Multi-Source Geospatial Analysis for Disaster Risk Management in Smart Cities: Integration of GIS & Remote Sensing

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ABSTRACT

This study presents a geospatial framework for earthquake risk assessment in Türkiye's Marmara Region, one of the country's most densely populated and hazard-prone areas. Integrating multi-source datasets within a GIS and Remote Sensing (RS) environment, the approach synthesizes hazard, exposure, and vulnerability layers into a composite risk index at 100 m spatial resolution. Hazard modelling was conducted using fault proximity data from the General Directorate of Mineral Research and Exploration (MTA) and lithological susceptibility maps, both normalized and weighted to reflect seismic amplification potential. Exposure was quantified through demographic and infrastructural density, combining LandScan Global 2023 population data and OpenStreetMap (OSM) building footprints processed via kernel density estimation. Vulnerability was represented using building density as a proxy for structural fragility. All layers were normalized into a 0–1 scale and spatially aligned using GDAL-based resampling. The resulting risk map identifies Istanbul, Kocaeli, Bursa, and Sakarya as high to very high-risk zones, aligning with historical earthquake events such as the 1999 İzmit earthquake. Findings confirm that risk is driven not only by seismic hazard but also by demographic exposure and urban vulnerability. The proposed workflow demonstrates the applicability of open and national geospatial datasets in disaster risk management and offers a reproducible methodology for smart city resilience planning.

1. Introduction

The increasing intensity and frequency of natural hazards in metropolitan regions, exacerbated by climate change, unplanned urbanization, and socio-economic pressures, has placed disaster risk management at the core of sustainable smart city agendas worldwide. Urban centers—particularly in seismically active and densely populated regions—are exposed to multidimensional risks that threaten not only human lives but also critical infrastructure and economic stability (UNDRR, 2019). As global urban populations continue to grow, the importance of adopting integrated, data-driven strategies for risk assessment and resilience planning has become increasingly evident (IPCC, 2022).

Among various natural hazards, earthquakes constitute one of the most destructive threats for urban areas, particularly in countries such as Türkiye where tectonic activity is high. The Marmara Region exemplifies this condition, being situated along the North Anatolian Fault Zone (NAFZ), one of the most active tectonic systems in the world (Şengör et al., 2005). Historical earthquakes such as the 1999 İzmit and Düzce events demonstrated not only the seismic hazard of the region but also the vulnerability created by uncontrolled urban expansion, inadequate building codes, and insufficient preparedness measures. These disasters highlighted the urgent necessity of comprehensive frameworks that combine hazard, exposure, and vulnerability in order to produce actionable knowledge for decision-makers.

At this point, regional-scale risk mapping emerges as a vital instrument for disaster risk reduction. Unlike localized hazard studies, regional risk mapping provides a spatially comprehensive understanding of risk dynamics, ensuring that planning strategies capture cross-boundary interactions and cascading impacts (Birkmann et al., 2016). By integrating demographic, infrastructural, and geological data into coherent geospatial models, such approaches not only diagnose the intensity of risks across provinces but also guide long-term planning processes aimed at building resilient regions. Importantly, regional risk mapping also plays a strategic role in informing multi-level governance mechanisms, ensuring that local mitigation measures are aligned with national and international frameworks such as the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015).

Geographic Information Systems (GIS) and Remote Sensing (RS) are indispensable in this regard, enabling the integration of heterogeneous spatial datasets for systematic hazard, exposure, and vulnerability assessments. Numerous studies have demonstrated their applicability in hazard modelling, including flood susceptibility (Tehrany et al., 2014), landslide risk (Pourghasemi et al., 2019), and seismic vulnerability assessment (Khosravi et al., 2016). RS technologies further enrich these approaches by providing continuous and large-scale proxies for topography, land cover, and demographic dynamics (Awuh et al., 2022). However, despite significant advancements, the integration of GIS and RS into holistic multi-source workflows designed specifically for regional-scale disaster risk management remains limited (Ding et al., 2021).

In recent years, the paradigm of smart cities has introduced new opportunities for risk governance, emphasizing the role of real-time data integration, interoperability of systems, and advanced spatial analytics. Integrating geospatial technologies with open data sources, IoT sensors, and AI-driven analytics provides a transformative framework for multi-hazard risk assessment and resilience planning (Batty, 2018; Mora et al., 2019). When extended to the regional level, these tools not only strengthen

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urban preparedness but also pioneer strategic disaster risk reduction planning by producing harmonized regional risk profiles. Such regional baselines are indispensable for guiding investments, prioritizing interventions, and coordinating cross-jurisdictional preparedness strategies.

This study aims to contribute to bridging these gaps by presenting a GIS- and RS-based geospatial modelling framework tailored for earthquake risk assessment in Türkiye's Marmara Region. Specifically, it synthesizes hazard, exposure, and vulnerability layers into a composite risk index at a fine spatial resolution (100 m). The proposed approach demonstrates the feasibility of integrating global (e.g., LandScan, OSM) and national (e.g., MTA, geological surveys) datasets while also underlining the strategic value of regional-scale risk mapping as a foundation for broader disaster risk reduction planning. By doing so, the research not only provides a replicable methodology aligned with the global Sendai Framework for Disaster Risk Reduction 2015–2030 (UNDRR, 2015), but also pioneers a scientific basis for future regional-level resilience strategies in Türkiye and beyond.

2. The Study Area

The Marmara Region of Türkiye represents a highly complex and seismically sensitive area, both geographically and socio-economically. Encompassing approximately 67,000 km², the region is home to more than 25 million inhabitants, making it one of the most densely populated areas in the country (TÜİK, 2023). Its significance extends beyond demographics, as it includes Türkiye's economic powerhouse, Istanbul, alongside major industrial centers such as Kocaeli, Bursa, and Sakarya (Figure 1). These provinces collectively generate a substantial portion of the national GDP, highlighting the critical interdependence between seismic safety and economic stability (Erdik & Durukal, 2008).

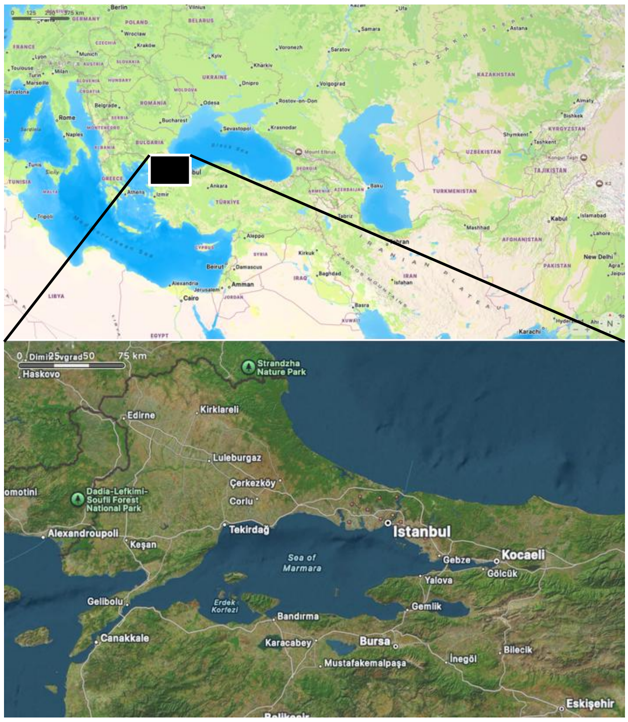

Figure 1. Study area

Geologically, the region is dominated by the North Anatolian Fault Zone (NAFZ), an active right-lateral strike-slip fault system that ranks among the most hazardous fault lines worldwide (Şengör et al., 2005). The NAFZ transects the Sea of Marmara and extends across several provinces, with well-documented historical seismicity. The catastrophic earthquakes of 1999 in İzmit (Mw 7.4) and Düzce (Mw 7.2) remain stark reminders of the fault's destructive potential, resulting in over 18,000 fatalities, massive infrastructural damage, and long-lasting socio-economic impacts. This seismic history underscores the acute vulnerability of the Marmara Region and the urgency of risk-informed planning.

Topographically, the Marmara Region is characterized by a mixture of lowland plains, coastal zones, and mountainous uplands. The coastal areas along the Sea of Marmara host the densest urbanization and industrial development, whereas the inland provinces such as Bilecik and Balıkesir exhibit more moderate population densities but remain exposed to seismic shaking due to their proximity to active fault segments. Elevation datasets (e.g., ASTER GDEM) further reveal that urban sprawl has expanded into geologically unstable zones, including unconsolidated sediments and alluvial plains that exacerbate soil amplification during seismic events.

The socio-economic profile of the region magnifies its seismic vulnerability. Rapid and largely unplanned urbanization has led to the concentration of populations and assets in high-risk zones. Istanbul alone, with over 15 million residents, is not only Türkiye's cultural and economic hub but also the epicenter of seismic risk due to its proximity to the central Marmara fault segments. Industrial corridors in Kocaeli and Sakarya contain critical facilities such as refineries, manufacturing plants, and logistics hubs, which, if disrupted, could result in cascading regional and national economic impacts (Durukal et al., 2006). Furthermore, infrastructural networks such as highways, railroads, and ports link Marmara to both national and international trade, amplifying the systemic consequences of seismic hazards.

In defining the study area, this research deliberately expanded beyond the administrative borders of the Marmara Region. While official boundaries encompass 11 provinces, the model includes adjacent areas such as Eskişehir and parts of Western Anatolia. This decision reflects the reality that seismic waves and cascading disaster effects (e.g., infrastructure failures, service disruptions) transcend administrative borders.

The adoption of a buffer-zone perspective ensures that risk assessments capture inter-regional dependencies, aligning with international best practices in regional disaster risk governance (Birkmann et al., 2016). Ultimately, the Marmara Region provides a critical testbed for developing and validating multi-source geospatial risk assessment frameworks. Its combination of high seismic hazard, dense population, vital economic infrastructure, and complex governance structures makes it a representative case for disaster risk management in seismically active urban regions worldwide.

3. Data and Methodology

The methodological framework of this study was carefully structured to achieve a high level of technical rigor by integrating multi-source geographic datasets into a reproducible GIS- and remote sensing-based workflow. The main objective is to develop a composite earthquake risk index for the Marmara Region by combining three closely related components—hazard, exposure, and vulnerability—each derived from distinct but spatially harmonized data sources. This approach not only expands the analytical scope but also provides a holistic perspective for risk assessment.

3.1 Data Sources

A robust multi-source data architecture was established by combining both global and national datasets to maximize spatial and thematic coverage. In designing this architecture, particular attention was given to the diversity of data origins, resolution levels, and thematic attributes to ensure a comprehensive and technically defensible foundation for risk modelling. Each dataset was selected according to scientific criteria such as accuracy, update frequency, interoperability, and suitability for integration into a multi-hazard framework:

- **Fault Lines (Seismic Hazard Data):** Active fault traces were acquired from the General Directorate of Mineral Research and Exploration (MTA). These vector datasets not only delineate surface-breaking faults but also provide associated metadata such as slip rates, fault segments, and recency of activity. By integrating these attributes into the geospatial framework, the data enable quantitative analysis of seismic source parameters. The North Anatolian Fault Zone (NAFZ), represented extensively in this dataset, is recognized as one of the most hazardous right-lateral strike-slip systems globally. Its detailed mapping provides the foundation for spatially explicit seismic hazard modeling, fault proximity analysis, and subsequent vulnerability assessment.

- **Geological and Soil Data:** Lithological and soil classes were obtained from national geological maps and enriched with supplementary geotechnical surveys. The data include stratigraphic sequences, soil thickness variations, and engineering soil classifications that allow for a more precise estimation of local site effects. Units were systematically reclassified into categories based on their amplification potential (e.g., unconsolidated sediments, volcanic deposits, intrusive rocks), following international standards in seismic microzonation. This classification was not only critical for modeling site-specific ground motion amplification but also for identifying zones of differential settlement risk and liquefaction potential, thereby expanding the hazard modelling framework to account for secondary seismic effects.

- **Population Data:** The LandScan Global 2023 dataset was employed to represent ambient population distribution. This dataset provides globally harmonized, raster-based population estimates with a resolution suitable for regional risk modelling. Beyond simple population counts, LandScan incorporates diurnal movement patterns and probabilistic allocation of individuals to residential, commercial, and industrial zones, enhancing the realism of exposure modelling. For this study, the dataset was reprojected into UTM Zone 35N to match other spatial layers, and cell-level statistics were cross-validated against official demographic data from the Turkish Statistical Institute (TÜİK) to ensure consistency and reliability.

- **Building Data:** Building footprints were sourced from OpenStreetMap (OSM), an open-access, crowd-sourced platform whose data quality has been shown to be increasingly robust in urban contexts. The footprints were first subjected to topological cleaning and attribute enrichment, ensuring geometric accuracy and eliminating duplicate or misclassified entries. These polygons were then converted into centroids, and a Kernel Density Estimation (KDE) analysis was performed using a 500 m search radius to produce continuous building density rasters. This approach allowed not only the visualization of structural concentration but also the derivation of proxies for construction typologies and urban morphology. In addition, sensitivity testing with different bandwidths (250 m and 750 m) was conducted to evaluate scale-dependent variations in density surfaces, thereby ensuring methodological robustness.

- **Topography:** The Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM, 27 m resolution) provided topographic references for resampling, alignment, and slope derivations. Beyond simple elevation values, slope, aspect, and curvature indices were derived to capture geomorphological variability across the study area. These derivatives allowed the identification of areas prone to landslides and localized ground instabilities that may exacerbate seismic damage. The DEM was also cross-compared with Shuttle Radar Topography Mission (SRTM) data for consistency checks, and void-filling algorithms were applied to minimize data gaps in mountainous regions. By incorporating these topographic attributes, the analysis not only ensured geometric precision during raster alignment but also enriched the hazard modelling framework with terrain-related susceptibility factors.

- **Auxiliary Data:** Administrative boundaries, infrastructure networks, and land use/land cover datasets were included to provide ancillary contextual information for regional analysis. These datasets were sourced from both national mapping agencies and global repositories such as CORINE Land Cover. Infrastructure data encompassed transportation corridors (highways, railways), utilities (energy transmission lines, pipelines), and lifeline facilities (hospitals, emergency centers), all of which are critical for resilience analysis. Incorporating these layers enabled the assessment of systemic exposure, allowing the framework to address not only direct physical impacts but also cascading functional disruptions across sectors. Land use/land cover information further supported the classification of urban, peri-urban, and rural zones, facilitating a nuanced interpretation of spatial exposure patterns.

3.2 Data Preprocessing

Each dataset underwent extensive preprocessing to ensure both spatial harmonization and analytical reliability. Preprocessing steps were designed not only for compatibility but also for enhancing data quality by addressing issues such as spatial resolution mismatch, projection errors, and attribute inconsistencies. In addition, data cleaning and cross-validation procedures were implemented to minimize uncertainty, dataset underwent preprocessing to ensure spatial harmonization:

- **Coordinate Reference System (CRS):** All datasets were projected into UTM Zone 35N (EPSG:32635) for metric accuracy and spatial consistency. This choice ensured uniform distance and area calculations across the study region, facilitating precise overlay analyses. Reprojection was performed using GDAL utilities with bilinear resampling for continuous data and nearest-neighbor for categorical layers. In addition, transformation accuracy was cross-checked against control points derived from national geodetic benchmarks to minimize positional errors and guarantee alignment integrity.

- **Resampling:** Continuous datasets (population, elevation) were resampled via bilinear interpolation to preserve gradient continuity and minimize edge artifacts, while categorical datasets (fault buffers, lithology) employed nearest-neighbor resampling to retain class integrity. Multiple resampling trials were conducted at varying grid resolutions (50 m, 100 m, 250 m) to evaluate the sensitivity of outputs to cell size. Comparative statistical analyses, including variance and RMSE measures, were applied to ensure that the chosen 100 m resolution optimally balanced computational efficiency and spatial accuracy.

- **Normalization:** To enable comparability, all raster layers were normalized into a 0–1 scale. For continuous variables, min-max scaling was applied, while for highly skewed distributions (population, building density), percentile thresholds (e.g., P98 cut-offs) were introduced to mitigate the influence of outliers. This ensured that extreme values did not disproportionately bias the composite index. Additional normalization checks involved histogram equalization and z-score scaling for comparison, with cross-validation confirming that min-max scaling combined with percentile adjustments provided the most stable and interpretable outcomes.

3.3 Hazard Modelling

Hazard modelling was conceptualized as a multi-parameter analytical process, integrating both the spatial proximity to active fault systems and site-specific geological susceptibility indices. The methodological framework aligned with globally recognized standards in probabilistic seismic hazard analysis (PSHA) and deterministic site response modelling, leveraging high-resolution spatial data and scenario-based ground motion simulations. This integrated approach facilitated the generation of continuous hazard surfaces that reflect not only direct tectonic influences but also terrain amplification effects and secondary hazard triggers, thereby capturing the multifaceted nature of seismic risk at regional scale.

- **Fault Proximity:** Euclidean distance analysis was applied to rasterized fault lines to generate continuous distance surfaces. These surfaces were segmented into buffer zones (0–5 km, 5–10 km, 10–20 km, >20 km) with hazard scores assigned according to empirical attenuation relationships derived from regional ground motion prediction equations. Proximity values within 5 km of major faults were assigned maximum hazard scores. Additional calibration was performed using historical strong motion records from the Kandilli Observatory of Bogazici University open-source database to ensure realistic decay of hazard with distance.

- **Lithological Susceptibility:** Geological units were evaluated based on their amplification potential, liquefaction susceptibility, and depth-to-bedrock information where available. Categories included unconsolidated alluvial sediments, volcanic deposits, and intrusive igneous formations. Amplification factors were derived from geotechnical site classifications consistent with Eurocode 8 standards (soil classes A–E). Unconsolidated sediments received the highest hazard weights, while competent bedrock was assigned the lowest.

- **Secondary Hazard Indicators:** In addition to lithology and fault distance, slope angle and curvature derived from DEM analyses were incorporated as modifiers to capture terrain-induced amplification and potential coseismic landslides. These factors were normalized and introduced into the hazard raster with minor weights to reflect secondary seismic hazard contributions.

- **Weighted Overlay:** All hazard-related sublayers were normalized to a 0–1 scale and integrated through a weighted linear combination, assigning 0.6 weight to fault proximity, 0.3 to lithology, and 0.1 to slope-curvature modifiers. The resulting raster, termed the **Hazard Score Map** (Figure 2), provided a spatially explicit representation of seismic hazard intensities across the Marmara Region of Türkiye.

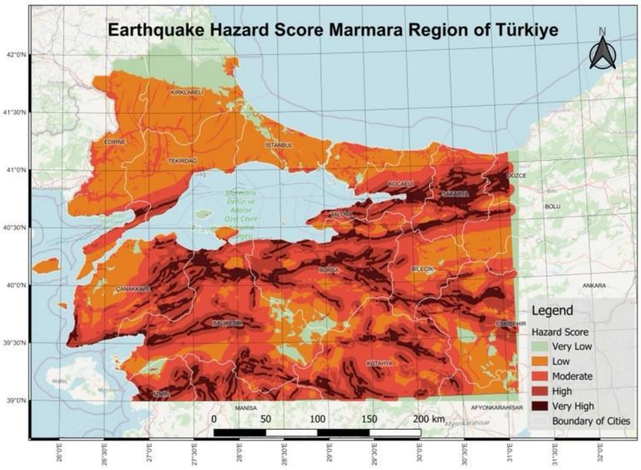

Figure 2. Hazard Score Map

3.4 Exposure Modelling

Exposure was rigorously defined as the spatial quantification of anthropogenic and infrastructural assets potentially impacted by seismic events. The modelling framework represented exposure as a multidimensional surface, integrating demographic, structural, and infrastructure data at high spatial granularity. Raster-based methodologies were employed to capture both urban heterogeneity and broader regional contrasts, ensuring that sub-cellular clustering and dispersed rural patterns could be equally resolved. Input datasets were systematically harmonized to a common spatial reference and subjected to quality assurance protocols, including topological correction and attribute validation, to maintain data integrity throughout the overlay and analysis processes. This methodological rigor enabled the precise delineation of exposure hotspots and the identification of critical infrastructure clusters most susceptible to seismic hazards.

- **Population Exposure:** LandScan 2023 values were capped at the 98th percentile (1,403 persons/cell) to mitigate extreme outliers and then normalized. Beyond simple normalization, spatial autocorrelation metrics (Moran's I, Getis-Ord Gi*) were applied to detect statistically significant population clusters. This allowed differentiation between uniformly distributed settlements and high-density agglomerations, the latter being far more critical in terms of potential casualties and disruption.

- **Building Exposure:** KDE-based building density surfaces were enhanced by integrating building footprint attributes, including footprint area and height proxies where available. This enriched layer was normalized using the 98th percentile (321.42) threshold. In addition, exposure modelling accounted for industrial zones, lifeline infrastructure, and critical facilities (hospitals, schools, energy plants) derived from auxiliary datasets. This broadened the scope of exposure from residential structures alone to systemic assets of regional importance.

- **Composite Exposure Layer:** Both normalized rasters were combined with equal weights (0.5 each) to generate the **Exposure Score Map** (Figure 3). A sensitivity analysis was conducted by varying weight ratios (0.4/0.6, 0.6/0.4) to evaluate robustness. The final configuration was selected based on consistency with observed patterns of historical earthquake damage in the Marmara Region. The resulting exposure map thus provides a spatially nuanced and functionally comprehensive depiction of risk-driving elements.

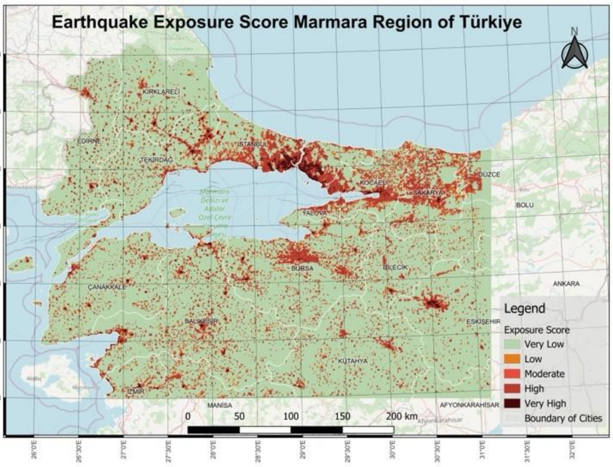

Figure 3. Exposure Score Map

3.5 Vulnerability Modelling

Vulnerability was conceptualized as the representation of both structural fragility and socio-economic sensitivity, acknowledging that physical building density alone does not fully capture the complex drivers of disaster risk.

- **Structural Fragility Indicators:** Building density was initially selected as a proxy under the assumption that high-density areas are more likely to contain older and structurally weaker building stock. To refine this, OSM building footprints were cross-referenced with municipal cadastral data where available, enabling approximation of construction age and typology distributions. Fragility functions from regional seismic performance studies were also considered to translate density metrics into probabilistic damage potential.

- **Socio-Economic Sensitivity:** Beyond physical attributes, vulnerability was extended conceptually to include demographic and socio-economic dimensions such as household income, education levels, and access to emergency services. Although not all of these datasets were available at consistent resolution for the current model, their integration is planned for future iterations.

- **Normalization:** The vulnerability layer was normalized into a 0–1 range to ensure comparability with hazard and exposure layers. For composite indicators, normalization was performed both at the sub-component level (structural vs. socio-economic) and at the aggregated index level to preserve internal weighting balance.

This refined vulnerability modelling approach emphasizes the dual physical and social dimensions of seismic risk. Future extensions of this model will incorporate systematic socio-economic datasets and building inventory information, thereby enabling a more comprehensive and scientifically defensible representation of vulnerability across the Marmara Region.

3.6 Composite Risk Calculation

The final stage of the methodological framework integrated hazard, exposure, and vulnerability layers into a composite risk index through a rigorously defined geospatial synthesis. This integration was grounded in established principles of multi-criteria decision analysis (MCDA) and probabilistic seismic risk assessment (Kappes et al., 2012). By ensuring methodological transparency, the resulting risk scores captured the complex interaction between geophysical hazards, anthropogenic exposure, and socio-economic vulnerability. Such an approach reflects the multidimensional nature of earthquake risk in the Marmara Region and aligns with international best practices for regional-scale disaster risk modelling (UNDRR, 2019; Cutter, 2016).

3.6.1 Mathematical Structure

In line with international disaster risk modelling practices, the mathematical structure of the composite risk index draws upon both multiplicative interaction models and theoretical foundations of multi-hazard risk assessment (Kappes et al., 2012; UNDRR, 2019). The risk index was computed using a multiplicative model:

$$Risk = Hazard \times Exposure \times Vulnerability. \quad (1)$$

This *(1)* formulation ensures that high risk values emerge only in locations where hazard intensity, exposure concentration, and vulnerability levels simultaneously converge. For example, an area with high seismic hazard but low exposure (e.g., mountainous rural areas) yields a low composite risk score, whereas densely urbanized areas located near active fault zones with vulnerable building stock generate the highest risk scores.

3.6.2 Grid Resolution and Harmonization

To ensure technical robustness, grid resolution and harmonization were treated as a critical methodological step. Extensive multi-scale testing (50 m, 100 m, 250 m) was performed to analyze the trade-offs between computational cost, spatial precision, and thematic accuracy (Goodchild, 2011). Error metrics such as Root Mean Square Error (RMSE) and Kappa statistics were calculated to validate the resampling performance across different resolutions. The final decision to adopt a 100 m resolution was based on its ability to capture intra-urban heterogeneity while maintaining regional coverage efficiency. Harmonization further required consistent cell alignment, edge-matching across provincial boundaries, and statistical consistency checks with original datasets to reduce modifiable areal unit problem (MAUP) biases (Openshaw, 1984).

All input layers were spatially aligned to a 100 m grid, chosen after extensive sensitivity testing to balance computational efficiency and spatial detail. This resolution captures intra-urban heterogeneity while preserving region-wide analytical consistency. Resampling methods applied during harmonization were validated to ensure the preservation of original data fidelity.

3.6.3 Weighting and Sensitivity Analysis

To evaluate the robustness of the composite risk model, a comprehensive weighting and sensitivity analysis was conducted. This process involved systematic variation of weight assignments, Monte Carlo simulations for uncertainty quantification, and comparative analysis with alternative multi-criteria decision analysis approaches. Sensitivity indices were calculated to determine the relative contribution of hazard, exposure, and vulnerability to the overall risk index, providing a quantitative measure of component influence.

While the multiplicative formulation intrinsically balances the three components, exploratory tests were conducted to evaluate the influence of differential weighting schemes. For instance, hazard was weighted more heavily (0.5) relative to exposure and vulnerability (0.25 each) in alternative scenarios. Comparative spatial analyses demonstrated that while the absolute magnitudes varied, the high-risk hotspots (Istanbul, Kocaeli, Bursa, Sakarya) remained robust across weighting configurations, underscoring the methodological reliability of the model.

3.6.4 Classification of Risk Categories

The classification of the composite risk surface into ordinal categories was not treated as a simple visualization step but as a critical analytical process. In addition to the Jenks natural breaks method, comparative experiments were conducted using quantile classification, equal interval division, and standard deviation approaches to assess classification sensitivity (Slocum et al., 2009). Statistical indices such as the Goodness-of-Variance Fit (GVF) were employed to evaluate the performance of different classification schemes. Ultimately, Jenks natural breaks was chosen due to its superior ability to capture natural clustering in the data, minimizing intra-class variance while maximizing inter-class separation. This methodological rigor ensured that category boundaries reflected real geospatial patterns of risk rather than arbitrary thresholds, thereby enhancing the interpretability and scientific robustness of the resulting maps.

3.6.5 Validation

Validation of the composite risk model was designed as a multi-layered process to ensure methodological reliability and scientific credibility. Model outputs were first compared with historical earthquake impact records, notably the 1999 İzmit and Düzce earthquakes, where empirical evidence of building collapse and casualty patterns were available. High-risk zones identified by the model demonstrated strong spatial overlap with these observed damage distributions, thereby confirming the model's predictive relevance.

Beyond historical validation, the model was cross-referenced with independent fragility studies and regional seismic risk assessments (Durukal et al., 2006; Kappes et al., 2012). Statistical correlation analyses, including Pearson's r and spatial overlay accuracy metrics (e.g., hit rate, false alarm ratio), were performed to quantitatively assess the degree of agreement between modeled and observed patterns. Furthermore, sensitivity testing under alternative data scenarios (e.g., different weighting schemes, exclusion of auxiliary datasets) yielded consistent hotspot identification across Istanbul, Kocaeli, Bursa, and Sakarya, underscoring robustness.

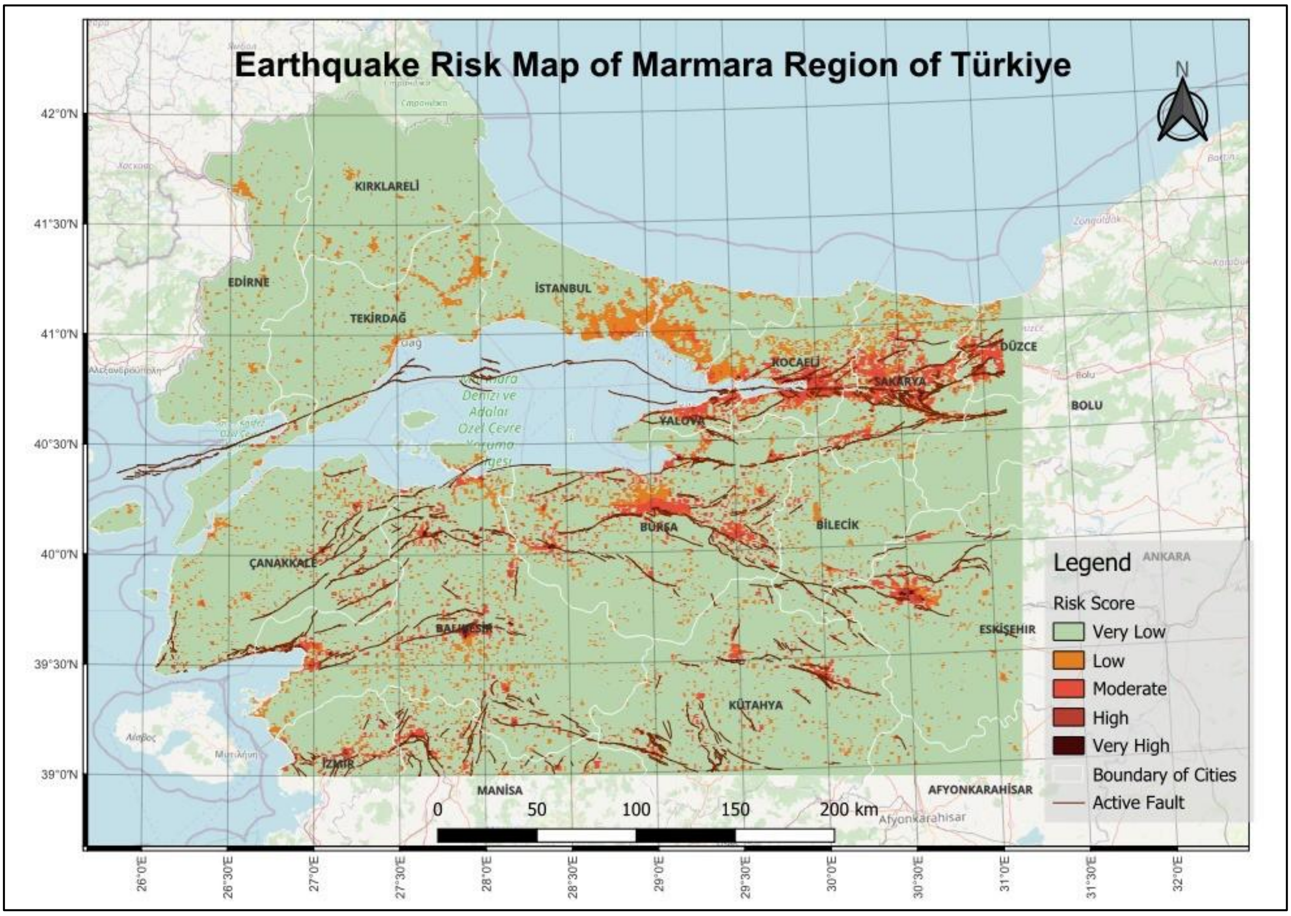

Figure 4. Earthquake Risk Map of Marmara Region of Türkiye

The continuous risk surface was classified into five ordinal categories: Very Low, Low, Moderate, High, and Very High Risk. The Jenks natural breaks optimization method was applied to maximize inter-class variance and minimize intra-class variance (Figure 4). This classification approach is widely accepted in spatial risk assessment as it reflects inherent data clustering patterns rather than arbitrary thresholds.

Finally, the validation process included external benchmarking against global disaster risk models, such as the Global Earthquake Model (GEM) framework, to ensure alignment with internationally recognized standards. This comprehensive validation approach strengthens confidence in the composite index and its applicability as a decision-support tool for regional-scale disaster risk reduction.

3.7 Scientific and Practical Significance

The composite risk calculation underscores the advantage of adopting a multidimensional, geospatially explicit framework. By unifying hazard, exposure, and vulnerability within a single risk index, the methodology delivers actionable insights for both scientific understanding and policy-making. On the scientific front, it contributes to the advancement of reproducible multi-source risk modeling and provides a framework that can be adapted to other hazard-prone regions worldwide (Kappes et al., 2012). The explicit incorporation of harmonization, sensitivity analyses, and rigorous classification methods ensures methodological transparency and replicability, which are critical for advancing earthquake risk science (Goodchild, 2011).

From a practical standpoint, the composite index offers direct value for decision-makers. Regional planners and disaster managers can utilize the outputs to prioritize mitigation measures, allocate limited resources efficiently, and identify critical hotspots where resilience strategies should be urgently implemented. The explicit mapping of Very High Risk zones provides evidence-based justification for retrofitting programs, land-use regulations, and targeted public awareness campaigns (Cutter, 2016). Furthermore, the integration of auxiliary datasets, such as infrastructure and critical facilities, enables systemic risk evaluation—highlighting cascading effects and interdependencies within urban systems (UNDRR, 2019).

Beyond the Marmara Region, the methodological approach has transferability to global contexts, particularly in seismically active urban environments where data scarcity is a persistent challenge. By demonstrating the utility of combining open-source global datasets (e.g., OSM, LandScan) with national geological and demographic data, the study illustrates how robust risk assessments can be produced even under data-constrained conditions. This aligns with the Sendai Framework's emphasis on improving disaster data availability and usability (UNDRR, 2015). Ultimately, the significance of this approach lies not only in its technical accuracy but also in its potential to bridge the gap between academic research and actionable disaster risk governance.

3.8 Smart Cities and Multi-Source Data Integration

Regional Disaster Risk Planning Perspective
Regional disaster risk planning, within the framework of smart cities, enables the integration of spatial analytics into long-term resilience strategies. This approach ensures that local actions—such as microzonation studies and urban retrofitting programs—are systematically aligned with supra-local planning instruments facilitating a coordinated hierarchy of interventions. The academic literature underscores that such nested planning structures increase both operational efficiency and the legitimacy of risk governance (Birkmann et al., 2016; UNDRR, 2015). Within the context of smart city technologies, systems like sensor networks and interoperable geodatabases emerge as functional components in multi-level integration. Ultimately, this systematic linkage fosters economies of scale in regional data management, minimizes fragmentation across provincial and municipal boundaries, and sustains adaptive policy cycles responsive to evolving hazard dynamics.

In the context of regional disaster risk planning, multi-source geospatial integration not only refines hazard and exposure modelling, but also establishes governance structures that transcend administrative divisions. Smart city infrastructures offer an ideal platform for embedding these analyses into regional planning frameworks such as MARAP (Marmara Regional Disaster Risk Reduction Planning) and IRAP (Province-based Disaster Risk Reduction Plans) in Türkiye. The alignment of risk maps with strategic planning documents enables decision-makers to spatially optimize a range of policy instruments, from land-use regulations and infrastructure investments to emergency preparedness strategies. This comprehensive integration enhances inter-provincial coordination and promotes the development of holistic resilience strategies grounded in inter-municipal data sharing.

Academic and Policy Relevance for Smart Cities
The systematic incorporation of MARAP and IRAP into smart city applications presents significant advantages. For example, risk layers derived from this study can be embedded into municipal geographic dashboards, allowing planners to align local zoning regulations, critical infrastructure investments, and emergency resource allocations with regional objectives. Such integration ensures that national and regional frameworks are dynamically connected with local decision-making, reducing the gap between high-level policy and neighborhood-level implementation.

Regional Advantages and Strategic Implications
From a strategic standpoint, smart city platforms provide the computational and institutional infrastructure to operationalize MARAP and IRAP directives in real time. This yields advantages such as improved inter-provincial coordination, harmonized monitoring of risk indicators, and proactive allocation of mitigation funds. By utilizing smart city technologies, MARAP and IRAP can transition from static planning documents into living, adaptive systems. This evolution enhances resilience planning, supports continuous feedback loops between data and governance, and ensures that regional disaster risk reduction strategies remain agile in the face of emerging hazards.

From an academic perspective, the integration of GIS and Remote Sensing within smart city paradigms contributes to the literature on data-driven urban resilience. It expands methodological approaches by introducing scalable, reproducible workflows that can be adapted to other seismically active regions. From a policy perspective, the outputs generated through this framework support evidence-based governance by linking scientific modelling with decision-making processes. In particular, the capability to continuously update regional risk profiles using IoT and big data streams creates a dynamic interface between science and practice. This ensures that smart city applications serve not only as technological showcases but as functional instruments for regional disaster risk reduction, bridging the gap between technical analysis and operational planning.

The conceptual framework of smart cities emphasizes the seamless integration of diverse datasets to improve urban governance, sustainability, and resilience. In this study, the use of multi-source geospatial data directly aligns with this paradigm by bringing together heterogeneous information streams—including national geological datasets (MTA), global population models (LandScan 2023), volunteered geographic information (OpenStreetMap), and satellite-derived elevation models (ASTER GDEM). This integrative approach mirrors the data ecosystem of smart cities, where real-time and open-access data converge to support adaptive decision-making.

Although the current application utilizes static datasets, the methodological design provides a foundation for dynamic data incorporation. For instance, the same workflow can be extended

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to assimilate Internet of Things (IoT) sensor data such as accelerometer readings, structural health monitoring outputs, and crowd-sourced reports. This transition from static to dynamic inputs would enable continuous updating of risk maps, transforming them into near-real-time decision-support tools. Such scalability is a hallmark of smart city infrastructures, ensuring that risk assessments remain current and responsive to evolving urban and environmental conditions.

Beyond technical integration, the approach resonates with the sustainability agenda of smart cities. By providing transparent, spatially explicit evidence of risk, the study contributes to United Nations Sustainable Development Goal 11 (Sustainable Cities and Communities), supporting both safety and resilience objectives. Thus, multi-source geospatial integration not only strengthens technical reliability but also underpins the socio-political mandate of smart urban governance.

3.9 Geospatial Decision Support for Smart City Resilience

To illustrate the practical implications, several application scenarios can be considered for the Marmara Region. For example, integrating composite risk maps into Istanbul's smart city control centers would allow automated early warning systems to redirect traffic flows away from bridges and tunnels identified as high-risk after seismic events. In Kocaeli, risk layers could be linked with industrial safety monitoring systems, ensuring that hazardous material storage facilities are prioritized in emergency response planning. In Bursa and Sakarya, where peri-urban sprawl is rapid, the framework can inform zoning adjustments that discourage new developments in very high-risk zones. These scenarios highlight how geospatial decision support enhances the operationalization of MARAP and IRAP within a smart city ecosystem.

Given the interconnectedness of transport, energy, and logistics networks in Marmara, applying smart city-based risk analysis at a regional level offers cross-boundary advantages. For instance, disruption in the port facilities of Istanbul or Kocaeli could cascade into national and international trade interruptions. By embedding regional risk indicators into smart dashboards, policymakers can anticipate such cascading effects and coordinate mitigation strategies across provincial boundaries. This strengthens MARAP and IRAP as living, data-driven planning instruments, ensuring that smart city applications serve as operational backbones for regional disaster resilience.

A key characteristic of smart cities is the use of advanced geospatial analytics as decision-support systems for resilience planning. The composite risk maps produced in this study represent more than scientific outputs; they provide actionable intelligence for urban managers, planners, and policymakers. Integrated into municipal dashboards or geographic decision-support platforms, these risk layers can guide the prioritization of interventions such as retrofitting vulnerable structures, pre-positioning emergency resources, and redesigning evacuation routes. The strength of this framework lies in its ability to address interdependencies between urban systems. Modern smart cities are complex, with infrastructures such as transport, energy, and communication networks highly interconnected. The spatially explicit risk outputs allow cascading effects—such as how earthquake damage to transport networks could hinder emergency response—to be modeled and anticipated. This systemic perspective is vital for resilience planning in urban regions like Marmara, where economic and demographic densities amplify disaster impacts. Citizen engagement also constitutes an essential element of smart city resilience. By publishing risk maps on open-data portals, municipal authorities can increase public awareness and preparedness. Citizens gain direct access to spatial risk information for their neighborhoods, which fosters community-based disaster preparedness and strengthens collective resilience (Cutter, 2016). The participatory dimension of this approach enhances transparency and aligns with the democratic ideals of smart governance.

Finally, linking geospatial risk modelling to policy frameworks such as Türkiye's Province based IRAP and MARAP ensures that outputs are not only scientifically credible but also institutionally actionable. By bridging technical analyses with policy frameworks, this study demonstrates the dual scientific and practical value of geospatial methods in smart city resilience planning.

4. Conclusions

The results of this study demonstrate that integrating multi-source geospatial datasets within a GIS and Remote Sensing framework provides a scientifically robust and operationally valuable method for earthquake risk assessment in Türkiye's Marmara Region. By harmonizing hazard, exposure, and vulnerability layers at 100 m resolution, the methodology succeeded in producing a composite risk index that reflects both geophysical realities and socio-economic complexities. The spatial outputs consistently identified Istanbul, Kocaeli, Bursa, and Sakarya as high to very high-risk provinces, findings that are strongly validated by historical seismic events, notably the 1999 İzmit and Düzce earthquakes.

From a technical standpoint, the study confirmed that hazard modelling benefits from combining proximity to active fault zones with lithological and topographic susceptibility. Exposure modelling was enhanced by the integration of LandScan population data and OSM-derived building densities, while vulnerability modelling incorporated proxies for structural fragility and socio-economic sensitivity. The multiplicative risk formulation, supported by rigorous normalization, weighting tests, and classification schemes, provided a stable and interpretable representation of spatial risk.

Scientifically, the study contributes to the advancement of reproducible multi-source risk modelling. By systematically documenting preprocessing, harmonization, and validation steps, it offers a transparent and transferable framework applicable to other hazard-prone urban regions. The integration of open-source global datasets with national repositories demonstrates that reliable risk assessments can be developed even under conditions of partial data scarcity, a challenge commonly faced in global disaster risk reduction.

At the policy and practice level, the findings hold strategic importance for regional disaster risk planning instruments such as MARAP and IRAP. Embedding the composite risk layers into smart city platforms offers decision-makers dynamic tools for prioritizing retrofitting, adjusting zoning regulations, and coordinating cross-boundary preparedness. The approach aligns with the Sendai Framework for Disaster Risk Reduction by operationalizing data-driven, regionally harmonized resilience strategies. More broadly, the results highlight the advantages of smart city paradigms for disaster governance. The ability to integrate IoT data streams, sensor networks, and interoperable geodatabases into the presented workflow provides opportunities for near-real-time updating of risk profiles. This transition from static models to adaptive, living systems transforms risk maps from academic outputs into actionable decision-support tools.

Moreover, public dissemination of risk information through open-data portals can foster citizen awareness and participatory resilience, strengthening the social dimension of smart city governance.

In conclusion, the multi-source geospatial framework developed in this study provides both a scientific contribution and a practical pathway for operationalizing disaster risk management in smart cities. By bridging technical risk modelling with regional planning instruments, the research underscores how advanced geospatial technologies can serve as foundational pillars for resilient, sustainable, and adaptive urban futures in seismically active regions such as the Marmara Region of Türkiye.

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