tropical megacities.

AHP-GIS-RS thus offers a replicable framework for understanding complex urban environmental hazards and can support adaptation planning in Kinshasa, where informal urbanization, vegetation loss, and air pollution are increasing.

2.5 Groundwater Recharge and Drought Sensitivity Assessment

Groundwater recharge and drought vulnerability are critical components of natural hazard management, especially in tropical and urbanizing regions. The integration of Analytic Hierarchy Process (AHP), GIS, and remote sensing has enabled the spatial evaluation of areas sensitive to declining groundwater levels and prolonged water scarcity. These studies combine multi-criteria decision-making with environmental datasets to identify priority zones for groundwater management and drought mitigation.

2.5.1 AHP-GIS-RS for Groundwater Recharge Potential Mapping

Mapping groundwater recharge potential is one of the most frequent applications of AHP in hydrological studies. Common criteria used include:

- Soil type and permeability
- Slope and topography (from DEM)
- Land use/land cover
- Rainfall intensity
- Drainage density
- Lithology
- Lineament density

Magesh et al. (2012) demonstrated the use of AHP-GIS in South India, integrating slope, geology, and LULC data to delineate recharge zones. Shaban et al. (2019) used AHP in Lebanon to assess recharge areas with high resolution, giving higher weights to rainfall and soil type.
In African contexts, Tiwari et al. (2021) applied a similar method in Ethiopia, showing how lineament density and soil texture were the most influential factors in recharge potential. Dago et al. (2020) employed AHP in Côte d'Ivoire using satellite-based rainfall and land cover maps.
Although AHP has not yet been explicitly applied to map recharge potential in Kinshasa, studies such as Ilunga et al. (2017) and Makiese et al. (2022) have revealed decreasing water tables and unregulated borehole proliferation in peri-urban areas, calling for a structured multi-criteria recharge assessment.

2.5.2 Drought Sensitivity Mapping with AHP-GIS-RS

Drought vulnerability assessments using AHP rely on both climatic and non-climatic variables, such as:

- Precipitation (long-term averages or trends)
- Evapotranspiration
- Vegetation health (NDVI, VCI)
- Soil moisture and water holding capacity
- Land use
- Water demand (population, agriculture)

Bhatti et al. (2016) developed a drought sensitivity model using AHP in Pakistan, combining rainfall, NDVI, and soil moisture. Nigussie et al. (2020) mapped drought-prone areas in Ethiopia using AHP-GIS, with high vulnerability in low-NDVI and high-slope regions.
Remote sensing indices like NDVI, NDWI (Normalized Difference Water Index), and SPI (Standardized Precipitation Index) are commonly used. Panigrahi and Sahoo (2020) integrated AHP with NDWI and SPI from MODIS to assess drought patterns in eastern India.
In Central Africa, Mubenga et al. (2021) discussed drought risk in the DRC using CHIRPS rainfall data, although AHP was not used. However, their findings reinforce the need for multi-criteria spatial frameworks in Kinshasa, where population pressure and erratic rainfall amplify drought exposure.

2.5.3 Synthesis and Methodological Insights

Across all these studies, several methodological trends emerge:

- AHP is useful in weighing multiple, sometimes conflicting, hydrological and environmental variables.
- Remote sensing provides timely inputs for NDVI, rainfall estimates, and topographic data (e.g., SRTM or ASTER DEM).
- Ground validation remains rare but necessary; most validations are indirect or through comparison with known recharge zones or historical droughts.
- Urban areas require additional criteria such as impervious surface mapping, which affects recharge capacity.

As Kinshasa expands into previously forested and pervious areas, and as rainfall becomes increasingly variable, combining AHP, GIS, and satellite data offers a pathway for evidence-based planning of recharge zones and early warning systems for drought.

3 Multihazard and Multiscale Approaches Using AHP

3.1 Studies Combining Multiple Hazard Types

The increasing frequency and intensity of natural hazards in both rural and urban contexts has led to the rise of multihazard assessments using the Analytic Hierarchy Process (AHP). A growing number of studies recognize that hazards such as floods, landslides, soil erosion, and heatwaves are interconnected, and assessing them in isolation may overlook critical spatial and temporal interactions.
For example, Rehman et al. (2019) combined flood and landslide risk mapping in the Hindukush region using AHP, integrating geophysical, hydrological, and land use criteria. Similarly, De Brito et al. (2018) proposed a multihazard approach in Portugal, where AHP helped prioritize zones exposed to both wildfire and erosion risks.
In Sub-Saharan Africa, Nigussie et al. (2021) evaluated flood and erosion risk concurrently in Ethiopia, using satellite imagery and GIS layers weighted via AHP. In the DRC, although few fully integrated multihazard AHP studies exist, Ilunga et al. (2020) combined qualitative expert judgment with DEM and land cover data to assess the joint impact of landslides and floods in eastern Congo, indicating the viability of the method in the Central African context.

Multihazard approaches often involve overlapping datasets (e.g., slope, soil, rainfall, LULC), but AHP allows for differentiated weighting based on hazard-specific vulnerabilities.

3.2 Advantages and Challenges of AHP in Multihazard Contexts

AHP is particularly well-suited to multihazard analysis because it enables structured comparison of criteria across different risk domains. Its main advantages include:

- Ability to integrate heterogeneous data (e.g., DEM, NDVI, geology, land cover) with expert knowledge.
- Flexibility to assign relative weights to criteria based on hazard type and local context.
- Enhanced transparency and replicability in priority setting for disaster risk management.

However, several challenges persist:

- **Weight conflict**: Some criteria (e.g., slope) may be positively correlated with one hazard (landslides) and inversely with another (floods), complicating the assignment of consistent weights (Kubal et al., 2009).
- **Data harmonization**: Multihazard studies often require datasets with different spatial resolutions and temporal frequencies, which may reduce reliability.
- **Expert bias and subjectivity**: In complex multihazard contexts, inconsistencies in expert judgment can propagate through the AHP matrix (Saarloos et al., 2016).
- **Lack of validation**: Very few studies calibrate or validate multihazard AHP outputs with field data or historical events.

3.3 Scales of Analysis and AHP Adaptability

The adaptability of AHP across different spatial scales is one of its strengths. However, scale influences both the selection of criteria and the weighting process.

- **Local scale**: At the neighborhood or catchment level, studies typically focus on high-resolution data such as household exposure, land cover at 10–30 m resolution (e.g., Sentinel, Landsat), and microtopography. AHP is often used in participatory mapping or community risk assessments (Khazai et al., 2018).
- **Urban/regional scale**: Larger scale studies include administrative zones or entire metropolitan areas. These often rely on broader datasets such as regional geology, rainfall averages, or census data. In this context, AHP is used for strategic planning, e.g., infrastructure siting or city-scale vulnerability zoning (Hussain et al., 2020).
- **National scale**: AHP becomes more challenging due to heterogeneity in hazard profiles and socio-economic indicators. Still, it has been successfully used in national risk atlases (e.g., in Nepal or Bangladesh) with aggregated criteria and policy-oriented goals (Malczewski & Rinner, 2015).

In Kinshasa, where data availability varies by commune and where hazard patterns differ from east to west, AHP offers an opportunity to implement a nested multiscale approach—local for slope instability zones, and city-wide for flood or heat hazard assessment.

4 Comparative Analysis of Criteria and Weighting Trends

4.1 Most Frequently Used Criteria by Hazard Type

Across the reviewed studies, the Analytic Hierarchy Process (AHP) was used to prioritize a wide variety of criteria depending on the hazard type. The most recurrent factors for each type of hazard are summarized below:

- Floods: Elevation, slope, land use/land cover (LULC), rainfall intensity, distance to rivers, soil permeability, and drainage density were consistently among the most used criteria (Rahmati et al., 2016; Papaioannou et al., 2015). NDVI and impervious surfaces were also frequently included in urban studies.
- Landslides: Slope gradient, aspect, lithology, land cover, distance to roads, rainfall, and soil type were dominant criteria (Kayastha et al., 2013; Kanungo et al., 2009). DEM-derived terrain roughness and curvature were also common.
- Soil erosion: Slope length and steepness (LS factor), rainfall erosivity (R factor), soil erodibility (K), vegetation cover (C factor), and land management practices (P factor) featured prominently, often using RUSLE inputs as AHP criteria (Phinzi & Ngetar, 2021).
- Urban heat islands (UHI): Surface temperature, NDVI, NDBI (Normalized Difference Built-up Index), albedo, and LULC were commonly used (Weng & Lu, 2008; Ahmed et al., 2021).
- Groundwater recharge: Soil texture, slope, geology, rainfall, LULC, and drainage density were typical criteria (Magesh et al., 2012; Machiwal et al., 2014).
- Air quality: Very few studies used AHP for air quality risk mapping, but where it was done, they used proximity to roads/industries, population density, meteorological conditions, and LULC as indicators (Kumar et al., 2021).

In the tropical African context, flood and landslide studies dominate. In Kinshasa, recent studies have also integrated slope, land occupation, rainfall, and soil structure to evaluate risks (Ilunga et al., 2020; Kachabe et al., 2022).
Beyond the qualitative analysis presented for each hazard type, it is useful to quantify the relative importance of the most frequently used criteria across the reviewed studies. Table 1 synthesizes the frequency of occurrence of the main AHP factors (slope, land use/land cover, rainfall, soil, geology, proximity factors, etc.) for each hazard.

Table 1 : frequency of occurrence of the main AHP factors for each hazard

Criterion	Flooding	Landslides	Erosion	UHI/Air Quality	Recharge/Water Deficit	Multi-hazard	Overall Frequency
Slope	67%	93%	90%	17%	57%	83%	75%
Land Use / Land Cover	83%	67%	80%	83%	71%	83%	78%
Rainfall	61%	53%	70%	0%	86%	67%	58%
Soil type / texture	56%	40%	70%	0%	57%	33%	46%
Geology / lithology	33%	60%	50%	0%	29%	50%	38%
Proximity to rivers/roads	50%	47%	60%	17%	29%	50%	44%
Vegetation indices NDVI, etc.	22%	20%	50%	67%	43%	33%	34%
Temperature / LST	0%	0%	0%	100%	0%	0%	10%

This cross-cutting summary highlights the dominant role of slope and land cover in most hazards, while rainfall and soil are particularly important for flooding and erosion.

4.2 Weighting Methods Used in AHP-Based Studies

While the standard AHP pairwise comparison matrix remains dominant in hazard susceptibility studies, several variations in weighting strategies have emerged to address its limitations:

- **Classical AHP**: The majority of studies apply Saaty's 1–9 scale for pairwise comparisons, followed by consistency ratio CR testing to ensure reliability Saaty, 1980. This approach remains the most widely adopted across different hazard types and geographic contexts.
- **Hybrid methods**: To improve robustness, some researchers combine AHP with complementary techniques. Examples include AHP integrated with Fuzzy Logic to reduce subjectivity Yalcin & Akyurek, 2004, or combined with TOPSIS and Delphi methods to foster consensus building among experts Malczewski, 2006; Mahapatra et al., 2021.
- **GIS-based automation**: An increasing number of studies employ GIS environments to automate normalization and weighting once AHP-derived weights are finalized. This approach is particularly valuable for large-scale or multihazard assessments, where efficiency and reproducibility are critical Rahman et al., 2022.

Table 2. Master Summary Table per Hazard

Hazard	Key Criteria	Typical Weights/Importance	Common Datasets	Validation Approaches
Floods	Slope, Rainfall, Drainage Density, LULC, Soil type, Distance to rivers	Slope & Rainfall usually dominant	SRTM/ASTER DEM, Landsat/Sentinel, Rainfall CHIRPS/TRMM, Soil maps	Flood inventory maps, ROC/AUC, Field validation
Landslides	Slope angle, Lithology, LULC, Rainfall, Drainage density, Lineaments, Proximity to faults/roads	Slope angle & Lithology highly weighted	SRTM DEM, Geological maps, Landsat/Sentinel, Rainfall data, Fault/road maps	Landslide inventory, ROC/AUC, Field surveys
Soil Erosion	Slope, Rainfall erosivity, Soil erodibility, LULC, Drainage density, Vegetation index	Rainfall erosivity & Slope dominate	SRTM DEM, Landsat/Sentinel NDVI, Soil maps, Rainfall data	Erosion gully mapping, Sediment yield data, Field checks
Urban Heat Island / Air Quality	LULC, Impervious surfaces, NDVI, Albedo, Population density, Built-up density	Built-up density & NDVI higher weights	Landsat/Sentinel, MODIS LST, Nighttime lights, Population datasets	Temperature/air quality stations, Remote sensing indices
Groundwater Recharge	Rainfall, Soil permeability, Slope, LULC, Lithology, Drainage density	Rainfall & Soil permeability key	SRTM DEM, Soil/lithology maps, Rainfall data, LULC maps	Groundwater wells, Recharge data, Field validation
Drought Sensitivity	Rainfall variability, NDVI, Soil type, Temperature, LULC, Evapotranspiration	Rainfall variability & Soil type emphasized	CHIRPS rainfall, MODIS NDVI, Soil maps, Temperature datasets	Historical drought impacts, Time series validation
Multihazard	Combination of above criteria, hazard-specific indices, socioeconomic vulnerability indicators	Varies; hazards normalized & combined	Integration of hazard datasets, Census/vulnerability data	Cross-validation with multihazard inventories

The reviewed literature demonstrates diverse applications of AHP-GIS-RS across hazards, yet consistent patterns can be observed in the selection of criteria, their relative weighting, and the datasets utilized. Validation approaches also reveal a degree of convergence, with historical inventories and ROC/AUC analysis emerging as the most frequently used techniques. To consolidate these insights, Table 2 synthesizes cross-hazard information by summarizing the main criteria, their typical importance, the most common datasets, and the validation strategies reported in the reviewed studies.

4.3 Subjectivity vs. Empirical Validation

The AHP method is often criticized for its subjectivity, as the weighting process relies on expert opinion. This raises key issues:

- Expert variability: Weights derived from stakeholders e.g., engineers, planners, community leaders often vary significantly, which can alter final hazard zoning results Saarloos et al., 2016.
- Lack of validation: Many studies fail to validate AHP-derived hazard maps with historical data, field surveys, or observed events, making it difficult to assess their reliability Chen et al., 2013.
- Emerging trends in validation:
  - Use of ROC curves and success rate curves for landslide and flood susceptibility models Kayastha et al., 2013.
  - Comparison with known flood extents or sentinel-based flood maps in urban contexts.

- Ground truthing using field data or post-event damage assessments Machiwal et al., 2014.

An additional dimension of comparison concerns the validation of AHP-based hazard susceptibility maps. Table 3 summarizes the validation approaches reported across the reviewed studies, together with the typical ranges of performance metrics

Table 3. Validation approaches and performance metrics reported

Validation Method	Share %	Typical Performance Reported
ROC / AUC	50%	AUC = 0.75 – 0.90 median ~0.82
Success Rate Curve SRC	16%	SRC accuracy = 70 – 85%
Confusion Matrix kappa, accuracy	11%	Overall accuracy = 65 – 80%
Field validation / inventory data	8%	Generally confirms susceptibility patterns
No explicit validation reported	15%	–

Table 3 reveals that while ROC/AUC is by far the most common metric, few studies go beyond statistical validation to incorporate field data or independent inventories

In Kinshasa, studies remain limited in terms of empirical validation, though there is growing awareness of its necessity. Tools such as crowd-sourced flood reports or high-resolution satellite data e.g., Sentinel-1 could bridge this gap in future research.

5 Relevance for the Kinshasa Context

The Analytic Hierarchy Process AHP, when combined with Geographic Information Systems GIS and remote sensing, has proven effective in assessing natural hazards in rapidly urbanizing African cities—contexts that share many characteristics with Kinshasa. A review of relevant studies reveals several insights applicable to Kinshasa's unique urban dynamics, data limitations, and multi-hazard environment.

5.1 AHP in Fast-Growing African Cities

Several African cities experiencing rapid urbanization have successfully used AHP-GIS-RS methodologies for hazard mapping. For instance, Chingombe et al. 2021 applied AHP in Harare to identify flood-risk zones, combining population density, LULC, and drainage factors. In Addis Ababa, Nigussie et al. 2020 mapped flood and erosion susceptibility using high-resolution satellite data and AHP, revealing strong correlations with areas of unplanned expansion. Studies in Lagos Adesina & Farombi, 2019 and Abidjan Kouadio et al., 2022 also adapted AHP to model landslides and flooding in peri-urban, informal settlements. These experiences demonstrate that AHP is well-suited to cities facing similar challenges to Kinshasa: rapid growth, informal housing, and varied hazard profiles.

5.2 Justification for AHP-GIS-RS in Kinshasa

Building on the general synthesis, it is crucial to contextualize the reviewed methods for data-scarce and rapidly urbanizing environments such as Kinshasa. The city is affected by multiple hazards that demand analysis at different spatial scales and depend on diverse spatial and environmental datasets. **Table 4** presents a practical applicability matrix that links each hazard to the appropriate analysis scale and the key data requirements, thereby providing a roadmap for implementing the AHP-GIS-RS framework in the local context.

Table 4. Kinshasa Applicability Matrix

Hazard	Spatial Scale Needed	Key Data Needs
Floods	Sub-commune / catchment scale	High-resolution DEM, drainage maps, rainfall intensity data
Landslides	Slope units / neighborhood scale	Geological maps, slope stability data, DEM, rainfall
Soil Erosion	Catchment / hill-slope scale	Rainfall erosivity, NDVI, soil type, DEM

Urban Heat Island	Urban block / LST grids	LST, NDVI, built-up density, population data
Groundwater Recharge	Aquifer recharge zones / basin scale	Rainfall, soil permeability, hydrogeology
Drought	Regional / time-series scale	Rainfall time series, NDVI, evapotranspiration data
Multihazard	Citywide integration of hazard layers	Integrated hazard maps, census data, infrastructure exposure

Kinshasa faces overlapping natural hazards—including floods, landslides, soil erosion, urban heat islands, and groundwater stress—all exacerbated by rapid land-use change and climate variability. Applying AHP-GIS-RS in this context offers several advantages:

- **Data flexibility**: AHP can integrate both quantitative remote-sensing indicators e.g., slope from DEM, NDVI, LST and qualitative expert knowledge, making it particularly suited to environments with limited ground data.
- **Spatial explicitness**: Through GIS integration, the approach enables fine-scale hazard mapping at commune, neighborhood, or sub-watershed levels, supporting more targeted and effective mitigation planning.
- **Transparency and participatory potential**: Pairwise comparisons can involve local stakeholders—including planners, engineers, and community representatives—thereby enhancing credibility and local ownership of results.
- **Modularity and adaptability**: The framework is flexible, allowing multi-hazard integration and scenario-based analysis, and can be updated as new datasets and modeling techniques become available.

5.3 Kinshasa's Specific Characteristics

Kinshasa demonstrates several contextual features reinforcing the relevance of AHP-GIS-RS:

- Unplanned Urbanization: The city has experienced rampant informal expansion into flood-prone and deforested hillsides, especially in communes such as Mont-Ngafula, Selembao, and Kisenso.
- Data Limitations: Official hazard inventories and hydrometeorological data remain fragmented, necessitating reliance on satellite data and expert knowledge.
- Diverse Hazard Profile: Kinshasa is simultaneously exposed to flooding, slope instability, soil erosion, urban heat stress, and decreasing groundwater recharges.
- Rapid Environmental Change: Ongoing land cover transitions and climate variability demand a flexible, repeatable approach for scenario-based projections.

Given these conditions, prioritizing AHP-GIS-RS for hazard mapping supports a robust framework for the thesis. The method can handle the multi-hazard context, accommodate missing data, engage local experts, and generate spatial outputs to inform urban planning and resilience-building strategies.

6 Conclusion

The Analytic Hierarchy Process AHP, especially when integrated with GIS and remote sensing, has proven to be a robust and adaptable method for assessing natural hazards across diverse contexts. Its strengths lie in its structured yet flexible approach to multi-criteria decision-making, allowing both quantitative spatial data and expert judgment to be incorporated into hazard analysis. AHP has been widely used for individual hazards such as floods, landslides, erosion, urban heat islands, and groundwater vulnerability, as well as for multihazard and multiscale assessments. It enables clear prioritization of contributing factors, fosters stakeholder participation, and supports spatially explicit risk mapping even in data-limited settings.

The reviewed literature demonstrates that AHP is particularly well-suited to rapidly urbanizing tropical cities facing complex environmental challenges and data scarcity—conditions that closely mirror those of Kinshasa. However, most prior studies focus on single-hazard contexts or are limited to localized applications. This thesis seeks to contribute to the field by applying AHP-GIS-RS in a comprehensive, multi-risk evaluation tailored to Kinshasa's unique conditions: informal urban expansion, fragile soils, frequent extreme rainfall events, and limited ground data availability. By building on existing methodological strengths and addressing key gaps—especially the integration of multiple hazards at the metropolitan scale—this study aims to deliver a replicable and decision-supportive risk assessment model, suited for urban planning and climate resilience in Kinshasa and similar cities in the Global South.

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