Identifying Vulnerable Communities for Targeted Emergency Planning in Al Haouz, Marrakech, Morocco.

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Abstract

This study develops a data-driven framework to identify vulnerable communes and select pilot sites for field surveys in the Al Haouz region. Six indicators—population density, elderly rate, children rate, number of households, disability rate, and availability of survey data—were integrated using the Entropy Weighting Method. A composite vulnerability score and spatial mapping were produced, highlighting priority communes. Seven communes were selected for field data collection, ensuring geographic diversity and feasibility. This approach supports an objective and scalable emergency planning process for disaster-prone regions, particularly for earthquakes.

Keywords: *Vulnerability Assessment, Entropy Weighting, Disaster Preparedness, GIS, Al Haouz Earthquake.*

Introduction

Data-driven approaches are increasingly transforming disaster preparedness. GIS, AI, and big data improve hazard prediction, emergency response, and recovery management [1]. Collaborative and cross-jurisdictional use of data enhances preparedness strategies [2]. Dynamic models also allow simulation of resilience and recovery patterns [3], while architectural frameworks help local governments improve response efficiency[4].

Integrating demographic and social indicators is essential for accurate vulnerability assessment. Previous studies highlight the contribution of population structure, mobility, and socio-economic conditions to disaster impacts [5–8]. The Entropy Weighting Method provides an objective way to assign weights based on data variability, avoiding subjective bias [9–13]. Its proven performance across fields makes it well suited for vulnerability mapping in Morocco.

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This research applies this methodology to Al Haouz to produce a transparent vulnerability map and guide pilot-site selection for emergency planning after the 2023 earthquake.

Study Area

Al Haouz, in the Marrakech-Safi region, is characterized by strong geographic contrasts: the Jebilet mountains to the north, the High Atlas to the south, fertile plains to the east, and peri-urban Marrakech to the west. These contrasts create disparities in accessibility, services, and infrastructure (Figure 1).

Rural southern communes face significant barriers to healthcare, with limited road networks and uneven distribution of services [14]. Hydrogeological conditions shaped by the synclinal structure of the region influence water availability and agricultural sustainability [15]. Social vulnerability is evident, particularly in rural belts where maxillofacial trauma is frequent due to poor road safety [16]. The 2023 earthquake highlighted severe weaknesses in traditional housing, especially in mountainous communes such as Talat N'Yacoub and Tizi N'Test [17].

These combined geographic, geological, and social conditions justify the need for an evidence-based vulnerability assessment.

Data used

Indicators were extracted from the *Profil sociodémographique de la zone sinistrée* (HCP, 2023) [18], covering commune-level statistics for Al Haouz and surrounding affected provinces. Selected indicators represent demographic vulnerability and availability of reliable survey data:

- population density
- number of households
- percentage of children (0–14)
- percentage of elderly (60+)
- disability rate
- availability of household survey data

These indicators align with international disaster-risk assessment practices [19–21].

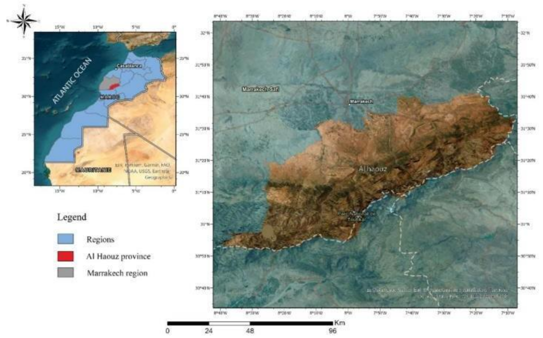

Figure1: Geographic Context and Study Area in AL Haouz Province

Methodology

A systematic workflow was developed to assess vulnerability using objective weights and spatial analysis (Figure 2).

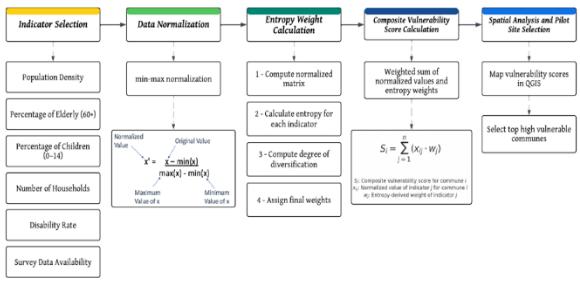

Figure2: Methodological Framework for Identifying Vulnerable Communities in Disaster Prone Regions

1. Indicator Selection

Six indicators were selected for their relevance to demographic and social vulnerability. Each indicator captures a specific dimension of exposure or sensitivity to disasters:

a) **Population Density:** Reflects the concentration of people and potential exposure levels, helping identify areas where evacuation and emergency response may be more challenging.

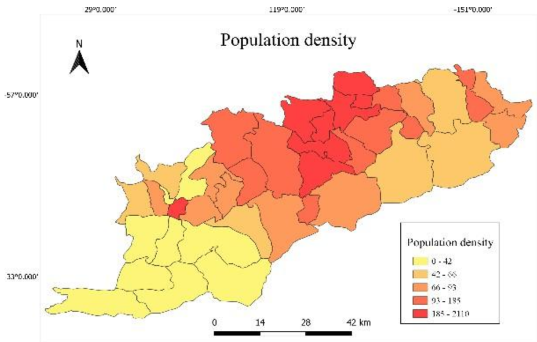

Figure3: Population density map of Al Haouz province.

b) **Percentage of Elderly (60+):** Indicates the presence of a highly dependent population requiring additional assistance during evacuation and recovery.

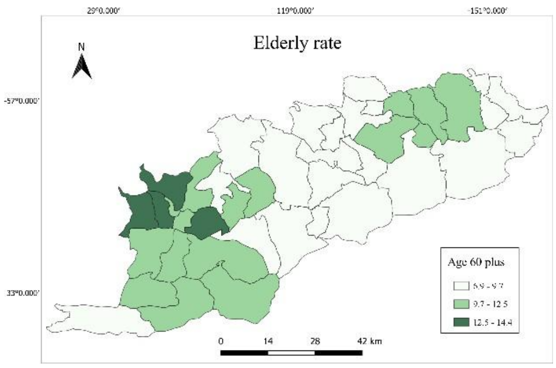

Figure4: Eldery rate map of Al Haouz province.

c) **Percentage of Children (0–14):** Highlights communities with a large dependent youth population needing adapted communication and support during emergencies.

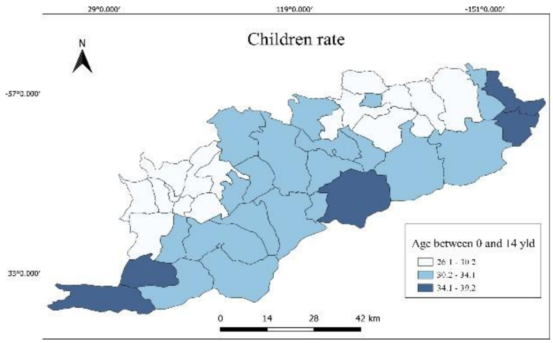

Figure5: Children rate map of Al Haouz province.

d) **Number of Households: Serves** as a proxy for population distribution and settlement patterns, guiding the scale of required household-level interventions.

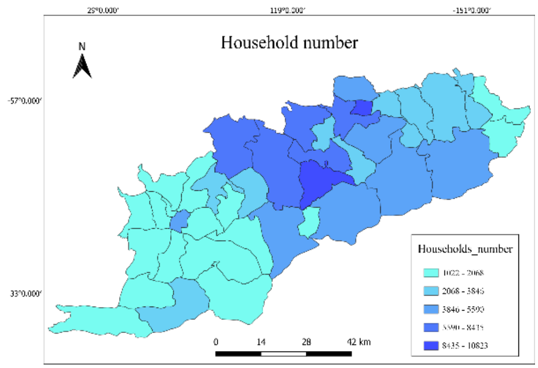

Figure6: Household y map of Al Haouz province.

e) **Disability Rate:** Identifies populations needing specialized care and accessible infrastructure during disaster response.

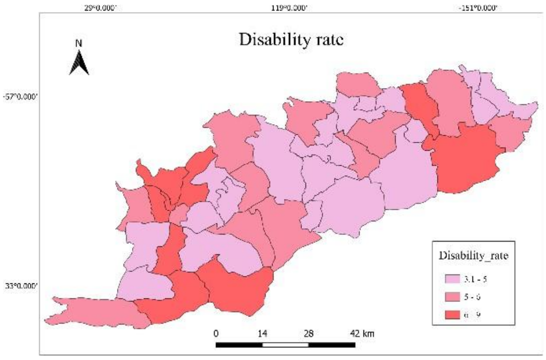

Figure7: Disability map of Al Haouz province.

Survey Data Availability: Ensures that selected communes have enough existing data to support further fieldwork and household survey implementation.

2. Data Normalization

Because indicators use different scales, min–max normalization was applied to standardize values between 0 and 1, ensuring equal comparability across communes [22].

Normalized Value
Original Value

(1) $$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Maximum Value of x
Minimum Value of x

Figure8: Min-Max Normalization Formula for Standardizing Indicator Values.

3. Entropy Weight Calculation

assign objective weights based on indicator variability:

1.Normalize indicator matrix
2.Compute entropy values
3.Calculate diversification (1 – entropy)
4.Derive weights by proportional diversification

This method prioritizes indicators with stronger discriminatory power and removes subjective bias[23].

4. Composite Vulnerability Score Calculation

Each commune's vulnerability was computed by summing normalized indicators multiplied by their entropy-based weights. Higher scores indicate higher vulnerability. This multi-criteria approach synthesizes demographic, social, and structural conditions into a single comparable index [22].

(2) $$S_i = \sum_{j=1}^{n} (x_{ij} \cdot w_j)$$

S_i: Composite vulnerability score for commune i
x_{ij}: Normalized value of indicator j for commune i
w_j: Entropy-derived weight of indicator j

Figure9: Computation of the Composite Vulnerability Score Using Entropy Weights.

5. Spatial Analysis and Mapping

Spatial analysis was conducted using QGIS, an open-source geographic information system (GIS) platform widely used for spatial data visualization and analysis. This step aimed to integrate the calculated vulnerability scores with geospatial data to support spatial interpretation and pattern recognition. The process involved several key tasks:

- Importing commune-level shapefiles obtained from official Moroccan GIS sources, providing accurate administrative boundaries and spatial reference.
- Joining sociodemographic data and vulnerability scores to the spatial layers, enabling each commune to be represented both geographically and numerically.
- Creating choropleth maps to visually represent the distribution of vulnerability scores, with color gradients used to indicate the degree of vulnerability across space.

This spatial representation of vulnerability enhances understanding by revealing geographic disparities, clustering patterns, and areas of concentrated risk. Similar GIS-based approaches have been successfully applied in post-disaster planning and risk assessment, such as the urban vulnerability mapping conducted in Greece following major natural hazards. The use of GIS in this context allows decision-makers and planners to link data-driven results with actionable, location-specific insights [24].

6. Commune Ranking and Pilot Site Selection

Following the calculation of composite vulnerability scores, all communes were ranked from highest to lowest to identify the areas most at risk. Based on this ranking, the top seven communes were selected as pilot sites for conducting household surveys aimed at validating the quantitative results and gathering qualitative insights into community vulnerability. The selection of these pilot sites was guided by the following criteria:

- High vulnerability score: Priority was given to communes with the highest composite scores, indicating elevated risk levels.
- Geographic diversity: Communes were chosen to represent a range of geographic settings, including mountainous areas, valleys, and rural centers, to ensure spatial representativeness.
- Data availability and logistical feasibility: Selected communes had sufficient existing data and accessibility to support survey

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implementation and follow-up analysis.

This multi-criteria selection strategy ensures that the pilot sites form a balanced and representative sample, similar to established sampling techniques such as Probability Proportional to Size (PPS) used in rural China [22], and stratified sampling approaches applied in the United States [21]. The household surveys conducted in these sites will serve to validate the modeled vulnerability levels and provide contextual information to refine emergency preparedness and planning strategies.

Results and discussion

The vulnerability assessment conducted across the communes of Al Haouz province reveals significant spatial variation in composite vulnerability scores, which range from 0.01712 to 0.0844. The highest levels of vulnerability are concentrated in the central and northeastern parts of the province, particularly in communes such as Tamesloht, Sidi Abdallah Ghiat, Ghmate, Ourika, Ait Faska, and Ait Ourir (Figure6). These areas exhibit elevated values in several key indicators, including population density, elderly and child dependency rates, disability prevalence, and number of households. The spatial classification using natural breaks allowed the differentiation of vulnerability into seven categories, with the selected pilot communes all located within the upper three vulnerability classes. In contrast, communes in the southern and southeastern parts of the province tend to have lower composite scores, indicating reduced vulnerability according to the selected indicators. The results underscore the value of using a composite index approach supported by the entropy weighting method and spatial analysis to capture multidimensional vulnerability. The high scores observed in the selected pilot communes point to the concentration of demographic and social 13 characteristics that increase susceptibility to hazards, particularly in the aftermath of the Al Haouz earthquake. The methodology allowed for an objective comparison across communes while preserving local specificities, and the map visualization highlights critical zones requiring urgent attention. This geospatial insight is crucial for informed decision-making, as it supports targeted resource allocation and strategic planning. Moreover, the selection of geographically diverse pilot communes including both densely populated valleys and remote mountainous areas ensures representativeness and supports future validation through household surveys. These findings reinforce the relevance of integrating statistical and spatial tools in vulnerability assessments, particularly in rural and disaster-prone regions.

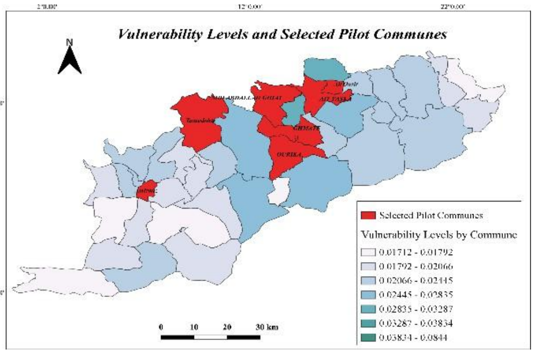

Figure10: Vulnerability Levels and Distribution of Selected Pilot Communes in Al Haouz Province

Conlusion

This study highlights the effectiveness of a data-driven, multi-criteria methodology in assessing vulnerability and informing emergency planning in Al Haouz Province, Morocco. By combining spatial analysis techniques with the Entropy Weighting Method, we established an objective and transparent framework for evaluating vulnerability levels across communes. This methodological 14 choice not only minimized the influence of subjective judgment in the weighting process, but also ensured that all indicators contributed meaningfully based on their intrinsic variability. The final vulnerability scores revealed notable spatial disparities across the region, with rural and mountainous areas showing higher levels of risk due to factors such as population aging, social isolation, and limited access to resources. The selection of seven pilot communes Aït Faska, Sidi Abdallah Ghiat, Tameslouht, Ghmate, Ourika, Aït Ourir, and Imizmiz was guided by both data driven rankings and considerations of geographic and demographic diversity. These sites offer a representative sample of the broader regional context, making them ideal for conducting the 150 planned household surveys. Overall, the results of this research provide a strong foundation for the design of a scalable and inclusive emergency preparedness plan. The integration of socio-demographic data with GIS based analysis serves as a powerful tool for policymakers, enabling more equitable resource allocation and targeted interventions in disaster-prone settings. Furthermore, the approach developed here can be replicated and adapted for other regions facing similar challenges, reinforcing the broader applicability and sustainability of the method.

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