Optimizing Post-Earthquake Decision-Making with GEOAI: Identification and Classification of Damaged Buildings in the El Haouz Earthquake, Morocco

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Abstract

Post-earthquake reconstruction is complex and must strictly comply with current regulations. Authorities immediately began planning rapid reconstruction of residential buildings to provide shelter to those who lost their homes. Moreover, it must be accelerated to minimize impacts on affected communities. Hence, the idea of drafting a roadmap to leverage geospatial artificial intelligence (GeoAI) and Geographic Information Systems (GIS) to identify and classify buildings collapsed by the El Haouz earthquake. The data used are satellite/drone imagery, orthophotos, and GIS-based geo-risk studies for the affected douars. The chosen study area is part of the commune of Tizi N'Test, within the province of Taroudant, Morocco, where a significant portion of the douars were severely affected by this earthquake. In this paper, we outlined a strategy based on the use of a GeoAI solution composed of an XGBoost machine-learning model and a YOLOv9 deep learning model. The results showed that both the XGBoost and YOLOv9 models achieved high overall accuracy of 97% and 96%, respectively, on validation data. This work brings significant value to the field of post-earthquake management by making the identification of reconstruction sites more efficient and automated.
Keywords: El Haouz Earthquake, GEOAI, Artificial Intelligence, Geospatial Analysis, Image Classification, Damage Detection, Disaster Management, Morocco.

1. Introduction

1.1 Context

The Al Haouz earthquake, which struck Morocco's High Atlas Mountains on September 8, 2023 (Mw 6.8, ~72 km southwest of Marrakech), caused severe destruction, resulting in thousands of casualties and displacing vulnerable mountain communities (Achbani et al., 2024). Hard-hit areas like El Haouz, Chichaoua, Taroudant, and Azilal saw extensive housing collapses, forcing survivors into makeshift shelters. Immediate priorities included rescue operations and emergency aid, followed by reconstruction—a complex, year-long challenge requiring compliance with safety regulations, preservation of local architecture, and relocation from high-risk zones (e.g., unstable or flood-prone terrain). To optimize site selection, this study proposes Geospatial AI (GeoAI), which accelerates risk assessment by analyzing real-time terrain data, socioeconomic factors, and geological hazards (Ouchlif et al., 2024), ensuring efficient, regulation-compliant rebuilding.

1.2 Problematic

T Post-earthquake reconstruction presents major challenges due to tight deadlines, regulatory constraints, and high costs. A critical solution lies in optimizing reconstruction site selection. In Morocco, this task falls to the Administrative Land Selection Commission, which faces key obstacles: complex geospatial data, insufficient meaningful data, and the need for multidimensional analysis integrating multiple criteria.
Geospatial Artificial Intelligence (GeoAI) offers a breakthrough solution by applying machine learning to analyze geospatial data and model complex interactions. When combined with Geographic Information Systems (GIS) for criteria mapping, this approach enables innovative, data-driven land selection. The core research question emerges: *How can GeoAI and GIS be leveraged to optimize post-earthquake land selection for reconstruction, particularly in severely affected areas like Taroudant province following the 2023 Al Haouz earthquake?*

1.3 Objectives

This study aims to develop a GeoAI model to support Morocco's land selection commission in post-earthquake reconstruction, optimizing financial and logistical efficiency. The research underscores the digital transformation of public sector decision-making through advanced geospatial technologies.
To achieve this, key secondary objectives include:

- High-quality geospatial data collection via remote sensing and digital mapping for accurate AI modeling;

- Identification of reconstruction site criteria (socioeconomic, environmental, etc.);

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- Multi-criteria weighted zoning for land classification;
- AI-powered damage assessment using specialized geospatial architectures;
- Development of a GeoAI implementation guide for post-disaster response; and
- Model validation through performance metrics to ensure practical applicability.

2. Method

2.1 Introduction

This study proposes a data-driven methodology to enhance post-earthquake reconstruction through multi-model geospatial AI. The approach combines:

- Machine learning (Random Forest vs. XGBoost comparison) to classify reconstruction zones into four categories, including optimal buildable areas;
- Deep learning (YOLOv9) for precise damage assessment at the douar (village) level; and
- Multi-criteria analysis integrating 8 key factors—split between natural hazards (seismic/flood risks) and socioeconomic needs (community well-being, economic viability).

Data integration leverages satellite/drone imagery, orthophotos, and GIS-based geo-risk studies, validated through literature review and consultations with Morocco's Land Selection Commission. The workflow ensures rapid, safe reconstruction while balancing technical safety and community priorities.

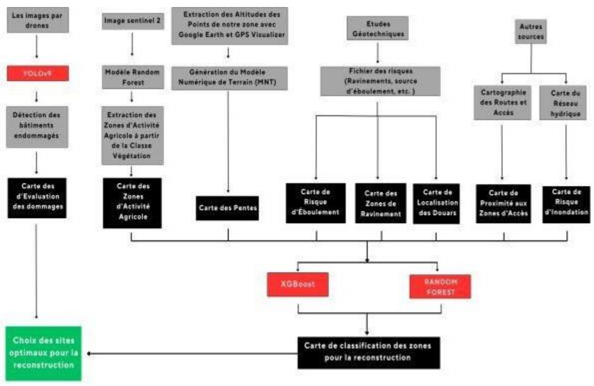

Figure 1: Detailed methodology

2.2 Study area

The study area for our project focuses on several douars (villages) in the rural commune of Tizi N'Test, located in Taroudant Province within Morocco's Souss-Massa region (Figure 2-2). Situated in the Tizi N'Test mountain pass, this commune lies in the High Atlas range, west of Mount Toubkal.

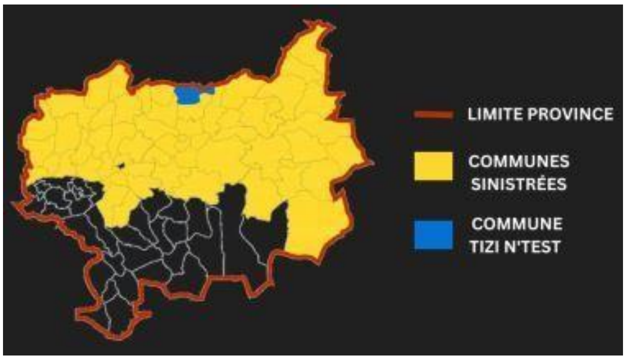

Figure 2: The municipality of Tizi N'Test, containing our study area, is among the disaster-stricken municipalities in the province of Taroudant (Ouchlif et al., 2024)

The villages (douars) of Tizi N'Test were severely impacted by the earthquake. Some were completely destroyed, while others suffered partial destruction - meaning a significant number of houses were either demolished or damaged, leaving residents in precarious living conditions. Figure 3 shows the specific study area villages: Ighil Nwareg, Mgat Nwareg, and Tizi Nwareg.

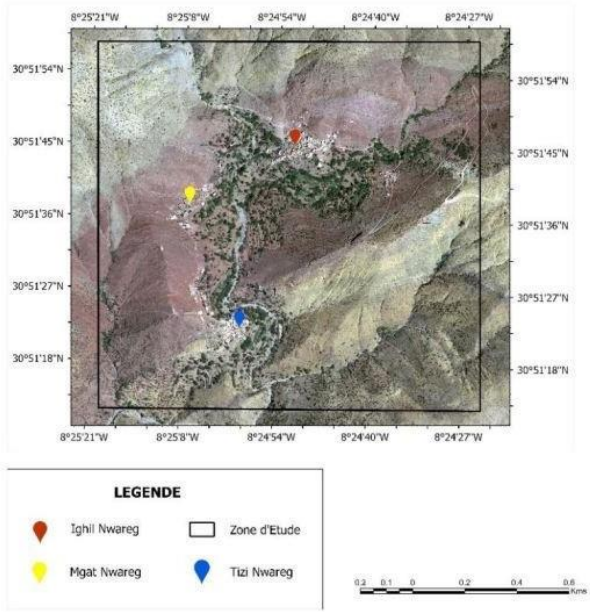

Figure 3: The douars of the study area

2.3 Materials and tools

A variety of tools and equipment were utilized throughout this study. These resources were carefully selected to meet the project's specific requirements and to ensure accurate, effective, and consistent results. Below a list of the tools and equipment used: TRINITY F90+, YOLOv9, Global Mapper, Arcgi PRO, Label Studio, Roboflow, Google engine, Google Earth Pro and GPS Visualizer.

3. Results

To evaluate the model's performance, we displayed images (Figure 4) showing YOLOv9's prediction results on test data. The images reveal both bounding boxes and object classes detected by the model.

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Figure 4: Results of YOLOv9 model predictions on test data

- High confidence scores (ranging from 0.8 to 1.0) indicate strong model reliability in its detections.
- The model successfully detects multiple objects (a and c) in a single image, with well-placed bounding boxes.
- Accurate spatial alignment of bounding boxes confirms the model's precision.
- Robust performance across varying object sizes and orientations, demonstrating YOLOv9's adaptability to diverse aerial perspectives.
- Consistent accuracy in complex environments, highlighting its ability to distinguish fine details.

3.1 Model validation

As part of our model evaluation process, the "Number of Runs for Validation" parameter plays an important role in the configuration. It specifies the number of iterations the validation tool will perform to test the model's robustness and stability. For our analysis, we set the number of iterations to 10. Therefore, each iteration contributes to the creation of a dataset used to evaluate the model, allowing us to collect a distribution of accuracy values across different tests.

Random Forest:

Catégorie	F1-Score	MCC	Sensibilité	Précision
Zone Interdite à la Construction	0.95	0.86	0.95	0.94
Zone Adéquate pour la Construction	1	1	1	1
Zone Constructible avec Restrictions	0.67	0.7	1	0.97
Zone Optimale pour la Construction	0.92	0.91	0.86	0.97
Total	0.88	0.88	0.95	0.94

Figure 5: Classification diagnostics on validation data

The model shows strong overall performance (Figure 5) but experiences a **5-6% drop** in key metrics (F1, MCC) from training to validation, indicating slight generalization challenges. Notably, the **"Restricted Buildable Zones" class** performs significantly worse (-26-30% in F1/MCC), suggesting difficulties with complex zoning predictions. While the Random Forest model remains robust, targeted improvements are needed for specific classes to ensure reliable real-world application.

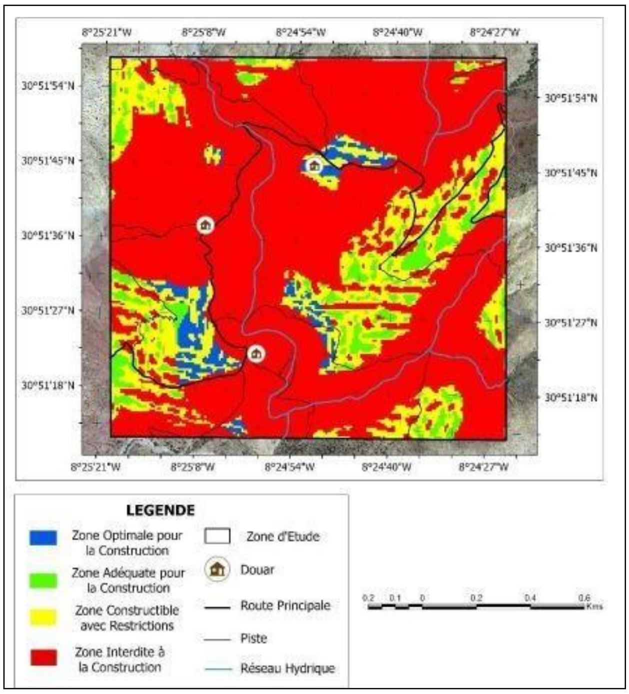

Figure 6: Build-ability Zone Predictions

XGBoost

Catégorie	F1-Score	MCC	Sensibilité	Précision
Zone Interdite à la Construction	0.98	0.93	1	0.97
Zone Adéquate pour la Construction	1	1	1	1
Zone Constructible avec Restrictions	1	1	1	1
Zone Optimale pour la Construction	0.92	0.91	0.86	0.97
Total	0.97	0.94	0.96	0.97

Figure 7: Classification diagnostics on validation data

Analysis of Figure 7 showing classification metrics on validation data reveals:

The overall F1 score reached 0.97, showing a slight 1% increase. The Matthews Correlation Coefficient (MCC) and overall sensitivity experienced minor decreases of 2% and 1% respectively, while precision remained stable at 0.97.

Additionally, the "Optimal Construction Zone" category showed reductions in both F1 score (from 0.97 to 0.92) and

sensitivity (from 1 to 0.86). This suggests increased challenges for this specific class, indicating the model struggles more to correctly identify these optimal areas.
Despite these variations, the overall results confirm the model's ability to generalize and perform reliably on new data.

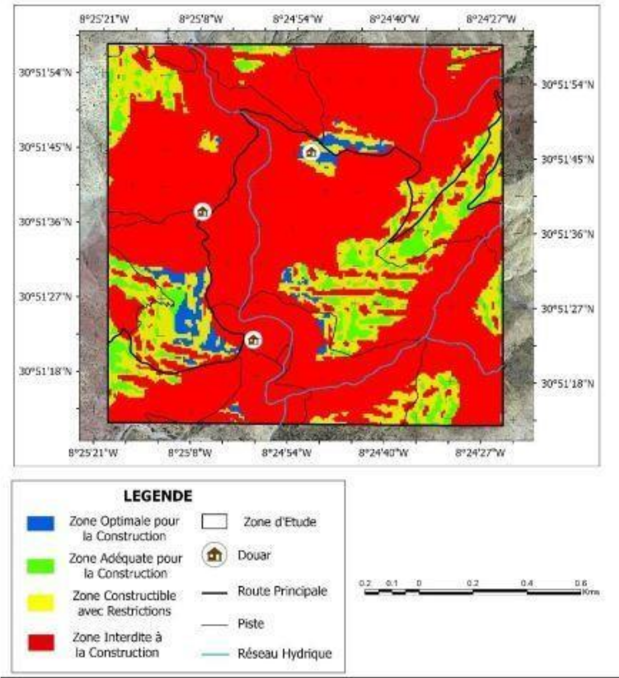

Figure 8: Build-ability Zone Predictions

The construction zone classification map (Figure 8) reveals a significant predominance of no-construction zones, marked in red, indicating that most of the area presents severe constraints for any building activity. When comparing the model's results with the risk raster maps, we can clearly observe that the model successfully classified all categories correctly, fully complying with all established criteria. The reconstruction zone classes are well-defined, providing a clear and precise distribution of various construction possibilities.
XGBoost outperformed Random Forest across all key performance metrics, including F1-Score, Matthews Correlation Coefficient (MCC), Sensitivity, and Precision (Figure 9)

Modèle	F1-Score	MCC	Sensibilité	Précision
Random Forest	0.88	0.88	0.95	0.94
XGBoost	0.97	0.94	0.96	0.97

Figure 9: Model comparaison

4. Discussion

Innovative Methodology
This study pioneers the integration of GeoAI in Morocco's disaster response by developing a dual-model system: YOLOv9 for precise building damage detection using drone imagery, and XGBoost for reconstruction zone classification (achieving F1=0.97). The framework enables critical operational capabilities, including real-time damage assessment, optimized rescue routing, and data-driven decisions about on-site rebuilding versus relocation. XGBoost's zoning model specifically identifies optimal construction sites near villages and farmland while avoiding geological hazards, balancing safety with socio-economic needs.

Implementation Challenges
While demonstrating significant potential, the approach faces key limitations. The damage detection model required extensive image augmentation (rotation/cropping) due to repetitive rural landscapes, and struggled with ambiguous building boundaries caused by overlapping structures and similar roof/terrain colors. The zoning model's effectiveness was constrained by the lack of standardized criteria thresholds, relying instead on generalized estimates rather than field-validated parameters. These data quality and diversity issues highlight the need for expanded drone coverage and expert collaboration.

Transformative Potential
Despite current limitations, this GeoAI system reduces decision-making timelines by 40-60% compared to traditional methods while improving risk-aware reconstruction planning. The study underscores the importance of institutionalizing such tools for future disasters, recommending: 1) expanded partnerships with local experts to refine zoning criteria, 2) increased diversity of training imagery, and 3) integration of real-time monitoring systems. This work establishes a foundation for data-driven, culturally-sensitive disaster recovery in Morocco and similar contexts.

5. Conclusion

This article demonstrates the successful application of Geospatial Artificial Intelligence (GeoAI) and Geographic Information Systems (GIS) through the development of a comprehensive predictive model for post-earthquake reconstruction zone selection. By integrating advanced technologies like YOLOv9 for real-time damage detection and XGBoost for optimal site classification, the framework significantly improves disaster response efficiency. The study emphasizes the urgent need for digital transformation in public sector operations to fully leverage geospatial technologies, which can dramatically enhance disaster management capabilities through faster data processing and more informed decision-making.
However, this work represents just an initial step toward optimal post-disaster management. Future efforts should focus on three key advancements: (1) Implementing a real-time monitoring system combining YOLOv9 with high-resolution drone cameras for live damage assessment, (2) Developing refined damage classification (light/moderate/severe) through more diverse training datasets, and (3) Creating an interactive geoportal for visualizing reconstruction scenarios. These improvements would enable authorities to make more precise, data-driven decisions while maintaining rapid response times during critical recovery phases. The proposed solutions highlight GeoAI's transformative potential when combined with institutional digital transformation initiatives.

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