T.C.
ISTANBUL GEDIK UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

DECISION SUPPORT SYSTEM FOR EARTHQUAKE DISASTER MANAGEMENT

MASTER THESIS

Diana Sabah Nimma ELBIDARI

Engineering Management Department

Master in Engineering Management English Program

MAY 2024
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TEZ JÜRİSİ

Dr. Öğr. Üyesi Tuğbay Burçin GÜMÜŞ
Danışman
İstanbul Gedik Üniversitesi

Dr. Öğr. Üyesi Özer ÖZTÜRK
Üye (İmza)
İstanbul Gedik Üniversitesi

Dr. Öğr. Üyesi Mert TOLON
Üye (İmza)
İstanbul Maltepe Üniversitesi

DECLARATION

I am Diana Sabah Nimma Elbidari as a result of this declare that this thesis titled “Decision Support System for Earthquake Disaster Management” is original work I did for the award of the master's degree in the faculty of Engineering Management Program. I also declare that this thesis or any part of it has not been submitted and presented for any other degree or research paper in any other university or institution. (30/05/2024).

Diana Sabah Nimma ELBIDARI

DEDICATION

I dedicate this thesis to my beloved family – my father, mother, brothers, and sister – whose unwavering support and encouragement have guided me throughout this journey. Your love and belief in me have fueled my determination to pursue knowledge and make a difference.

To my esteemed supervisor, Assist. Prof. Dr. Tuğbay Burçin, thank you for your guidance, expertise, and invaluable mentorship. Your insights have shaped my understanding and inspired me to strive for excellence in the field of earthquake disaster management.

I also extend my gratitude to the dedicated faculty members at Istanbul Gedik University, whose passion for teaching has enriched my academic experience and broadened my horizons.

This thesis is a testament to the collective effort and dedication of those who have supported and believed in me. Thank you for being my pillars of strength.

FOREWORD

In the name of Allah, the Most Gracious, the Most Merciful.

As I embark on presenting this thesis, I reflect on the journey that has led me to this moment with profound gratitude and humility. The culmination of years of study, research, and dedication, this thesis represents a significant milestone in my academic and personal growth.

The subject matter of this thesis, a decision support system for earthquake disaster management, is born out of a deep sense of responsibility and commitment. After the earthquake on February 6th in Turkey, and being a master's student in engineering management, I took it upon myself to make the topic of my thesis in this field, aiming for my department and university to play a role in saving humanity in Turkey and the world from the devastating earthquakes to come. This work reflects my passion for utilizing technology and innovation to address pressing societal challenges.

I extend my heartfelt appreciation to my supervisor, Assist. Prof. Dr. Tuğbay Burçin, whose guidance, wisdom, and unwavering support have been instrumental in shaping the direction and focus of this research. His expertise and mentorship have been invaluable assets throughout this endeavor.

I also sincerely thank my beloved family – my father, mother, brothers, and sister – for their unconditional love, encouragement, and understanding. Their sacrifices and belief in me have strengthened and motivated me.

Furthermore, I am grateful to the esteemed faculty members at Istanbul Gedik University for their dedication to excellence in education and their commitment to nurturing the next generation of scholars and leaders.

Lastly, I would like to acknowledge the support of my peers, colleagues, and friends, whose encouragement and camaraderie have enriched my academic journey and made this accomplishment possible.

As I conclude this foreword, I am filled with a sense of anticipation and hope for the impact that this research may have in advancing our understanding of disaster management and contributing to the well-being of our society.

May Allah guide and bless our endeavors.

May 2024 Dian Sabah Nimma ELBIDARI

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ABBREVIATION

DSS	: Decision Support Systems
MCDM	: Multi-Criteria Decision Making
EEW	: Earthquake Early Warning
SDSS	: Spatial Decision Support System
DMO	: Disaster Management Ontology
NDMA	: National Disaster Management Authority
SAW	: Simple Additive Weighting
SPCTM	: Stochastic Pedestrian Cell Transmission Model
GIS	: Geographic Information Systems
OLAP	: Online Analytical Processing
JIT	: Just-In-Time
AI	: Artificial Intelligence
ML	: Machine Learning
IoT	: Internet of Things
CEQID	: Cambridge Earthquake Impacts Database
WSM	: Weighted Sum Model
WPM	: Weighted Product Model
AHP	: Analytic Hierarchy Process
TOPSIS	: Technique for Order Preference by Similarity to Ideal Solution
ELECTRE	: Elimination and Choice Expressing Reality
PROMETHEE	: Preference Ranking Organization Method for Enrichment Evaluation
GP	: Goal Programming
MOEAs	: Multi-Objective Evolutionary Algorithms
GRA	: Grey Relational Analysis
AFAD	: Turkish Disaster and Emergency Management Presidency

DECISION SUPPORT SYSTEM (DSS) FOR EARTHQUAKE DISASTER MANAGEMENT

ABSTRACT

The global occurrence of earthquakes has continued to be a significant area of concern due to the possible impact earthquakes can have on human lives, properties, and even a nation's economy. Earthquake has proven to be the most devastating natural hazard experienced in man's existence on Earth. Earthquake occurrences have always been related to the seismicity of a particular region. Regions with high seismicity tend to experience frequent earthquakes, while regions with low seismicity tend to have a low rate of earthquake occurrence. Turkey, China, India, Japan, and a few other countries have had a high rate of earthquake occurrence in the past years due to their high seismicity, which has led to significant setbacks in their economies at the times of the events. This thesis focuses on developing a decision support system (DSS) to enhance disaster management in the aftermath of earthquakes. Earthquakes are highly destructive natural hazards, often resulting in extensive damage to infrastructure and the loss of human lives. Effective disaster management is crucial but faces multiple challenges, like acquiring timely data, optimally allocating limited resources, and coordinating complex response efforts. A specialized DSS can aid authorities by integrating analytics into the decision-making process. The main challenge is providing decision-makers with essential earthquake impact information to coordinate emergency response and recovery. The chaotic aftermath causes delays in rescue operations, suboptimal resource allocation, and preventable secondary losses. There is a need for a DSS that can rapidly analyze disaster data and optimize post-earthquake decision-making. The methodology involves designing a modular DSS architecture focused on disaster management needs, like real-time monitoring, damage assessments, and strategy recommendations. It integrates a mathematical model using seismic, population, and building data to estimate casualties, injuries, and shelter needs. Multi-criteria decision-making (MCDM) methods prioritize response efforts. The system is validated using real earthquake data. This data is based on the 2023 Turkey earthquake, taking Kahramanmaraş province as case study. The goal is to optimize rescue operations, allocate resources effectively, rebuild critical infrastructure, and restore normalcy with minimal losses. The study focuses on the real-world application and validation of theoretical models in the aftermath of the 2023 Kahramanmaraş earthquake in Turkey. These evaluate the estimated versus actual casualties, showcasing the precision of the Python-based mathematical model used. It also extends the analysis to injury predictions and shelter needs, highlighting the model's reliability in post-disaster scenarios. Additionally, the multi-criteria decision-making approach is used to prioritize areas for resource allocation and rescue efforts. The study also introduces a DSS website, designed to enhance disaster response efficiency. The estimation of casualty’s post-earthquake in the Kahramanmaraş province of Turkey was remarkably accurate, with the proposed model drawing more than 98% accuracy. Similarly, the estimated number of injuries had an accuracy of 91.386%, affirming the effectiveness of the proposed model. The study also

estimates the number of people who need shelter, confirming the robustness of the proposed model with an accuracy of 98.683%. Based on the MCDM approach, the study suggests Onikişubat city as the most needed city for resources and rescue efforts, followed by Dulkadiroğlu and Elbastan. The DSS website, with a simple and effective user interface, aims to enhance the rapid action of authorities by providing essential information and prioritizing the most affected locations that need immediate attention for resources and rescue efforts. Finally, the study's methodical approach and the robustness of the proposed models demonstrate the potential for building an intelligent decision support system to effectively manage earthquake disaster response and recovery.

Keywords: *Earthquake Disaster Management, Decision Support Systems (DSS), Multi-Criteria Decision Making (MCDM).*

DEPREM AFET YÖNETİMİNE YÖNELİK KARAR DESTEK SİSTEMİ (DSS) TASARLANMASI

ÖZET

Depremlerin küresel görülme sıklığı, insan hayatları, mülkler ve hatta bir ulusun ekonomisi üzerindeki olası etkileri nedeniyle önemli bir endişe kaynağı olmaya devam etmektedir. Deprem, insanın Dünya'da var olduğu süre boyunca deneyimlediği en yıkıcı doğal afet olarak kanıtlanmıştır. Deprem olayları her zaman belirli bir bölgenin sismik aktivitesiyle ilişkilendirilmiştir. Yüksek sismik aktiviteye sahip bölgeler sık sık deprem yaşarken, düşük sismik aktiviteye sahip bölgelerde deprem görülme oranı düşüktür. Türkiye, Çin, Hindistan, Japonya ve birkaç diğer ülke, geçmiş yıllarda yüksek sismik aktiviteleri nedeniyle yüksek oranda deprem yaşamıştır, bu da olayların yaşandığı zamanlarda ekonomilerinde önemli aksaklıklara yol açmıştır. Bu tez, depremlerin ardından afet yönetimini geliştirmek için bir karar destek sistemi (KDS) geliştirmeye odaklanmaktadır. Depremler, genellikle altyapıda geniş çaplı hasara ve insan hayatı kaybına yol açan, son derece yıkıcı doğal afetlerdir. Etkili afet yönetimi hayati önem taşımakta ancak zamanında veri elde etme, sınırlı kaynakları optimal şekilde tahsis etme ve karmaşık müdahale çabalarını koordine etme gibi çoklu zorluklarla karşı karşıyadır. Özelleştirilmiş bir KDS, karar verme sürecine analitik entegrasyonu sağlayarak yetkililere yardımcı olabilir. Ana meydan okuma, acil müdahale ve iyileştirme çalışmalarını koordine etmek için karar vericilere temel deprem etki bilgilerini sağlamaktır. Kaotik sonrası durum, kurtarma operasyonlarında gecikmelere, suboptimal kaynak tahsisine ve önlenebilir ikincil kayıplara yol açmaktadır. Afet verilerini hızlı bir şekilde analiz edebilen ve deprem sonrası karar verme sürecini optimize edebilen bir KDS'ye ihtiyaç vardır. Metodoloji, gerçek zamanlı izleme, hasar değerlendirmeleri ve strateji önerileri gibi afet yönetimi ihtiyaçlarına odaklanan modüler bir KDS mimarisi tasarlamayı içerir. Sismik, nüfus ve bina verilerini kullanarak tahmini ölüm, yaralanma ve barınak ihtiyaçlarını hesaplayan bir matematiksel model entegre eder. Çok kriterli karar verme (ÇKDV) yöntemleri, müdahale çabalarını önceliklendirir. Sistem, gerçek deprem verileri kullanılarak doğrulanır. Bu veriler, 2023 Türkiye depremine dayanmaktadır ve Kahramanmaraş ilini vaka çalışması olarak ele almaktadır. Amaç, kurtarma operasyonlarını optimize etmek, kaynakları etkili bir şekilde tahsis etmek, kritik altyapıyı yeniden inşa etmek ve minimal kayıplarla normalleşmeyi sağlamaktır. Çalışma, 2023 Kahramanmaraş depreminin ardından teorik modellerin gerçek dünyada uygulanması ve doğrulanmasına odaklanmaktadır. Bu, tahmini ile gerçek ölüm sayılarını değerlendirerek, kullanılan Python tabanlı matematiksel modelin hassasiyetini sergilemektedir. Aynı zamanda analizi yaralanma tahminlerini ve barınma ihtiyaçlarını da kapsayacak şekilde genişleterek modelin afet sonrası senaryolardaki güvenilirliğini vurguluyor. Ayrıca kaynak tahsisi ve kurtarma çalışmaları için alanların önceliklendirilmesi amacıyla çok kriterli karar verme yaklaşımı kullanılmaktadır. Çalışma aynı zamanda afet müdahale verimliliğini artırmak için tasarlanmış bir DSS web sitesini de tanıtıyor. Türkiye'nin Kahramanmaraş ilindeki deprem sonrası can kayıplarının tahmini, önerilen modelin %98'den fazla doğruluk oranıyla dikkat çekici derecede doğruydu. Benzer şekilde, tahmini yaralanma sayısının %91,386'lık bir doğruluğu vardı ve bu da önerilen modelin etkinliğini doğruluyordu. Çalışma aynı zamanda barınmaya ihtiyaç duyan kişi sayısını da tahmin ederek önerilen modelin sağlamlığını %98,683 doğrulukla doğruluyor. MCDM yaklaşımına dayalı olarak yapılan çalışmada, kaynak ve kurtarma çalışmaları açısından en çok ihtiyaç duyulan şehir olarak Onikisubat şehri öne çıkarken, onu Dulkadiroğlu ve Elbasan takip ediyor. Basit ve etkili bir kullanıcı arayüzüne sahip DSS web sitesi, gerekli bilgileri sağlayarak ve kaynaklar ve kurtarma çalışmaları için acil müdahaleye ihtiyaç duyan, en çok etkilenen konumlara öncelik vererek yetkililerin hızlı eylemini artırmayı amaçlamaktadır. Son olarak, çalışmanın yöntemsel yaklaşımı ve önerilen modellerin sağlamlığı, deprem felaketine müdahale ve iyileştirmeyi etkili bir şekilde yönetmek için akıllı bir karar destek sistemi oluşturma potansiyelini göstermektedir.

Kelimeler : *Deprem Afet Yönetimi, Karar Destek Sistemleri (KDS), Çok Kriterli Karar Verme (ÇKKV)*

1. INTRODUCTION

1.1 Study Topic

Global occurrence of earthquakes has continued to be a significant area of concern due to the possible impact earthquakes can have on human lives, properties, and even a nation's economy. Earthquake has proven to be the most devastating natural hazard experienced in man's existence on Earth (Oluwafemi et al., 2018). Earthquake occurrence has always been in relation to the seismicity of a particular region. Regions with high seismicity tend to experience frequent earthquakes, while regions with low seismicity tend to have a low rate of earthquake occurrence. China, India, Japan, and a few other countries have had a high rate of earthquake occurrence in the past years due to their high seismicity, which has led to significant setbacks in their economy at the times of the events. An earthquake is a term used to describe a sudden slip on a fault and the resulting ground shaking and radiated seismic energy caused by the slip, volcanic or magmatic activity, or other sudden stress changes in the earth (Noy et al., 2022). Worldwide, more than one million earthquakes occur yearly, or an average of two a minute. A major earthquake in an urban area is one of the worst natural disasters. During the last four decades (1970-2017), earthquakes have been responsible for over a million deaths around the world in Armenia, China, Ecuador, Guatemala, Haiti, Iran, India, Indonesia, Japan, Mexico, Pakistan, Peru, and Turkey (Khorshidian and Fayazi, 2023), (*2023 Turkey-Syria Earthquake - Center for Disaster Philanthropy*, n.d.). Excessive urbanization in various seismically active parts of the world has led to megacities with population densities of 20,000 to 60,000 inhabitants per square kilometer. Such cities are highly vulnerable to earthquake hazards, which include high case fatality rates for trauma, asphyxiation, hypothermia, and acute respiratory insufficiency, in addition to fractures and other injuries caused by the destruction of infrastructure. Figure 1.1 shows the cost and causalities caused by earthquakes for four decades. This Figure illustrates the importance of Decision Support Systems (DSS) to deal with such challenges, i.e., earthquakes.

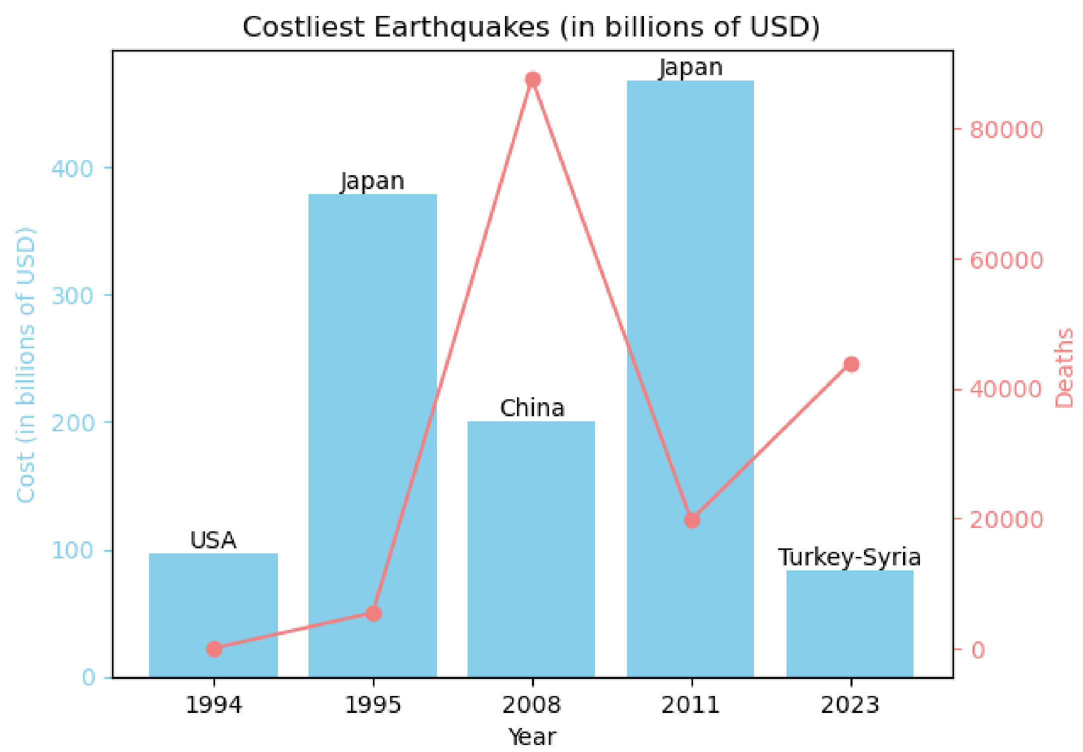


Figure 1.1: The Cost and Casualty of Earthquakes in Four Decades

Source: (Khorshidian and Fayazi, 2023), (*2023 Turkey-Syria Earthquake - Center for Disaster Philanthropy*, n.d.)

Given these challenges, there is a pressing need for effective decision-making tools to manage and mitigate the impact of these natural disasters. This is where the DSS comes into play. A DSS is a computer-based information system that supports business or organizational decision-making activities. DSSs serve an organization's management, operations, and planning levels and help make decisions that may be rapidly changing and not easily specified in advance. DSSs include knowledge-based systems. A properly designed DSS is an interactive software-based system intended to help decision-makers compile useful information from raw data, documents, personal knowledge, or business models to identify and solve problems and make decisions (Fersini et al., 2017). Typical information that a decision support application might gather and present are inventories of information assets, including legacy and relational data sources, cubes, data warehouses, data marts, comparative production figures between one period and the next, or the projected revenue figures based on production and demand assumptions. They are designed to compile helpful information from various sources, including raw data, documents, personal knowledge, and business models, to help decision-makers identify and solve problems and make decisions.

In earthquake management, a DSS could gather and present information such as seismic data, historical earthquake occurrences, infrastructure data, population data, and economic data. This information could be used to predict potential earthquake occurrences, assess the potential impact, and develop effective response strategies. For instance, the system could help decision-makers determine the most vulnerable areas, allocate resources effectively, and plan for potential evacuations. Thus, applying DSS in earthquake management could significantly reduce the devastating impact of earthquakes on human lives and economies.

1.2 Purpose of Thesis

The purposes of the thesis are as follows:

- To propose a DSS framework for managing earthquake disasters to help decision-makers analyze complicated information and make well-informed decisions.
- To propose a mathematical model to assess the casualty, injury, and the number of needed shelters using minimum available information.
- To harness the power of information technology, with a particular emphasis on web technology, to aid decision-making procedures and deliver crucial seismic data to decision-making authorities and the public.

1.3 Literature Review

A substantial body of research has been dedicated to applying DSS in various facets of disaster management. This literature review will delve into these diverse studies, highlighting the significant contributions made by numerous researchers in this field. In contrast, the second section will discuss works that use mathematical models for post-earthquake causalities and damages assessments.

1.3.1 DSS in disasters

The following works provide a comprehensive overview of how DSS has been utilized to enhance disaster management strategies:

Cavdur F. and Sebatli A. (2019) address the complexities of disaster response management, emphasizing the role of information technology in decision support. They introduce a tool for allocating temporary disaster response facilities under uncertain demand. The tool, featuring a database, decision engine, and user interface, utilizes a two-stage stochastic programming framework to account for post-disaster uncertainties. The authors posit this flexible tool could significantly enhance decision-making in disaster relief operations.

Susilowati et al., (2021) explore disaster-prone areas in Tanggamus Regency, susceptible to floods, landslides, and earthquakes. The study addresses the complexity and subjectivity in identifying high-risk areas, which may be overlooked in government disaster awareness initiatives. It introduces the Simple Additive Weighting (SAW) method for identifying these regions based on predefined criteria, including data on various disasters. The result is a prioritized list of areas requiring special attention from local authorities.

Chang et al., (2022) discuss Taiwan's earthquake vulnerability and the need for effective evacuation strategies. They introduce the Stochastic Pedestrian Cell Transmission Model (SPCTM), a simulation framework for evacuation, using actual data on urban infrastructure and earthquake impacts. The model, backed by the Taiwan Earthquake Impact Research and Information Application platform, simulates population movement in a cellular traffic network. An alternative model and an empirical study in Taipei underscore the models' potential in informing infrastructure design, evacuation strategies, and post-disaster decisions.

Cremen et al. (2022) address the shortcomings of current Earthquake Early Warning (EEW) systems, which lack a risk based DSS. They propose a next-generation, risk-informed EEW DSS that uses multi-criteria decision-making and considers potential system malfunctions. The DSS is demonstrated at the Gioia Tauro seaport in Italy, a high seismic hazard area. It conducts real-time seismic risk analyses for various scenarios, considering uncertainties and the port's interconnected elements. The results and user risk preferences help define risk informed EEW warning thresholds.

Chinnaraju and Kumar Chandran, n.d. (2022) emphasize the importance of coordinated efforts in emergency planning and management for nuclear safety. They highlight the increasing role of Geographic Information Systems (GIS) in disaster response and recovery, given their ability to integrate spatial and site-specific information. The paper presents a GIS-based decision support system that combines spatial data and atmospheric dispersion modeling to provide real-time support for nuclear emergency management. This system strengthens emergency planning and ensures public safety and the environment.

Latifa et al., (2022) introduce an intelligent decision support system for disaster management. It encourages collaboration, resource identification, and real-time decision-making through videoconferencing. The system includes case reasoning, ontology, and similarity measurement modules, providing a structured plan and updated resource inventory. Its effectiveness was validated in a province in western Algeria, demonstrating its potential to enhance disaster management efficiency.

González-Ramírez et al., (2023) discuss the complexity of container handling operations at maritime terminals, highlighting the need for resiliency in decision-making due to potential disturbances. They propose a DSS concept to aid these operations, considering potential disruptions. The chapter includes an empirical analysis of the main disturbances affecting port operations based on a survey conducted at four ports in Chile. The authors present their findings and provide recommendations to enhance the resilience and efficiency of container handling operations.

Fang et al., (2023) discuss the challenges in integrating geospatial resources in disaster management due to various gaps. They propose a service-oriented collaborative approach, integrating geospatial resources and task chains into a distributed Spatial Decision Support System (SDSS). This system, collaboratively built by data contributors, model contributors, GIS developers, and business experts, enables responders to deliver timely, accurate information during a disaster. The approach is implemented as a geospatial service platform for disaster response (GeoDR) and has demonstrated effectiveness in four joint exercises and operations in China.

Shukla et al., (2023)examine the impact of geographical and environmental factors on disaster occurrence and the role of India's National Disaster Management Authority (NDMA) in disaster management. They introduce the Disaster Management Ontology (DMO), a framework that aids task distribution and provides a knowledge-driven decision support system for victim assistance. The DMO utilizes ontology for knowledge integration, a DSS ruleset in Semantic Web Rule Language, and a graph for interactive taxonomy.

1.4 Hypothesis

The hypotheses for the thesis are as follows:

1. The use of a DSS framework specifically designed for handling seismic catastrophes would greatly improve the decision-making capabilities of those in charge.
2. Using minimal information to evaluate earthquake effects, injuries, and shelter requirements, a mathematical model in the DSS framework will enhance emergency planning and potentially reduce casualties and property damage post-earthquake.
3. Integrating web technology into the DSS framework will speed up crucial seismic data sharing, leading to better decision-making by authorities and the public and, thus, a more prepared society for earthquake disasters.

2. THEORETICAL BACKGROUND

This chapter discusses the theoretical foundations that review developing and applying a DSS for earthquake disaster management. By understanding the existing literature, theories, and practices, we can better position our methodology within the broader context of disaster management and information systems.

2.1 Decision Support Systems

A Decision Support System (DSS) is an interactive, computer-based system that aids users in judgment and decision-making processes. It provides data storage and retrieval but enhances the traditional information access and retrieval functions with support for model building and model-based reasoning. DSSs serve an organization's management, operations, and planning levels and help make decisions that may be rapidly changing and not easily specified in advance. The concept of DSS dates to the 1960s and 1970s, with the advent of computer-aided models that assisted in decision-making and planning (Burstein and Holsapple, 2008). Over the years, DSS has evolved from simple model-driven systems to more sophisticated, user-friendly platforms that integrate various data sources, analytics, and decision-making techniques.

2.1.1 Definition and Evolution of DSS

DSS has evolved significantly since its inception, adapting to the changing technological landscape and organizational needs. DSS emerged as a natural evolution from Transaction Processing Systems, indicating a move towards more complex, decision-centric system designs (Arnott, 2004).

The study and development of DSS is an applied discipline, deriving knowledge and theories from various other disciplines. This multi-disciplinary approach has been crucial in addressing the myriad of research questions and concerns raised by individuals developing and utilizing DSS, making the field both practical and theoretically rich (Power, 2007). Evolutionary development has been at the core of DSS theory and practice. The terms 'adaptive' and 'evolutionary', often used in describing DSS, reflect the organic nature of DSS development, as these systems have continually adapted to meet the emerging needs of organizations (Arnott, 2004). Historically, DSS has expanded into various categories, including communications-driven, data-driven, document-driven, knowledge-driven, and model-driven DSS. This diversification reflects the broadening scope and application of DSS in response to the evolving decision-making challenges faced by organizations (García-Alcaraz et al., 2023).

A bibliometric review from 1977 to 2021 highlights the evolution of DSS, tracking the burgeoning research and applications reflected in academic and professional publications. The continuous research and discussions in this field indicate an ongoing evolution aimed at enhancing the effectiveness of DSS in aiding decision-making processes within organizations (García-Alcaraz et al., 2023).

2.1.2 Components of DSS

The typical components that constitute a DSS are essential for its functionality and efficacy in aiding decision-making processes within organizations. These components provide the structure and resources necessary for the system to operate efficiently. As shown in Figure 2.1, the core components of a DSS include the database, software system or model, and user interface:

1. **Database**: The database is the repository of all necessary data that the DSS will utilize in its operations. It contains pertinent information related to the situation, which might be derived from internal and external sources. The database is crucial for storing historical and current data that can be analyzed to provide insightful recommendations or decisions (Fazlollahi et al., 1997).

Figure 2.1: The Three Main DSS Components

Source: (DSS, 2020).

2. **Software System or Model**: The software system or model component encompasses the algorithms, models, and analytical tools used to process the data from the database and generate insights or solutions. This part of the DSS is essential for analyzing the data meaningfully to aid decision-making processes. It includes a Model Management System, which stores models that managers can utilize for various decision-making scenarios, such as forecasting demand or assessing the organization's financial health (CFI Team, 2020).
3. **User Interface**: The user interface is the gateway through which users interact with the DSS. It is designed to be intuitive and user-friendly, ensuring that individuals can effectively use the system to extract the necessary information. The user interface may include dashboards, reporting tools, and other interactive elements that allow users to customize their interactions with the DSS, making it a vital component for ensuring the usability and accessibility of the System (Sonia Kukreja, 2021)

Together, these components work in harmony to provide a robust and effective DSS capable of assisting in complex decision-making processes by offering insightful data analysis and user-friendly interactions. Each component plays a pivotal role in ensuring that the DSS can fulfill its intended function of aiding in decision-making within an organizational setting.

2.1.3 DSS Types

As illustrated in Figure 2.2, the DSS has different types, namely, Communication-driven DSS, Data-driven DSS, Document-driven DSS, Knowledge-driven DSS and Model-driven DSS:

Figure 2.2:The Main Types of DSS

Source: (DSS, 2020)

1. **Communication-driven DSS:** Communication-driven DSS facilitates effective communication, collaboration, and coordination among team members. They are particularly beneficial in scenarios where collective decision-making is crucial. These systems provide platforms for real-time or asynchronous communication, document sharing, and collaborative work environments through web or client-server architectures. They are instrumental in aligning individual efforts towards common organizational objectives and ensuring that decisions are made with a shared understanding and consensus.

2. **Data-driven DSS:** Data-driven DSS is essential for organizations that rely heavily on data analytics for decision-making. They provide the tools and interfaces necessary for querying databases, data warehouses, or data marts to extract relevant data. Managers, staff, and vendors use these systems to analyze data, generate reports, and derive actionable insights. They support a wide range of analytical operations, including data mining, Online Analytical Processing

(OLAP), and statistical analysis, empowering users to make data-driven decisions.

3. **Document-Driven DSS:** Document-driven DSS primarily focuses on retrieving and managing unstructured documents. They employ advanced search algorithms, indexing, and other document retrieval techniques to locate relevant documents based on specified keywords or search criteria. These systems are invaluable in scenarios where decision-making requires the analysis of large volumes of textual documents, such as legal documents, technical manuals, or archived records. By efficiently managing and retrieving necessary documents, they expedite the decision-making process and ensure that decisions are well-informed.

4. **Knowledge-driven DSS:** Knowledge-driven DSS, also known as Expert Systems or Knowledge Bases, encapsulate the expertise and knowledge of human experts in a specific domain. They use rule-based systems, artificial intelligence, or machine learning algorithms to provide advice, recommendations, or solutions to problems. These systems are instrumental in scenarios requiring specialized knowledge for decision-making, such as medical diagnosis, financial planning, or product selection. They augment the decision-making capabilities of users by providing expert advice and guidance.

5. **Model-driven DSS**: Model-driven DSS are sophisticated systems designed to assist in the analysis of complex decisions. They incorporate mathematical models, simulation techniques, and optimization algorithms to analyze scenarios and evaluate options. Users can manipulate the models, adjust parameters, and observe the impacts on outcomes to make well-informed decisions. These systems are particularly beneficial in strategic planning, resource allocation, and other high-stakes decision-making scenarios where a thorough analysis of options is imperative.

The categorization of DSS into these five types reflects the diverse range of decision-making needs across different organizational contexts. Each type of DSS is tailored to address specific decision-making aspects, enabling organizations to choose and implement the DSS that best aligns with their operational requirements and strategic objectives.

2.1.4 Applications of DSS

The applications of DSS span across a multitude of fields, underscoring its versatility in aiding decision-making processes. Following is an overview of the various fields where DSS has been applied:

1. Finance and Credit Loan Verification: DSS applications are crucial in the financial sector, particularly in credit loan verification, where they help assess the creditworthiness of individuals or entities, thereby assisting in making informed lending decisions (Fairlie, 2023).

2. Healthcare and Medical Diagnosis: In healthcare, DSS aids in medical diagnosis by analyzing patient data to provide diagnostic suggestions or treatment plans, significantly improving healthcare delivery and patient outcomes (Blazek, 2022).

3. Business Management: Various types of business management tasks benefit from DSS applications. For instance, real-time reporting facilitated by DSS is invaluable for organizations engaged in Just-In-Time (JIT) inventory management, helping them maintain optimal inventory levels and streamline supply chain operations (Phillips-Wren et al., 2021).

4. Engineering, Agricultural, and Rail Projects: DSS applications are used in evaluating bids on engineering, agricultural, and rail projects, aiding in selecting the most viable proposals based on a thorough analysis of various factors.

5. Aviation: In aviation, DSS plays a pivotal role in risk assessment and decision-making concerning air traffic management, flight planning, and other critical operational aspects (Cankaya et al., 2023).

6. Surface Transportation and National Security: The application of DSS extends to surface transportation and national security, where it supports decision-making in a wide variety of settings, ensuring safe and efficient transportation systems and bolstering national security measures (Seth Linden, 2019).

7. Agriculture: DSS helps farmers solve complex issues related to crop production by collecting and analyzing data from various sources, thereby providing insightful recommendations for critical decision-making processes (Ren et al., 2022).

8. Inventory Management and Sales Optimization: DSS applications are instrumental in managing inventory by evaluating stock levels, predicting product demand, and aiding in sales optimization by analyzing sales data and monitoring existing revenue patterns. This usage is crucial for maintaining a business's cash flow and profitability and making informed decisions regarding sales strategies (Fernandez et al., 2021).

9. Retail: In the retail sector, AI-powered DSS applications are employed to spot future trends, set prices, decide on store layouts, and power live chat bots, thus enhancing customer engagement and optimizing operational efficiency.

The applications above underscore the breadth of DSS's versatility in various fields, enhancing decision-making processes, operational efficiency, and overall organizational performance. Through integrating data analytics, modeling, and interactive interfaces, DSS is an invaluable tool in navigating the complexities inherent in decision-making across many sectors (Fernandez et al., 2021).

2.2 Recent Advancements in DSS

In recent years, the DSS field has seen great developments using Artificial Intelligence, Machine Learning and Big Data analyses. These technologies are paramount to the modern DSS, leading to the ability to handle a huge amount of data, discover covered patterns and derive more precise and timely insights. Use of AI and ML Algorithms - AI/ML algorithms have improved the predictive abilities of DSS to predict future trends and events, resource allocation and decision making in advance (Rosati et al., 2020). Also, the rise in Cloud Computing, DSS have become available in the web, which makes it feasible and scalable that decision making tools are accessible from anywhere and anytime. This change has broadened the applicability and affected the influence of DSS across industries and in various organizational echelons (Cheng et al., 2018).

2.3 Challenges and Limitations

Implementing and using DSS is an easier genome compared to an adopted factor. Data quality is the hardest bug to solve. A successful DSS depends on accurate and dependable data to provide valuable intelligence. What Damages DSS as it the case with Business Intelligence (BI), DSS is also only as good as the data that underlies it, which means that poor data quality, incomplete or inconsistent data, and data silos can seriously damage the effectiveness of DSS and lead to suboptimal decisions. Moreover, user resistance may be a major obstacle to the successful implementation of DSS. Microsoft said that we still hesitate to use automatic decision-making tools in the decision-making process and we still like the traditional methods more. To combat this reluctance, proper change management, user training, and tangible benefits of DSS must be conveyed. In addition, the application of DSS requires, in many cases, specific knowledge like data analysis, modeling, and interpretation. For companies, this could mean providing employee training and development programs to develop the knowledge within their organization (Ara et al., 2021).

It is crucial to be aware of the limitations of DSS as well. While these systems are great decision-making tools, they are not infallible. DSS generates its output based on historical data, and it may not always capture all proper intricacies of the real-world conditions. Biased or inconsistent information may lead to ineffective decision making, especially if the data that one builds the model on is skewed or not diverse. Also, DSS should not be viewed as a replacement for human judgment and expertise. Human intuition, experience and context understanding still play an important role in making decisions in complex and ambiguous circumstances. So, it can be seen that DSS is a support system that used along with human decision-making because the DSS has not to replace the human decision making completely.

2.4 Future Trends and Research Directions

As it has been already mentioned, DSS are not likely to disappear at the moment. Some of them are currently used to make decision-making faster and more effective, and advances in technologies create great opportunities for their development. For example, such technologies as Natural Language Processing (NLP) or natural language processing and voice-based interfaces can positively influence the ways in which programmers and users communicate with DSS. Innovations that make DSS more intuitive can also be valuable. One of the most promising trends is connected with Augmented Reality (AR) or augmented reality. In conjunction with better types of dashboards and interfaces, AR can facilitate the use of DSS for non-professionals.

Another perspective is closely associated with the idea of the development of more adaptive and context-aware DSS. Using technologies such as data mining, it is possible to create models that will be able to adapt to different types of data and situations. Similar tools will be more likely to provide the most relevant and personalized information. It is also necessary to remember about the problems modern organizations face and their growing interest in sustainability and social impact. Using DSS to assist decision-making is a very prospective field for research.

2.5 Earthquake Disaster Management

Earthquakes are natural phenomena that result from the sudden release of energy in the Earth's crust, leading to seismic waves that cause the ground to shake. Understanding the basics of earthquakes involves delving into their causes, types, and effects.

Earthquakes primarily occur due to tectonic forces generated by the movement of Earth's plates. These plates are in constant motion, and stress accumulates when interacting at their boundaries. Once this stress surpasses the friction holding the rocks together, it is released as an earthquake. One significant observation is that almost 80% of earthquakes result from the stress accumulated from previous earthquakes at the exact location. This stress is stored as displacements against gravity and static elastic deformations of the plates (Nasirin and Birks, 2003).

The types of earthquakes can be categorized based on their causes and the geological activity that induces them. For instance, tectonic earthquakes are the most common and are caused by the movement of the Earth's crust. Additionally, the dynamics of tectonic plates can be understood as resembling a densely packed granular medium near a jamming transition, leading to a mixture of transient and intermittent fault slip behaviors over tectonic timescales (Flambaum et al., 2020).

The effects of earthquakes can range from minor ground shaking to major shifts in the Earth's crust, leading to widespread destruction. In extreme cases, the rapid release of energy in the form of seismic waves can cause buildings to collapse, landslides, tsunamis, and even change the Earth's rotation. Moreover, the 2011 MW=9.0 Tohoku earthquake in Japan demonstrated how great earthquakes could induce differential static stress changes across tectonic plates, potentially modulating the motions of proximal crustal blocks (Meade and Loveless, 2017).

Earthquakes are essential in shaping the Earth's landscape and profoundly affect human civilization. Understanding their causes, types, and effects is crucial for preparing and mitigating their impacts.

2.6 Earth Structure

The earth structurally mainly divided into Crust, Mantle, and Core as shown in Figure 2.3. According to the plate tectonic theory the crust, that is the outermost solid layer of the earth, consists of lithospheric plates (Figure 2.4) which float over the viscous layer of mantle and maintains dynamic equilibrium state of ‘isostasy’ thus implying that the crust forming plates (Figure 2.5) moves away, toward and past each other over the mantle with slow speed. When friction/interaction between two plates happens, it releases sudden energy waves along the earth's crust that we call seismic activity /earthquakes (Siddiquie, 2020). A planet where the boundary between two plates is typically punctuated by faults or some other form of structural defect. Faults are not continuous but typically are sections of a fault zone or fault belt that formed along a bedrock discontinuity in response to ground movement (Siddiquie, 2020).

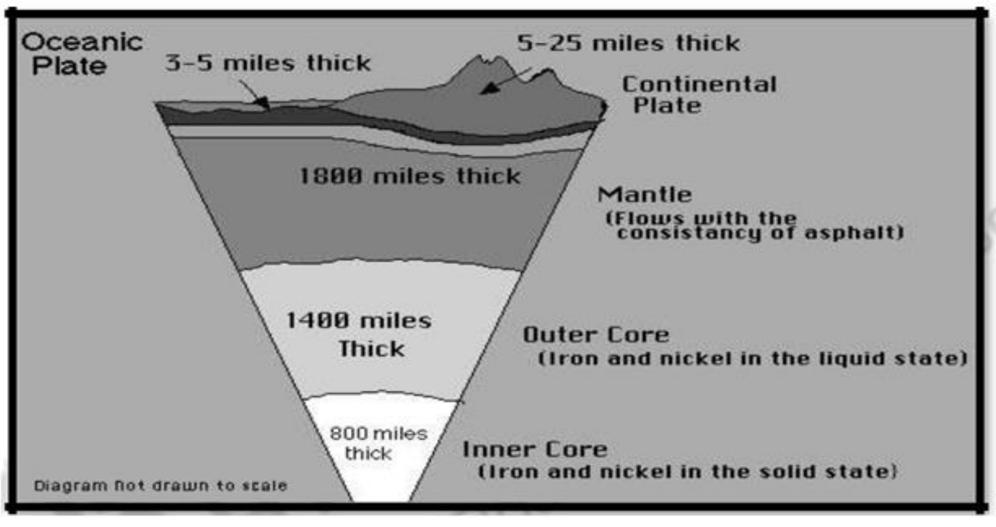


Figure 2.3: Layers of Earth

Source:(Siddiquie, 2020)

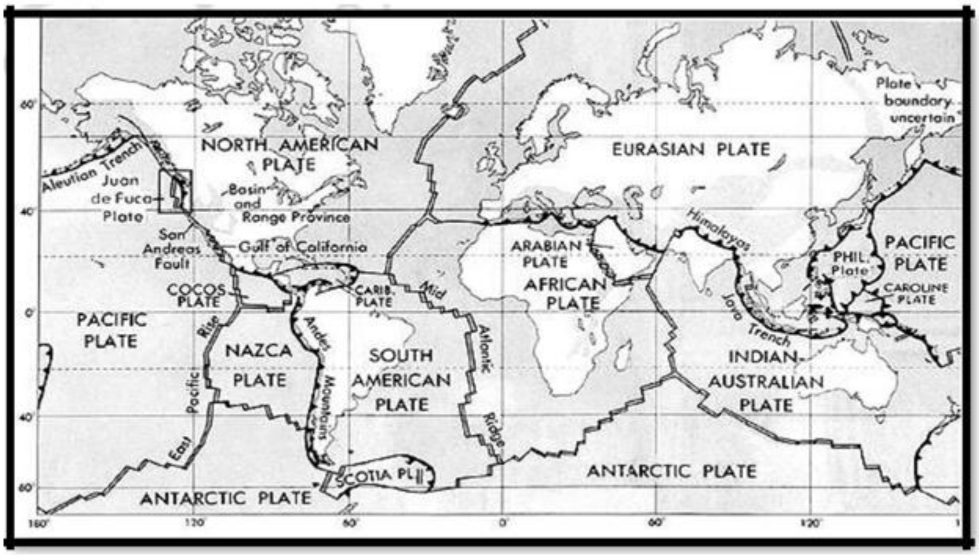


Figure 2.4: Plates According to Plate Tectonic Theory

Source: (Siddiquie, 2020)

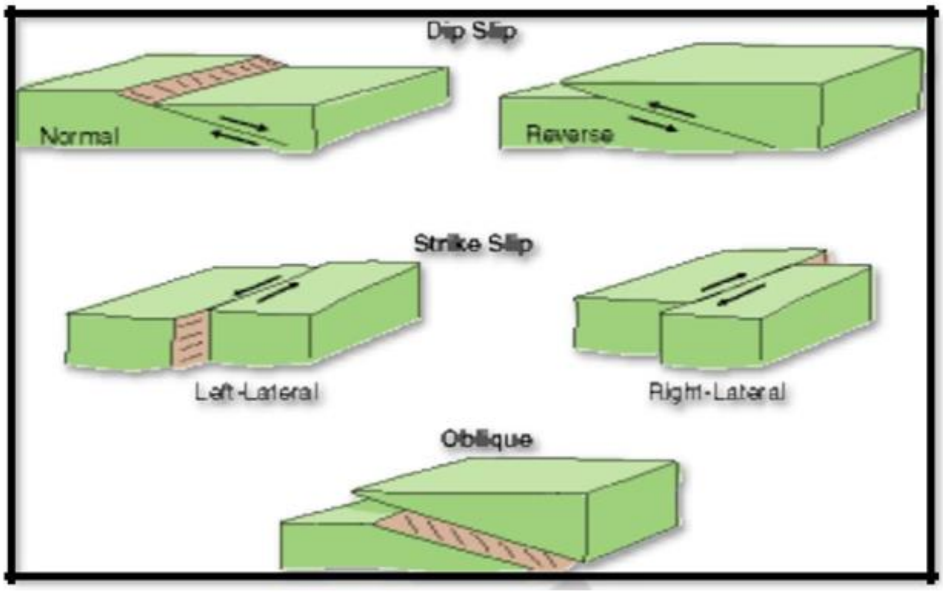


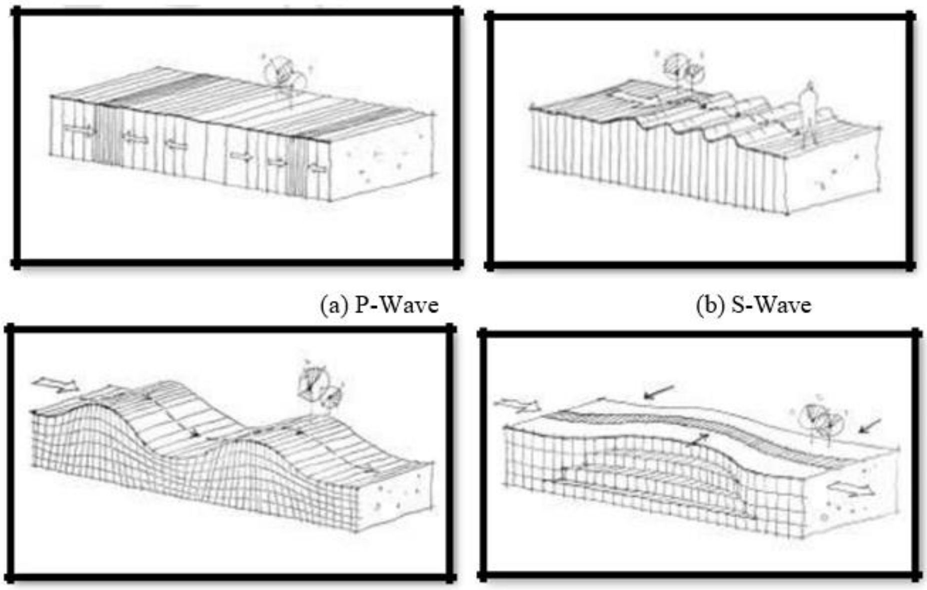
Figure 2.5: Types of Faults

Source: (Siddiquie, 2020)

When an earthquake occurs, the rock blocks move in the fault of line of weakness this creates seismic waves which spread like ripples on the surface of the earth, in all directions at the same time. The Waves are mainly classified into two categories (See Figure 2.6):

(a) P-Wave and S-Wave: Both of them are body waves. The latter is propagated by P-Wave, the fastest one, close to sound wave; s-waves has end velocity, slower than the previous one and more destructive. It cannot be used to travel through water.

b) Surface Waves: Rayleigh and Love Waves The surface moves both vertically and horizontally during Rayleigh or Ground Roll, causing vehicles and objects on the surface to bounce up and down. They are slower than S-waves. Love Waves are responsible for horizontal ground motion - the shaking of the ground back and forth.



(a) P-Wave (b) S-Wave

(c) Rayleigh Wave (d) Love Wave

Figure 2.6: Ground Motion during Earthquake

Source: (Siddiquie, 2020)

2.7 Measuring Earthquake

By the velocity and motion of the waves, one can measure earthquakes using instruments such as seismographs and accelerometers. They monitor the displacement, velocity, and acceleration state of the ground due to the seismic waves. This release center of energy can then be mapped by measuring such waves, and the distance of that center of release of energy from the location of the instruments (Siddiquie, 2020). This point at the interior of the earth, that center point from where energy is released is Known as the Point of Origin or earth’s axis, and the point on the earth’s surface, that is situated above the earth’s axis is known as the epicenter (see Figure 2.7)

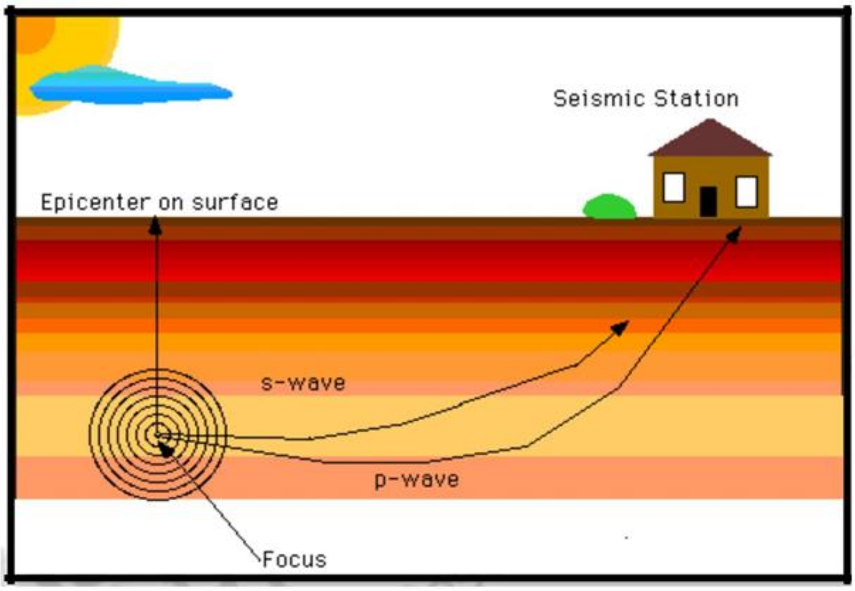


Figure 2.7: Focus (Hypocenter), Epicenter

Source: (Siddiquie, 2020)

2.8 Phases of Earthquake Disaster Management

Disaster management, especially in earthquakes, is a systematic process involving a series of coordinated activities and tasks to prepare for, respond to, and recover from disasters. The primary objective is to minimize the adverse impacts of hazards and ensure swift and effective recovery. As shown in Figure 2.3, the process can be broadly categorized into four main phases: mitigation, preparedness, response, and recovery.

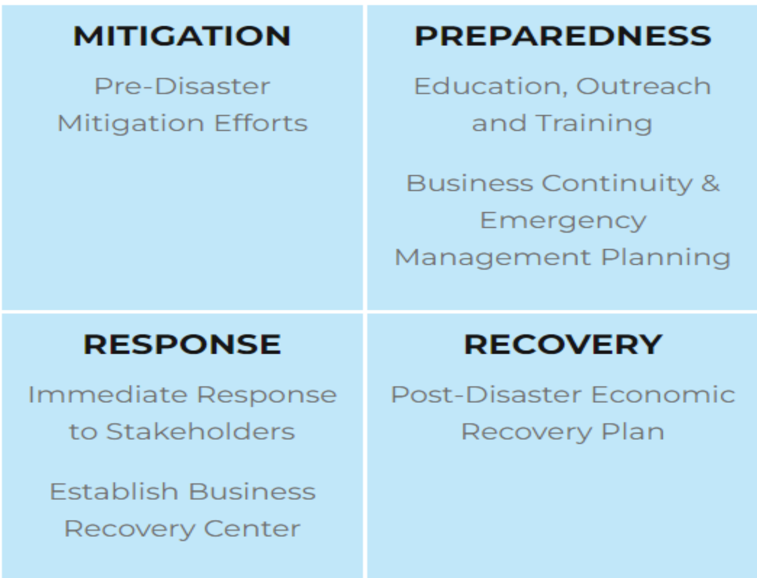


Figure 2.8: The Four Phases of Disaster Management

Source: (RYE Team, 2019).

1. **Mitigation**

Mitigation involves reducing the risk of earthquake disasters by minimizing the potential adverse impacts. This can be achieved by implementing building codes, land-use planning, and retrofitting vulnerable structures. The goal is to make communities more resilient to earthquakes. For instance, the study by Zhang et al. introduced a comprehensive stage-wise decision framework to support resilience planning for roadway networks, emphasizing the importance of pre-disaster mitigation (Zhang and Wang, 2016).

2. **Preparedness**

Preparedness focuses on developing plans and procedures to ensure that communities are ready to cope with an earthquake when it occurs. This includes training, drills, establishing early warning systems, and ensuring that resources are available and organized. For example, the Route Advisor for Disaster-Affected Regions (RADAR) framework operates on high-level algebraic representations of regions to devise strategies for routing essential services in a disaster-affected area (Johnson et al., 2020).

3. **Response**

The response phase is activated immediately after an earthquake and involves actions to save lives, protect property, and meet the basic needs of the affected population. Efficient response requires rapid assessment of the situation and deployment of resources. Meidani and Nabian's study highlights the importance of accelerating infrastructure system reliability analysis for effective response, especially in transportation networks(Nabian & Meidani, 2018).

4. **Recovery**

Recovery is the final phase and aims to restore the affected area to its previous state or even better. This involves rebuilding infrastructure, health care, and rehabilitation of the affected population. The study by Wang on the Lushan Earthquake emphasizes the long-lasting payment post-disaster, indicating that while there might be temporary benefits in terms of growth rate and competitiveness, there are permanent declines in production factors (Zhang et al., 2022).

Effective earthquake disaster management requires a holistic approach that encompasses all four phases. By understanding and integrating these phases, communities can enhance their resilience and capacity to cope with and recover from earthquakes.

2.9 Challenges in Post-Earthquake Management

The aftermath of an earthquake presents many unique challenges that necessitate a coordinated and efficient approach to post-disaster management. These challenges span various domains, from immediate response to long-term recovery, and understanding them is crucial for effective disaster mitigation and management.

- **Information Acquisition and Communication:** One of the primary challenges in the immediate aftermath of an earthquake is acquiring accurate information from different regions of the affected area. With traditional communication infrastructures often compromised, there is a growing reliance on social media platforms, such as Twitter, for real-time information exchange (Prakash et al., 2020). However, processing this vast amount of data to extract valuable information requires sophisticated techniques, including text classification, location determination, and priority calculations for rescue operations.
- **Infrastructure Restoration:** The restoration of the built environment, including buildings and transportation networks, is a complex task. The recovery of a community's building portfolio is particularly challenging due to the intricacies and dimensionality of the problem (Lin & Wang, 2017). Efficient strategies are required to prioritize and schedule repairs, ensuring the swift return of essential services and facilities.
- **Resource Allocation and Scheduling:** Effective rescue and recovery operations hinge on the optimal allocation of resources and scheduling of tasks. This involves determining the priority of rescue tasks based on information classification, considering resource constraints, and developing adaptive multitask hybrid scheduling algorithms(Choksi and Zaveri, 2019).
- **Food Security:** Natural disasters, including earthquakes, can threaten food security for households across all social strata. Addressing food security post-disaster requires a holistic approach that considers restoring various elements of the built environment. Ensuring a stable food supply chain and addressing

potential disruptions is paramount for community well-being (Choksi and Zaveri, 2019).

- **Coordination and Decision-Making:** The vast amount of data generated during and after an earthquake, combined with the situation's urgency, necessitates efficient decision-making frameworks. Tools and algorithms that can assist in making strategic decisions based on real-time data, are essential for effective post-earthquake management (Kosaka et al., 2023).

2.10 Data-Driven Decision-Making in Disaster Management

2.10.1 Importance of Data in Decision Making

Data-driven decision-making has revolutionized the field of disaster management. Integrating real-time information from various sources, such as sensors deployed in affected areas and social media platforms, provides invaluable insights into the evolving situation on the ground(Qadir et al., 2016). This enhanced situational awareness enables emergency responders to make informed decisions, allocate resources effectively, and implement timely interventions. Furthermore, data analysis from past disasters can offer lessons for future preparedness and response strategies (Sarker, 2022).

2.10.2 Types of Data Relevant to Earthquake Management

Effective earthquake management requires a comprehensive understanding of various data types:

1. **Seismic Data:** This includes information about the earthquake's magnitude, depth, and location. Advanced seismic monitoring systems provide real-time data, enabling early warning and rapid response (Bilal et al., 2022).

2. **Geographical Data:** Geographic Information Systems (GIS) offer insights into the topography, land use, and infrastructure of the affected area, aiding in damage assessment and recovery planning (Thomas, 2020).

3. **Historical Earthquake Data:** Analyzing patterns from past earthquakes can help predict future seismic activities and understand the potential impact on specific regions (Gasperini et al., 1999).

4. **Real-time Disaster Data:** Platforms like social media provide real-time updates from affected individuals, offering insights into the immediate needs and challenges (Shan et al., 2019).

Incorporating these diverse data sources into a unified decision-making framework is crucial for a holistic and effective approach to earthquake management.

2.11 Role of Technology in Disaster Management

Integrating technology in disaster management has transformed how societies prepare for, respond to, and recover from disasters. With the advent of advanced information and communication technologies, there has been a paradigm shift in disaster prediction, monitoring, and management systems (Sakurai and Murayama, 2019).

2.11.1 Information Systems in Disaster Response

Historically, information systems have played a pivotal role in disaster response. These systems, encompassing a broad range of technologies and methodologies, facilitate real-time information collection, processing, and dissemination. Their primary objective is to enable decision-makers, first responders, and relief agencies to make informed choices during crises, ensuring that aid reaches those in dire need promptly and efficiently (Sakurai and Kokuryo, 2014).

The significance of information systems in disaster response can be traced back to times when communication was primarily manual. As technology evolved, so did the methods of collecting and disseminating information. Today, with the advent of advanced technologies, the scope and capabilities of these systems have expanded exponentially (Abdel-Basset et al., 2020). They now integrate various data sources, from ground sensors to satellite imagery, providing a comprehensive view of the disaster-stricken area.

Sensors deployed in affected areas play a crucial role during natural disasters, such as earthquakes, floods, or hurricanes. These sensors, which can be terrestrial, aerial, or even satellite-based, collect data about the environment. This includes information about ground movements, water levels, and atmospheric conditions. The data gathered is then transmitted to centralized systems, where it is processed and analyzed (Hildmann and Kovacs, 2019). This real-time data provides invaluable insights into the evolving situation on the ground, enabling authorities to gauge the severity of the disaster and allocate resources accordingly.

In addition to sensors, social networks like Twitter and Facebook have emerged as vital sources of information during disasters. People trapped or affected by the disaster often turn to these platforms to communicate their whereabouts, conditions, and immediate needs. When aggregated and analyzed, this user-generated content provides a grassroots perspective of the disaster, complementing the data from official sources. Moreover, these platforms enable two-way communication, allowing authorities to disseminate vital information, such as evacuation routes or safety instructions, to the affected populace.

Integrating cloud computing into disaster response has further enhanced the capabilities of information systems. Cloud platforms offer scalable storage and processing power, ensuring that vast data can be handled efficiently (Nanda et al., 2023). The Cloud4BigData application, for instance, is a testament to the potential of cloud technologies in disaster management. This application supports the entire disaster management data lifecycle by leveraging cloud computing, the Internet of Things (IoT), and social computing technologies. From data ingestion and processing to alert dissemination, every aspect is streamlined, ensuring timely and effective response (Jiang, 2020).

Furthermore, integrating Artificial Intelligence (AI) and Machine Learning (ML) into these systems has opened up new avenues for predictive analysis. These systems can predict potential future disasters by analyzing historical data, allowing for better preparedness. They can also identify patterns and trends in real-time data, enabling authorities to anticipate challenges and strategize accordingly (Abid et al., 2021).

However, while the benefits of information systems in disaster response are undeniable, they also come with challenges. Ensuring the accuracy and reliability of data, especially from unverified sources like social media, is paramount. There's also the challenge of data overload, where the sheer volume of information can be overwhelming, making it challenging to extract meaningful insights (Teri and Musliman, 2019). Moreover, with the increasing reliance on digital systems, cybersecurity becomes a concern. Ensuring the privacy and security of the data, especially when dealing with sensitive information, is crucial.

The information systems have revolutionized disaster response, transforming it from reactive to proactive. By providing real-time insights and facilitating efficient communication, these systems ensure that disaster response is timely, coordinated, and effective. As technology continues to evolve, it is anticipated that the role of information systems in disaster response will only become more significant, making them an indispensable tool in the face of adversity.

2.11.2 Integration of DSS in disaster management

Decision Support Systems (DSS) have been at the forefront of technological advancements in disaster management. These systems, designed to assist decision-making, leverage data, analytical models, and user-friendly interfaces to provide actionable insights (Fang et al., 2023). Integrating DSS into disaster management frameworks has been a game-changer, enabling authorities to transition from intuition-based decisions to data-driven strategies (Fang et al., 2023).

2.11.3 The DSS in disaster management

The inception of DSS in disaster management can be traced back to the need for a systematic approach to handle the complexities associated with disasters. Traditional methods, often reliant on manual processes and limited data, were inadequate in the face of large-scale disasters. The integration of DSS offered a solution, providing a structured mechanism to analyze vast amounts of data and generate actionable insights.

- **Benefits**

1. **Enhanced Decision-Making:** One of the primary advantages of DSS is its ability to provide real-time insights (Fang et al., 2023; Jaskulak et al., 2020). DSS offers a comprehensive view of the disaster-stricken area by processing data from various sources, including sensors, satellite imagery, and social media. This enables authorities to make timely and informed decisions, whether evacuating a vulnerable population or dispatching relief teams to the most affected regions (Erlei et al., 2020).
2. **Resource Optimization:** Efficient resource allocation is crucial during disasters. With its analytical capabilities, DSS ensures that resources, power, equipment, or aid, are allocated judiciously (Jana et al., 2022). By analyzing

the severity and scale of the disaster, DSS can prioritize areas in dire need, ensuring that aid is reached promptly.

3. **Predictive Analysis:** The ability to predict potential future disasters is a significant advantage offered by DSS (Brandtner, 2023). By analyzing historical data, patterns, and trends, DSS can forecast potential disaster scenarios. This predictive capability allows authorities to be better prepared, devising strategies and mobilizing resources in anticipation.

- **Challenges:** Data overload in the digital age has ushered in an era of big data. While this vast amount of data offers numerous insights, it also presents challenges. Sifting through this data to extract meaningful insights can be daunting. Despite its advanced algorithms, DSS can sometimes struggle with data overload, leading to potential delays in decision-making.

1. **Security Concerns:** As with any digital system, DSS is susceptible to cyber threats (Susanto et al., 2020). Ensuring the privacy and security of the data, especially sensitive information like the affected populace's personal details, is paramount. Authorities need to invest in robust cybersecurity measures to safeguard the integrity of the system.
2. **Integration Issues**: Integrating DSS with existing systems, especially in regions with outdated infrastructure, can be technically challenging (Nuša Farič, 2023). It may require significant resources, both in terms of finances and manpower. Moreover, ensuring seamless interoperability between different systems is crucial for the efficient functioning of DSS.

The integration of DSS in disaster management has been transformative. While challenges persist, the benefits offered by DSS, from enhanced decision-making to predictive analysis, are undeniable. As technology continues to evolve, it is anticipated that DSS will play an even more significant role in shaping the future of disaster management, ensuring that societies are better equipped to handle adversities.

2.12 Multi-Criteria Decision-Making (MCDM) in DSS

Multi-criteria decision-making (MCDM) is a sophisticated approach that facilitates decision-making by considering multiple criteria simultaneously

(Pardiyono and Indrayani, 2019). In Decision Support Systems (DSS), MCDM has emerged as a pivotal tool, enhancing the system's ability to provide comprehensive and nuanced recommendations. By integrating MCDM into DSS, decision-makers can navigate complex scenarios more effectively, ensuring that decisions are not only data-driven but also holistically consider multiple facets of a problem (Zarandi et al., 2021).

2.12.1 Historical perspective on MCDM in DSS

The origins of MCDM can be traced back to operations research and management science, where the need to evaluate multiple criteria for optimal decision-making was recognized. As DSS evolved, the potential of integrating MCDM became evident. Early applications of MCDM in DSS were primarily in sectors like finance and supply chain management, where decisions often involved balancing multiple objectives (Kumar and Tiwari, 2021).

However, as the complexities of global challenges grew, the applicability of MCDM in DSS expanded to diverse fields, including environmental management, healthcare, and, notably, disaster management (Göncü and Çetin, 2022). For instance, decision-makers often grapple with multiple competing priorities in disaster response scenarios, such as immediate relief, infrastructure restoration, and long-term recovery. MCDM, when integrated into DSS, provides a structured framework to evaluate these priorities against various criteria, ensuring a balanced and effective response.

2.12.2 Applications of MCDM in DSS

The following are some of the essential applications of MCDM in DSS:

1. Resource Allocation: In scenarios where resources are limited, MCDM helps decision-makers allocate them optimally by evaluating criteria like urgency, impact, and feasibility(Ma et al., 2022).

2. Risk Assessment: MCDM allows for a comprehensive risk assessment by considering multiple factors, such as probability, severity, and potential impact(Zhang H. et al., 2023).

3. Strategic Planning: For long-term strategies, MCDM aids in evaluating various options against criteria like sustainability, cost-effectiveness, and potential benefits(Ma et al., 2022).

4. Stakeholder Engagement: MCDM facilitates stakeholder engagement by providing a platform to weigh different perspectives and priorities, ensuring that decisions are inclusive and considerate of diverse viewpoints (Chowdhury and Paul, 2020).

2.12.3 Challenges and considerations

While MCDM offers numerous advantages, its integration into DSS is not without challenges- (Zhang H. et al., 2023) (Chowdhury and Paul, 2020) (Štilić and Puška, 2023):

1. **Complexity:** MCDM models can be intricate, requiring expertise to set up and interpret.
2. **Subjectivity:** The process of assigning weights to different criteria can be subjective, potentially leading to biases.
3. **Computational Intensity:** Some MCDM methods, especially large datasets, can be computationally intensive.
4. **Data Quality:** The effectiveness of MCDM is contingent on the data quality. Inaccurate or incomplete data can lead to suboptimal decisions.

Integrating Multi-criteria decision-making into Decision Support Systems represents a significant advancement in the field of decision sciences. By providing a holistic framework to evaluate multiple criteria, MCDM ensures that decisions are comprehensive, balanced, and aligned with overarching objectives. As technology and methodologies continue to evolve, it is anticipated that MCDM will play an even more central role in shaping the future of DSS, making it an indispensable tool for modern decision-makers.

2.13 Types of MCDM

Multi-criteria decision-making (MCDM) is a comprehensive field encompassing various methods and techniques to simultaneously address the complexities of evaluating multiple criteria. Over the years, several MCDM methods have been developed, each with its unique approach and application. Here's an overview of some of the prominent types of MCDM (Štilić and Puška, 2023), (Taherdoost and Madanchian, 2023), (Divya et al., 2021), (Eren and Katanalp, 2022):

1. Weighted Sum Model (WSM): One of the simplest MCDM methods, WSM involves assigning weights to each criterion and then summing up the weighted scores of each alternative. The alternative with the highest total score is considered the best.

2. Weighted Product Model (WPM): Similar to WSM, WPM assigns weights to criteria. However, instead of summing, it multiplies the weighted scores. This method is advantageous when considering criteria with exponential impacts.

3. Analytic Hierarchy Process (AHP): Developed by Thomas L. Saaty in the 1970s, AHP breaks down a decision problem into a hierarchy of subproblems. Pairwise comparisons are made, and eigenvalues are used to calculate the weights. It's beneficial for complex decision-making scenarios with multiple levels of criteria.

4. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS): This method ranks alternatives based on their proximity to an ideal solution and their distance from a negative-ideal solution. The option closest to the ideal and farthest from the negative ideal is preferred.

5. Elimination and Choice Expressing Reality (ELECTRE): ELECTRE involves eliminating alternatives that do not meet certain criteria thresholds. It then ranks the remaining alternatives based on concordance and discordance indices.

6. Preference Ranking Organization Metod for Enrichment Evaluation (PROMETHEE): This method uses pairwise comparisons and preference functions to rank alternatives. It provides two types of rankings: PROMETHEE I for partial ranking and PROMETHEE II for complete ranking.

7. Goal Programming (GP): GP is an optimization technique focusing on achieving multiple goals. It involves setting target values for each criterion and minimizing deviations from these targets.

8. Multi-Objective Evolutionary Algorithms (MOEAs): These are optimization algorithms that evolve solutions over time. They are particularly useful for problems with multiple conflicting objectives, where traditional optimization methods may not be applicable.

9. Fuzzy MCDM: Recognizing that decision-making often involves ambiguity, fuzzy MCDM incorporates fuzzy set theory. It allows for evaluating criteria that are not precisely defined, making it suitable for scenarios with subjective or imprecise data.

10. Grey Relational Analysis (GRA): Used for situations with incomplete or uncertain information, GRA evaluates the relationship between alternatives based on their similarity to a reference sequence.

The diverse range of MCDM methods reflects the complexities inherent in decision-making processes. The choice of method often depends on the nature of the problem, the available data, and the decision-maker's preferences. As challenges in decision-making continue to evolve, so will the methods of MCDM, ensuring that it remains a dynamic and vital field in operations research and management science.

2.14 Mathematical Models

Mathematical models are essential tools in various fields that allow us to understand and predict complex phenomena. Technological advancements have greatly improved the accuracy and efficiency of mathematical models, enabling us to make more informed decisions and solve intricate problems. In the context of earthquake events, mathematical models play a crucial role in predicting casualties. Using seismic data, structural engineering principles, and population density mapping, mathematical models can be utilized to estimate the potential impact of an earthquake on human settlements. By incorporating factors such as building integrity, proximity to fault lines, and population distribution, these models can provide valuable insights into the potential casualties that may occur in an earthquake. The accuracy of these mathematical models, coupled with real-time data updates, enables emergency response teams and policymakers to make informed decisions regarding evacuation plans, resource allocation, and mitigation strategies (Urrutia et al., 2014).

Work in (Shang et al., 2022) propose a comprehensive research paper on assessing post-earthquake healthcare service accessibility. It presents a framework integrating the modified two-step floating catchment area (2SFCA) method and seismic fragility analysis. The framework utilizes spatial data, travel cost calculations, and accessibility measurements. Key equations include:

1. Supply-to-Demand Ratio:

$$R_j = \sum \frac{S_j}{D_k} \text{ for } k \text{ in } d_{kj} \leq d_0 \tag{2.1}$$

Where S_j is the capacity of each hospital, D_k is the population at each demand location, and d_{kj} is the travel cost from demand location k to hospital j.

2. Accessibility at Demand Location:

$$AF_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j \tag{2.2}$$

Where AF_i is the accessibility at demand location i, and R_j is the supply-to-demand ratio.

3. Effects of Debris and Bridge Damage on Travel Time: Includes equations for calculating travel time changes due to debris and bridge damage. For example:

$$v_{\text{collapsed}} = R \cdot v_0$$

(2.3)

Where $v_{\text{collapsed}}$ is the post-earthquake travel speed, R is the ratio of areas unaffected by debris, and v_0 is the normal travel speed.

4. Health Care Service Demand: Equations for calculating the demand for medical staff and patient beds post-earthquake, like:

$$DMS = 0.1039\omega \cdot N$$

(2.4)

Where DMS is the demand for medical staff, ω is a zone coefficient, and N is the number of injured people.

These equations form a part of a broader analysis framework, which includes seismic fragility analysis, casualty estimation, and hospital capacity assessment post-earthquake. The framework is aimed at evaluating the accessibility of health care services in a post-earthquake scenario, considering the damage to infrastructure and changes in the availability of medical resources.

Work in (Aleskerov et al., 2005.) focuses on a decision support system for estimating earthquake-related casualties and damage. It includes various equations and models to calculate the potential impact of earthquakes on buildings, human lives, and the need for temporary shelters. These calculations consider factors like building types, construction quality, population distribution, and earthquake intensity. The equations provide a quantitative basis for predicting the scale of damage and casualties in different scenarios, aiding in disaster management and preparedness. This approach is particularly useful in areas with less-developed infrastructure, where accurate prediction and rapid response are crucial, following the two main mathematical models discussed in the work:

1. **Estimation of building damage**

In the estimation of the building damage model, earthquake intensities are defined as a set $Q = \{VII, VIII, IX\}$, and construction typologies are defined as a set $C = \{c_1, \ldots, c_m\}$. The function for estimating building damage is expressed as $Q \times C \rightarrow D_1 \times D_2 \times D_3 \times D_4$, where each D_i ranges from 0 to 100, and the sum of D_i equals 100%. The values D_1, D_2, D_3, and D_4 represent the collapsed/heavy, moderate, slight, and no damage percentages, respectively. This model combines the HAZUS software's extensive damage and complete collapse categories into one category: 'collapsed/heavy damage'.

2. **Estimation of human losses and injuries**

The model assesses human losses and earthquake injuries, considering construction typology and building damage. It introduces a function λ, which evaluates the percentages of deaths (p_1), seriously injured (p_2), moderately injured (p_3), slightly injured (p_4), and unaffected (p_5) people in a cluster for each damage level d. This function is expressed as $C \times D \rightarrow P_1 \times P_2 \times P_3 \times P_4 \times P_5$, with each P_i ranging from 0 to 100% and the sum of these percentages equaling 100%. The model underscores that casualty rates vary by region, as demonstrated by comparisons of earthquake impacts in Turkey, Japan, and the US. It emphasizes the need for context-specific casualty rates and considers individual behavior during earthquakes in buildings, suggesting that building design, such as robust stair cores, can influence fatality rates.

However, in the literature, many well-known models will be discussed in the next section.

2.15 Coburn and Spence Model

According to Coburn and Spence (1992) model for estimating earthquake fatalities is based on a formula that includes the number of fatalities due to structural damage (KS). The formula is:

$$KS = D_5 \cdot [M_1 \cdot M_2 \cdot M_3 \cdot (M_4 + (1 - M_4) \cdot M_5)] \tag{2.5}$$

Here, KS is the number of fatalities, D_5 is the number of collapsed buildings, M_1 to M_5 are parameters representing various factors like the average number of people in each collapsed building, the percentage of occupants trapped, and the mortality rates at and post-collapse. The model highlights the importance of building type and search and rescue effectiveness on post-collapse mortality.

2.16 So and Spence Model

The model by So and Spence(2013a), for global casualty estimation uses empirical data from the Cambridge Earthquake Impacts Database (CEQID). It calculates the total number of fatalities (K) as:

$$K = \sum_i \sum_l \left[O_{il} \times P_{il} \times (D_{il} \times LS_i + D4_{il} \times L4_i)\right]$$

(2.6)

In this formula, various factors are considered: average occupancy rate (O_{il}), total resident population in a building class at a location (P_{il}), proportions of collapsed (D_{il}) and heavily damaged $(D4_{il})$ buildings, and lethality rates for collapsed (LS_i) and heavily damaged $(L4_i)$ buildings. The model classifies building vulnerability into four classes, aiding in more accurate fatality estimations.

2.17 Zuccaro and Cacace Model

The model by Zuccaro and Cacace for evaluating seismic casualties in Italy is based on four parameters: casualty percentage by building type and damage level, mean number of inhabitants by building type, occupancy rate by time, and touristic index by location and period (Altman et al., 2013) . The number of deaths (Nd) and injuries (Ni) is determined using the expressions:

$$Nd = TI_c \sum_{t=1}^{4} \sum_{j=1}^{5} N_{t,j} NO_t QD_{t,j} \quad (2.7)$$

$$Ni = TI_c \sum_{t=1}^{4} \sum_{j=1}^{5} N_{t,j} NO_t QI_{t,j}$$

(2.8)

Where:

Nd and Ni are the total number of deaths and injuries, respectively.

TI_c is the touristic index by city.

t represents the building type, ranging from 1 to 4.

j indicates the damage level, ranging from 1 to 5.

$N_{t,j}$ is the number of buildings of type t with damage level j.

NO_t is the number of occupants by building type at the time of the event.

$QD_{t,j}$ and $QI_{t,j}$ are the proportions of deaths and injuries, respectively, by building type and damage level.

The model correlates casualties with structural damage, focusing on damage levels D4 and D5, and includes the building's structural type in its analysis.

Although there are numerous models in the literature, most of these mathematical models necessitate specific and comprehensive information about the earthquake. However, such detailed information is often unavailable or outdated, requiring time to collect or update. Consequently, new models must be developed with the aim of estimating casualties using easily obtainable information.

2.18 Summary

The chapter comprehensively explores the theoretical foundations central to DSS in the context of earthquake disaster management. Revisiting these core theories underscores the evolution and significance of DSS as a pivotal tool in addressing the multifaceted challenges of earthquakes. These theoretical underpinnings not only shed light on the motivations behind the development of DSS but also highlight the challenges encountered in its design and application. Understanding these foundational elements is crucial, as they offer insights into the cognitive decision-making processes, ensuring that DSS aligns with the user's needs. Moreover, the chapter emphasizes the symbiotic relationship between theory and practice, suggesting that a deep understanding of these theories can guide the optimization of DSS for earthquake management. In essence, this chapter bridges the gap between theoretical constructs and their real-world applications, equipping readers with a holistic perspective on the transformative potential of DSS in earthquake disaster response.

3. METHODOLOGY

The chapter begins by highlighting that the scope of the DSS will be focused on the post-disaster phase, specifically on coordinating emergency response and recovery efforts. It then lays out the key steps involved: identifying the problem and objectives, collecting and managing relevant data, designing system architecture and functionalities tailored for post-earthquake decision-making, developing specialized decision-making tools for risk assessment, emergency response planning and recovery strategy generation, integrating system components, testing and validating the system, implementing and training users, and continually evaluating and improving the DSS. The methodology leverages a data-driven approach, using predictive modeling and seismic, geographic, and historical earthquake data analysis to power the DSS insights and recommendations. This comprehensive process aims to create an intelligent DSS to support critical decision-making for rescue operations, resource allocation, infrastructure rebuilding, and community recovery after an earthquake.

3.1 Methodology Steps

As defined earlier, DSS is an information technology environment that can be used to help humans learn from past earthquakes, record them understand and plan for future mitigation, and hope will reduce the disaster risk in the future. However, in this thesis, the scope is the post-disaster (Earthquake) damage assessment based on based information only. The thesis will focus on coordinating emergency response and aiding recovery efforts by supplying the authorities with the three essential pieces of information that can help make decisions: The number of deaths, injuries, and the number of people who need shelter. Figure 3.1 illustrates the general steps that will be followed in this thesis to achieve the thesis objectives.

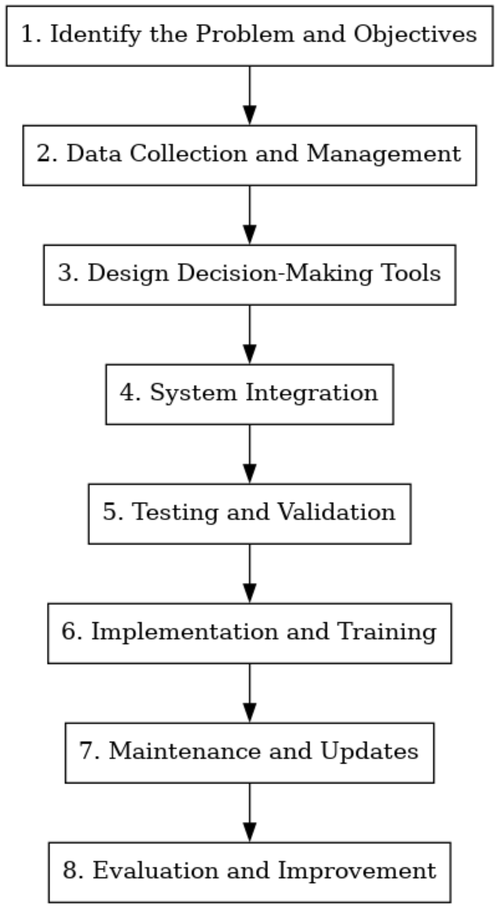


Figure 3.1:The Methodology Steps

3.1.1 Identifying problem and objectives

The first step in developing the earthquake DSS is to identify the problem and objectives the system aims to address. As outlined in Chapter 1, the main problem is the enormous challenges in providing essential information for coordinating effective emergency response and recovery efforts after a devastating earthquake. The chaotic aftermath often leads to delays in rescue operations, suboptimal allocation of resources, and losses that could have been minimized with better preparedness. The general goal is to build an intelligent DSS that can analyze disaster data to enhance and optimize post-earthquake decision-making processes by providing the needed information to make the right decisions and direct rescue efforts and resources in the right direction. By identifying these issues and mapping out the intended functionality, this first step clarifies the motivations, goals, and desired outcomes before proceeding with DSS development. This ensures the system is designed expressly to address the unique decision-making challenges in the aftermath of earthquake disasters.

3.1.2 Data collection and management

On 6 February 2023, two devastating earthquakes (see Figure 3.2), measuring 7.7 and 7.6 magnitude on the Richter Scale, struck Pazarcık and Elbistan in Kahramanmaraş, Türkiye(*Türkiye-Syria Earthquakes February 2023 | UN Connecting Business Initiative (CBi)*, n.d.). The initial earthquake was followed by over 3,100 aftershocks, including a 7.6-magnitude earthquake that hit Elbistan, according to the Turkish Disaster and Emergency Management Presidency (AFAD). Impacts have been felt across the 10 provinces in which a state of emergency has been declared (Adıyaman, Gaziantep, Kilis, Hatay, Malatya, Diyarbakır, Adana, Osmaniye, Kahramanmaraş and Şanlıurfa) and Elazığ, with Hatay, Kahramanmaras and Gaziantep reportedly hardest hit (*Türkiye-Syria Earthquakes February 2023 | UN Connecting Business Initiative (CBi)*, n.d.).

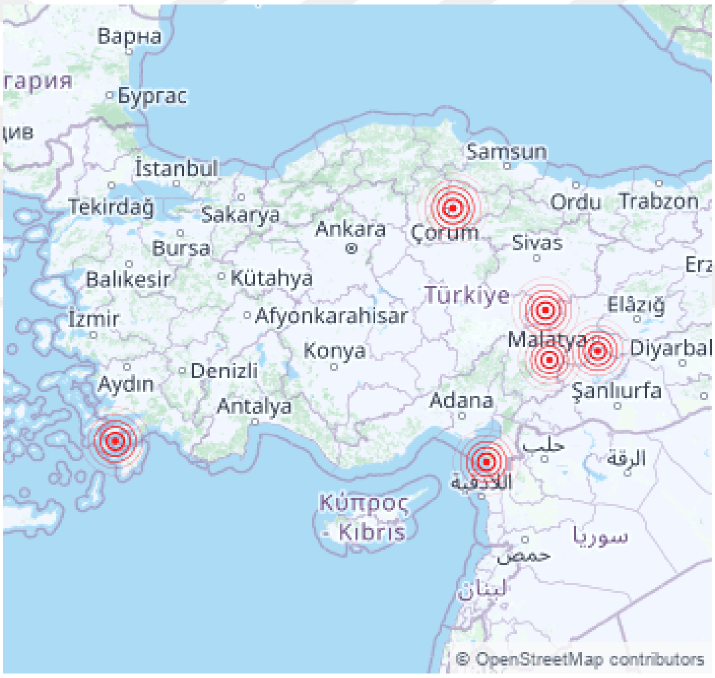


Figure 3.2: Turkish Cities Affected by 2023 Earthquake

Source: (Türkiye-Syria Earthquakes February 2023 | UN Connecting Business Initiative (CBi), n.d.).

The case study of this thesis focused on the 2023 Turkish earthquake, specifically in Kahramanmaraş province; the data used in the thesis is collected from the following resource illustrated in Table 3-1.

Table 3.1: The Main Resource of the Collected Data

The source	Description	Reference
Open Data Soft	Turkish earthquake dataset	(*Türkiye-Syria Earthquakes February 2023 | UN Connecting Business Initiative (CBi)*, n.d.)
World Data	Earthquakes in Turkey statistics	(*Recent Earthquakes and Their Magnitudes in Turkey*, n.d.)
Türkiye Earthquakes Recovery and Reconstruction Assessment	Detailed report that covers all the causalities and budding damages of all affected area of 2023 earthquake.	(World Bank, 2023)

Source: (Türkiye-Syria Earthquakes February 2023 | UN Connecting Business Initiative (CBi), n.d ; Recent Earthquakes and Their Magnitudes in Turkey, n.d. and World Bank, 2023)

The Kahramanmaraş province suffers 12711 deaths and 9,243 injuries based on reference (*Sağlık Bakanı Koca: 10 Ilde 17 Bin 929'u Hekim Olmak Üzere 143 Bin 829 Personelimiz Hizmet Veriyor*, n.d.). Table 3.2 shows the cities that follow the Kahramanmaraş province with their populations and population density in Density/km². However, in this thesis, the goal is to have the following basic data to answer the following questions:

1. How many died?
2. How many were injured?
3. How many people need shelters?

Thus, the required data is:

a) The population of the targeted city that suffers earthquake.
b) Population density in km^2
c) The number of buildings and their types.
d) The magnitude of the earthquake is the Richter scale.

Table 3.2: The affected cities' populations and density under Kahramanmaraş Province

City	Population	Density/km²
Afşin	83,324	60.1
Çağlıyancerit	25,692	61.6
Dulkadiroğlu	216,701	190.0
Ekinözü	13,833	23.2
Elbistan	139,855	141.0
Göksun	52,845	27.2
Nurhak	13,706	11.2
Onikişubat	357,870	188.6
Pazarcık	72,270	40.5
Türkoğlu	66,546	158.4

Source: (MSIP, 2023).

3.2 System Design for Post-Earthquake Rescue Efforts and Decision Making

The design of the DSS will be tailored to support post-earthquake rescue efforts and decision-making processes. This will involve incorporating specific functionalities and features to aid these areas. The following is the illustration of the mathematical models that the researcher developed but not similar depending on previous works (Aleskerov et al., 2005; Manfredi et al., 2023; Rakes et al., 2014; Shang et al., 2022)

3.2.1 Mathematical model

In this section, the proposed mathematical models of: Estimated Casualties, Number of Injuries and the Number of people who need shelter are discussed. These mathematical models have designed and developed based on the objective of estimating the required information using as basic information as possible.

A. **Estimated Casualties:** To calculate both types of casualties, *Death* and *Injuries*, the same mathematical model can be used by using different scaling factors δ, i.e., for calculating the number of deaths, the scaling factor $\delta=2\times10^{-7}$, while calculating the number of injuries, the scaling factor is $\delta=2.5\times10^{-7}$.

The mathematical model proposed for estimating earthquake casualties in different cities is based on several key parameters and calculations, starting with Eq. (3.1):

1. Scaled Estimated Casualties for Each City:

$$C_{city,scaled} = \frac{\sum_{bt\in Building\ Types} C_{bt}}{\delta}$$

(3.1)

Here, $C_{city,\ scaled}$ represents the scaled estimated casualties for a city, calculated by dividing the sum of estimated casualties for each building type C_{bt}.

2. Scaled Total Estimated Casualties Across All Cities:

$$C_{total,\ scaled} = \frac{\sum_{c\in Citie} C_{city,\ scaled}}{\delta} \quad (3.2)$$

- This part sums up the scaled estimated casualties from each city.
- c represents a city in all cities (denoted as *Cities*).
- $C_{total,\ scaled}$ Here, $C_{total,\ scaled}$ represents the total scaled estimated casualties across all cities, and $C_{city,\ scaled}$ is the scaled estimated casualties for each city as previously defined in Eq.(3.1)
- In this equation:
- $\sum_{c\in Cities} C_{city,\ scaled}$ calculates the sum of the scaled estimated casualties for each city.
- The division by δ again scales down this total to provide a scaled estimate of the overall casualties.
- This summation effectively aggregates the scaled casualties from all individual cities into a single total causality.
- Where:
- C_{bt} : Estimated casualties for each building type (bt) in the city.

Building type casualty estimation:

$$C_{bt}=N_{bt,\ adj} \times P_{city} \times O_{bt} \times I \times V_d \text{ (for Resident type buildings} \quad (.3.3)$$

$$C_{bt}=N_{bt,\ adj} \times P_{city} \times O_{bt} \times I \text{ (for other building types)} \quad (3.4)$$

Where:

- $N_{\text{bt, adj}}$: Adjusted number of buildings of type b_t in the city (adjusted for population density).
- P_{city} : Population of the city.
- O_{bt} : Occupancy rate for building type *bt*.
- I : Intensity impact factor (based on Richter scale intensity).
- V_{d} : Vulnerability factor for building typed (applicable for different types of residential buildings).

Adjusted Number of Buildings:

$$\mathrm{N_{bt,\ adj}} = \mathrm{N_{bt}} \times \left(\frac{\mathrm{D_{city}}}{\mathrm{D_{baseline}}}\right) \tag{3.5}$$

Where:

- N_{bt} : Original number of buildings of type bt.
- D_{city} : Population density of the city.
- $D_{\text{baseline:}}$: Baseline population density for adjustment.

Baseline population density for adjustment" means this is the initial or reference population density used in calculations, comparisons, or analyses. It serves as the starting point or the 'norm' from which changes are measured or expected. In various studies or projects, understanding the baseline is crucial for evaluating the impact of interventions, developments, or changes over time.

Intensity Impact Factor:

$$\mathrm{I} = \min\left(\frac{\text{Richter Scale Intensity}}{10}, 1.0\right) \tag{3.6}$$

Vulnerability Factor (for Resident type buildings):

$\mathrm{V_d} = \{1, 1.5, 2\}$ Depending on the construction type (enforced (1), semi-enforced (1.5), non-enforced (2)).

The values of $\mathrm{V_d}$ empirically derived.

This mathematical model considers various factors like the number and type of buildings, population density, occupancy rates, and the earthquake's intensity. It adjusts the number of facilities in each city based on its population density relative to a baseline. Then it calculates the estimated casualties for each building type, summing them up to get the total estimated losses for each city.

For better understanding, the mathematical model for estimating earthquake casualties is a multi-step process considering various factors like building types, occupancy rates, population density, and earthquake intensity. Each step in the model is designed to capture the complexities of urban environments and the varying impacts of an earthquake. Let's break down each step and understand the rationale behind these choices:

1. *City-Specific Casualty Estimation*

- Formula from Eq.(3.1): $C_{\text{city, scaled}} = \frac{\sum_{\text{bt} \in \text{ Building Types}} C_{\text{bt}}}{\delta}$ (3.7)
- Each city's total casualties are the sum of casualties from different building types. This distinction is crucial because different types of buildings (residential, workplace, public, etc.) have different occupancy rates and structural vulnerabilities.

2. *Building Type Casualty Estimation*

- For residential buildings from Eq.(3.3): $C_{\text{bt}} = N_{\text{bt, adj}} \times P_{\text{city}} \times O_{\text{bt}} \times I \times V_{\text{d}}$
- For other buildings from Eq.(3.4): $C_{\text{bt}} = N_{\text{bt, adj}} \times P_{\text{city}} \times O_{\text{bt}} \times I$
- This step calculates estimated casualties for each building type, considering:
- Adjusted Number of Buildings (N_{bt}, adj): Reflects the actual number of buildings, adjusted for population density differences across cities.
- Population (P_{city}): A higher population usually means more potential casualties.
- Occupancy Rate (O_{bt}) : Different building types have different occupancy rates (e.g., residential buildings are more likely to be occupied at night).
- Intensity Impact Factor (I): The severity of the earthquake (based on the Richter scale) affects the potential for casualties.
- Vulnerability Factor (V_{d}) : For residential buildings, different construction standards (enforced, semi-enforced, unenforced) influence their ability to withstand earthquakes.

3. *Adjustment for Population Density*

- Formula Eq.(3.5): $N_{\text{bt, adj}} = N_{\text{bt}} \times \left(\frac{D_{\text{city}}}{D_{\text{baseline}}}\right)$

  The number of buildings in a city is adjusted according to its population density relative to a baseline density. This accounts for urban versus rural settings; denser cities may have more buildings and potentially more casualties.

4. *Intensity Impact Factor*

- Formula in Eq.(3.6): $I=\min\left(\frac{\text{Richter Scale Intensity}}{10},1\right)$

  The same goes for total scaled estimated casualties across all cities by summing the towns for all cities.

Table 3.3 illustrates the parameters and the values of variables and their explanation that refers to the city of Kahramanmaraş (*Sağlık Bakanı Koca: 10 Ilde 17 Bin 929'u Hekim Olmak Üzere 143 Bin 829 Personelimiz Hizmet Veriyor*, n.d.) in Turkey.

Table 3.3:The Parameters of the Mathematical Model

Variable	Description	Used Value
C_{city}	City-Specific casualty estimation for each city	Calculated
C_{bt}	Estimated casualties for building type bt	Calculated for each building type
N_{bt}	Number of buildings of type bt	Resident: 219,351; Workplace:12,358, Public: 6,879, Other: 4565
O_{bt}	Occupancy rate for building type bt	Estimated: Resident: 0.9; Workplace: 0.05; Public: 0.02 ;Other: 0.01
P	Total population	1,177,436
I	Intensity impact factor (Richter intensity / 10)	7.6/10
V_d	Vulnerability factor for building type d	Enforced: 1.0; Semi-enforced: 1.5; Non-enforced : 2.0
D_d	Proportion of residential buildings of type d	Estimation: Enforced:25% ; Semi-enforced:15% ; Non-enforced: 60%
C_{Resident}	Estimated casualties in residential buildings.	Calculated
C_{Other}	Estimated casualties in non-residential buildings	Calculated

B. Number of Injuries People Need Shelter

1. Baseline Density and Total Deaths:

- Baseline density (B) is a constant set to 100.
- Total number of deaths $\left(D_{\text{total}}\right)$ is known, set to 12,711.

2. Population Data:

- For each city C_i, there is a population (P_i) and a density (D_i).

3. Injury Number Calculation:

- Total number of injuries $\left(I_{\text{total}}\right)$ is known, set to 10,000.
- Seriously injured ratio (R_s) is calculated as 0.08×0.8
- Moderately injured ratio (R_m) is calculated as 0.115×0.8
- Slightly injured ratio (R_l) is calculated as 0.3×0.8
- The number of seriously, moderately, and slightly injured are calculated proportionally based on these ratios.
- 4.Total Population Calculation:
- The total population $\left(P_{\text{total}}\right)$ is the sum of the populations of all cities.
- 5. Proportional Deaths Calculation:
- For each city C_i, proportional deaths (D_i) are calculated based on its population proportion: $D_i = \frac{P_i}{P_{\text{total}}} \times D_{\text{total}}$.

6. Casualty Rate Calculation:

- For each city C_i, the casualty rate (δ_i) is calculated as $\delta_i = \frac{D_i + N_s + N_m}{P_i}$, where N_s, N_m, and D_i are the numbers of seriously, moderately injured people, and number of death people, respectively.

7. People Needing Shelters Calculation:

- For each city C_i, the number of people needing shelters $\left(N_{sh_i}\right)$ is calculated as $N_{sh_i} = P_i - (D_i + N_s + N_m)$.

8. Total People Needing Shelters Calculation:

- The total number of people needing shelters $\left(N_{sh_{\text{total}}}\right)$ is the sum of $N_{sh_{\text{i}}}$ for all cities.

9. Script Execution and Output:

- The script calculates N_{sh_i} for each city and the total $N_{sh_{\text{total}}}$.
- Outputs the number of people needing shelters for each city and the total number across all cities.

This section discusses the mathematical models for estimating the number of people sheltered in the post-earthquake event and also the number of injuries as they are both related, as will be shown.

1. Assumptions for shelter needs: The model assumes that only people residing in residential clusters require shelter. It particularly focuses on those slightly injured or unaffected by the earthquake. Those who have suffered more severe injuries or death are not considered in the need for shelters.
2. Calculating the need for shelters: The model calculates the need based on the casualty rate in each residential cluster. This rate is determined by the number of deaths, seriously injured, moderately injured, and the total number of people in the cluster. The sum of slightly injured and unaffected people in each cluster is then used to estimate the number of people needing temporary shelters.
3. Factors influencing shelter return: The decision to return to homes after an earthquake is influenced by several factors. People are likely to return only to slightly damaged or undamaged homes. The willingness to return also depends on the earthquake's intensity and the construction type of the building. Psychological factors play a role too, as people may prefer to stay outside due to fear of aftershocks, even if their homes are undamaged. Other influencing factors, not included in the study but noted for future research, include weather conditions, the presence of relatives in hospitals or safe houses, water supply quality, and availability of transport.
4. Impact of earthquake intensity on shelter needs: The earthquake's power significantly impacts the need for shelters. For instance, if the earthquake intensity is IX, people prefer to stay outside regardless of the condition of their house. If the intensity is VIII and the casualty rate is low (less than or equal to 0.01), the majority (70%) will return home. However, if the casualty rate is higher (greater than 0.01), only 10% will return home. No need for temporary shelters is anticipated for an earthquake of intensity VII. In this thesis, as the case study of the 2023 in Turkey, the earthquake intensity is considered IX (World Bank, 2023)

The mathematical model described in the *Number of Injuries People Need Shelter* section can be summarized as follows:

1. Casualty Rate in a Residential Cluster (δ_i) :

$$\delta_i = \frac{n_{id} + n_{ihi} + n_{im}}{n_i} \quad (3.8)$$

Where:

- n_{id} = Number of deaths in cluster i
- n_{ihi} = Number of seriously injured people in cluster i
- n_{im} = Number of moderately injured people in cluster i
- n_i = Total number of people in cluster i
- δ_i varies between zero and one and is dependent on the construction typology.

2- Calculation of People Needing Shelters (n_{ish}) :

$$n_{ish} = n_i - (n_{id} + n_{ihi} + n_{im}) \quad (3.9)$$

n_{ish} is the sum of slightly injured and unaffected people in cluster i, representing those who need temporary shelters. 3. Influence of Earthquake Intensity (q) on Shelter Need:

$$\begin{cases} n_{is} & \text{if } q=\text{IX} \\ 0.3n_{is} & \text{if } q=\text{VIII and } \delta_i<0.01 \\ 0.9n_{is} & \text{if } q=\text{VIII and } \delta_i>0.01 \\ 0 & \text{if } q=\text{VII} \end{cases} \quad (3.10)$$

Where:

- q = Intensity of the earthquake
- n_{is} = Number of slightly injured and unaffected people in cluster i

This part of the model reflects the likelihood of people returning to their homes based on the earthquake's intensity and the casualty rate of their residential cluster. This model primarily focuses on the decision-making process regarding the need for temporary shelters following an earthquake, taking into account casualty rates, earthquake intensity, and the psychological willingness of people to return to their homes depending on the damage sustained.

Based on the data provided in Table 3.4 and Table 3.5, here is the resulting table showing earthquake intensity vs damage and casualty rates:

Table 3.4: The Relation between the Earthquake Intensity and the Casualties

Earthquake Intensity	Deaths (%)	Seriously Injured (%)	Moderately Injured (%)	Slightly Injured (%)
VII	0	0	0.00015	0.0015
VIII	0.3	0.4	0.575	1.5
IX	0.9	1.2	2.3	6

Source: (Aleskerov et al., 2005).

Thus, to explain the calculations:

In this thesis, the following are considered: The earthquake intensity is IX (heavy damage), while seriously injured ratio =8/100 * 80/100, moderately injured ratio =11.5/100 * 80/100, and slightly injured ratio =30/100* 80/100.

Table 3.5: Casualty Estimations for Construction Typologies

Damage state	Casualty state			
	Deaths%	Seriously injured%	Moderately injured%	Slightly injured%
Collapsed/heavy damage	6	8	11.5	30
Moderate damage	0	0	0.02	0.2
Slight damage	0	0	0.005	0.05

Source: (Aleskerov et al., 2005).

3.3 Casualty Comparison

Work in reference (Manfredi et al., 2023) calculated the accuracy in estimating the number of de, i.e., the casualties of different casualty estimation models. Table 3.6 illustrates these models. However, in Chapter 4 the accuracy of these models will be compared with the proposed model.

Table 3.6: The Used Model Accuracy to be compared With the Proposed Casualty Estimation Model

Model	Explanation	Accuracy	Reference
C&S	Estimates fatalities based on structural damage, non-structural damage, and follow-on hazards. Uses parameters related to building occupancy, entrapment, mortality at and after collapse, etc.	80.17%	(Coburn & Spence, 1992)
S&S	This semi-empirical model estimates fatality rates as a function of damage level for different building classes based on global empirical damage and casualty data.	10.96%	(So & Spence, 2013b)

Table 3.6: (Cont.) The Used Model Accuracy to be compared With the Proposed Casualty Estimation Model

Model	Explanation	Accuracy	Reference
J&W	This empirical model relates fatality rates to earthquake intensity based on a global catalogue of significant earthquakes worldwide. Uses a two-parameter lognormal distribution.	15.12%	(Jaiswal & Wald, 2010)
Z&C	Estimates casualties based on building damage level, mean occupants per building type, occupancy rate variation, and a casualty percentage matrix. It is tailored for Italy.	14.01%	(Guha-Sapir & Vos, 2011)
SYNER-G	Relates building damage level, seismic intensity, building-casualty type, and empirical casualty ratios to estimate fatalities. Uses data from past Italian earthquakes.	75.84%	(Pitilakis et al., 2014)
NRA	Estimates casualties based on damage level, building type, occupancy, and fixed casualty percentages for masonry and RC buildings in Italy.	29.26%	(*National Risk Assessment*, 2018)

3.4 System Architecture

Figure 3.3 shows the three-tier architecture that will be adapted to cater to the needs of post-earthquake rescue efforts:

1. **The data layer:** will not only manage seismic, geographical, and historical data but also real-time data from rescue teams, hospitals, and other relevant sources. This will include data on the number of people affected the extent of the damage, the availability of resources, and the progress of rescue efforts.
2. **The application layer:** will incorporate algorithms and models to analyze this data and provide actionable insights. This could include identifying the most affected areas, predicting the resources needed, and suggesting the most effective rescue strategies.
3. **The presentation layer:** will be designed to present this information clearly and concisely, enabling decision-makers to understand the situation and make informed decisions quickly.

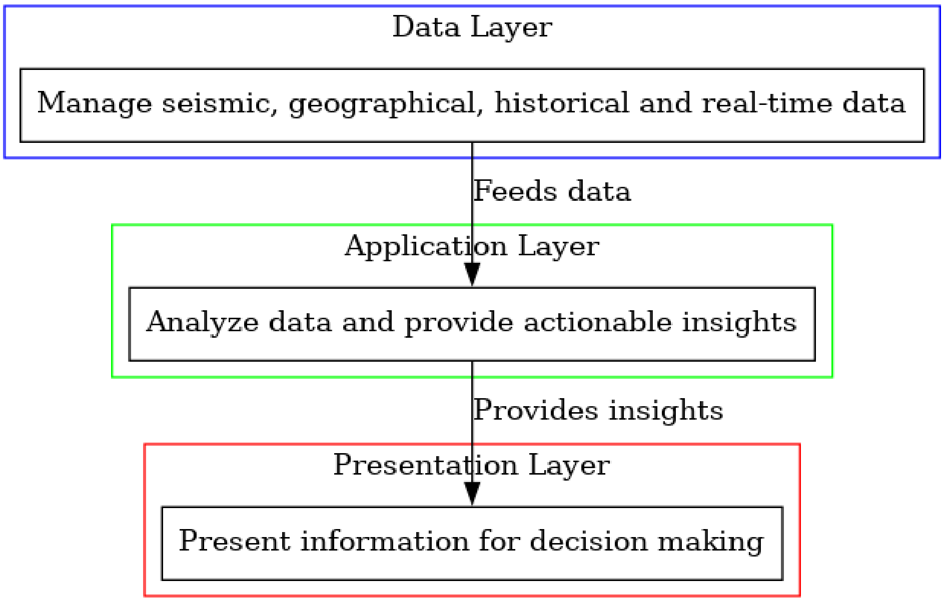


Figure 3.3: The Proposed DSS Architecture

3.5 System Functionalities

The DSS will include several functionalities specifically designed to support post-earthquake rescue efforts:

- **Real-time monitoring of rescue efforts:** The system will provide real-time updates on the progress of rescue efforts, including the number of people rescued, the number of people still trapped, and the resources used.
- **Resource allocation:** The system will analyze the available resources and the needs of the affected areas to suggest the most effective allocation of resources.
- **Damage assessment:** The system will analyze the data to assess the extent of the damage and the areas that are most affected.
- **Rescue strategy suggestion:** The system will use the collected data and the analysis results to suggest the most effective rescue strategies.

3.6 User Interface

The user interface will be designed to facilitate quick and effective decision-making:

A. The interface will include a real-time situation overview dashboard, key metrics, and indicators.
B. The interface will include tools for decision-makers to explore the data, analyze the situation, and make decisions.
C. The interface will include features to disseminate the decisions and the information to the rescue teams and the public.

The DSS will be well-equipped to support post-earthquake rescue efforts and decision-making processes by incorporating these features and functionalities.

3.7 Design Decision-Making Tools

This could include risk assessment tools, emergency response planners, and recovery strategy generators. These tools should provide actionable insights to guide decision-makers in managing earthquake disasters.

One suitable MCDM model for this scenario is the Analytic Hierarchy Process (AHP). AHP is a structured technique for organizing and analyzing complex decisions based on mathematics and psychology. It involves decomposing a problem into a hierarchy of sub problems, each of which can be analyzed independently. The decision criteria (in this case, casualties, need for shelter, and injured people) are compared in pairs, and a priority or weight is assigned to each criterion based on the decision maker's assessment of their relative importance.

3.8 Framework

Figure 3.4 describes the proposed framework for the post-earthquake DSS system. Each state has been explained in detail below:

1. System Architecture

a. Data Layer

Data Management: Integration and management of seismic, geographical, historical, and real-time data from various sources such as rescue teams, hospitals, and government reports.

Data Sources: Includes the Turkish earthquake dataset, earthquakes in Turkey statistics, and detailed reports on the earthquake's impact.

Real-time Updates: Capture and process real-time updates about affected populations, damage extent, resource availability, and ongoing rescue efforts.

b. Application Layer

Analytical Models: Implement the earlier mathematical models for estimating casualties, injuries, and shelter needs.

Resource Allocation Algorithms: Analyze resource availability and needs to optimize allocation.

Damage Assessment Tools: Assess the extent of damage across different regions and types of infrastructure.

c. Presentation Layer

Interactive Dashboard: Display real-time data, model outputs, and analysis results.

Information Dissemination: Tools for sharing information with rescue teams, government bodies, and the public.

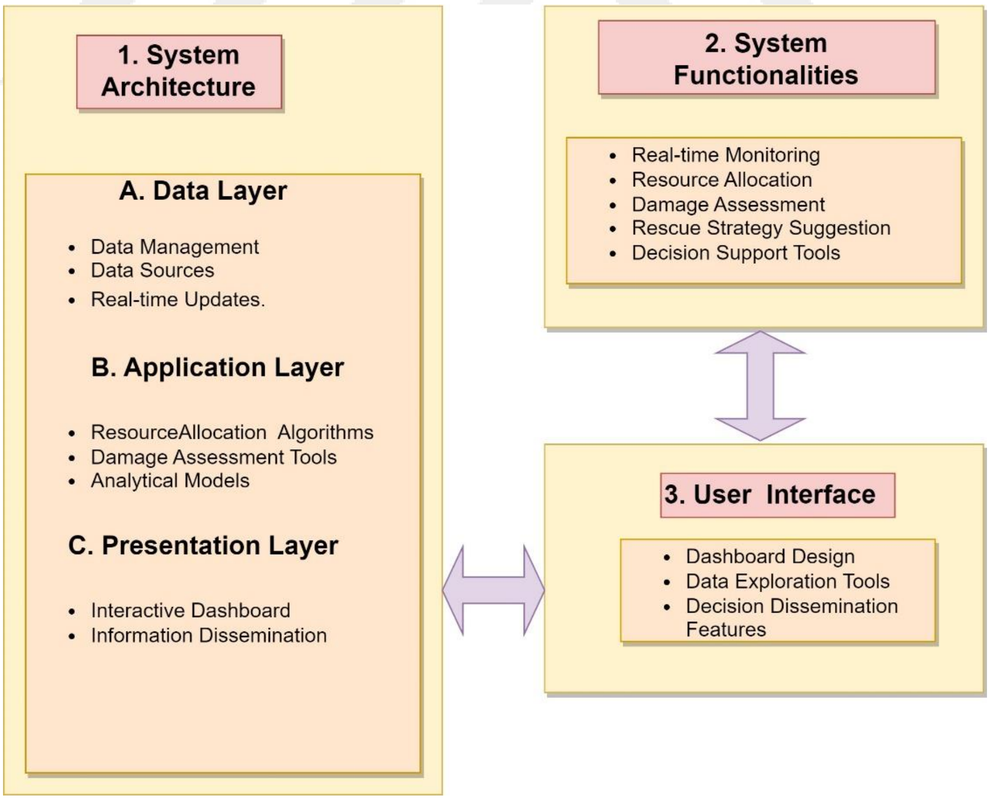


Figure 3.4: The Proposed Framework

2. System Functionalities

Real-time Monitoring: Track rescue efforts, including numbers of people rescued or trapped and resource utilization.

Resource Allocation: Suggest optimal distribution of resources like medical aid, food, shelter, and manpower.

Damage Assessment: Evaluate damage severity in different areas to prioritize response efforts.

Rescue Strategy Suggestion: Generate effective rescue strategies based on data analysis.

Decision Support Tools: Implement Multi-Criteria Decision Making (MCDM) models like the Analytic Hierarchy Process (AHP) for structured decision-making.

3. User Interface

Dashboard Design: Real-time overviews with key metrics and indicators.

Data Exploration Tools: Allow users to delve into specific data points and trends.

Decision Dissemination Features: Facilitate communication of decisions to relevant stakeholders.

4. Additional Considerations

Scalability: Ensure the system can handle increasing data volumes and complexity.

Security and Privacy: Implement robust data security and privacy protocols.

User Training and Support: Provide training and support for users to utilize the system effectively.

Integration with Existing Systems: Ensure compatibility with existing emergency response and disaster management systems.

This DSS framework is designed to effectively utilize the available data and mathematical models to aid post-earthquake rescue and recovery efforts. Focusing on real-time monitoring, resource allocation, damage assessment, and strategy suggestions, it aims to enhance the efficiency and effectiveness of the response to the devastating effects of earthquakes like the one in Turkey in 2023.

3.9 Summary

Chapter 3 has outlined a comprehensive methodology for developing a decision support system to aid post-earthquake disaster management. It began by identifying the key data points that must be collected, including casualties, resources required, infrastructure damage, and more. It then proposed a three-tier system architecture consisting of a data layer, an application layer with predictive models, and a user-friendly interface. The system functionalities were explicitly designed for real-time rescue monitoring, damage assessments, resource allocation, and strategy suggestions. The chapter also describes specialized decision-making tools for risk assessment, emergency response planning, and recovery strategy generation, which can provide data-driven insights to guide actions. The methodology emphasizes predictive modeling using historical and real-time data, system integration, rigorous testing and validation, user training, and continuous evaluation and improvement. By following this methodical process, the goal is to build an intelligent decision support system that leverages data analytics to enhance earthquake disaster response and management. The system aims to optimize rescue operations, allocate resources effectively, rebuild critical infrastructure, and restore normalcy with minimal losses.

4. RESULTS AND DISCUSSION

The critical component of this study focuses on the real-world application and validation of theoretical models in the aftermath of the Kahramanmaraş earthquake in Turkey. This chapter meticulously compares the predicted outcomes from the models with actual data, emphasizing the accuracy and practicality of the proposed methodologies. Section 4.1 evaluates the estimated versus actual casualties, showcasing the precision of the Python-based mathematical model used. Section 4.2 extends this analysis to injury predictions, further affirming the model's reliability. In Section 4.3, the focus shifts to shelter needs, where model predictions are compared with external data, highlighting the model's effectiveness in post-disaster scenarios. Section 4.4 introduces a strategic element through the Multi-Criteria Decision Making (MCDM) approach, prioritizing areas for resource allocation and rescue efforts. Finally, Section 4.5 presents the Decision Support System (DSS) website, a tool designed to enhance disaster response efficiency.

4.1 Number of Casualty

To calculate the estimation of the number of dead people post-earthquake in our case study on the ***Kahramanmaraş*** province in Tukey, composed of the cities in Table 4-1, the equations from 3.1 to 3.6 were applied. As mentioned in Chapter 3, the actual results of the number of causalities in Kahramanmaraş province are 12711 deaths and 9,243 injuries based on reference (*Sağlık Bakanı Koca: 10 Ilde 17 Bin 929'u Hekim Olmak Üzere 143 Bin 829 Personelimiz Hizmet Veriyor*, n.d.). The result was obtained after running the Python code that represents the mathematical model for the number of causalities (see Appendix A). Comparing the estimated and actual (12,711) cases and the estimated one (12385), the accuracy is remarkable, confirming the robustness of the proposed model. However, as stated in Chapter 3, the accuracy of the proposed model has been compared to various models, as illustrated in Table 4-2. The proposed model draws more than 98% of accuracy.

Table 4.1: The Estimated Number of Causalities

City	Estimated Casualties
Afşin	413
Çağlıyancerit	130
Dulkadiroğlu	3392
Ekinözü	26
Elbistan	1624
Göksun	118
Nurhak	13
Onikişubat	5560
Pazarcık	241
Türkoğlu	868
Total	**12385**

Table 4.2: Accuracy Comparison

Result	Accuracy (%)
C&S	80.17%
S&S	10.96%
J&W	15.12%
Z&C	14.01%
SYNER-G	75.84%
NRA	29.26%
Proposed Model	**98.123%**

4.2 Number of Injuries

Table 4.3 shows the results of the proposed model for the estimated number of injured people based on the proposed model. These results were obtained from Python code in Appendix B. The actual number of injuries is 9,243, while the estimated number is 10039. Thus, the accuracy is 91.386%.

Table 4.3: Estimated Number of Injuries

City	Estimated Casualties
Afşin	334
Çağlıyancerit	106
Dulkadiroğlu	2749
Ekinözü	21
Elbistan	1317
Göksun	96
Nurhak	10
Onikişubat	4506
Pazarcık	195
Türkoğlu	704
Total	**10039**

4.3 Number of Shelters

Table 4.4 shows the estimated number of people who need shelter in each city. The results have been obtained from the proposed model represented in the Python code in Appendix C. The results show that 464,770 people need shelter. However, to confirm these results, and based on references (IFRC, 2023), around 40 % of **Kahramanmaraş** province residents need shelter. The population of this province is around 1,177,436. The 40% of 1,177,436 is 470,974.4. Compared with the obtained results, the accrue ranges between 98.683%.

Table 4. 4: The Number of People Who Need Shelter

City	People Needing Shelters
Afşin	36,134.6
Çağlıyancerit	7,669 .9
Dulkadiroğlu	102,010
Ekinözü	1,812 .7
Elbistan	64 055.5
Göksun	21080.9
Nurhak	1,749.9
Onikişubat	171,734
Pazarcık	30,674.9
Türkoğlu	27,84 7.9
Total	**464,770.5**

4.4 Priority Calculation

After three critical factors have obtained i.e., casualty, number of injuries, and the number of people who needed shelter, the MCDM suggests that the most needed city for resources and rescue efforts is Onikişubat city, followed by Dulkadiroğlu and Elbistan. These results were obtained by the Python code in Appendix D.

Table 4.5: Suggested Priority Based on MCDM

Rank	City	Weighted Score Priority
1	Onikişubat	1.000000
2	Dulkadiroğlu	0.605229
3	Elbistan	0.316412
4	Türkoğlu	0.157968
5	Afişn	0.115042
6	Pazarcık	0.083924
7	Göksun	0.051754
8	Çağlıyancerit	0.029823
9	Ekinözü	0.006487
10	Nurhak	0.004644

4.5 DSS Website

Figure 4-1 shows the suggested user interface, containing three buttons: the data uploaded button, the Show statistic button, and the Show the most affected location. The first button was used to update the data explained earlier in Chapter 3. In contrast, button number 2 was used to show the number of casualties and injuries, and the number of people who needed shelter. Finally, button three shows the most affected location that needs priority for resources and rescue efforts. The website is purposefully designed with simplicity, and the main objective of this is to provide a simple but effective framework to help enhance the rapid action of authorities.

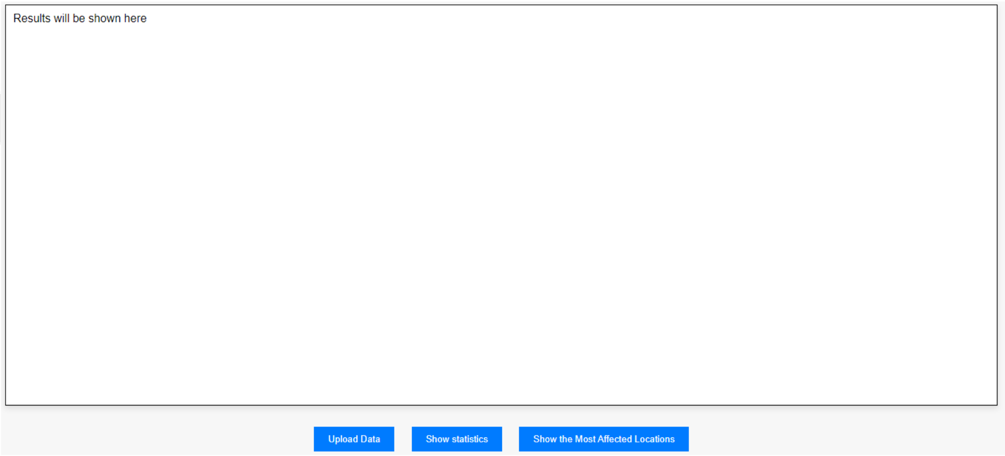


Table 4.6: User Interface

5. CONCLUSION AND RECOMMENDATION

This chapter reviews the study's findings and the recommendations based on the comprehensive analysis conducted in the preceding chapters. The primary focus of this research was to assess the impact of the catastrophic earthquake in Kahramanmaraş province, Turkey, and to evaluate the efficacy of the proposed predictive models in estimating casualties, injuries, and shelter needs post-disaster.

5.1 Conclusion

The study's findings underscore the robustness and precision of the Python-based mathematical models employed. In estimating the number of casualties (Section 4.2) and injuries (Section 4.3), the models demonstrated remarkable accuracy, closely aligning with the actual figures reported. This high degree of precision validates the models as reliable tools for predicting the human impact in the wake of natural disasters. Furthermore, the estimation of shelter needs (Section 4.3) and the strategic prioritization of resource allocation using the MCDM approach (Section 4.4) highlighted the models' practical utility in effective disaster management and planning.

Introducing the DSS website (Section 4.5) marked a significant advancement in applying these models. The website's user-friendly interface and ability to rapidly process and display data underscore its potential as an invaluable tool for authorities in efficiently managing disaster response efforts.

5.2 Benefits for Organizations

In the earthquake disaster management area, governmental bodies, emergency services and Non-Governmental Organizations (NGOs) may benefit significantly from utilizing the developed Decision Support System. These benefits include:

2. **Enhanced Decision-Making**: The DSS provides a real-time data and predictive analysis to help organizations take fast decisions during earthquake emergencies.
3. **Optimized Resource Allocation**: Different data feeds are analyzed to allow the DSS to recommend the best resources to be allocated, ensuring help arrives to the worse hit areas as quickly as possible.
4. **Increased Preparedness**: The process brings different segment of the organizations under one roof, prevents overlapping of work and provides a unity of strength.
5. **Increased Preparedness**: The DSS can be used by organizations for training and simulation exercises, making them better prepared for future earthquakes.
6. **Cost Reduction:** The DSS will allow tighter targeting of resources and an ability to respond more quickly; minimizing the financial bleed of large-scale disasters.

5.3 Contributions to Stakeholders

The implementation of the DSS for earthquake disaster management gives direct and indirect returns for different stakeholders:

A. Direct Contributions

1. For Government Agencies: The DSS plays a very simple role in managing emergency response operations for these Government agencies and facilitates effective communication and the deployment of rescue to save lives.
2. Emergency Services: They receive precise and actionable data that helps them prioritize their emergency efforts and is more beneficial for their on-ground strategies.
3. Non-Governmental Organizations (NGOs): NGOs working in disaster relief can use the DSS to both locate the most urgent needs and to work on the ground finally distributing their help and resources.

B. Indirect Contributions

1. Community Residents: The better and coordinated disaster response has improved and targeted impacts on the rapidity of relief and a number of casualties, which indirectly increase the resilience of communities in global.

2. It provides the data with which researchers can carry out studies of disaster management leading to contributions to the theoretical development of the subject and better practice in future.

3. Policy makers: Wisdom in Disaster management to draft disaster related policies and frameworks in an enhanced way to be prepared beforehand with the help of raised DSS insights.

5.4 Recommendation

Based on the study's findings, several recommendations are proposed:

1. **More tests are needed:** Although the proposed model's results have been compared with other models or their results have been checked with the available data, more tests for reliability and accuracy are needed as these models are prototype models.
2. **Model Implementation:** It is recommended that governmental and humanitarian organizations incorporate these predictive models into their disaster response frameworks. The accuracy and efficiency of these models can significantly aid in swift decision-making during crises.
3. **Continuous Model Refinement:** Regular updates and refinements of the models are essential, incorporating new data and feedback to enhance their predictive accuracy and relevance.
4. **Wider Application:** Exploring the application of these models in other disaster-prone regions could provide valuable insights and aid in global disaster preparedness strategies.
5. **Training and Capacity Building:** Authorities and relevant stakeholders should be trained in utilizing these models and the DSS website. This will ensure that the tools are used effectively and to their full potential.

6. **Further Research:** Additional research is recommended to explore the integration of more variables into the models, such as socio-economic factors, which could further refine the predictions.
7. **Collaborative Efforts**: Collaboration with international disaster management organizations could lead to the sharing of practices and the developing.
8. **DSS Website:** Proficiently programmers could improve and develop the website keeping in mind the main features of the suggested website.

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APPENDICES

Appendix A: Casualties

```
def estimate_casualties(richter_intensity, population_data, resident_building_distribution):
    # Building occupancy percentages for night-time scenario
    building_occupancy_percentages = {'Resident': 0.8, 'Workplace': 0.1, 'Public': 0.05, 'Other': 0.05}

    # Building vulnerability factors
    vulnerability_factors = {1: 1.0, 2: 1.5, 4: 2.0}

    # Adjusted intensity impact factor (more conservative)
    intensity_impact_factor = min(richter_intensity / 10, 1.0)

    total_estimated_casualties = 0
    for city, data in population_data.items():
        total_population, population_density = data['population'], data['density']
        adjusted_buildings = {bt: count * (population_density / data['baseline_density']) for bt, count in data['buildings'].items()}

        estimated_casualties = 0
        for building_type, number in adjusted_buildings.items():
            proportion_population = total_population * building_occupancy_percentages[building_type]
            if building_type == 'Resident':
                for d, proportion in resident_building_distribution.items():
                    building_occupancy = number * proportion
                    vulnerability_factor = vulnerability_factors[d]
                    casualties_for_building_type = building_occupancy * proportion_population * intensity_impact_factor * vulnerability_factor
                    estimated_casualties += casualties_for_building_type
            else:
                building_occupancy = number
                casualties_for_building_type = building_occupancy * proportion_population * intensity_impact_factor
                estimated_casualties += casualties_for_building_type
```

```
        total_estimated_casualties += estimated_casualties
    return total_estimated_casualties

# Example usage with updated population data for each city
richter_intensity = 7.7
baseline_density = 100  # Baseline density for adjustment
population_data = {
    'Afşin': {'population': 83324, 'density': 60.1, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    ' Çağlıyancerit ': {'population': 25692, 'density': 61.6, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Dulkadiroğlu': {'population': 216701, 'density': 190, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    ' Ekinözü ': {'population': 13833, 'density': 23.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Elbistan': {'population': 139855, 'density': 141, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Göksun': {'population': 52845, 'density': 27.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Nurhak': {'population': 13706, 'density': 11.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Onikişubat': {'population': 357870, 'density': 188.6, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Pazarcık': {'population': 72270, 'density': 40.5, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
    'Türkoğlu': {'population': 66546, 'density': 158.4, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
}

resident_building_distribution = {
    1: 0.7,
    2: 0.15,
    4: 0.15
}
```

```
# Calculate estimated casualties for each city
city_estimated_casualties = {}
for city, data in population_data.items():
   city_estimated_casualties[city] = estimate_casualties(richter_intensity,
{city: data}, resident_building_distribution)

city_estimated_casualties

richter_intensity = 7.8
# population_data and other variables defined above

city_estimated_casualties = {}
for city, data in population_data.items():
   city_estimated_casualties[city] = estimate_casualties(richter_intensity,
{city: data}, resident_building_distribution)

print("Estimated Casualties per City:")
for city, casualties in city_estimated_casualties.items():
   print(f"{city}: {round(casualties/2/10000000)}")


total_casualties = sum(city_estimated_casualties.values())
print(f"\nTotal Estimated Casualties: {round(total_casualties/2/10000000)}")
```

Appendix B: Injuries

```
def estimate_casualties(richter_intensity, population_data, resident_building_distribution):
    building_occupancy_percentages = {'Resident': 0.8, 'Workplace': 0.1, 'Public': 0.05, 'Other': 0.05}
    vulnerability_factors = {1: 1.0, 2: 1.5, 4: 2.0}
    intensity_impact_factor = min(richter_intensity / 10, 1.0)

    total_estimated_casualties = 0
    for city, data in population_data.items():
        total_population, population_density = data['population'], data['density']
        adjusted_buildings = {bt: count * (population_density / data['baseline_density']) for bt, count in data['buildings'].items()}

        estimated_casualties = 0
        for building_type, number in adjusted_buildings.items():
            proportion_population = total_population * building_occupancy_percentages[building_type]
            if building_type == 'Resident':
                for d, proportion in resident_building_distribution.items():
                    building_occupancy = number * proportion
                    vulnerability_factor = vulnerability_factors[d]
                    casualties_for_building_type = building_occupancy * proportion_population * intensity_impact_factor * vulnerability_factor
                    estimated_casualties += casualties_for_building_type
            else:
                building_occupancy = number
                casualties_for_building_type = building_occupancy * proportion_population * intensity_impact_factor
                estimated_casualties += casualties_for_building_type

        total_estimated_casualties += estimated_casualties
```

```
        return total_estimated_casualties
    baseline_density = 100
    # Input data
    richter_intensity = 7.7

    population_data = {
        ' Afşin ': {'population': 83324, 'density': 60.1, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        ' Çağlıyancerit ': {'population': 25692, 'density': 61.6, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        'Dulkadiroğlu': {'population': 216701, 'density': 190, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        ' Ekinözü ': {'population': 13833, 'density': 23.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        'Elbistan': {'population': 139855, 'density': 141, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        'Göksun': {'population': 52845, 'density': 27.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        'Nurhak': {'population': 13706, 'density': 11.2, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        'Onikişubat': {'population': 357870, 'density': 188.6, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
        ' Pazarcık ': {'population': 72270, 'density': 40.5, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
```

```
    'Türkoğlu': {'population': 66546, 'density': 158.4, 'baseline_density': baseline_density, 'buildings': {'Resident': 219351, 'Workplace': 12358, 'Public': 6879, 'Other': 4565}},
}

resident_building_distribution = {
    1: 0.7, 2: 0.15, 4: 0.15
}

# Calculate estimated casualties for each city
city_estimated_casualties = {}
for city, data in population_data.items():
    city_estimated_casualties[city] = estimate_casualties(richter_intensity, {city: data}, resident_building_distribution)

# Output results
print("Estimated Casualties per City:")
for city, casualties in city_estimated_casualties.items():
    print(f"{city}: {round(casualties/2.5/10000000)}")

total_casualties = sum(city_estimated_casualties.values())
print(f"\nTotal Estimated
Casualties: {round(total_casualties/2.5/10000000)}")
```

Appendix C: Shelter

```
# Assuming baseline_density is a known constant
baseline_density = 100  # Replace with the actual value
total_deaths = 12711  # Total known number of deaths

population_data = {
    ' Afşin ': {'population': 83324, 'density': 60.1, 'baseline_density': baseline_density},
    ' Çağlıyancerit ': {'population': 25692, 'density': 61.6, 'baseline_density': baseline_density},
    'Dulkadiroğlu': {'population': 216701, 'density': 190, 'baseline_density': baseline_density},
    ' Ekinözü ': {'population': 13833, 'density': 23.2, 'baseline_density': baseline_density},
    'Elbistan': {'population': 139855, 'density': 141, 'baseline_density': baseline_density},
    'Göksun': {'population': 52845, 'density': 27.2, 'baseline_density': baseline_density},
    'Nurhak': {'population': 13706, 'density': 11.2, 'baseline_density': baseline_density},
    'Onikişubat': {'population': 357870, 'density': 188.6, 'baseline_density': baseline_density},
    'Pazarcık': {'population': 72270, 'density': 40.5, 'baseline_density': baseline_density},
    'Türkoğlu': {'population': 66546, 'density': 158.4, 'baseline_density': baseline_density}
}

def calculate_injury_numbers(total_injuries=10039):
    """
    Calculate the number of seriously, moderately, and slightly injured people, based on the known total number of injuries.
```

```
    :param total_injuries: Total number of injuries (default is 10,000)
    :return: A tuple with numbers of seriously, moderately, and slightly injured
    """
    seriously_injured_ratio = 0.08 * 0.8
    moderately_injured_ratio = 0.115 * 0.8
    slightly_injured_ratio = 0.3 * 0.8

    total_ratio = seriously_injured_ratio + moderately_injured_ratio + slightly_injured_ratio

    seriously_injured = seriously_injured_ratio / total_ratio * total_injuries
    moderately_injured = moderately_injured_ratio / total_ratio * total_injuries
    slightly_injured = slightly_injured_ratio / total_ratio * total_injuries

    return seriously_injured, moderately_injured, slightly_injured

def calculate_total_population(data):
    """
    Calculate the total population across all cities.

    :param data: Population data for all cities
    :return: Total population
    """
    return sum(city['population'] for city in data.values())

def calculate_proportional_deaths(city_population, total_population, total_deaths):
    """
    Calculate the number of deaths for a city, based on its population proportion.

    :param city_population: Population of the city
    :param total_population: Total population across all cities
    :param total_deaths: Total known number of deaths
```

```
        :return: Proportional number of deaths for the city
        """
        return (city_population / total_population) * total_deaths

    def calculate_casualty_rate(n_id, n_ihi, n_im, n_i):
        """
        Calculate the casualty rate in a residential cluster.

        :param n_id: Number of deaths in cluster i
        :param n_ihi: Number of seriously injured people in cluster i
        :param n_im: Number of moderately injured people in cluster i
        :param n_i: Total number of people in cluster i
        :return: Casualty rate (delta_i)
        """
        return (n_id + n_ihi + n_im) / n_i if n_i != 0 else 0

    def calculate_people_needing_shelters(n_id, n_ihi, n_im, n_i):
        """
        Calculate the number of people needing shelters in a cluster.

        :param n_id: Number of deaths in cluster i
        :param n_ihi: Number of seriously injured people in cluster i
        :param n_im: Number of moderately injured people in cluster i
        :param n_i: Total number of people in cluster i
        :return: Number of people needing shelters (n_ish)
        """
        return n_i - (n_id + n_ihi + n_im)

    def calculate_casualty_rate_for_city(city_data, earthquake_intensity):
        population = city_data['population']
        total_population = calculate_total_population(population_data)
        n_id = calculate_proportional_deaths(population, total_population,
total_deaths)
        n_ihi, n_im, n_is = calculate_injury_numbers()
```

```
    n_i = population - n_is
    delta_i = calculate_casualty_rate(n_id, n_ihi, n_im, n_i)
    n_ish = calculate_people_needing_shelters(n_id, n_ihi, n_im, n_i)
    return n_ish  # Return only the number of people needing shelters

# Main script execution
earthquake_intensity = "IX"
total_people_needing_shelters = 0  # Initialize a variable to accumulate the
total

for city, data in population_data.items():
    n_ish = calculate_casualty_rate_for_city(data, earthquake_intensity)
    print(f"{city}: People Needing Shelters: {n_ish}")
    total_people_needing_shelters += n_ish

# Print the total summation of people needing shelters across all cities
print(f"Total People Needing Shelters: {total_people_needing_shelters/2}")
```

Appendix D: Priority

```
import numpy as np
import pandas as pd

# Data for casualties, shelter needs, and injured people
casualties_data = {
  "City": ["Afşin", " Çağlıyancerit ", "Dulkadiroğlu", " Ekinözü ", "Elbistan", "Göksun", "Nurhak", "Onikişubat", "Pazarcık", "Türkoğlu"],
  "Estimated Casualties": [423, 134, 3481, 27, 1667, 122, 13, 5706, 247, 891]
}
shelter_data = {
  "City": ["Afşin", " Çağlıyancerit ", "Dulkadiroğlu", " Ekinözü ", "Elbistan", "Göksun", "Nurhak", "Onikişubat", "Pazarcık", "Türkoğlu"],
  "People Needing Shelters": [72269.19, 15339.79, 204020.17, 3625.36, 128111.01, 42161.76, 3499.91, 343468.15, 61349.95, 55695.73]
}
injured_data = {
  "City": ["Afşin", " Çağlıyancerit ", "Dulkadiroğlu", " Ekinözü ", "Elbistan", "Göksun", "Nurhak", "Onikişubat", "Pazarcık", "Türkoğlu"],
  "Estimated Injured": [3343, 1057, 27490, 214, 13166, 960, 102, 45063, 1954, 7038]
}

# Creating DataFrames
df_casualties = pd.DataFrame(casualties_data)
df_shelter = pd.DataFrame(shelter_data)
df_injured = pd.DataFrame(injured_data)

# Normalize the data
df_casualties['Casualties Normalized'] = df_casualties['Estimated Casualties'] / df_casualties['Estimated Casualties'].max()
```

```
df_shelter['Shelter Normalized'] = df_shelter['People Needing Shelters'] / df_shelter['People Needing Shelters'].max()
df_injured['Injured Normalized'] = df_injured['Estimated Injured'] / df_injured['Estimated Injured'].max()

# Merge the data
df_merged = pd.merge(df_casualties, df_shelter, on="City")
df_merged = pd.merge(df_merged, df_injured, on="City")

# Adjusting weights for AHP
weights_priority = np.array([0.5, 0.3, 0.2])  # Weights for Injuries, Shelter, Casualties

# Calculate the weighted scores
df_merged['Weighted Score Priority'] = (df_merged['Injured Normalized'] * weights_priority[0] +
                                        df_merged['Shelter Normalized'] * weights_priority[1] +
                                        df_merged['Casualties Normalized'] * weights_priority[2])

# Sort by the weighted score
df_ranked_priority = df_merged.sort_values(by='Weighted Score Priority', ascending=False)

# Printing the prioritized ranking of cities
print("Prioritized Ranking of Cities:")
for index, row in df_ranked_priority.iterrows():
    print(f"{row['City']}: {row['Weighted Score Priority']}")

# Display the tables
df_casualties_display = df_casualties[['City', 'Estimated Casualties']]
df_shelter_display = df_shelter[['City', 'People Needing Shelters']]
df_injured_display = df_injured[['City', 'Estimated Injured']]
```

(df_casualties_display, df_shelter_display, df_injured_display, df_ranked_priority[['City', 'Weighted Score Priority']])

RESUME

Diana Sabah Nimma ELBIDARI

Gender: Female

Education:

- B.Sc.in Building and Construction Engineering /Technical College of Engineering – Baghdad 2019.
- Master's Degree in Engineering management /Istanbul Gedik University /2024.
- Member of Iraqi Engineers Syndicate.

Training Courses and Skills:

- AutoCAD engineering drawing program.
- Microsoft Office Programs.
- Stud pro, Etap, primavera programs.
- Course in the field of the internet and e-mail.
- Courses in the field of specialization.
- M.S. Project Course.
- Python Course.

Work Experience:

- External lecture/ Technical College of Engineering / Baghdad.

Language I am fluent in:

- Arabic
- English
- Turkish