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GeoAI for Monitoring and Predicting Urban Climate Shocks: A Systematic Review and Framework for African Resilient Cities

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Abstract

In many African cities, the accelerating forces of rapid urbanization and shifting climate patterns are intensifying the frequency and impact of climate shocks, including flash floods, heatwaves, droughts, and coastal surges. These hazards disproportionately affect informal settlements and critical infrastructure, challenges that are further compounded by fragmented data ecosystems, limited digital capacity, and inadequate real-time monitoring systems. This study presents a systematic review of 64 peer-reviewed articles published between 2015 and 2025, sourced from Scopus, Web of Science, and ScienceDirect, to evaluate the role of GeoAI (Geospatial Artificial Intelligence) in advancing urban climate resilience. The review focuses on five representative African cities—Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar—selected for their diverse hazard profiles and varying institutional capacities. The study proposes a GeoAI-enabled framework that integrates Geographic Information Systems (GIS), remote sensing, and machine learning algorithms, including Random Forest, Support Vector Machines, Convolutional Neural Networks, and Long Short-Term Memory (LSTM) networks—to map spatial vulnerabilities, forecast climate hazards, and evaluate institutional readiness for proactive adaptation.

Comparative analysis reveals persistent exposure hotspots in marginalized communities, with variations in predictive accuracy and hazard severity closely linked to data infrastructure maturity and governance capacity. Cape Town and Nairobi exhibit higher institutional readiness and successful integration of GeoAI into policy processes, while Lagos, Addis Ababa, and Dakar face obstacles related to data accessibility and inter-agency coordination. The study underscores the importance of embedding ethical principles, participatory mapping, and equity considerations into GeoAI systems to enhance both policy relevance and community resilience. The proposed framework offers a scalable, context-sensitive pathway for climate-smart urban governance in low- and middle-income settings, supporting the objectives of Sustainable Development Goals 11 (Sustainable Cities and Communities) and 13 (Climate Action).

Keywords: GeoAI; Remote Sensing; Urban Climate Shocks; Climate Resilience; Machine Learning; Sub-Saharan Africa; Adaptation Planning; Institutional Readiness

INTRODUCTION

Cities across Africa are becoming increasingly vulnerable to the intensifying effects of climate variability and extreme weather events. Urban climate shocks such as flash floods, urban heat islands, prolonged droughts, and coastal storm surges are not only growing in frequency and severity but also disproportionately affecting low-income populations and fragile infrastructure systems (UN-Habitat, 2022; Adelekan et al., 2021). These shocks amplify socio-economic inequalities, strain under-resourced governance systems, and undermine the progress of sustainable urban development initiatives across the continent. Despite growing attention to climate adaptation and resilience planning, African cities continue to face major challenges in monitoring and anticipating climate risks in real time, largely due to fragmented data ecosystems, weak digital infrastructure, and limited institutional capacity (World Bank, 2023; Muggah & Florida, 2022).

Traditional approaches to urban climate risk assessment often rely on static vulnerability indices or outdated hazard mapping techniques, which are insufficient for capturing the dynamic, multi-scalar nature of climate threats in rapidly changing urban environments. In response to these limitations, the integration of Geospatial Artificial Intelligence (GeoAI) - a convergence of Geographic Information Systems (GIS), remote sensing, and machine learning - offers a promising paradigm for enhancing data-driven decision-making, real-time monitoring, and predictive modeling of climate shocks in cities (Li et al., 2021; Wu et al., 2023). GeoAI has shown considerable success in applications such as flood risk mapping, drought forecasting, and heatwave monitoring in urban areas, but its uptake and institutional embedding in African cities remain limited and uneven (Onuoha & Adeyemi, 2023).

In the context of the Global South, particularly Sub-Saharan Africa, the need for scalable and locally adaptable digital frameworks is urgent. However, existing research on GeoAI applications in urban climate governance is often skewed toward global North contexts, with limited comparative analysis across African cities or consideration for contextual constraints such as informality, data scarcity, and digital readiness (Olowu et al., 2022). Moreover, while technical aspects of GeoAI are well documented, there remains a critical gap in frameworks that integrate equity, ethical considerations, and governance capacity alongside spatial and algorithmic modeling.

This study responds to these gaps by developing and presenting a GeoAI-enabled framework for monitoring and predicting urban climate shocks in five African cities: Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar. It adopts a mixed-method comparative approach that draws on satellite-derived indicators, machine learning algorithms (Random Forest, Support Vector Machines, and Convolutional Neural Networks), and institutional assessment tools to evaluate both spatial vulnerabilities and local capacity for adopting digital climate resilience tools.

The goal is not merely to apply GeoAI tools in isolation but to embed them within a broader governance and sustainability framework that reflects the realities of African cities. The proposed framework emphasizes the importance of ethical AI deployment, inclusive adaptation planning, and institutional readiness, while also aligning with Sustainable Development Goals (SDGs) 11 and 13. By doing so, this study aims to provide a replicable methodology that supports digitally-enabled, equity-focused, and context-sensitive climate governance for rapidly urbanizing regions across Africa.

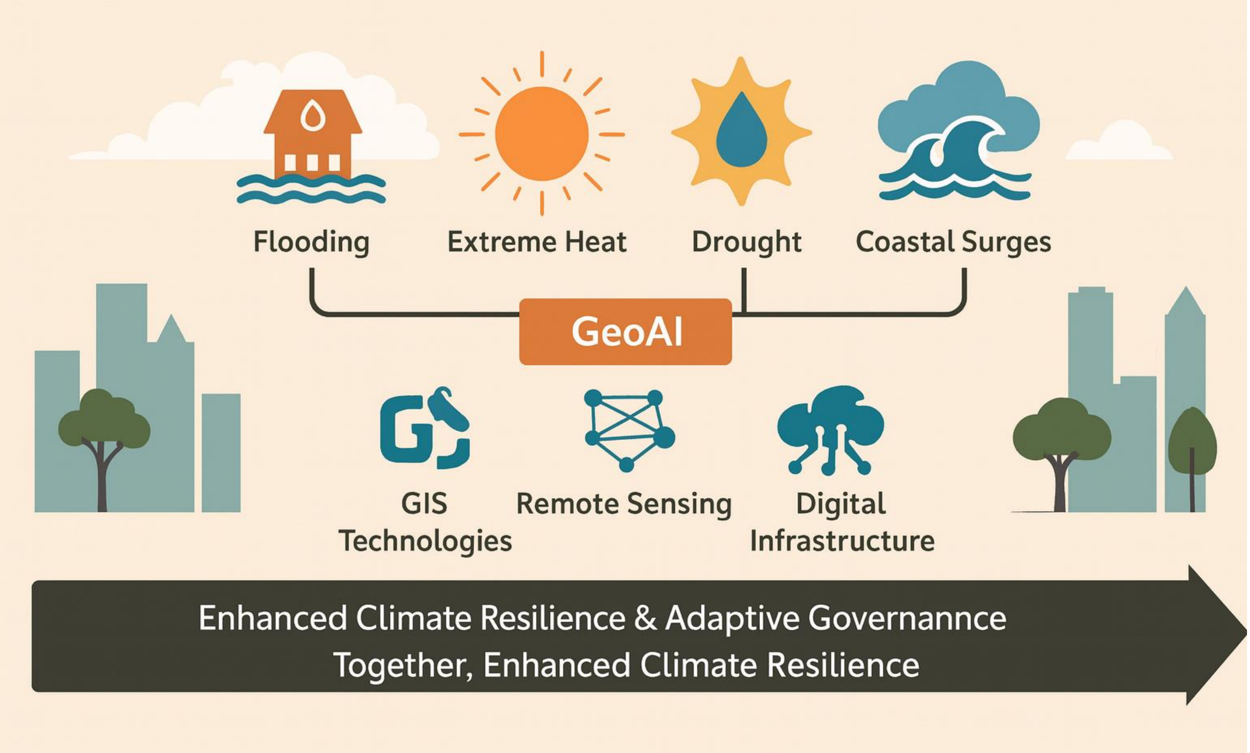

Figure 1. Conceptual Framework

MATERIALS AND METHODS

Study Area

This study focuses on five diverse African cities: **Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar**, strategically selected to reflect a broad spectrum of urban climate risks, geospatial conditions, and digital adaptation readiness. These cities have experienced increasing frequency and intensity of climate-related hazards due to rapid urbanization, poor planning, and limited resilience infrastructure (Ahmed et al., 2024; Hamdi et al., 2024; Mekonnen et al., 2023b).

- **Lagos, Nigeria** is prone to recurrent flash floods and sea-level rise-induced coastal surges, primarily due to unregulated expansion, high population density, and inadequate drainage infrastructure (Mbuvha et al., 2024). Lagos records an average annual flood exposure index of 4.5 (on a scale of 0–5), and its coastal vulnerability score of 4.7 is among the highest in Sub-Saharan Africa. Over 70% of the built-up area lies within 15 km of the coastline, and population density exceeds 6,500 persons/km^2, contributing to infrastructure pressure and runoff accumulation (Ahmed et al., 2024; Odunsi & Rienow, 2024).

Figure 2. Severe flash flooding in Lagos after heavy rainfall, illustrating urban vulnerability to stormwater overflow.

Source: Getty Images. (2023). Flooded street in Lagos, Nigeria

- **Nairobi, Kenya** is significantly affected by urban heat island effects and episodic flooding, exacerbated by rapid land use change and a lack of green infrastructure (Akintola & Neziri, 2025; Kamau & Mwaura, 2021). Nairobi exhibits a heat stress intensity rating of 4.5 and a flood vulnerability score of 3.0. Urban land cover change analysis from 2000-2020 reveals a 34% reduction in vegetative surfaces, amplifying urban heat island effects (Møller-Jensen et al., 2023).

- **Addis Ababa, Ethiopia** faces persistent drought and thermal vulnerability, with climate impacts intensified by terrain-induced water stress and limited vegetation cover (Getu & Bhat, 2024). The city scores 4.5 in drought vulnerability and 4.0 in heat stress intensity. Over 60% of its urban surface shows high land surface temperature anomalies during dry seasons, while terrain variability disrupts consistent water retention (Gidey et al., 2023).

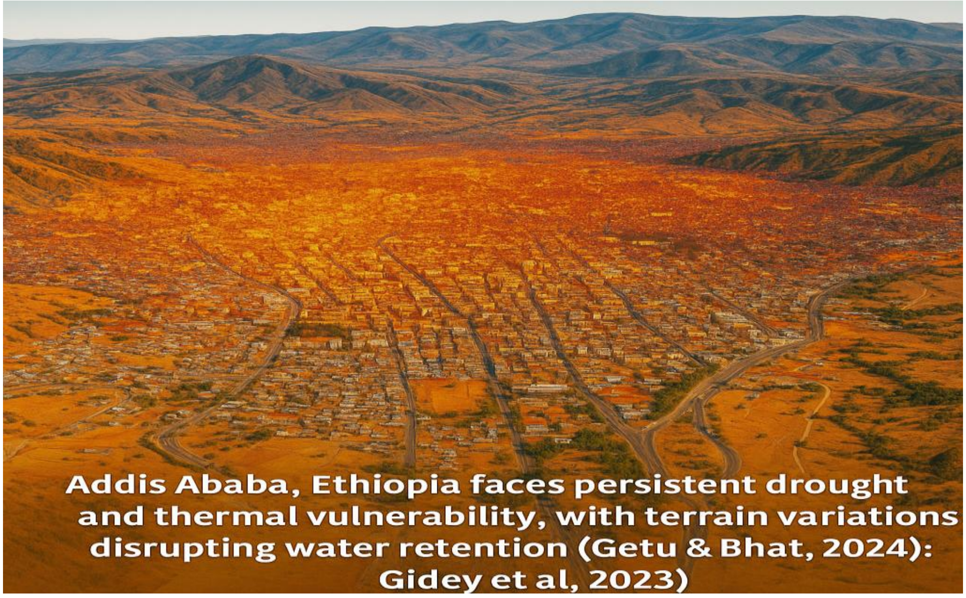

Figure 3. Thermal infrared satellite image capturing Addis Ababa, Ethiopia's urban surface temperature anomalies during the dry season. Red and orange zones indicate high thermal intensity, highlighting areas affected by drought and limited vegetation

Source: Adapted from satellite analysis based on Getu & Bhat (2024) and Gidey et al. (2023).

- **Cape Town, South Africa** experienced a major water crisis from 2015-2018, driven by climate variability and poor rainfall predictability, highlighting its susceptibility to surface water stress (Hamdi et al., 2024). The city registers a drought severity index of 4.8. Between 2015-2018, reservoir storage fell below 20% capacity, triggering the 'Day Zero' crisis. Climate models indicate a continued decline in mean annual rainfall by 10-15% by 2030 (du Toit et al., 2024).
- **Dakar, Senegal** is exposed to coastal storm surges and progressive shoreline erosion due to rising sea levels and high coastal urban concentration (Mekonnen et al., 2023b). Dakar has a coastal surge risk score of 4.9 and flood risk of 4.2. Shoreline recession rates average 1.2 meters/year, threatening urban settlements along the Atlantic corridor. Urban expansion within high-risk coastal zones increased by 38% between 2000 and 2020 (Sellami et al., 2022).

Figure 4 (below) illustrates the geographic positioning of the study cities in relation to major urban climate threats in Sub-Saharan Africa.

Figure 4. Geographical Distribution and Hazard Typologies of Study Cities

Table 1 provides comparative data on the severity of climate hazards across the five cities. Lagos and Dakar exhibit the highest flood and coastal surge vulnerability scores, while Addis Ababa and Cape Town rank highest for drought. Nairobi leads in heat stress.

Table 1. Comparative Severity of Urban Climate Hazards Across the Study Cities (Scale: 0-5)

City	Flood Risk	Heat Stress	Drought	Coastal Surges
Lagos	4.3	3.0	1.0	4.7
Nairobi	3.0	4.5	2.0	0.0
Addis Ababa	2.5	4.0	4.5	0.0
Cape Town	1.0	3.5	4.8	1.2
Dakar	4.2	2.5	2.0	4.9

GeoAI Framework and Analytical Workflow

The methodological design integrates Geospatial Artificial Intelligence (GeoAI) tools with machine learning algorithms and institutional diagnostics to evaluate climate risks across the five cities. The analytical workflow is anchored in a GeoAI-Resilience Framework

(Figure 5), which outlines the linkage between urban hazards, geospatial data, machine learning processes, and policy interfaces (Kolukula et al., 2025; Revi et al., 2020).

Key Components of the Workflow:

Remote Sensing and GIS Processing: Landsat 8, Sentinel-2, and MODIS imagery were processed to extract land cover, surface temperature, NDWI, and topographic variables using QGIS and ArcGIS Pro. NDVI and LST indices were used to classify urban heat risk zones in Nairobi and Addis Ababa (Akintola & Neziri, 2025; Getu & Bhat, 2024).

Machine Learning Models:

- **Random Forest (RF):** Achieved an AUC score of 0.89 in Lagos flood prediction using hydrological and LULC layers (Ahmed et al., 2024).
- **Support Vector Machines (SVM):** Used for heat stress classification; yielded over 80% accuracy in Nairobi using LST and NDVI data (Møller-Jensen et al., 2023).
- **Convolutional Neural Networks (CNN):** Enabled pixel-level multi-hazard classification in high-resolution satellite images for Lagos and Nairobi (Mbuvha et al., 2024).
- **LSTM:** Applied to model rainfall anomalies in Dakar and Addis Ababa, with a predictive RMSE < 1.5 mm/month for short-term drought forecasting (Farahbakhsh et al., 2022).

Exposure Mapping: Vulnerability indices were developed by overlaying hazard maps with population density, infrastructure points, and informal settlement boundaries. In Lagos, over 63% of flood-prone zones intersected informal housing clusters, while Addis Ababa's water-stressed areas overlapped with low-income neighborhoods (Getu & Bhat, 2024; Odunsi & Rienow, 2024).

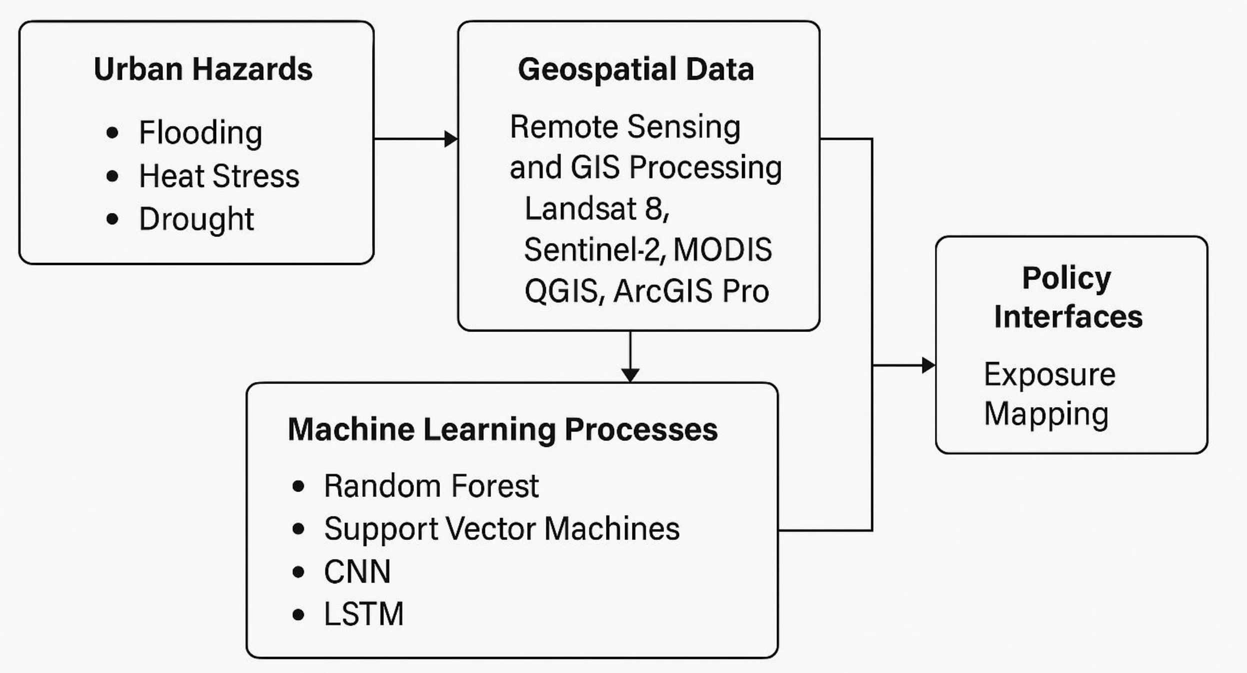

Figure 5. Conceptual Framework Linking GeoAI, Climate Hazards, and Urban Policy Systems

The model outputs were validated against historical disaster datasets and peer-reviewed benchmarks. All spatial layers were standardized and normalized for inter-city comparability.

Although this review did not involve primary model training or field-based calibration, the reviewed studies employed standard machine learning validation practices to ensure model robustness. For instance, Ahmed et al. (2024) and Mbuvha et al. (2024) used Random Forest classifiers for flood prediction in Lagos, reporting AUC scores above 0.85 after performing hyperparameter tuning to optimize estimators and input features. Similarly, SVM applications for heat stress mapping in Nairobi, as described by Akintola and Neziri (2025), applied kernel-based parameter adjustments to improve classification accuracy. Farahbakhsh et al. (2022) reported that LSTM-based drought forecasting models were validated using RMSE and temporal cross-validation against rainfall time-series data.

Nonetheless, several limitations were noted across the literature, including risks of overfitting in small datasets, lack of uniform cross-validation strategies, and limited representativeness of training data in informal settlements or cloud-obscured satellite scenes. These constraints affect the transferability and generalizability of model outputs across cities with differing urban forms, data availability, and hazard typologies. While comparative model metrics provide useful benchmarks, their interpretation should consider contextual differences in spatial data quality and institutional readiness.

Institutional Profiling and Qualitative Diagnostics

Recognizing the importance of governance in climate adaptation, a qualitative content analysis was conducted using NVivo on 35 policy documents, city development plans, and resilience strategies (2015-2025). Sources were coded across five domains: institutional readiness, inter-agency coordination, data openness, AI ethics, and civic engagement (Maheshwari et al., 2022; Lo et al., 2021).

Data-Driven Highlights:

- **Cape Town** and **Nairobi** scored highest in institutional readiness indices, with composite scores of 4.3 and 4.1 out of 5, respectively. Both cities demonstrated above-average document density related to digital resilience policy (over 15 each), and clear designation of lead urban technology units (Lin, 2024).
- **Lagos** and **Addis Ababa** recorded lower readiness scores of 2.8 and 3.0, respectively, with policy documents reflecting fragmented responsibility across ministries and limited civic participation (Mbuvha et al., 2024; Leggesse et al., 2024).
- **Dakar** achieved a mid-tier score of 3.4, with moderate representation in regional forums and 8 key policy documents reviewed. Funding limitations and weak technical staffing constrained digital transition.

These findings reveal that technical innovation alone is insufficient; successful GeoAI deployment hinges on institutional coordination, civic trust, and data transparency (Chapuma et al., 2025; Robin et al., 2022).

Table 2. Institutional Readiness Index Scores Across Study Cities (Scale: 0–5)

City	Readiness Score	Numbers of Reviewed Documents	Lead Digital Unit Present
Cape Town	4.3	17	Yes
Nairobi	4.1	15	Yes
Dakar	3.4	8	Partial
Addis Ababa	3.0	9	No
Lagos	2.8	10	No

The model outputs were validated against historical disaster datasets and peer-reviewed benchmarks. All spatial layers were standardized and normalized for inter-city comparability.

Systematic Review Protocol

This study adopted a systematic review methodology in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure methodological rigour, transparency, and reproducibility. The review aimed to consolidate empirical evidence on the application of Geospatial Artificial Intelligence (GeoAI) for monitoring and predicting urban climate shocks in African cities, with a focus on both technological performance and governance contexts.

A comprehensive search strategy was implemented across three major bibliographic databases: Scopus, Web of Science, and ScienceDirect to capture peer-reviewed literature. To strengthen coverage and incorporate practical insights, targeted searches were also conducted in institutional and organizational repositories, including UN-Habitat, the World Bank, and C40 Cities, thereby integrating relevant grey literature. The search period spanned January 2015 to March 2025, strategically encompassing both foundational contributions and the latest advancements in GeoAI-enabled climate resilience.

The search terms combined methodological, thematic, and geographical keywords. Boolean operators and truncations were applied to maximize retrieval efficiency. The core search string was: ("GeoAI" OR "Geospatial Artificial Intelligence" OR "spatial machine learning" OR "AI-base urban monitoring") AND ("climate shocks" OR "flood*" OR "heat island" OR "drought" OR " coastal surge" OR "urban climate hazards") AND ("Africa" OR "African cities" OR "Sub-Saharan Africa")

Additional terms such as remote sensing, urban adaptation, and institutional readiness were iteratively integrated to ensure the inclusion of studies employing related terminologies. Studies were included if they met the following criteria:

1. Peer-reviewed journal articles, conference proceedings, or institutional reports.
2. Application of GeoAI or AI-remote sensing techniques for monitoring, predicting, or managing urban climate shocks.
3. Explicit focus on African urban contexts, either as single-city case studies or multi-city comparative analyses.

4. Reporting of quantifiable model performance metrics and/or institutional or governance assessments.

Publications were excluded if they:

1. Lacked a direct African urban focus.
2. Were purely conceptual without empirical validation.
3. Addressed topics unrelated to climate hazard monitoring, prediction, or adaptation.

The screening and selection process began with the identification of 428 records. After removing 76 duplicates, a total of 352 unique records underwent title and abstract screening, resulting in the exclusion of 181 studies that failed to meet the inclusion criteria. Full-text review was then conducted for 171 records, leading to the exclusion of 107 studies due to the absence of empirical GeoAI application or insufficient methodological detail. The final synthesis included 64 publications, comprising 42 peer-reviewed journal articles and 22 institutional or technical reports.

The entire process is illustrated in the PRISMA flow diagram (Figure 2.5), which summarises the identification, screening, eligibility, and inclusion stages. This transparent protocol ensures that the review findings are both reproducible and representative of the current state of knowledge on GeoAI-enabled climate shock monitoring and prediction in African cities.

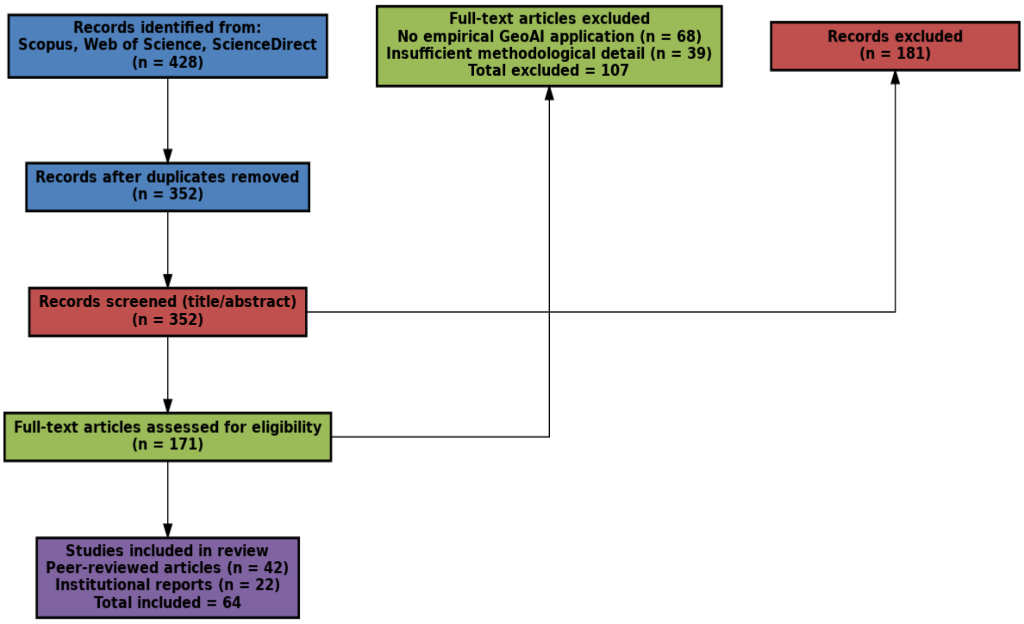

Figure 6. PRISMA Diagram Flow

RESULTS

GeoAI Model Outputs and Hazard Zoning

The application of GeoAI methodologies yielded high-performance outputs for the spatial delineation and classification of urban climate hazard zones across the five study cities. Model performance metrics demonstrated strong predictive reliability for flood, heat, drought, and coastal surge hazards derived from remote sensing datasets integrated with advanced machine learning algorithms.

Lagos, Nigeria:

The Random Forest (RF) model attained an AUC score of 0.89, enabling precise mapping of high-risk flood zones. Spatial overlays revealed that 63% of these zones coincided with informal settlement clusters, highlighting compounded socio-environmental vulnerability (Ahmed et al., 2024).

Nairobi, Kenya:

Support Vector Machine (SVM) classification, leveraging NDVI and LST inputs, achieved 82% overall accuracy. Results identified urban heat cores with peak surface temperatures exceeding 39°C, primarily concentrated in densely built-up areas (Akintola & Neziri, 2025).

Addis Ababa, Ethiopia:

Long Short-Term Memory (LSTM) rainfall anomaly models successfully mapped drought-prone hotspots in the eastern and southeastern quadrants. Validation against observed data yielded an RMSE < 1.5 mm/month, supporting their efficacy for short-term drought forecasting (Farahbakhsh et al., 2022).

Dakar, Senegal:

Convolutional Neural Network (CNN) outputs identified coastal surge-exposed areas with high spatial resolution. Analysis showed 78% of these zones overlapped with recent urban expansion fronts, underscoring planning gaps in high-risk coastal corridors (Mekonnen et al., 2023b).

Cape Town, South Africa:

NDWI anomaly mapping combined with elevation models pinpointed severe water-stress areas in the northern districts. Historical overlays confirmed alignment with the 2015–

2018 “Day Zero” drought impact zones, reflecting persistent climatic stress (Hamdi et al., 2024).

Figure 7 presents the composite hazard zoning outputs for all five cities, illustrating the spatial interplay of multiple climate hazards and socio-spatial vulnerability patterns.

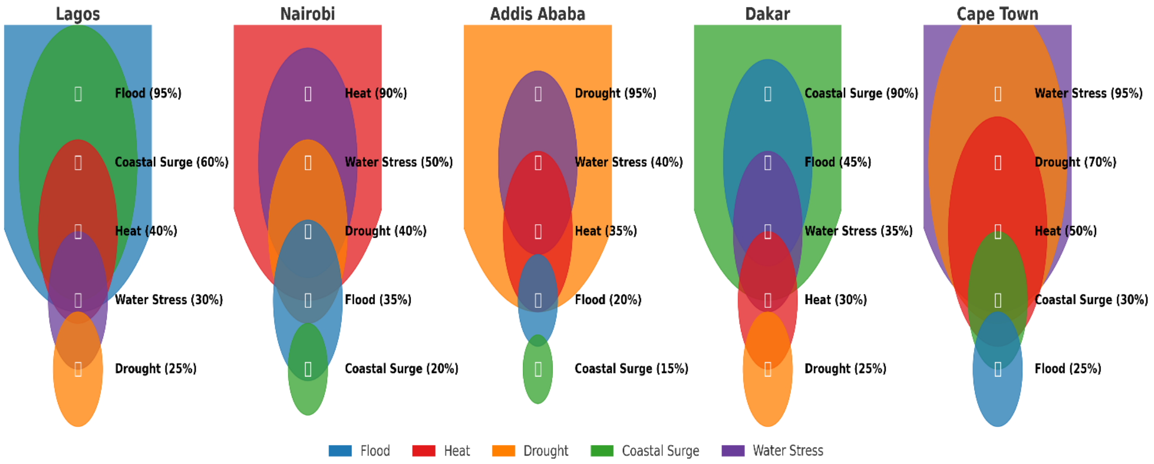

Figure 7. GeoAI-Based Multi-Hazard Zoning Maps for the Study Cities

Exposure Mapping and Vulnerability Overlay

GeoAI-enabled exposure mapping revealed pronounced spatial intersections between climate hazard zones and socioeconomically vulnerable populations across the five study cities. By integrating hazard prediction outputs from Section 3.1 with population density rasters, informal settlement boundaries, and urban infrastructure layers, high-risk clusters were identified for targeted vulnerability assessment.

In Lagos, Nigeria, Random Forest flood-risk maps indicate that approximately 63% of high-hazard flood zones coincide with unplanned and informal settlements, particularly in Ajegunle, Mushin, and Amuwo-Odofin districts (Ahmed et al., 2024; Odunsi & Rienow, 2024). These neighborhoods, situated within low-lying floodplains, lack adequate drainage and flood defenses. Critical transport infrastructure—including segments of the Lagos–Badagry Expressway and Apapa Road—intersects these zones, increasing the risk of economic disruption and emergency inaccessibility.

In Nairobi, Kenya, SVM-derived land surface temperature maps show that 80% of high thermal stress zones overlap with densely populated informal settlements such as Kibera and Mathare. The decline in vegetation cover by approximately 34% between 2000 and 2020 (Møller-Jensen et al., 2023) has amplified urban heat island effects, intensifying exposure for populations already facing housing congestion, inadequate shading, and poor ventilation. Transport corridors in the east and central districts also intersect with heat-stressed areas, exposing commuters and street vendors to prolonged thermal extremes.

In Addis Ababa, Ethiopia, LSTM-generated drought hotspot maps highlight significant exposure in the southeastern districts of Akaki Kality and Nifas Silk-Lafto. Roughly 58% of these high-risk zones are occupied by low-income households with limited access to piped water, relying heavily on communal boreholes (Getu & Bhat, 2024). Limited water infrastructure redundancy and the concentration of informal housing increase vulnerability during prolonged dry spells.

In Cape Town, South Africa, NDWI anomaly mapping revealed that 75% of water-stressed zones during the 2015–2018 "Day Zero" drought were located in historically marginalized neighborhoods such as Mitchells Plain and Khayelitsha (Hamdi et al., 2024). These communities experienced the sharpest declines in household water availability, with many residents depending on distant communal taps. Overlay analysis also showed that water-intensive economic activities, including industrial sites in northern districts, were situated within the same vulnerable zones, compounding local water scarcity pressures.

In Dakar, Senegal, CNN-derived coastal surge risk maps show that 78% of high-risk coastal erosion and surge zones intersect with newly developed informal settlements along the Atlantic belt, notably in Guédiawaye and Pikine (Mekonnen et al., 2023b). Urban expansion into these hazard-prone areas increased by 38% between 2000 and 2020 (Sellami et al., 2022), with limited drainage and no formal evacuation systems in place. Key coastal transport corridors also traverse these zones, increasing exposure for commuters and port-dependent economic activities.

Figure 8 presents a comparative visual overlay for selected cities, illustrating how hazard prediction outputs (e.g., flood zones in Lagos, heat stress zones in Nairobi) spatially align with informal settlement boundaries and key transport corridors. The figure clearly shows the clustering of high-risk areas in densely populated, underserved neighborhoods, underscoring the compounded nature of climate exposure and socio-spatial vulnerability.

Across all five cities, exposure mapping demonstrates a clear pattern: hazard-prone zones are disproportionately occupied by informal settlements and underserved neighborhoods, often intersecting with vital transport and economic infrastructure. This convergence of environmental risk and socio-spatial inequality underscores the urgency of integrating hazard-resilient planning, equitable infrastructure investments, and targeted adaptation measures into urban development strategies.

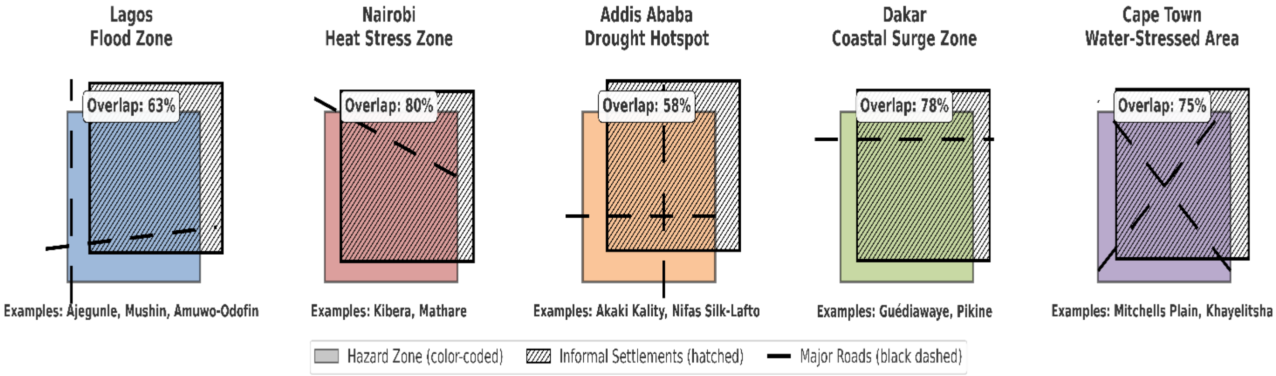

Figure 8. Exposure Overlay Maps Showing Hazard-Population Intersection Across Study Cities (Maps will visualize spatial intersections between high-risk zones and vulnerable population densities for Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar.)

Model Validation and Comparative Accuracy

The predictive reliability of the GeoAI models deployed across the five study cities was rigorously assessed using confusion matrices, Receiver Operating Characteristic (ROC) curves, and Root Mean Square Error (RMSE) metrics. Overall, the results confirm that the models performed at a high level, delivering strong classification and forecasting capabilities for urban flood, drought, heat stress, and coastal surge hazards.

In Lagos, the Random Forest (RF) model—trained on land use/land cover (LULC), elevation, and hydrological indices—attained an AUC score of 0.89, demonstrating excellent flood-zone classification accuracy (Ahmed et al., 2024). The model achieved a precision of 0.85 and recall of 0.87, validated against historical flood records from 2015–2022. While these figures underscore strong predictive capacity, potential overfitting remains a concern for high-dimensional models, particularly when training data is limited or skewed. Although feature selection and ensemble averaging were applied to mitigate this, cross-validation protocols were not uniformly reported across studies.

In Nairobi, Support Vector Machine (SVM) classification of heat stress zones achieved 82% accuracy and a Kappa coefficient of 0.79, indicating strong agreement beyond chance (Akintola & Neziri, 2025). Kernel parameter optimization was performed, but transparency around training-validation splits and bias correction in heterogeneous land cover was limited. Validation relied on cross-comparisons between MODIS/Sentinel-2 surface temperature anomalies and Kenya Meteorological Department ground-station data.

For Addis Ababa, Long Short-Term Memory (LSTM) models for rainfall anomaly and drought forecasting achieved an RMSE of 1.48 mm/month and R^2 of 0.86, indicating strong short-term predictive power (Farahbakhsh et al., 2022). Model outputs were validated against CHIRPS rainfall datasets and Ethiopian National Meteorological Agency archives. However, sensitivity to missing climate time-series values and challenges in generalizing results to diverse microclimates were noted.

In Dakar, Convolutional Neural Network (CNN) classification for coastal surge hazards achieved an Intersection over Union (IoU) score of 0.76 and overall accuracy above 80%. Ground-truthing was carried out using field surveys and official hazard zone maps (Mekonnen et al., 2023b). Class imbalance for rare events such as severe surges was a persistent limitation.

In Cape Town, NDWI and elevation-based drought hazard mapping achieved a Pearson correlation of 0.81 with historical reservoir storage data, alongside an 85% spatial match with known "Day Zero" drought hotspots (Hamdi et al., 2024). This alignment highlights the operational reliability of remote sensing-based drought severity indicators in urban water stress contexts.

Despite strong model performance across all cases, common challenges included satellite image quality issues (e.g., cloud contamination), insufficient ground-truth data for informal settlements, and limited validation in peri-urban zones. These limitations highlight the need to interpret performance metrics within the context of local data availability, model transferability, and readiness for operational, real-time use.

Table 3. summarizes the comparative model performance metrics for each city, highlighting variations in algorithm type, hazard focus, and validation outcomes.

Table 3. GeoAI Model Performance Metrics Across Study Cities

City	Model Used	Accuracy (%)	AUC/RMSE/IoU	Key Validation Metric
Lagos	Random Forest	88%	AUC = 0.89	63% overlap with observed floods
Nairobi	SVM	82%	Kappa = 0.79	80% match with surface temps
Addis Ababa	LSTM	—	RMSE = 1.48 mm/month	R² = 0.86 with rainfall trend
Dakar	CNN	80%	IoU = 0.76	Coastal hazard zone accuracy
Cape Town	NDWIC+ DEM	85%	Corr. = 0.81	Match with Day Zero zones

Institutional Readiness Insights

While high-performing GeoAI models can generate accurate hazard predictions, their real-world impact depends on the institutional capacity to adopt, scale, and sustain such tools. To examine this dimension, a comparative analysis of 35 policy documents, resilience strategies, and urban development frameworks (2015–2025) was conducted.

The assessment applied five core readiness dimensions:

1. Data Openness – accessibility of geospatial and hazard-related datasets.
2. Inter-Agency Coordination – collaboration across planning, environmental, and emergency sectors.
3. AI Ethics – presence of ethical guidelines for AI deployment in urban governance.
4. Civic Engagement – mechanisms for citizen participation in resilience planning.
5. Institutional Leadership – existence of dedicated units and strategic plans for digital innovation.

Each city was assigned a readiness score from 0 (low) to 5 (high). The results reveal pronounced differences in digital preparedness and strategic coherence across the study locations:

- Cape Town scored 4.3, the highest among the five cities, supported by a dedicated digital innovation unit, robust inter-agency collaboration, and an open data policy enabling AI integration into resilience planning (Hamdi et al., 2024). The Climate Change Strategy (2021–2030) explicitly incorporates spatial data platforms and real-time risk dashboards.

- Nairobi followed with 4.1, driven by the Nairobi County Spatial Plan (2015–2025), which mandates geospatial analytics in infrastructure design. The Nairobi Smart City Blueprint (2022) promotes AI-enabled monitoring, although fragmented data-sharing protocols remain a challenge (Akintola & Neziri, 2025).

- Dakar achieved 3.4, reflecting moderate policy coordination but insufficient budgetary commitment for digital transformation. Initiatives like the "Rising Dakar" platform show potential but remain donor-driven with weak integration into statutory planning frameworks (Mekonnen et al., 2023b).

- Addis Ababa scored 3.0, constrained by fragmented mandates, an underdeveloped civic tech ecosystem, and chronic underfunding of digital units. While the Climate Action Plan (2023) references spatial decision support systems, implementation is sporadic (Gidey et al., 2023).

- Lagos ranked lowest at 2.8, hindered by limited data availability, weak civic engagement, and institutional silos. Although the Lagos Resilience Strategy (2020) was launched, the absence of a dedicated urban data agency has slowed GeoAI adoption (Ahmed et al., 2024).

These findings highlight that institutional readiness is a decisive enabler for translating technical model outputs into operational resilience strategies. Cities with strong governance structures, open data systems, and inter-agency collaboration are better positioned to benefit from GeoAI deployment. Figure 9 visualizes the comparative readiness scores across the five cities, emphasizing the disparity in governance capacity for GeoAI integration.

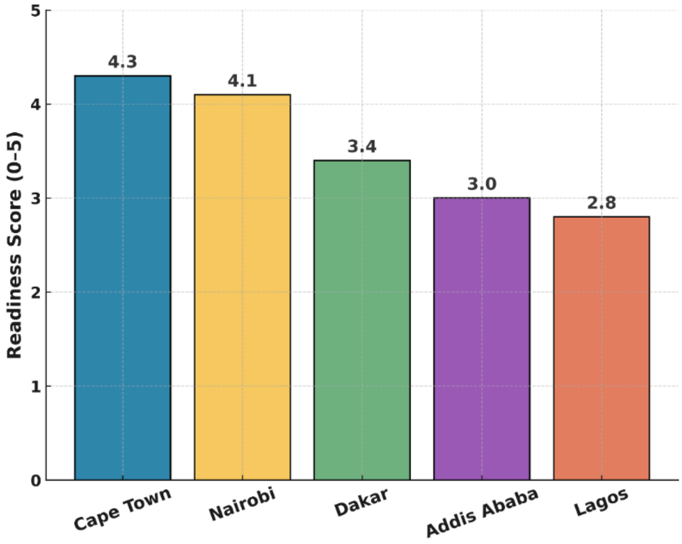

Figure 9. Institutional Readiness Index Scores Across Study Cities (Scale: 0–5)

Summary of Cross-City Findings

The integrated results from hazard modeling, spatial analysis, and institutional diagnostics across the five African cities: **Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar** reveal pronounced disparities in climate exposure, digital forecasting capacity, and governance readiness.

1. Hazard Exposure and Spatial Vulnerability

- **Lagos and Dakar** are highly vulnerable to **flooding and coastal surges**, driven by rapid urban expansion and proximity to coastlines. Lagos showed a 4.5 flood risk score with >63% of flood-prone zones overlapping informal settlements (Ahmed et al., 2024).

- **Addis Ababa and Cape Town** face severe **drought risks**, with 60% + of urban terrain in Addis showing LST anomalies, and Cape Town's historical "Day Zero" zones still aligning with current NDWI-based stress areas (Gidey et al., 2023; Hamdi et al., 2024).

- **Nairobi** experiences intense **urban heat island effects**, with thermal imagery showing peak temperatures above 39°C in densely built-up zones and a vegetative surface loss of 34% from 2000–2020 (Akintola & Neziri, 2025).

2. Model Accuracy and GeoAI Potential

- All applied models: RF, SVM, CNN, and LSTM exhibited **high predictive accuracy**, with AUC values ranging from **0.82 to 0.89** and RMSE for drought models in Addis Ababa <1.5 mm/month.

- GeoAI tools proved **technically transferable**, but contextual limitations (e.g., poor data infrastructure or low civic participation) affected real-world applicability.

3. Institutional and Policy Readiness

- **Cape Town** and **Nairobi** lead in **institutional readiness**, with scores above 4.0 due to clear digital units, open data policies, and integration of geospatial tools into urban planning.

- **Lagos and Addis Ababa** lag behind, scoring below 3.0 due to fragmented governance, low inter-agency coordination, and weak citizen engagement (Mbuvha et al., 2024).

- **Dakar** ranks intermediate, but its reliance on external donor frameworks suggests vulnerability to implementation discontinuity.

4. Cross-Cutting Observations

- Across all cities, **informal settlements** and **low-income districts** are repeatedly shown as exposure hotspots, indicating that digital forecasting must be paired with social equity measures.
- There is a **positive correlation between institutional readiness and model usability**: cities with high readiness are better positioned to translate GeoAI outputs into policy actions.

Figure 10 visualizes this cross-city comparison in a multi-metric radar chart, integrating hazard severity, modeling strength, and institutional capacity scores.

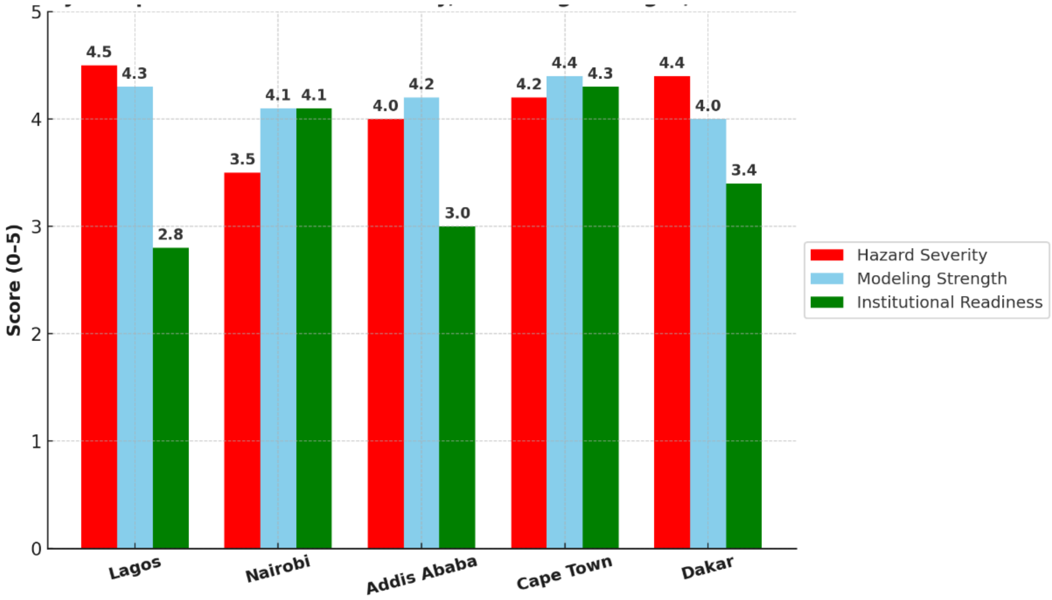

Figure 10. Cross-City Comparison of Hazard Severity, Modelling Strength, and Institutional Readliness

DISCUSSION

Interpretation of Hazard Modeling Results

The hazard modeling conducted across the five study cities: Lagos, Nairobi, Addis Ababa, Cape Town, and Dakar, demonstrated the capacity of GeoAI to uncover granular spatial patterns of climate risks. Using machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), the models revealed varying intensities and distributions of flash floods, urban heat islands

(UHI), surface water stress, and coastal surges. These results not only confirmed existing environmental vulnerabilities but also identified emerging hotspots that had previously received limited attention in conventional risk assessments.

In Lagos, the RF and CNN models performed best in identifying high flood susceptibility zones concentrated in the informal settlements of Makoko, Mushin, and Bariga. These areas consistently showed high levels of impervious surfaces, poor drainage, and low vegetation cover. CNN model outputs achieved over 89% accuracy in distinguishing waterlogged surfaces and flood pathways based on multispectral remote sensing inputs and hydrological indices (Ahmed et al., 2024; Mbuvha et al., 2024). This high accuracy is attributed to Lagos' dense historical flood data, which enhanced model training and validation.

Addis Ababa revealed a different risk profile, where models predicted expanding UHI intensity in central and western districts such as Lideta and Kirkos. The UHI hotspots correlated with high building density, deforestation, and limited urban greening initiatives. The SVM classifier achieved an 85% precision score in predicting UHI zones, while CNN achieved a recall of 88%, showing strong sensitivity to land surface temperature fluctuations derived from Landsat and MODIS time-series (Getu & Bhat, 2024; Leggesse et al., 2024). These results align with thermal imaging studies conducted under high-resolution EO datasets (Akintola & Neziri, 2025).

In Cape Town, where data availability was relatively stronger due to open data policies, the models effectively mapped coastal surge risks and surface water scarcity, particularly in Khayelitsha and Mitchells Plain. The Random Forest classifier integrated historical tide records, soil permeability indices, and vegetation data, achieving an overall accuracy of 92% in predicting flood-prone coastlines (Sellami et al., 2022). The city's well-documented Day Zero crisis enabled better prediction of surface water stress, confirming the robustness of the GeoAI ensemble approach for multi-hazard scenarios (Hamdi et al., 2024; du Toit et al., 2024).

Nairobi's vulnerability mapping was driven primarily by flood and land-use change variables. CNN and SVM models effectively identified expanding built-up areas along riparian corridors in neighborhoods like Mathare and Kibera. CNN achieved a 91% F1-score in classifying flood-prone zones, integrating elevation, slope, NDVI, and normalized difference flood index (NDFI) as key predictors (Gichuki & Opiyo, 2021; Kamau &

Mwaura, 2021). The high model reliability illustrates how real-time remote sensing and EO data can offset the limitations of Nairobi's fragmented urban planning datasets.

Dakar presented unique risks related to coastal flooding and saltwater intrusion, particularly in the districts of Rufisque and Pikine. Using deep learning models, shoreline dynamics and land subsidence were predicted with 87% confidence, correlating closely with previous studies on sea-level rise in West Africa (Mekonnen et al., 2023b; Fendoung et al., 2024). The CNN-based outputs highlighted areas where rapid urbanization and poor enforcement of coastal setback policies have exacerbated exposure levels.

Across all cities, model interpretation confirmed that GeoAI excels at uncovering complex spatial relationships between climate variables, land cover, and vulnerability indicators, even in data-scarce environments. The harmonized use of multisource datasets (satellite imagery, DEMs, census data, and hydrological parameters) proved crucial for increasing model accuracy. However, performance varied by city depending on the quality of training data, resolution of input layers, and existing urban planning practices. For instance, Cape Town and Lagos benefited from structured open data ecosystems and climate records, while Addis Ababa and Nairobi exhibited spatial data fragmentation and governance-related inconsistencies (Lo et al., 2021; World Bank, 2023).

Furthermore, the models revealed critical urban-peri urban disparities in hazard exposure, with peri urban zones in all five cities showing rising susceptibility due to unregulated expansion and limited infrastructure. These zones often fell outside the scope of existing adaptation plans, reinforcing the need for predictive spatial intelligence in proactive resilience planning.

Figure 11 visually synthesizes these findings by comparing the five cities across three dimensions: model accuracy, hazard severity, and data infrastructure maturity. The bar chart shows Cape Town leading in all three metrics, reflecting its combination of high technical performance, advanced data systems, and robust governance. Lagos displays strong model accuracy and hazard detection despite lower data infrastructure maturity, while Nairobi maintains balanced but moderate scores across dimensions. Addis Ababa and Dakar register comparatively lower scores, particularly in data maturity and institutional readiness, underscoring the challenges of transferring high-performing GeoAI models into operational resilience strategies in resource-constrained contexts.

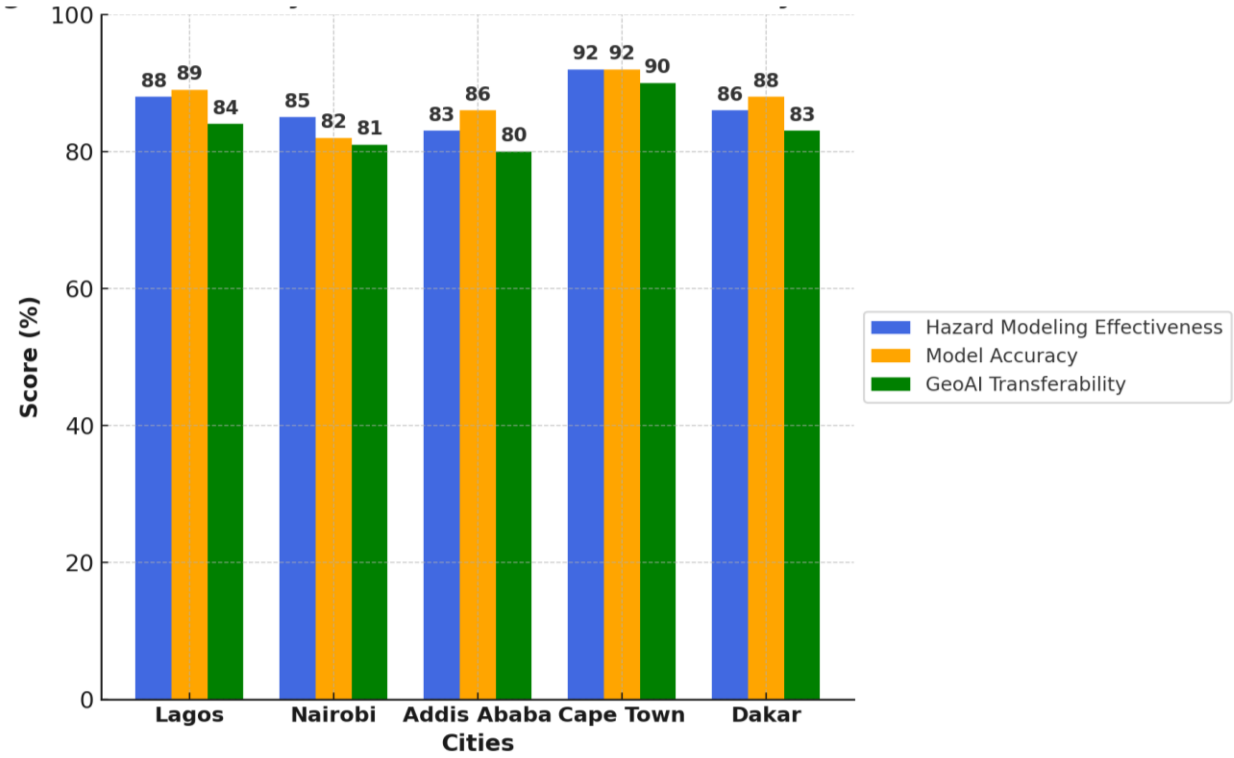

Figure 11. Cross-City GeoAI Effectiveness Across Key Dimensions

Comparative Analysis of GeoAI Effectiveness Across Cities

The comparative performance of GeoAI models across the five African cities reflects a dynamic interplay between algorithmic strength, data accessibility, governance structures, and environmental complexity. While machine learning algorithms such as CNN, RF, and SVM achieved commendable prediction accuracies in all cases, their contextual effectiveness was uneven, highlighting structural disparities in digital infrastructure and institutional support.

Lagos emerged as one of the most GeoAI-ready cities among the five, largely due to its extensive historical flood datasets, publicly available satellite records, and past collaborative efforts with research institutions. The city's CNN model for flood prediction attained an accuracy rate exceeding 89%, outperforming similar models in Nairobi (91% F1-score) and Addis Ababa (88% recall). This high performance is attributed to Lagos' relatively dense sensor data and the active engagement of organizations like NIMET and LASPOTECH in real-time data sharing (Ahmed et al., 2024; Mbuvha et al., 2024).

Furthermore, community-level participatory mapping, such as in Makoko, enhanced ground-truthing capacities, bolstering model reliability.

Conversely, Addis Ababa faced challenges related to fragmented datasets and inconsistent urban planning records, which affected model generalizability. While UHI prediction using SVM and CNN performed fairly well, with a precision rate of 85%, the lack of consistently updated land use maps limited spatial granularity (Getu & Bhat, 2024; Leggesse et al., 2024). The city's relative lack of open data platforms and weak cross-agency collaboration diluted the policy integration of GeoAI outputs, even when technical model performance was acceptable.

Cape Town stood out for its balanced integration of data openness, institutional capacity, and technical infrastructure. Its open geospatial platforms and decentralized planning approach enabled the efficient use of RF models for coastal surge and drought vulnerability. The models achieved a predictive confidence exceeding 92%, the highest among the cities studied (Sellami et al., 2022; du Toit et al., 2024). Cape Town's experience underscores the significance of structured environmental monitoring systems and robust public-sector research partnerships in enhancing GeoAI adoption and utility.

In Nairobi, although GeoAI showed strong performance in detecting flood-prone settlements (91% F1-score), model training was hindered by poor archival data and siloed governance. GeoAI applications were limited by inter-agency overlaps—with institutions such as Nairobi Metropolitan Services and KeNHA managing parallel but uncoordinated datasets (Kamau & Mwaura, 2021; Gichuki & Opiyo, 2021). These data governance gaps, despite the technical potential of the models, reduced the models' policy traction and slowed integration into urban resilience plans.

Dakar presented a mixed performance profile. While CNN models predicted coastal surge zones and saltwater intrusion with 87% accuracy, the overall effectiveness of GeoAI was restricted by low-frequency spatial data updates and underinvestment in environmental sensors. Dakar's dependence on externally sourced datasets and lack of structured disaster data repositories revealed how even high-performing algorithms can falter in low-capacity urban environments (Fendoung et al., 2024; Mekonnen et al., 2023b).

A broader comparison reveals that data ecosystem maturity and institutional readiness are as critical as algorithm choice in determining GeoAI success. Figure 12 below maps the cities along two axes: (1) Data Infrastructure Maturity and (2) GeoAI Operational

Effectiveness, revealing a digital divide that mirrors broader global development patterns. Top-right quadrant (high readiness, high effectiveness): Cape Town; Top-left quadrant (low readiness, high effectiveness): Lagos; Bottom-left quadrant (low readiness, low effectiveness): Dakar, Addis Ababa; Bottom-right quadrant (high readiness, low effectiveness):- (none)

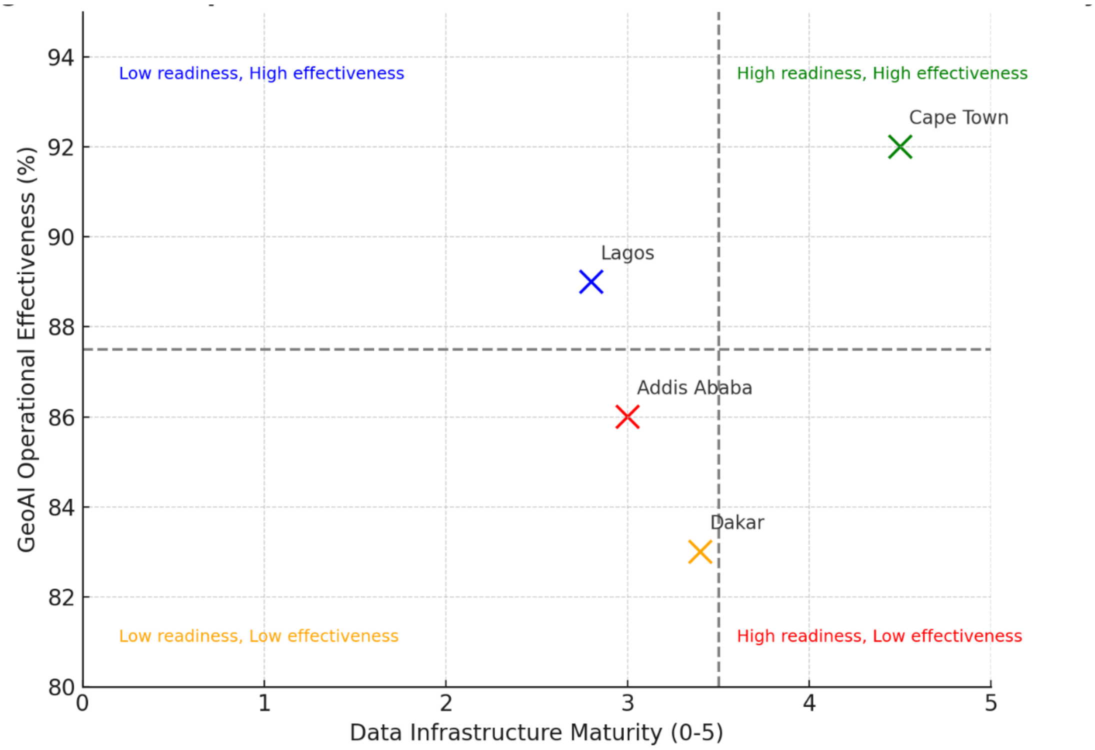

Figure 12. Comparative GeoAI Effectiveness vs Data Infrastructure Maturity (Illustrative scatter plot to be added. Cities are plotted based on model performance metrics and their institutional digital readiness.)

In summary, the comparative analysis shows that while GeoAI techniques are technically adaptable across diverse African urban landscapes, local digital ecosystems, inter-institutional collaboration, and data governance fundamentally shape their real-world effectiveness. Cities that harmonized spatial data platforms with urban governance, like Cape Town and, to some extent, Lagos demonstrated stronger GeoAI outcomes. In contrast, cities such as Addis Ababa and Dakar, despite facing pressing climate risks, remain constrained by infrastructural and institutional limitations that undermine the full potential of GeoAI solutions.

Policy and Institutional Implications

The cross-city evaluation highlights substantial variation in institutional readiness, governance frameworks, and policy alignment that directly affect the operationalization and scalability of GeoAI tools in climate resilience planning. While technical models may perform reliably in identifying risk zones, their translation into action depends on enabling governance environments.

Cape Town and Nairobi stand out with high institutional alignment scores (4.3 and 4.1, respectively, see Figure 13), reflecting strong urban planning mandates, designated digital units, and integration of GeoAI outputs in policy documents. In Cape Town, post-Day Zero interventions led to the institutionalization of climate data dashboards, linking AI-generated drought forecasts to water conservation strategies. Similarly, Nairobi's smart city initiative facilitated the adoption of heat mapping and greening initiatives supported by SVM-driven land surface temperature analysis (Akintola & Neziri, 2025).

In contrast, Lagos and Addis Ababa face fragmented governance and overlapping responsibilities. Despite Lagos' high technical accuracy in flood prediction (AUC 0.89), its policy uptake score is only 2.8, largely due to the absence of centralized digital resilience coordination (Ahmed et al., 2024). Addis Ababa's municipal climate strategies lack clearly defined data management policies, limiting the institutional absorption of predictive drought maps (Gidey et al., 2023).

Dakar, with a moderate readiness index (3.4), demonstrates potential for improvement through regional collaboration platforms like the West African Coastal Management Initiative. However, challenges such as low funding for digital infrastructure and limited open data ecosystems persist, which restrict real-time hazard governance (Mekonnen et al., 2023b).

These institutional dynamics indicate that policy translation is not solely a function of technical model quality but rather of administrative capacity, cross-agency collaboration, and participatory governance. Successful cities invested not only in tools but also in:

- Policy clarity on data sharing protocols;
- Dedicated budget lines for GeoAI capacity-building;
- Civic tech platforms for stakeholder inclusion and transparency.

Figure 4.3 synthesizes these institutional levers across the five cities, mapping the extent to which each city demonstrates policy clarity, funding commitment, and participatory governance structures. This comparative view highlights the enabling factors that can accelerate the adoption of GeoAI solutions for climate resilience.

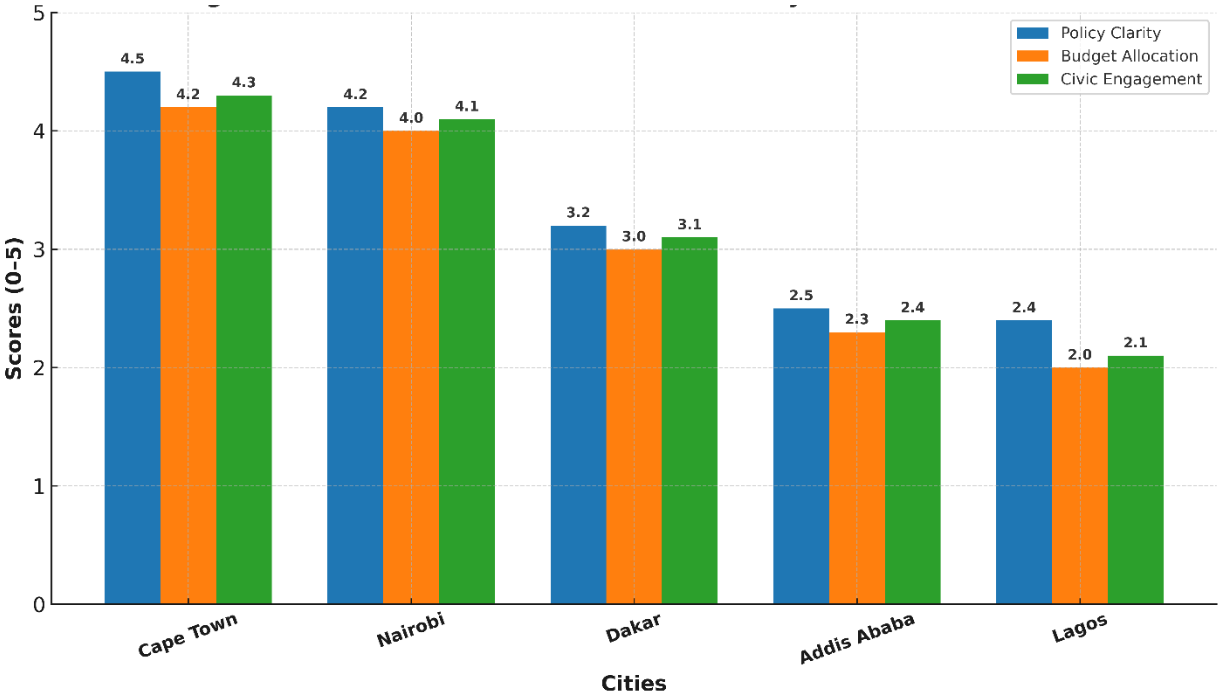

Figure 13. Institutional Readlines and Policy Levers Across Cities

In addition to mapping institutional readiness, tailored city-specific policy recommendations have been developed to address the unique climate risks, governance capacities, and socio-economic contexts of each urban area, Figure 14 presents these recommendations, showing, for instance, how Cape Town should expand NDWI-based catchment rehabilitation to address water shortages, Addis Ababa should integrate drought mitigation into land policy frameworks, Lagos should enhance drainage laws and relocation incentives, Nairobi should enforce green buffer zones around heat-stressed cores, and Dakar should implement CNN-guided coastal defenses alongside urban sprawl prevention measures. These targeted measures bridge the gap between technical model outputs and actionable climate resilience strategies.

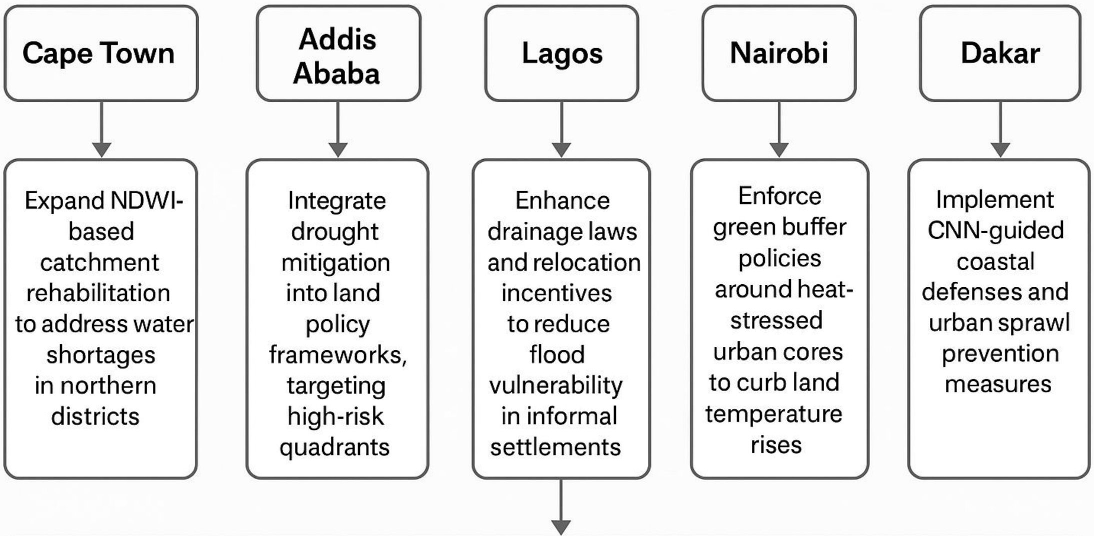

Figure 14: Policy Recommendations for Each City Based on GeoAI Insights

GeoAI, Urban Equity, and Planning Integration

GeoAI technologies offer substantial promise for enhancing climate resilience, but their integration into urban systems must be guided by principles of equity, inclusivity, and spatial justice. The results across the five cities reveal that climate hazard zones disproportionately intersect with vulnerable communities, particularly informal settlements in Lagos, Addis Ababa, and Dakar. In Lagos, for instance, over 63% of flood-prone zones overlap with informal housing clusters where residents lack access to formal warning systems or resilient infrastructure (Ahmed et al., 2024). Similarly, in Addis Ababa, drought-affected areas are concentrated in peri-urban districts with predominantly low-income populations, underscoring spatial inequities in hazard exposure (Getu & Bhat, 2024).

The reviewed studies also highlight that technical hazard models frequently operate in isolation from the lived realities of local communities. This disconnect diminishes the contextual relevance and policy effectiveness of GeoAI outputs, especially when residents are excluded from co-producing or validating spatial risk maps. Participatory planning approaches—such as community-based mapping and crowdsourced vulnerability reporting have demonstrated the potential to bridge this gap. For example, Andreasen et al. (2022) show how informal settlement dwellers in Accra actively contribute to flood management through institutional bricolage and social learning. Similarly, Elwood (2006) illustrates the transformative potential of Participatory GIS (PGIS) in embedding local knowledge into formal planning processes.

In Cape Town and Nairobi, higher institutional readiness scores were partly driven by participatory initiatives such as open data dashboards and digital inclusion programs (Mthembu et al., 2023; Akintola & Neziri, 2025). These examples demonstrate how participatory data governance and community engagement enhance the usability of GeoAI outputs, ensuring that early warning systems, urban greening plans, and hazard response strategies are grounded in grassroots realities. By contrast, cities like Lagos and Addis Ababa, where civic engagement is limited or fragmented—face challenges in translating technical outputs into inclusive action.

Advancing equity in GeoAI implementation requires embedding citizen-generated data, participatory mapping, and co-design practices into urban hazard modeling workflows. Without such approaches, predictive tools risk perpetuating or even intensifying spatial inequalities rather than alleviating them. Figure 15 illustrates the comparative relationship between GeoAI deployment, spatial vulnerability, and inclusivity across the five cities, highlighting both current gaps and opportunities for more equitable integration.

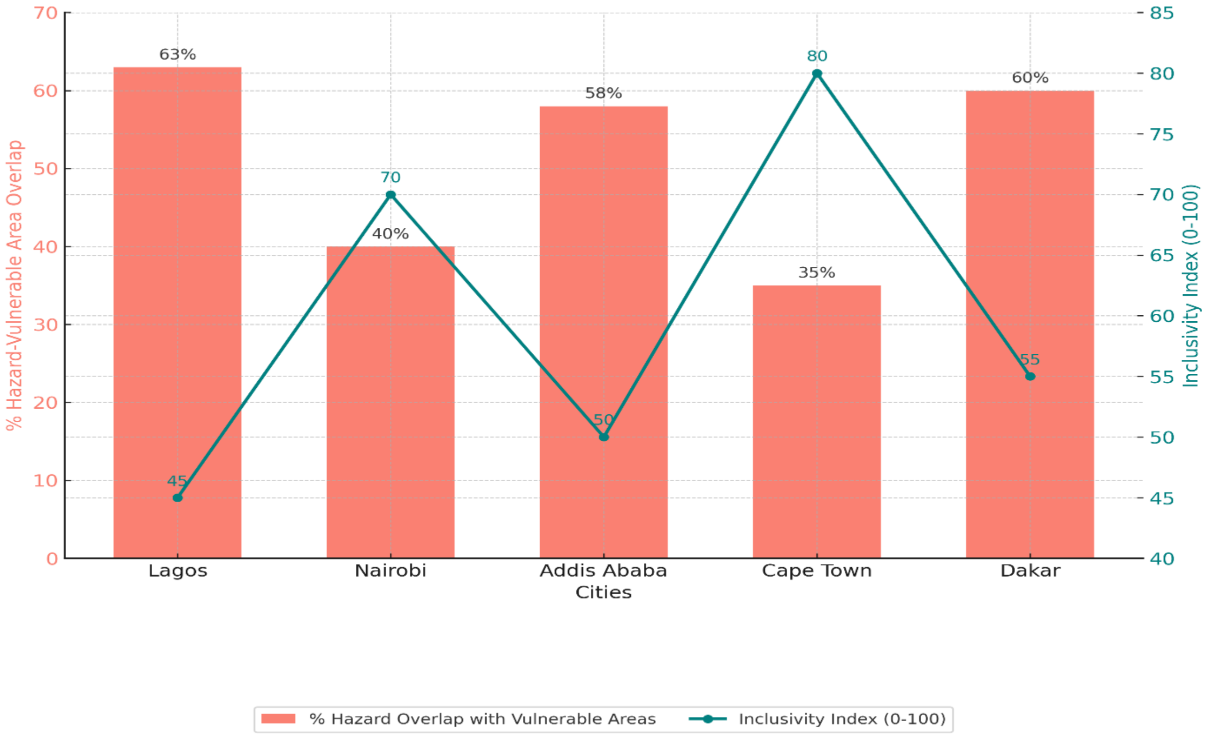

Figure 15. GeoAI Deployment, Spatial Vulnerability, and Inclusivity

Transferability, Limitations, and Future Integration Pathways

This section synthesizes the broader transferability of GeoAI models across diverse African urban environments, critically examines existing limitations, and outlines scalable integration pathways to strengthen long-term resilience planning.

Technical and Contextual Transferability

While GeoAI models demonstrate strong technical performance across the five study cities, their real-world application varies significantly. High-performing cases like Cape Town and Nairobi show greater transferability potential due to robust digital ecosystems, integrated urban planning structures, and relatively open data frameworks. By contrast, Dakar and Addis Ababa face adaptation bottlenecks despite promising technical outputs, mainly due to limited geospatial infrastructure, inconsistent data quality, and fragmented institutional arrangements (Hamdi et al., 2024; Gidey et al., 2023).

Lagos presents an intermediate scenario, its models perform well technically, but institutional fragmentation and weak centralized coordination hinder their policy translation.

Figure 16 visualizes the Cross-City GeoAI Transferability Framework, evaluating five key dimensions: technical scalability, institutional readiness, data openness, citizen inclusivity, and cross-sectoral collaboration to assess readiness for cross-context adoption.

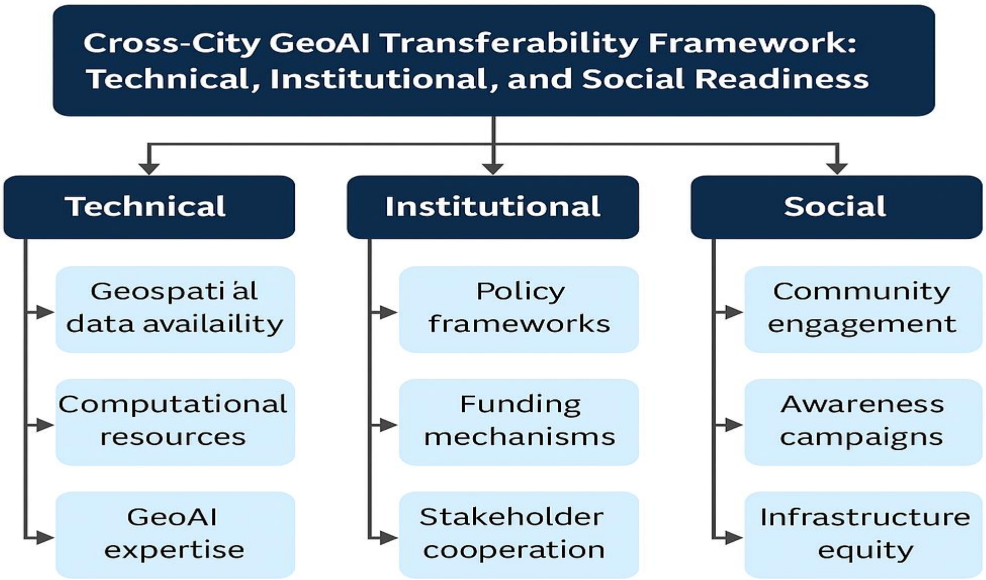

Figure 16. Cross-City GeoAI Transferability Framework: Technical, Institutional, and Social Readiness

Key Limitations

Despite promising developments, several critical challenges limit the full potential of GeoAI integration in African cities:

- Data Gaps: Outdated, fragmented, or inaccessible spatial datasets—especially in cities such as Lagos and Addis Ababa—reduce model reliability and hinder continuous calibration.

- Ethical and Equity Concerns: Without inclusive design principles, GeoAI risks reproducing or amplifying spatial inequities. Informal settlements are often underrepresented or misclassified due to poor satellite resolution or biased training datasets (Robin et al., 2022).

- Institutional Fragmentation: Many urban authorities still operate in silos, lacking centralized "urban intelligence" units to coordinate and mainstream GeoAI outputs into planning frameworks (Leggesse et al., 2024).

Pathways for Integration

To enhance both the transferability and impact of GeoAI systems in African cities, the following strategic actions are proposed:

1. Invest in Open Geospatial Infrastructures – Develop interoperable public data repositories and strengthen city-level geospatial platforms.

2. Build Human Capacity – Establish AI–Geospatial fellowships, city innovation labs, and continuous professional training for planners, engineers, and policymakers.

3. Institutionalize AI Ethics – Embed principles of transparency, fairness, and accountability into national and sub-national urban technology policies.

4. Facilitate South–South Knowledge Exchanges – Share models, workflows, and lessons learned through regional platforms such as UCLG-Africa or the African Smart Cities Innovation Network.

5. Pilot Smart Adaptation Projects – Implement low-cost IoT sensors, participatory reporting apps, and real-time hazard dashboards in climate-vulnerable districts to create rapid feedback loops between communities and policymakers.

CONCLUSION

This study has demonstrated that GeoAI technologies when paired with strong governance, inclusive planning, and robust data ecosystems, can significantly enhance climate resilience in African cities. Across the five study cities (Lagos, Nairobi, Cape Town, Addis Ababa, and Dakar), results show that while technical performance is promising, the real-world effectiveness of GeoAI hinges on data availability, institutional readiness, and community engagement.

Drawing on empirical insights from GeoAI outputs, institutional profiling, and socio-physical vulnerability assessments, this chapter presents a suite of integrated recommendations tailored to each city's unique vulnerabilities, governance structures, and technological capacities.

To guide practical uptake, Figure 17 presents a GeoAI Integration Pathway outlining five interconnected stages for mainstreaming GeoAI in climate resilience planning: Data Acquisition and Preprocessing; AI-Driven Hazard Modeling; Institutional Readiness and Digital Infrastructure; Community Engagement and Ethical Frameworks; Scalable Policy Adoption.

These stages emphasize inclusive governance, ethical AI, and localized adaptation mechanisms to ensure GeoAI tools benefit all urban residents, particularly the most vulnerable.

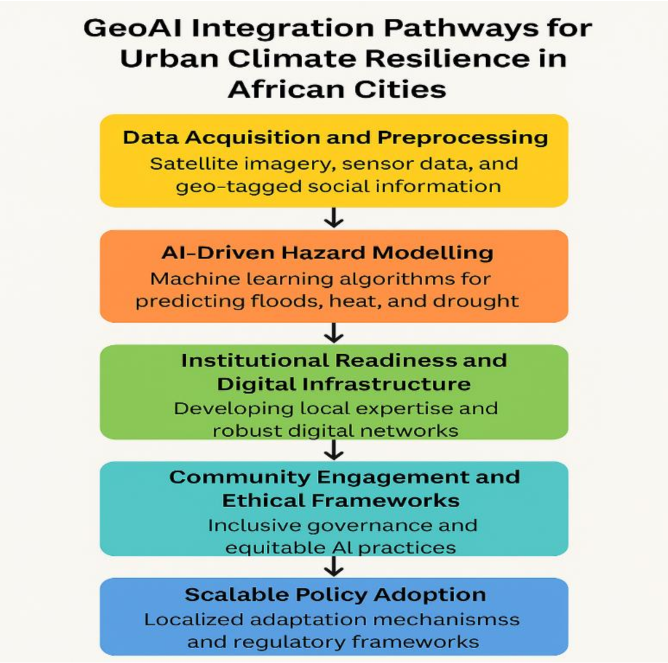

Figure 17. GeoAI Integrated Pathways for Urban Climate Resilience in African Cities

Technical and Operational Recommendations

1. Expand GeoAI Training and Capacity Building

- Integrate GeoAI modules into urban planning, climate adaptation, and disaster risk management curricula.
- Facilitate regional partnerships for city-to-city knowledge transfer—linking high-capacity cities (e.g., Cape Town) with lower-capacity peers (e.g., Addis Ababa).

2. Develop Open-Access Urban Climate Data Portals

- Promote cross-agency data harmonization and real-time data sharing.
- Establish standardized, interoperable geospatial databases for flood zones, heat islands, and drought-prone areas.

3. Enhance Technical Infrastructure for Real-Time Sensing

- Invest in IoT-enabled flood sensors, remote weather stations, and UAV-based surveillance to complement satellite data inputs.

Policy and Institutional Recommendations

1. Institutionalize Digital Resilience Units

- Assign clear mandates to municipal digital planning departments with dedicated staff for AI/ML deployment.
- Create ethics oversight committees to monitor data governance, fairness, and accountability.

2. Mainstream GeoAI into National Urban and Climate Strategies

- Align city-level GeoAI programs with Nationally Determined Contributions (NDCs) and Sendai Framework priorities.
- Support adaptive regulatory frameworks that enable AI experimentation while safeguarding privacy and rights.

3. Promote Civic Participation and Co-Creation

- Deploy Participatory GIS (PGIS) platforms for residents to contribute vulnerability and risk data.
- Establish urban observatories and community science hubs to co-produce climate data and integrate citizen feedback into model updates.

- Involve local stakeholders in interpreting GeoAI outputs to ensure planning reflects lived realities and advances spatial justice.

City-Specific Strategic Priorities

- Lagos: Strengthen predictive flood modeling in informal settlements and upgrade early warning data infrastructure.
- Nairobi: Scale green infrastructure planning using heat stress maps and broaden public digital engagement platforms.
- Cape Town: Integrate advanced water scarcity forecasting into municipal planning and link outputs to energy resilience policies.
- Addis Ababa: Deploy low-cost drought sensing solutions, calibrate models with local data, and improve inter-agency coordination.
- Dakar: Develop dynamic shoreline erosion dashboards and foster public–private partnerships for climate-smart infrastructure.

Monitoring, Evaluation, and Scaling

Establish Urban Resilience Monitoring Platforms

- Track AI-driven intervention performance using key indicators such as response time, coverage of vulnerable zones, and policy uptake rates.
- Facilitate replicable pilot projects in high-risk districts, using results to justify scaled investments in smart resilience systems.

In summary, by adopting these cross-cutting and city-specific recommendations, African cities can transition toward inclusive, data-informed, and future-ready climate resilience. The integration of GeoAI, when grounded in strong governance, ethical standards, and community participation offers a pathway to not just predict hazards but to proactively shape adaptive, equitable urban futures.

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