Integration of Spatial Data from Heterogeneous Sources and Their Handling in a Dashboard for Earthquake Disaster Management

Saeideh Abbaspour[1*], Mahmoud Reza Delavar[2], Saman Ghaffarian[3]

[1] MSc. Student, GIS Dept., School of Surveying and Geospatial Eng., College of Engineering, University of Tehran, Iran - abbaspour.saeideh@ut.ac.ir

[2] Center of Excellence in Geomatic Eng. in Disaster Management and Land Administration in Smart City Lab., School of Surveying and Geospatial Eng., College of Engineering, University of Tehran, Iran - mdelavar@ut.ac.ir

[3] Department of Risk and Natural Disaster Reduction, UCL, UK - s.ghaffarian@ucl.ac.uk

KEY WORDS: Business Intelligence, Spatial Data Integration, ETL Process, Decision-Making, Disaster Management

ABSTRACT:

The increasing volume and diversity of spatial data generated from heterogeneous sources such as geosensor networks, aerial and satellite sensors, and volunteered geospatial information necessitate the integration of these disparate datasets for informed decision-making in natural disaster management, particularly earthquakes. This study aims to design and implement Extract, Transform, Load (ETL) processes to integrate heterogeneous spatial data and visualize the results in management dashboards to enhance earthquake disaster management in Tehran Municipality District 2. Diverse datasets including building height, population, urban dilapidation, fault lines, building materials and structures, slope, and historical seismic events were collected and processed using Python libraries such as GeoPandas and Pandas, and stored in a PostgreSQL spatial database. In addition, seismic vulnerability modeling of buildings was conducted using the Random Forest algorithm and the results were presented through a Power Business Intelligence (BI) techniques dashboard. The novelty of this research lies in combining advanced data mining and BI techniques with customized ETL processes for spatial data and developing an intelligent dashboard equipped with machine learning algorithms to assist in analysis and enable interactive user exploration of various scenarios, thereby improving disaster resource management and prediction capabilities. The findings demonstrate that integrated data approaches and specialized BI tools significantly enhance the quality and speed of decision-making in earthquake disaster management. Over 1,200 spatial records were processed and integrated into a centralized database using the Python-based ETL, significantly enhancing analytical accuracy and response times in disaster management.

1. Introduction

In the information age, organizations face a massive volume of data (Sohrabi et al., 2016). BI systems, utilizing tools such as ETL processes, data warehouses, and data mining, enable the cleansing and integration of data to uncover new patterns for effective decision-making (Panrungsri and Sangiamkul, 2017). In the field of disaster management, data integration leads to the creation of geospatial analytical dashboards that help identify high-vulnerability areas and plan preventive measures. This approach enhances organizational resilience and reduces disaster-related damages (Elvas et al., 2022). Data integration is the process of unifying data from diverse sources into a coherent, centralized view, forming a critical component of system integration(Mohammadi et al., 2006). BI enables organizations to extract meaningful insights from complex data, addressing the critical challenges of information processing in an increasingly data-driven environment(Asghar et al., 2009). There are two types of spatial data including tabular (e.g., CSV[2],Excel) and raster formats(e.g., satellite images), each providing complementary information for spatial analysis(Peronato and 2021). Effective disaster management requires a comprehensive understanding of data types, their interconnections, and involved organizations. Spatial data and system integration are crucial for creating an integrated information system that optimizes the disaster management process across multiple sectors. Some systems and projects, including the National Incident Management System (NIMS) of the U.S. Federal Emergency Management Agency (FEMA) and the Disaster Management Modeling System(CRISMA) project, are more aligned with a unified and integrated disaster management system and provide suitable architecture for information. Particularly, the Disaster Research and Management Infrastructure in Germany (DEFNAK)information infrastructure, designed based on the FEMA model including workflows, information systems, integrated databases, and technology infrastructure, can be proposed as an efficient model for designing an integrated disaster management information system (Manafi, 2017). In the 2018 Jinsha River basin landslide, multi-source data integration, spatial-temporal simulation, and visual vulnerability assessment enabled effective decision-making and emergency management, mitigating potential threats to downstream residents(Liu et al., 2021). Data stored in separate databases cannot be queried comprehensively. Extracting information requires individual queries, leading to inefficiency and increased time consumption. The objectives of spatial data integration for informed disaster management are as follows (Peronato et al.,2021):

Facilitate querying by providing a unified data structure instead of using different structures for each data source.

Assess compatibility among various data sources.

Ensure uniform conditions for data access across all datasets, considering factors such as available bandwidth and the number of queries.

[*] Corresponding author

[2] Comma-Separated Values

https://doi.org/10.5194/isprs-annals-X-4-W8-2025-1-2026

Reduce pressure on primary data sources by eliminating specific queries.

Introduce a new structure that is more aligned with the specific needs of the domain.

Improve access to data sources that are not always available and provide a real-time gateway for accessing their data.

Given the increasing frequency and severity of natural disasters (particularly earthquakes) in urban areas, there is an urgent need to develop data-driven infrastructures to support timely and intelligent decision-making. This study aims to investigate the feasibility and effectiveness of integrating heterogeneous spatial data using BI processes and the implementation of analytical dashboards for earthquake disaster management in Tehran Municipality District 2. The central research question is how spatial data from various sources can be unified through ETL techniques and Python-based tools to support prediction, analysis, and action throughout different stages of a disaster. The expected outcomes include enhancing the accuracy of assessing physical seismic vulnerability in urban structures, improving resource allocation strategies, and strengthening organizational resilience. Therefore, this research seeks to address the following key questions:

How can an intelligent spatial management dashboard be implemented through the integration of spatial data and services?

What are the essential features of a smart, location-based management dashboard that can support effective decision-making?

To what extent can information integration improve the efficiency of earthquake disaster management?

Based on the nature of available datasets and prior pilot assessments, the hypothesis of the research is that the available spatial and structural data are of sufficient quality to support predictive modeling and risk assessment. The rest of the paper is structured as follows: Literature review is presented in Section 2. Section 3 presents data integration methods. Section 4 elaborates research methodology. Section 5 explains the case study. Section 6 concludes the paper and suggests some recommendations for future research.

2. Literature Review

Hasani et al. (2015) explored global geospatial information management, focusing on spatial data integration, system interoperability, and capacity building to optimize decision-making processes and reduce operational costs through collaborative frameworks.

Wiemann and Bernard (2016) Spatial data integration aims to enhance geospatial data accessibility and usability through advanced techniques like semantic web technologies and crowdsourcing, while addressing challenges such as technical complexity, data quality variations, and legal constraints

Panrungsri and Sangiamkul (2017) research developed a Business Intelligence model for disaster management in Thailand, addressing data integration challenges and demonstrating how multidimensional data warehouses can enhance decision-making during crises like floods and landslides.

Elvas et al. (2022) explored how to improve disaster management in Lisbon using big data and analyzed patterns of incidents such as floods and building collapses. Using the CRISP-DM[3] method and firefighting data from 2011 to 2018, it was shown that certain incidents occur more frequently at specific times and in central areas, and older buildings are more vulnerable. The results led to the creation of visual analysis dashboards for more effective resource management during crises and emphasized the importance of data integration and analysis in enhancing urban resilience to incidents.

3. Data Integration Methods

3.1 Extract, Transform, and Load (ETL) processes extract, clean, and transfer various heterogeneous data from different sources to a data warehouse. This ensures that data is centrally and uniformly accessible (Asghar et al., 2009). ETL processes optimize data management for advanced analytical projects, including dashboards, spatial analysis, and machine learning applications (Ali and Wrembel, 2017); (Dos Santos, 2024)

3.2 Enterprise Service Bus (ESB) systems create a communication platform for various applications. This allows applications to easily share information and establish better communication between systems. However, it is based on accessing and integrating different systems without a unified database, which limits the ability to perform various analytical queries (Breest, 2006).ESB systems are suitable for complex environments with multiple systems and high data exchange volumes.

3.3 Data virtualization technique allows users to have an up-to-date and unified view of data available in data organizations. These integrated data can be easily provided to applications and analysts, facilitating decision-making. Data virtualization typically requires access to data sources and cloud services. However, data virtualization is not always the best choice. It is not recommended for applications involving large volumes of data or complex data transformations and cleaning, as these can slow down the performance of source systems. In addition, if there is no single reliable data source, this method is not recommended (Bologa, 2011). Data virtualization is especially recommended for organizations that need a quick with limited infrastructure required for a data warehouse project. In this study, given the need to collect spatial data from heterogeneous sources, the ETL method was selected as the main data integration approach. There are various tools available for implementing ETL processes for spatial data. We have compared two spatial ETL tools including Pentaho Kettle and Safe FME for integrating spatial data along with Python libraries (Table 1). Python was used as the development tool as it has powerful libraries such as Geopandas, Pandas, SQLAlchemy and Psycopg2 for data processing, converting to GeoJSON format, and loading into PostgreSQL.

Fetures	SafeFME	Penraho Kettle (Open Source Version)	Python Libraries (such as Fiona/Geopandas)

[3] Cross-Industry Standard Process for Data Mining

Focused on spatial data	Yes	Yes(GeoKettle)	Yes(such as GeoPandas.ogr2ogr)
Server automation	Yes	Yes	Yes(such as Luigi)
Customization	Limited	Limited	Yes(Python code)
Free	No	Yes(Open Source Version)	Yes(such as Frictionless)
Transformation Files	Fine(ProprietaryBinary)	.ktr(XML)	Python code

Table 1 . Comparison of ETL Tools (Peronato, 2021)

4. Research Methodology

The collected data in this study pertains to the year 2006 and includes the average number of building floors, population count, old and unsafe urban structures, Tehran faults, building materials and structural types, area slope, and recent earthquake occurrences in Tehran.

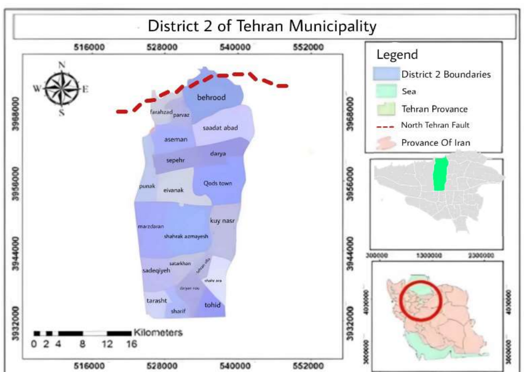

Figure 1. Location of the Study Area (Tehran Municipality District 2)(Amiri et al., 2021)

The data used in this study pertains to a simulation of earthquakes happened in the urban blocks of Tehran Municipality District 2 (Located in the northwest of Tehran), formatted as .SHP, Excel, and CSV, extracted from the MySQL database and files. The result of this study is the ETL modeling using Python libraries, with the data warehouse designed in the PostgreSQL database.

Earthquake data, including magnitude, depth, and location, are also stored in the database and can be used for historical scenario analyses. In addition, users can input custom earthquake parameters (e.g., magnitude and depth) through the dashboard to simulate new scenarios. This interactive feature enables dynamic integration of user-defined inputs with spatial data layers and facilitates real-time vulnerability analysis using machine learning (ML) algorithms (such as Random Forest).

A management dashboard is a tool that helps managers and decision-makers access key organizational information and data visually and comprehensively. This tool includes a collection of charts, graphs, and indicators (Few, 2006).

Today, visual analytics dashboards are highly important for decision support systems in disaster management, as the frequency of such disasters continues to increase. Data integration forms the foundation for the effective performance of management dashboards. Without proper integration, dashboards may display incomplete or incorrect information, leading to incorrect decision-making (Pinna and Castelnovo, 2019).

For decision-making in crises, especially during events like earthquakes, type of the selected dashboard including strategic, analytical and operational dashboards can significantly impact the efficiency and effectiveness of disaster management. In the following section the specific needs and features of the dashboards at different stages of an earthquake disaster (before, during, and after the earthquake) have been examined.

4.1 Strategic Dashboard: The goal of this dashboard is to monitor long-term trends and forecasts to prepare the organization or various regions for potential crises, i.e., before the disaster. For example, it is used to assist predicting the extent of damage at different intensities and depths of an earthquake (Rahman et al., 2017).

4.2 Analytical Dashboard: The goal of this dashboard is to deeply analyze real-time data and provide accurate information for immediate decision-making based on online data, which is useful during the disaster (Rahman et al., 2017).

4.3 Operational Dashboard: The goal of this dashboard is to track status and operations in real-time during the disaster, with data being received momentarily (Rahman et al., 2017).

In the dashboard presented in this research, data from the data warehouse were used to predict the physical seismic vulnerability of building blocks in Tehran Municipality District 2 at the block and neighborhood level due to an earthquake using the Random Forest (RF) algorithm. Based on the analyses in the dashboard, areas needing renovation can be identified, and necessary actions can be taken. In addition, areas predicted to have high vulnerability can be reviewed in terms of emergency facilities such as hospitals or fire stations, and if these facilities do not exist, necessary actions can be taken for their establishment. Furthermore, using Web API[4]s helps transfer real-time data to the dashboard, indicating the location of the earthquake and where rescue operations should be undertaken. This information can improve response time during the disaster. After the disaster, by analyzing the affected areas based on the intensity, depth, and location of the earthquake, the most affected areas can be prioritized for necessary measures to distribute and send medical, health, food, and temporary shelter services.
The designed dashboard is a combination of strategic, analytical, and operational dashboards under the title of a management dashboard, covering various objectives before, during, and after the disaster.

[4] Application Programming Interface

There are many tools available for developing dashboards including:

- Google Data Studio
- Tableau
- Microsoft Power BI
- ArCGIS Dashboard

Although ArcGIS Dashboard is one of the powerful tools for displaying and monitoring spatial data, offering features such as connection to geospatial information systems (GIS) services, displaying charts, maps, and Key Performance Indicators (KPIs) in an integrated dashboard which is considered a very suitable and efficient option for projects focused on monitoring spatial status or visualizing GIS data without the need for complex analytical processing (Case, 2022a), it was not implemented in this research due to technical and operational reasons. The most significant limitation of ArcGIS Dashboard in this research was its inability to directly execute ML algorithms and interact intelligently with the user. While this capability is available in Power BI Desktop through support for running Python scripts and real-time user interaction, such support is not provided in ArcGIS Dashboard. In this research, one of the objectives was to integrate spatial and non-spatial data and display the results in an interactive analytical environment, with a focus on the output of machine learning models, which ArcGIS Dashboard could not technically fulfill (Esri, 2024).

In Table 2, dashboard creation tools are compared with each other.

Features	Power BI	Tableau	Google Data Studio	ArcGIS Dashboard
Web API support	Yes	Yes	Yes	Limited(with add-ons)
Database connection	Yes	Yes	Yes	Yes
Web deployment	Yes	Yes	Yes	Yes
Python scripting	Yes	Yes	Yes	Limited(ArcPy)
User intraction(input/filter)	Yes	Yes	Yes	Limited
GeoJSON support	Yes	Yes	Yes	Yes
Geographic Maps(GIS)	Yes	Very advanced	Yes(Google Maps)	Yes(Native)
Ease of use	Medium	User-friendly	Very fast	User-friendly
Cost	Free+Commercial	Commercial	Free	Commercial
M.L algorithm support	Yes	Yes	No	Limited

Table 2. Comparison of Dashboard Creation Tools (Vijay Krishnan et al., 2017; Apriani et al., 2022a; Case, 2022a; Patel, 2021)

Power BI is a powerful and efficient BI tool used to create interactive dashboards and attractive reports. Developed by Microsoft, it includes a suite of software services and various applications (Vijay Krishnan et al., 2017).While tools like Dash or Tableau are stronger in some features, using Power BI for a government organization can be a more logical choice (Apriani et al., 2022b; Case, 2022b; Vijay Krishnan et al., 2017; Patel, 2021). The compatibility with organizational infrastructure and software are outlined below:

Power BI such as Microsoft Office and Active Directory are Microsoft products typically used by organizations to be integrated with the Microsoft ecosystem, authentication with organizational accounts, to provide high security and compliance with IT standards (Microsoft Corporation, 2024).

From an economic perspective, Power BI is more cost-effective compared to other similar tools in the business intelligence and dashboarding domain, such as Tableau, especially for organizations whose IT infrastructure is based on Microsoft products. These features make Power BI an attractive choice for organizations with budget constraints and a need for seamless integration with existing systems (Microsoft Corporation, 2024). Flexibility in Connecting to Data Sources and Development Capability with Python and R.

5. Case study

In this study, after collecting spatial and attribute data from heterogeneous sources (such as SHP, CSV, and Excel files), the ETL process was carried out using Python libraries, and the cleaned data were integrated into a centralized PostgreSQL database. Figure 2 illustrates the resulting data model, designed based on a semi–star (snow-star) schema. In this structure, various dimension tables (including building information, population, fault lines, land slope, and urban fabric)are linked to a central fact table representing seismic vulnerability assessments. Earthquake data, including magnitude, depth, and location, are also stored in the database and can be used for historical scenario analyses. In addition, users can input custom earthquake parameters (e.g., magnitude and depth) through the dashboard to simulate new scenarios. This interactive feature enables dynamic integration of user-defined inputs with spatial data layers and facilitates real-time vulnerability analysis using machine learning algorithms (such as Random Forest). As such, Figure 2 not only represents the technical foundation of the data infrastructure but also reflects the core decision-support architecture underpinning disaster management dashboards powered by spatial analytics and predictive modeling.

For Tehran Municipality Disaster Mitigation and Management Organization (TMDMMO), where its spatial data and system integration for disaster prevention and mitigation is in early stages, and needs a quick setup with managerial use, a strong yet simple dashboard, stable and secure tools, low cost, having the ability to interact with other organizations considering a simple user interface with official support, Power BI is a more suitable option.
The dashboard can be shared on the web, and the link can be emailed to the intended individuals. However, for running Python scripts, the system administrator needs to register the organization's domain as a verified domain in the Power BI Admin Portal (Figure 2)

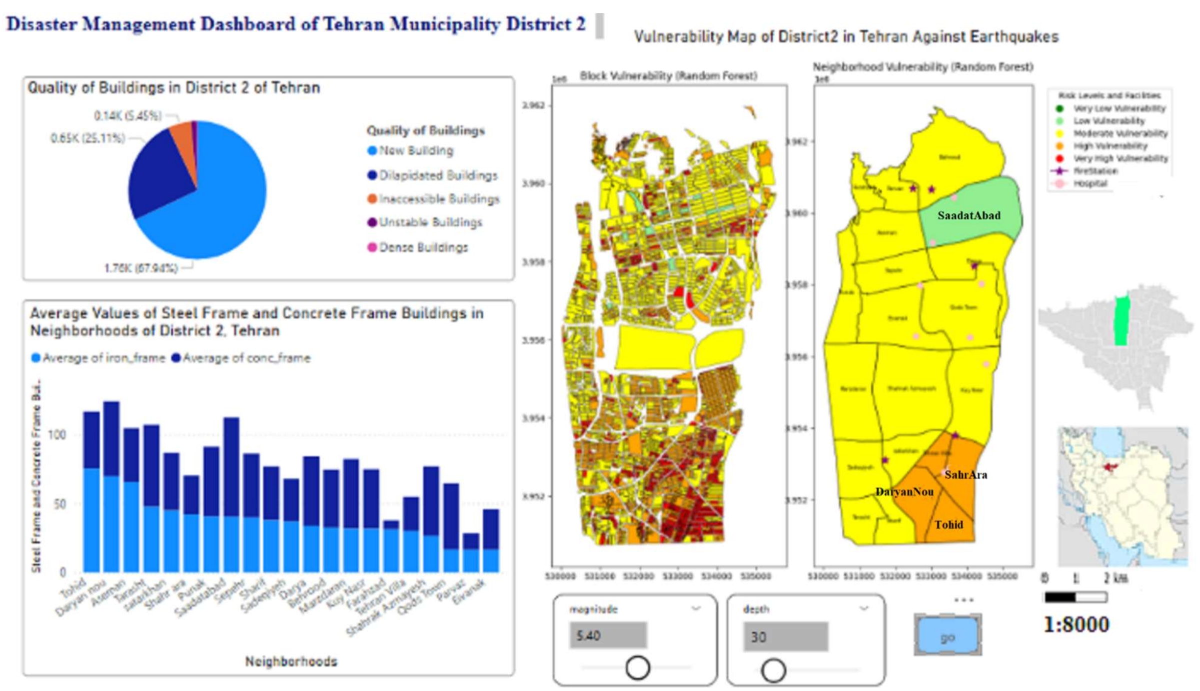

Figure 2. Dashboard Designed with Power BI Desktop

Pie chart designed in dashboard has been utilized to provide a general overview of the physical quality of buildings across the district. It highlights the proportion of buildings exposed to higher seismic risks and identifies areas in need of renovation or structural reinforcement. For example, newly constructed buildings constitute 67% of the total building stock in the area, while buildings characterized by dense and inaccessible urban fabric comprise the lowest percentage.

Bar Chart has been utilized a comparative analysis of the average number of buildings with steel frames and concrete frames across different neighborhoods in District 2 of Tehran. The use of distinct colors (e.g., blue and purple) illustrates the distribution of structural types within each neighborhood. This comparison aids in evaluating seismic vulnerability at the neighborhood level based on structural type and informs decisions regarding retrofitting priorities.

For instance, the Tohid neighborhood, Daryan Nou neiborhood , ShahrAra Neighborhood (southeast of Tehran Municipality District 2) has a higher concentration of steel-frame buildings, which may contribute to its elevated seismic vulnerability. In contrast, Saadat Abad (Tehran Municipality District 2) has a greater number of concrete-frame buildings, indicating potentially higher structural resilience in that area. To predict the seismic vulnerability levels of urban blocks in District 2, a model based on the Random Forest algorithm was developed. The model classifies each urban block into risk categories (e.g., low, moderate, high). The resulting map visualizes each block with a color corresponding to its predicted vulnerability level. Given that Power BI supports Python script execution, parts of this analysis can be run in the backend of the dashboard. One of the most prominent features of the developed dashboard is the integration of interactive capabilities, ML algorithms, and real-time Python scripting within the Power BI Desktop environment, transforming it into a dynamic and intelligent analytical tool.

In this framework, the end user can input parameters such as earthquake intensity and depth directly into the dashboard interface. Once these parameters are submitted, the embedded Python script is triggered, and the Random Forest algorithm computes the seismic vulnerability levels of urban blocks in District 2 based on the selected seismic conditions. For instance, under a scenario of 5.4 Richter magnitude and 30 km depth, the Tohid,Daryan Nou,Shahr Ara neighborhoods exhibits significantly higher vulnerability.This dashboard design incorporates three core features:

Intelligence: due to the use of machine learning algorithms and dynamic data-driven analysis.

Interactivity: allowing users to input analytical parameters and receive targeted outputs.
Dynamism: enabled through real-time execution of algorithms and potential integration with web APIs and external systems.

Although the dashboard currently does not integrate live Web API connections (due to security protocols at the Tehran Disaster Management and Mitigation Organization) Power BI fully supports real-time data connectivity, including live earthquake alerts and rescue operation monitoring. This capability could facilitate future dashboard development toward real-time analytics and decision-making. It is important to note that Power BI Desktop alone does not provide built-in authentication or role-based access control at the user level. For organizations requiring secure and controlled access, dashboards should be published on Power BI Report Server or Power BI Service (Pro/Premium). In addition, organizations with an SQL Server Enterprise license can utilize Power BI Report Server as part of their infrastructure (Microsoft Corporation, 2024).

6. Conclusion and Future Directions

This study explored the integration of spatial and non-spatial data to design an intelligent, location-aware dashboard that supports proactive earthquake disaster management. In addressing the core research questions including how to implement such a dashboard, what features are essential and how effective data integration can be in seismic crisis response, a practical prototype was developed using Power BI enhanced by Python-based ETL processes and ML. The research confirms the first hypothesis, asserting that while urban and seismic datasets are often fragmented, they are nonetheless of sufficient quality to support reliable seismic vulnerability modeling. The use of Random Forest algorithm enabled accurate classification of urban blocks into seismic vulnerability zones (very low vulnerability, low vulnerability, medium vulnerability, high vulnerability and very high vulnerability).

The dashboard developed in this study offers several unique advantages:

Localization and High Spatial Accuracy: Unlike generalized international dashboards, this system is specifically designed for Tehran Municipality District 2, providing detailed insights at the urban block level.

Scenario-Based Interactivity: While most existing dashboards are static and data-display oriented, this dashboard supports interactive analysis based on hypothetical earthquake scenarios defined by the user.

Integration with Local Government Infrastructure: Built with Power BI, the dashboard can be seamlessly integrated into organizational Information Technology (IT) systems and workflows commonly used by local agencies.
The proposed dashboard demonstrates significant potential as an innovative and practical tool for:

Urban planners, to prioritize building retrofitting projects, disaster managers, to simulate earthquake impacts and assess various risk scenarios and non-technical decision-makers, who benefit from simplified visuals such as maps and charts that enhance understanding and situational awareness.

This research contributes to the field through:

Embedding live spatial modeling and ETL pipelines within Power BI: a rare combination in disaster analytics.

Allowing interactive scenario simulations: users can input earthquake magnitude and depth and instantly visualize shifting vulnerability patterns.

Demonstrating the potential of hybrid low-code platforms (Power BI + Python) to serve both technical and non-technical stakeholders: reducing barriers to adoption.

Providing a localized a model: that is focused on blocks and neighborhoods.

References

Ali, S. M. F. and Wrembel, R., 2017: From conceptual design to performance optimization of ETL workflows: current state of research and open problems, The VLDB Journal, 26, 777-801.

Apriani, D., Aan, M., and Saputra, W. E., 2022: Data visualization using google data studio, Int. J. Cyber IT Serv. Manag Journal, 2, 11-19.

Asghar, S., Fong, S., and Hussain, T., 2009: Business intelligence modeling: A case study of disaster management organization in Pakistan, 2009 Fourth International Conference on Computer Sciences and Convergence Information Technology, 673-678,

Bologa, A.-R. and Bologa, R., 2011: A Perspective on the Benefits of Data Virtualization Technology, Informatica Economică journal, 15, 110-118, 2011.

Breest, M., 2006: An introduction to the enterprise service bus, Hasso-Plattner-Institute for IT Systems Engineering at the University of Potsdam, Prof.-Dr.-Helmert-Str, 2-3, 2006.

Case, S. N., 2022: Creating An ArcGIS Dashboard For Climate Data Management And Visualization, 2022

dos Santos, L. B. L. S., 2024: Leveraging business intelligence through ETL processes and Power BI dashboard development, Thesis,Universidade de Lisboa (Portugal), 2024.

Elvas, L. B., Gonçalves, S. P., Ferreira, J. C., and Madureira, A.,2022. Data fusion and visualization towards city disaster management: Lisbon case study, EAI Endorsed Transactions on Smart Cities, 6.

New to ArcGIS Dashboards: https://mediaspace.esri.com/media/t/1_w7oxg26v, last access:2024 june 30.

Few, S., 2006: Information dashboard design: The effective visual communication of data, O'Reilly Media, Inc.2006.

Liu, J., Konečný, M., Du, Q., Xu, S., Ren, F., and Che, X.,2021: The latest progress of data fusion for integrated disaster reduction intelligence service, 12, 265-267.

Manafi, S. S., 2017: Integrated Crisis Management and Its Implementation Barriers [In Persian], Tehran Urban Planning and Research Center
Report.

Power BI Documentation, last access: 2025.

Mohammadi, H., Binns, A., Rajabifard, A., and P. Williamson, I., 2006: Spatial Data Integration, Conferance for Asia and the Pacific2006.

Panrungsri, T. and Sangiamkul, E., 2017: Business Intelligence Model for Disaster Management: A Case Study in Phuket, Thailand, ISCRAM,

Patel, A., 2021: Data Visualization Using Tableau.

Peronato and , K., 2021: GUIDELINES FOR THE DATA INTEGRATION PROCESS.

Pinna, R. and Castelnovo, S., 2019: Interactive dashboards and data integration: design and tool development for museums,.

Rahman, A. A., Adamu, Y. B., and Harun, P., 2017: Review on dashboard application from managerial perspective, 2017 International Conference on Research and Innovation in Information Systems (ICRIIS), 1-5,

S. Hasani, , A. S.-N., and , M. J.-N., 2015: Spatial Data Integration using Ontology-Based Approach, International Conference on Sensors & Models in Remote Sensing & 23–25 Nov 2015, 10.5194/isprsarchives-XL-1-W5-293-2015, 2015.

Sohrabi, B., Raeesi Vanani, I., and Forouzandeh Jonaghani, R., 2016: Classification and Analysis of Factors Affecting the Efficient Use of Integrated Information Systems in Iranian Government Organizations[In Persian].

Vijay Krishnan , S.Bharanidharan, and G.Krishnamoorthy, 2017: Research Data Analysis with Power BI, 11international caliber2017, Anna University,Chennai, India2017.

Wiemann, S. and Bernard, L., 2016: Spatial data fusion in spatial data infrastructures using linked data, International Journal of Geographical Information Science, 30, 613-636, 10.1080/13658816.2015.1084420.