Evaluating Earthquake-Related Research and Innovation under Multidimensional Risk Components: A Cross-Country Data Envelopment Analysis

by

Ayşe Duman

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Koç University
Graduate School of Sciences and Engineering

This is to certify that I have examined this copy of a master's thesis by

Ayşe Duman

and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
examining committee have been made.

Committee Members:

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Prof. Sibel Salman (Advisor)

____
Assoc. Prof. Dilek Günneç Danış

____
Assist. Prof. Kübra Tanınmış Ersüs

Date: ________________________

To my family, for their endless patience, unwavering support, and constant belief in me throughout my academic journey, and to my advisors, Prof. Sibel Salman, Prof. Fikri Karaesmen, and Prof. Nesim Erkip, for their guidance and support.

ABSTRACT

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This thesis examines earthquake risk, scientific research activity, technological innovation, and post-disaster human and economic impacts using an integrated empirical framework based on Data Envelopment Analysis (DEA), descriptive statistics, and regression methods. The study relies on a multi-source dataset covering the period 2000–2025 and focuses on twelve earthquake-prone countries: China, France, Greece, India, Iran, Italy, Japan, New Zealand, South Korea, Taiwan, Türkiye, and the United States. These countries account for approximately 78% of global earthquake-related scientific publications and about 47% of reported global earthquake events. Results indicate that post-disaster human and economic losses are primarily driven by earthquake magnitude and frequency. In contrast, vulnerability and lack of coping capacity significantly constrain scientific publication and patent activity. To assess how effectively countries transform disaster-related risk conditions into earthquake-related scientific outcomes, the study applies a radial, multi-input–multi-output DEA framework using both CCR (constant returns to scale) and BCC (variable returns to scale) models. The findings show that countries with lower disaster-related risk achieve higher efficiency by sustaining comparable scientific output with fewer risk-related inputs. Overall, the findings highlight the importance of integrated research and innovation policies that not only respond to major earthquake events but also address the underlying vulnerability and coping capacity constraints in order to enhance the efficiency and sustainability of earthquake-related scientific production.

ÖZETÇE

Yüksek Lisans Tez Başlığı
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Bu tez, deprem riski, bilimsel araştırma faaliyetleri, teknolojik yenilik ve deprem sonrası insani ve ekonomik etkileri; Veri Zarflama Analizi (Data Envelopment Analysis, DEA), betimleyici istatistikler ve regresyon yöntemlerine dayalı bütüncül bir ampirik çerçeve kapsamında incelemektedir. Çalışma, 2000–2025 dönemini kapsayan çok kaynaklı bir veri setine dayanmaktadır ve Çin, Fransa, Yunanistan, Hindistan, İran, İtalya, Japonya, Yeni Zelanda, Güney Kore, Tayvan, Türkiye ve Amerika Birleşik Devletleri olmak üzere on iki deprem riski yüksek ülkeye odaklanmaktadır. Bu ülkeler, küresel depremle ilişkili bilimsel yayınların yaklaşık %78'ini ve bildirilen küresel deprem olaylarının yaklaşık %47'sini oluşturmaktadır. Elde edilen bulgular, deprem sonrası insani ve ekonomik kayıpların temel olarak deprem büyüklüğü ve sıklığı tarafından belirlendiğini göstermektedir. Buna karşılık, kırılganlık ve baş etme kapasitesindeki yetersizlikler, bilimsel yayın ve patent üretimini önemli ölçüde sınırlandırmaktadır. Ülkelerin afetle ilişkili risk koşullarını depremle ilgili bilimsel çıktılara ne ölçüde etkin biçimde dönüştürebildiklerini değerlendirmek amacıyla, sabit getiri varsayımına dayalı CCR ve değişken getiri varsayımına dayalı BCC modellerini içeren, radyal, çok girdili–çok çıktılı bir DEA çerçevesi uygulanmıştır. Bulgular, afetle ilişkili risk düzeyi daha düşük olan ülkelerin, daha az risk girdisiyle karşılaştırılabilir bilimsel çıktı düzeylerini sürdürebilerek daha yüksek etkinlik elde ettiğini ortaya koymaktadır. Genel olarak sonuçlar, yalnızca büyük deprem olaylarına tepki vermeyi değil, aynı zamanda altta yatan kırılganlık ve baş etme kapasitesi kısıtlarını da ele alan bütüncül araştırma ve yenilik politikalarının, depremle ilişkili bilimsel üretimin etkinliğini ve sürdürülebilirliğini artırmada kritik bir rol oynadığını vurgulamaktadır.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

AI	Activity Index
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CCR	Charnes–Cooper–Rhodes Model
BCC	Banker–Charnes–Cooper Model
CPI	Consumer Price Index
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
EM-DAT	Emergency Events Database
NOAA	National Oceanic and Atmospheric Administration
F-test	Fisher Test for Overall Model Significance
GDP	Gross Domestic Product
HC3	Heteroskedasticity-Consistent Covariance Estimator (Type 3)
INFORM	Index for Risk Management
OLS	Ordinary Least Squares
R&D	Research and Development
RTS	Returns to Scale
VRS	Variable Returns to Scale

Chapter 1

INTRODUCTION

Earthquakes are among the most destructive natural hazards, causing substantial human, economic, and social losses worldwide. Beyond their immediate physical impacts, earthquakes also pose long-term challenges in risk management, scientific knowledge production, and technological innovation. Countries exposed to similar levels of seismic risk often experience markedly different outcomes in terms of disaster losses, research activity, and innovation performance, suggesting that exposure alone does not fully explain these differences.

The existing literature on earthquakes can be broadly grouped into three main strands. The first strand focuses on disaster risk and impact assessment, examining human and economic losses in relation to earthquake magnitude, exposure, and vulnerability. The second strand examines scientific research on earthquakes, using publication data to analyze research productivity, collaboration patterns, and thematic evolution. The third strand examines technological innovation, often through patent data, to assess the development of earthquake-related technologies, including monitoring systems, early warning mechanisms, and resilient infrastructure solutions. While these strands provide valuable insights, they are rarely analyzed within a unified empirical framework.

This thesis aims to bridge this gap by jointly examining disaster risk, scientific research output, and technological innovation in earthquake-prone countries. The study integrates multiple data sources, including disaster impact data, multidimensional risk indicators, bibliometric publication records, and patent statistics, to construct a comprehensive cross-country dataset. The analysis focuses on a group of high-seismicity countries observed over time, allowing for both cross-sectional and temporal comparisons.

Methodologically, the thesis adopts a two-stage analytical approach. In the first stage, Data Envelopment Analysis (DEA) is employed to evaluate the relative efficiency of countries in transforming disaster-related risk conditions into scientific research outputs under different scale assumptions. This efficiency-based perspective provides insight into cross-country differences in research performance beyond simple output comparisons. In the second stage, a set of empirical regression models is used to examine the determinants of four key outcome dimensions: scientific publications, human losses, economic losses, and earthquake-related patent activity. These models explicitly account for disaster risk components, earthquake magnitude levels, and research capacity indicators.

The empirical results reveal clear differences across outcome types. Scientific publication and patent activity are primarily driven by research capacity variables, such as research and development expenditure and human capital, rather than by disaster risk or earthquake occurrence. In contrast, human and economic losses are strongly influenced by earthquake magnitude, highlighting the dominant role of physical event severity in shaping disaster impacts. These findings demonstrate that disaster risk, knowledge production, and innovation are governed by distinct mechanisms and should not be treated as interchangeable outcomes.

By integrating risk indicators, disaster impacts, scientific output, and technological innovation within a unified analytical framework, this thesis makes three main contributions to the literature. First, it provides a comparative assessment of how countries respond differently to similar seismic risks across multiple dimensions. Second, it distinguishes between capacity-driven and impact-driven outcomes in the context of earthquakes. Third, it provides empirical evidence to inform disaster risk reduction strategies by highlighting the importance of sustained research investment and institutional capacity alongside traditional risk mitigation efforts.

The remainder of the thesis is organized as follows. Chapter 2 reviews the relevant literature on earthquake risk, scientific research, technological innovation, and efficiency measurement methods. Chapter 3 describes the data sources and presents descriptive analyses. Chapter 4 reports the results of the DEA and empirical regression models. Finally, Chapter 5 summarizes the main findings and discusses their implications.

Chapter 2

LITERATURE REVIEW

This chapter reviews the existing literature related to earthquake risk, scientific research, technological innovation, and efficiency measurement methods. The purpose of this chapter is to provide a structured overview of the main research areas that form the conceptual foundation of this thesis.

Section 2.1 reviews the literature on earthquake risk and disaster impacts, focusing on the socio-economic, environmental, and human consequences of seismic events. This section provides a general background on how earthquake risk and disaster impacts have been conceptualized and assessed in previous studies.

Section 2.2 examines the literature on scientific research related to earthquakes. Bibliometric studies analyzing publication trends, research productivity, and international collaboration patterns are reviewed to understand how earthquake-related scientific knowledge has evolved over time.

Section 2.3 reviews studies on technological innovation and earthquake-related patents. This section focuses on patent-based analyses that evaluate technological development in areas such as earthquake-resistant construction, monitoring systems, and early warning technologies.

Section 2.4 discusses the literature on measuring research and innovation performance. Various indicators used to assess scientific output and innovation activity—including publication-based and patent-based measures—are reviewed, along with their main strengths and limitations.

Section 2.5 introduces Data Envelopment Analysis (DEA) as a methodological framework for measuring efficiency. This section presents the theoretical foundations of DEA and discusses its key modeling components.

Section 2.6 reviews studies that apply Data Envelopment Analysis in disaster and risk-related contexts. The focus is on cross-country and disaster-oriented applications that evaluate relative efficiency under multiple inputs and outputs.

Section 2.7 provides an overview of Data Envelopment Analysis models used in the literature. Subsection 2.7.1 introduces the basic concepts of DEA, 2.7.2 discusses alternative model orientations under multiple inputs and outputs, and 2.7.3 examines scale assumptions with particular emphasis on constant and variable returns to scale.

Finally, Section 2.8 summarizes the main research gaps identified in the literature and clearly outlines the contribution of this thesis in relation to existing studies.

2.1 Earthquake Risk and Disaster Impacts in the Literature

Earthquake risk assessment has been widely studied in the disaster management literature due to the severe human and economic losses caused by seismic events. Early research in this field mainly focused on physical hazard characteristics, such as earthquake magnitude, frequency, and ground motion intensity. These studies provided important insights into seismic behavior but were limited in explaining cross-country differences in disaster impacts [Kramer, 1996].

Subsequent studies emphasized that earthquake impacts cannot be explained by hazard characteristics alone. Researchers increasingly highlighted the role of socio-economic vulnerability, institutional capacity, and preparedness levels in shaping disaster outcomes. Highly cited studies show that countries with similar seismic exposure may experience very different levels of fatalities and economic losses due to differences in income, governance, and disaster management capacity [Kahn, 2005, Cutter et al., 2003].

To systematically document disaster impacts, global databases have been developed and widely used in empirical studies. The Emergency Events Database (EM-DAT) is one of the most commonly used sources, providing standardized data on earthquake-related deaths, the affected population, and economic damage across countries and over long time periods [Guha-Sapir et al., 2015]. EM-DAT-based studies enable cross-country comparisons and have been used to analyze trends in earthquake impacts, as well as the relationship between development levels and disaster losses [Noy, 2009].

In addition to event-based databases, composite risk indices have been introduced to capture the multidimensional nature of disaster risk. These approaches integrate hazard exposure with vulnerability and lack of coping capacity, allowing for more comprehensive assessments of earthquake risk. Well-established frameworks emphasize that disaster risk is the outcome of the interaction between natural hazards and socio-economic conditions, rather than a purely natural phenomenon [Cardona et al., 2012, Birkmann, 2013].

Recent studies increasingly adopt integrated perspectives that combine physical hazard characteristics with socio-economic, institutional, and governance-related factors in earthquake risk assessment. This line of research argues that disaster risk emerges from the interaction between natural hazards and human systems, rather than from seismic activity alone [Wisner et al., 2004, Birkmann, 2013].

Several highly cited studies demonstrate that countries with similar levels of seismic exposure may experience substantially different disaster outcomes due to differences in preparedness, coping capacity, and institutional effectiveness [Kahn, 2005, Noy, 2009]. In this context, vulnerability-oriented frameworks emphasize that development level, governance quality, and investment in risk reduction play a decisive role in shaping earthquake impacts [Cardona et al., 2012, UNDRR, 2022].

More recent contributions further highlight the importance of integrating risk assessment with resilience and capacity indicators. These studies argue that measuring disaster risk without considering countries' ability to respond to and recover from earthquakes provides an incomplete picture [Cutter, 2016, Hallegatte et al., 2016]. As a result, multidimensional risk frameworks and composite indices have become increasingly common in cross-country disaster assessments [**?**, UNDRR, 2022].

This integrated view of earthquake risk is closely aligned with the motivation of this thesis, which examines how countries operating under different risk conditions transform available research resources into earthquake-related scientific and technological outputs.

2.2 Scientific Research on Earthquakes in the Literature

Scientific research on earthquakes has expanded significantly over the past decades, driven by major seismic events and increasing awareness of disaster risk. A large body of literature examines earthquake-related scientific output to understand how knowledge production evolves over time and how research activity differs across countries. These studies generally rely on bibliometric methods and large academic databases to analyze publication patterns, citation structures, and collaboration networks [Moed, 2005].

Highly cited bibliometric studies show that earthquake research output tends to increase sharply after major seismic events. Researchers argue that destructive earthquakes often act as catalysts for scientific activity by attracting funding, international collaboration, and policy attention [Wang and Waltman, 2014, Chen et al., 2016]. These post-disaster research surges are commonly observed in countries that experience high-magnitude earthquakes, suggesting a strong link between disaster exposure and scientific response.

Studies on the geographical distribution of earthquake-related research indicate that scientific output is highly concentrated in a small number of countries, particularly those with strong research infrastructure and funding capacity [King, 2004, Adams, 2013]. While countries such as the United States, China, and Japan dominate global publication volume, other highly seismic countries produce fewer publications despite facing substantial earthquake risk [Wang et al., 2020]. This imbalance raises questions about the efficiency and focus of earthquake-related research across countries.

Another important stream of literature examines collaboration patterns in earthquake research. Highly cited studies show that international collaboration plays a key role in increasing research visibility and citation impact [Glänzel, 2004, Persson et al., 2010]. These studies suggest that countries with higher levels of international collaboration tend to produce more influential earthquake-related research, even when their total publication volume is relatively small.

In addition to publication quantity, several researchers emphasize the importance of thematic focus in earthquake research. Bibliometric analyses highlight that earthquake-related studies cover diverse themes such as hazard analysis, structural engineering, early warning systems, and disaster response and recovery [Zhang et al., 2018]. Recent studies increasingly examine whether scientific research aligns with societal needs, particularly in high-risk countries [Bornmann, 2013].

Overall, the literature suggests that scientific research on earthquakes is strongly shaped by disaster experience, research capacity, and collaboration networks. However, most existing studies focus on publication counts and citation-based indicators, while limited attention is given to how efficiently countries transform research resources into earthquake-related knowledge. This gap directly motivates the approach adopted in this thesis, which evaluates earthquake-related research performance within an efficiency framework.

2.3 Technological Innovation and Earthquake-Related Patents in the Literature

Technological innovation is widely recognized as a key component of earthquake risk reduction and disaster mitigation. Advances in engineering design, monitoring technologies, and early warning systems play an essential role in reducing physical damage and human losses caused by seismic events. In the innovation literature, patent data are commonly used as indicators of technological output because they capture applied knowledge and problem-oriented research outcomes [Griliches, 1990, OECD, 2009].

A growing body of research investigates technological innovation related to natural disasters through patent-based analyses. These studies focus on technological developments in areas such as earthquake-resistant construction, structural reinforcement, seismic monitoring, and sensor technologies [Johnstone et al., 2010, Popp, 2010]. Patent statistics allow researchers to compare innovation performance across countries and over time, providing insights into how scientific knowledge is transformed into practical solutions.

Several highly cited studies emphasize that innovation activity related to disaster risk is unevenly distributed across countries. Countries with strong research infrastructure and sustained public R&D support tend to dominate patent production, while many high-risk countries generate relatively few disaster-related patents despite significant exposure to seismic hazards [Dechezleprêtre and Sato, 2017, Archibugi and Pianta, 1992]. This observation suggests that absolute patent counts alone may not fully reflect countries' innovation performance.

An influential contribution to the earthquake-specific innovation literature is provided by Bae et al., who analyze the efficiency of public research activities in terms of knowledge spillovers, with a focus on earthquake R&D accomplishments [Bae et al., 2017]. Using patent data as innovation outputs, the authors evaluate how effectively public R&D investments are converted into technological outcomes across earthquake-prone countries. Their findings show substantial cross-country differences in innovation efficiency, even among countries facing similar seismic risks.

The study by Bae et al. highlights that technological innovation related to earthquakes should be assessed within an efficiency framework that considers both inputs and outputs [Bae et al., 2017]. The authors argue that knowledge spillovers, institutional quality, and research system characteristics play a crucial role in explaining differences in patent-based innovation performance. This perspective has been echoed by other studies emphasizing the importance of knowledge diffusion and absorptive capacity in disaster-related innovation systems [Cohen and Levinthal, 1990, Furman et al., 2002].

Additional research extends this discussion by examining the relationship between public policy, regulation, and technological innovation. Studies show that targeted policies and public investment can stimulate innovation in risk-related technologies, including those relevant to earthquake preparedness and mitigation [Porter and van der Linde, 1995, Popp, 2010]. However, policy effectiveness varies significantly across countries, depending on institutional capacity and research system maturity.

Recent studies also highlight the importance of integrating patent-based innovation measures with broader risk and resilience frameworks. Researchers argue that evaluating technological innovation without considering disaster risk exposure and socio-economic conditions may lead to misleading conclusions [Hallegatte et al., 2016, UNDRR, 2022]. As a result, cross-country analyses increasingly adopt multi-dimensional approaches that combine innovation indicators with risk and capacity measures.

Overall, the literature suggests that earthquake-related patents provide a valuable measure of technological responses to seismic risk. Nevertheless, most existing studies focus on innovation outputs or knowledge spillovers in isolation, while limited attention is given to comprehensive efficiency assessments that jointly consider research inputs, technological outputs, and risk conditions. This gap directly motivates the approach adopted in this thesis, which evaluates earthquake-related technological innovation using a multi-input and multi-output efficiency framework across high-seismicity countries.

2.4 Measuring Research and Innovation Performance in the Literature

Measuring research and innovation performance has been a central topic in the science, technology, and innovation literature. Researchers have developed various indicators to evaluate scientific output, technological development, and national research capacity. These indicators are widely used in cross-country comparisons and policy-oriented studies [Moed, 2005, OECD, 2015]. One of the most common approaches to measuring research performance relies on bibliometric indicators derived from scientific publications. Measures such as publication counts, citation counts, and citation-based indices are frequently used to assess research productivity and scientific impact [King, 2004, Bornmann, 2013]. Bibliometric indicators provide valuable insights into knowledge production patterns; however, they mainly capture research output volume and visibility rather than research efficiency.

In parallel, innovation performance is often measured using patent-based indicators. Patent counts, patent families, and citation-weighted patent measures are commonly employed to assess technological output and inventive activity across countries [Griliches, 1990, OECD, 2009]. Patent data are particularly useful for capturing applied research outcomes and technological responses to societal challenges, including disaster risk. Several studies combine bibliometric and patent indicators to provide a more comprehensive picture of national research and innovation systems [Furman et al., 2002, Archibugi and Pianta, 1992]. These composite approaches allow researchers to compare countries in terms of both scientific knowledge production and technological development. However, most of these measures remain descriptive and focus on absolute output levels.

A key limitation of traditional research and innovation indicators is their inability to account for differences in input resources. Countries vary substantially in terms of research funding, human capital, and institutional capacity, which makes direct comparisons based on output indicators potentially misleading [Adams, 2013, OECD, 2015]. As a result, high output levels do not necessarily imply high performance or effective use of resources. To address this issue, several authors argue that performance assessment should explicitly consider the relationship between inputs and outputs [Coelli et al., 2005]. This perspective emphasizes efficiency rather than absolute production, highlighting how effectively research resources are transformed into scientific and technological outputs. Such an approach is particularly relevant in contexts where countries operate under heterogeneous conditions, including differences in risk exposure and socio-economic structure. In the context of disaster-related research and innovation, these limitations are even more pronounced. Countries facing similar earthquake risks may exhibit very different levels of research and innovation output due to variations in research capacity and resource allocation [Bae et al., 2017]. Therefore, measuring performance solely based on publication or patent counts may fail to capture meaningful differences in effectiveness.

Overall, the literature suggests that while bibliometric and patent-based indicators provide important information on research and innovation activity, they are insufficient for evaluating relative performance across countries with different resources. This has motivated the use of efficiency-based approaches that jointly consider multiple inputs and outputs, which are reviewed in the following section.

2.5 Data Envelopment Analysis in the Literature

Data Envelopment Analysis (DEA) is a non-parametric efficiency measurement method used to evaluate the relative performance of decision-making units (DMUs) operating with multiple inputs and multiple outputs. DEA relies on linear programming techniques to construct an empirical efficiency frontier based on observed data and measures the performance of each DMU relative to this frontier [Charnes et al., 1978]. The method is particularly suitable for contexts in which production processes are complex and difficult to represent through a predefined functional form.

The relative efficiency of a DMU is measured as the ratio of weighted outputs to weighted inputs and is evaluated through comparison with other DMUs in the sample. A DMU that attains an efficiency score of 100% is considered efficient and lies on the efficiency frontier, while DMUs with efficiency scores below this threshold are regarded as inefficient. One of the defining characteristics of DEA is that each DMU is allowed to select the set of input and output weights that maximizes its own efficiency score, subject to the condition that the same weights do not yield an efficiency score greater than unity for any other DMU [Cherchye et al., 2007]. This endogenous weight selection mechanism enables performance evaluation without imposing prior assumptions regarding the relative importance of inputs and outputs.

DEA does not require assumptions about the functional form of the production function or the statistical distribution of inefficiency. This feature distinguishes DEA from parametric efficiency analysis methods and makes it well-suited for applications in research and development activities, public sector performance assessment, and other areas where the input–output relationship cannot be explicitly specified [Cooper et al., 2007]. The ability to handle multiple inputs and outputs measured in different units further enhances the applicability of DEA in multidimensional evaluation settings.

In addition to providing a single efficiency score for each DMU, DEA offers valuable benchmarking information by projecting inefficient units onto the efficient frontier. These projections identify potential improvement targets and reference units that represent best-practice performance. By focusing on the best-performing DMUs rather than average behavior, DEA facilitates meaningful performance comparisons among heterogeneous units operating under different conditions [Cooper et al., 2007].

Despite its methodological strengths, DEA also exhibits certain limitations. As an extreme-point technique, DEA is sensitive to noise, measurement errors, and outliers, since the efficiency frontier is constructed based on observed best-performing units. Data inaccuracies may therefore directly affect estimated efficiency scores [Cooper et al., 2007]. Moreover, the non-parametric nature of DEA complicates the use of conventional statistical hypothesis testing, although bootstrap-based approaches have been developed to address inference-related issues.

Computational complexity is another limitation, as DEA requires solving a separate linear programming problem for each DMU. While this can be demanding for large datasets, advances in computational power and specialized DEA software have substantially reduced this concern in practical applications [Cooper et al., 2007]. Additional challenges arise when aggregating performance across different dimensions into a single efficiency measure or when DMUs engage in multiple heterogeneous activities [Ramanathan, 2003]. Furthermore, DEA is generally less sensitive to intangible, qualitative, or categorical factors that may be important in certain evaluation contexts.

2.6 Data Envelopment Analysis in Disaster and Risk Contexts

Data Envelopment Analysis (DEA) is a non-parametric efficiency measurement method originally developed to evaluate the relative performance of decision-making units (DMUs) operating under similar conditions [Charnes et al., 1978]. DEA is particularly suitable for contexts in which multiple inputs and multiple outputs must be considered simultaneously, without requiring the specification of an explicit functional relationship between inputs and outputs [Coelli et al., 2005].

The core principle of DEA is the construction of a best-practice efficiency frontier based on observed data. Early DEA models assumed constant returns to scale

(CRS), implying proportional changes between inputs and outputs [Charnes et al., 1978]. Subsequent extensions introduced variable returns to scale (VRS), allowing for the identification of scale inefficiencies and enabling more flexible performance evaluation across heterogeneous units [Banker et al., 1984]. These methodological developments are especially relevant in cross-country analyses, where countries differ substantially in size, resource endowments, and institutional capacity.

Due to these characteristics, DEA has been widely applied in studies assessing research and innovation performance. Existing research suggests that DEA provides a more appropriate framework than single-indicator or regression-based approaches when evaluating how efficiently research inputs are transformed into scientific and technological outputs [Furman et al., 2002, Guan and Zuo, 2014]. By explicitly linking inputs such as R&D expenditure and human capital to outputs such as publications and patents, DEA allows for meaningful efficiency comparisons across countries.

In recent years, the application of DEA has expanded to disaster and risk-related contexts. Studies in this area emphasize that disaster outcomes and preparedness levels are influenced not only by hazard exposure, but also by the efficiency with which available resources are allocated and utilized [Zhou et al., 2018]. DEA has therefore been used to assess disaster management efficiency, emergency response performance, and resilience capacity at both regional and national levels [Liu and Sharp, 2017].

A recurring finding in disaster-focused DEA studies is that countries facing similar levels of risk may experience markedly different outcomes due to differences in institutional effectiveness, preparedness, and learning from past events [Noy, 2009]. These results underline the importance of focusing on efficiency rather than absolute output levels when evaluating disaster risk management performance.

DEA has also been applied to analyze public research efficiency within disaster-related innovation systems. A particularly relevant contribution is the study by Bae et al., which evaluates the efficiency of public earthquake-related R&D activities by incorporating knowledge spillovers and patent-based innovation outputs [Bae et al., 2017]. Their findings show that efficiency differences play a key role in explaining cross-country variation in technological innovation among countries exposed to similar seismic risks.

One major advantage of DEA in disaster contexts is its ability to accommodate heterogeneous operating environments. Unlike regression-based methods, DEA does not impose a single average relationship between inputs and outputs. Instead, each DMU is evaluated relative to the most efficient peers, making DEA well-suited for cross-country analyses involving diverse risk profiles and institutional structures [Banker et al., 1984, Coelli et al., 2005].

Recent methodological advances have further strengthened the applicability of DEA in disaster and risk analysis. These include dynamic DEA models, network DEA frameworks, and approaches that incorporate undesirable outputs such as fatalities or economic losses [**?**, Seiford and Zhu, 2007]. Such extensions are particularly relevant for disaster research, where negative outcomes are an inherent part of the system being evaluated.

More recent studies apply DEA to assess disaster management efficiency and resilience capacity using integrated and risk-adjusted frameworks. For instance, Zhang et al. employ DEA to evaluate disaster resilience by jointly considering risk exposure, emergency response capacity, and recovery outcomes, revealing significant efficiency differences across regions [Zhang et al., 2019]. Similarly, Chen et al. demonstrate that incorporating risk-adjusted indicators into DEA models leads to more realistic assessments of disaster preparedness performance [Chen et al., 2020].

DEA has also been increasingly used in studies examining public R&D and innovation efficiency in the context of societal challenges. Recent research shows that evaluating research efficiency under heterogeneous conditions, such as environmental or disaster risk, requires flexible non-parametric methods capable of handling multiple inputs and outputs [Gao and Zheng, 2021, Li et al., 2022]. These studies argue that DEA is particularly suitable for analyzing research systems operating under uncertainty and uneven risk exposure.

Furthermore, dynamic and network DEA models have been introduced to capture the intertemporal and sequential nature of knowledge production and application. Dynamic DEA allows researchers to analyze changes in efficiency over time, while network DEA explicitly models different stages of knowledge diffusion and application [Tone and Tsutsui, 2014, Li and Wang, 2023]. These approaches are especially relevant for disaster-related research and innovation systems, where knowledge generation and application occur across multiple stages.

Overall, the literature confirms that DEA provides a robust and flexible framework for evaluating efficiency in disaster and risk contexts. By jointly considering multiple inputs and outputs under heterogeneous risk conditions, DEA enables more comprehensive cross-country comparisons. These methodological advances directly support the analytical approach adopted in this thesis.

2.7 Data Envelopment Analysis Models

Data Envelopment Analysis (DEA) encompasses a wide range of model formulations for measuring efficiency under different assumptions about production technology and performance evaluation. The earliest and most widely used DEA model is the CCR model, proposed by Charnes, Cooper, and Rhodes [Charnes et al., 1978]. The CCR (Charnes–Cooper–Rhodes) model assumes constant returns to scale (CRS), implying that proportional changes in inputs lead to proportional changes in outputs and that inefficiency arises solely from technical factors.

To relax the CRS assumption, Banker, Charnes, and Cooper introduced the BCC model [Banker et al., 1984]. The BCC (Banker–Charnes–Cooper) model allows for variable returns to scale (VRS) and enables the decomposition of inefficiency into technical inefficiency and scale inefficiency. This feature makes the BCC formulation particularly suitable for evaluating decision-making units operating at different scales. Both CCR and BCC models are classified as radial models, as they assess efficiency through proportional contraction of inputs or proportional expansion of outputs.

Several alternative DEA models have been developed to address the limitations of radial efficiency measures. The Russell measure proposed by [Russell, 1978] provides a non-radial efficiency assessment by accounting for individual input and output inefficiencies. Similarly, the Free Disposal Hull (FDH) model introduced by [Deprins et al., 1984] relaxes the convexity assumption of the production frontier, resulting in a more flexible representation of production technology with weaker structural assumptions.

Additive and non-radial DEA models were further formalized by [Charnes et al., 1985], explicitly incorporating slack variables related to input excesses and output shortfalls. In this context, the slacks-based measure (SBM) developed by [Tone, 2001] directly evaluates inefficiency through input and output slacks rather than proportional adjustments. SBM and additive models are particularly useful when slacks play a critical role in performance evaluation. Extensions of these models to super-efficiency settings allow efficient decision-making units to be ranked beyond the efficiency frontier [Andersen and Petersen, 1993, Tone, 2002]. Classical DEA models, by contrast, are unable to discriminate among efficient units.

DEA models have also evolved to accommodate uncertainty, complexity, and structural characteristics of real-world production systems. When inputs and outputs are not deterministic, stochastic and fuzzy DEA models are employed to account for randomness, ambiguity, and imprecision in the data. Stochastic DEA models incorporate random disturbances and are suitable for environments characterized by uncertainty, though they often yield complex formulations and non-unique outcomes. Fuzzy DEA models, on the other hand, allow the use of imprecise and ambiguous input and output data without requiring explicit probabilistic assumptions [Kao and Liu, 2000, Guo and Tanaka, 2001].

Further extensions include cross-efficiency models, which enable peer-evaluation and provide more discriminating rankings of decision-making units, and hierarchical or multi-level DEA models, which utilize hierarchical input–output structures to handle large numbers of variables and multi-stage decision processes. Multi-criteria DEA models differ from standard DEA formulations in that each criterion represents an independent objective function, with no prior preference imposed among them. Such models are particularly relevant when performance evaluation involves multiple conflicting objectives.

DEA has also been extended to capture internal production structures and dynamic performance. Network DEA models explicitly represent intermediate products and sub-processes within decision-making units, allowing inefficiencies that traditional DEA models may overlook to be identified [Färe and Grosskopf, 2000]. Productivity-oriented DEA models, such as the Malmquist Productivity Index, analyze productivity change over time by decomposing it into efficiency change and technological progress components [Färe et al., 1994].

Given the diversity of available DEA models, selecting an appropriate formulation depends on the data characteristics, the production process structure, and the analysis objectives. When efficiency evaluation has important policy or managerial implications, it is recommended to apply multiple DEA models, compare the results, and incorporate expert knowledge before reaching a final conclusion [Cooper et al., 2006].

Recent studies have further extended DEA models to address uncertainty, multi-dimensional decision structures, and emerging application domains. Stochastic DEA models incorporate random disturbances into efficiency measurement and have been applied to settings characterized by uncertainty and noise [Tsionas and Papadakis, 2010, Jin et al., 2014]. Multi-criteria DEA models treat each evaluation criterion as an independent objective function and are particularly suitable for problems involving multiple conflicting performance dimensions [Al-Shammari, 1999, Köksalan and Tuncer, 2009].

Super-efficiency DEA models have been employed to improve discrimination among efficient decision-making units by allowing efficiency scores to exceed unity [Li et al., 2007]. In parallel, classical DEA models have been adapted to new application areas, demonstrating their continued relevance in modern efficiency analysis [Jin et al., 2014]. Slack-based DEA models have also gained attention for their ability to explicitly account for input excesses and output shortfalls in performance evaluation [Chang and Yu, 2014].

Fuzzy DEA models extend the traditional framework to environments characterized by imprecise and ambiguous data, enabling efficiency analysis without strict probabilistic assumptions [Azadeh et al., 2014]. In addition, multi-level DEA models utilize hierarchical input–output structures to accommodate complex systems with large numbers of variables and multiple decision layers [Wang et al., 2014]. These recent developments highlight the ongoing methodological evolution of DEA and its adaptability to increasingly complex and uncertain decision-making environments.

Different DEA models have been developed to address specific methodological needs, each offering distinct advantages while also presenting certain limitations. Classical DEA models, such as CCR and BCC, provide a robust framework for efficiency measurement; however, they cannot discriminate among efficient decision-making units, as all units on the efficiency frontier receive the same efficiency score. This limitation has motivated the development of super-efficiency models, which allow efficient units to obtain efficiency scores greater than unity and thus enable ranking among efficient DMUs, although such models may occasionally yield impractical or unstable results [Andersen and Petersen, 1993].

Non-radial DEA models, including the Russell measure and additive models, were introduced to overcome the limitations of radial efficiency measures. The Russell model is capable of differentiating the performance of efficient DMUs by considering individual input and output inefficiencies, but it requires solving non-linear programming problems and does not necessarily improve discrimination power when a DMU is already efficient under radial measures [Russell, 1978]. The additive DEA model developed by [Charnes et al., 1985] simultaneously accounts for possible input reductions and output expansions via slack variables. While additive and slack-based models are effective in capturing inefficiencies related to input excesses and output shortfalls, they do not always provide a precise scalar measure of efficiency and may exhibit limited discriminatory power in efficiency rankings [Zhu, 2003].

The Free Disposal Hull (FDH) model relaxes the convexity assumption of the production frontier and imposes weaker restrictions on production technology. This flexibility allows FDH to represent production processes more realistically in certain contexts; however, the lack of convexity may also lead to reduced comparability and sensitivity to extreme observations [Deprins et al., 1984]. Cross-efficiency models extend classical DEA by incorporating peer evaluation and are often used to improve ranking accuracy among DMUs, although they may neglect the true underlying efficiency values due to averaging across evaluators.

DEA models have also been extended to environments characterized by uncertainty and imprecision. Stochastic DEA models incorporate random disturbances into efficiency measurement and are suitable for analyzing decision-making units operating under uncertainty, providing a more realistic representation of real-world economic environments. Nevertheless, stochastic DEA formulations, particularly in continuous-time settings, tend to be computationally complex and do not yield a single deterministic efficiency outcome. Fuzzy DEA models address ambiguity in input and output data by allowing imprecise and linguistic variables to be incorporated into the analysis. While fuzzy DEA models offer flexibility and do not require price information, they may produce infeasible solutions, ignore exogenous influences, and face challenges in statistical inference and efficiency improvement interpretation [Kao and Liu, 2000, Guo and Tanaka, 2001].

Hierarchical and multi-level DEA models utilize structured input–output hierarchies to accommodate complex systems involving multiple decision layers and large numbers of variables. These models are often integrated with multi-criteria decision-making techniques, such as the Analytic Hierarchy Process (AHP), to incorporate priority structures and both quantitative and qualitative information. Although such approaches provide valuable insights for complex decision problems, they involve increased methodological complexity and may suffer from rank reversal issues and computational burden [Cooper et al., 2006]. Network DEA models further extend the traditional framework by explicitly modeling internal sub-processes and intermediate products, enabling the detection of inefficiencies that conventional DEA models may overlook. However, inconsistencies between multiplier and envelopment formulations may limit the interpretability of divisional efficiency results [Färe and Grosskopf, 2000].

Given the diversity of DEA model formulations and their respective strengths and weaknesses, the application of multiple DEA models and the comparison of results are often recommended, particularly in studies with significant policy or managerial implications. Incorporating expert knowledge alongside empirical findings can further enhance the robustness and credibility of efficiency evaluations [Cooper et al., 2006].

The application of Data Envelopment Analysis (DEA) in natural disaster analysis remains relatively limited; however, existing studies demonstrate that DEA-based efficiency measures can effectively capture vulnerability and resilience levels in disaster-prone regions. One of the earliest contributions in this field was provided by [Wei et al., 2004], who applied DEA to assess regional vulnerability to natural disasters in China, showing that efficiency scores can serve as meaningful indicators of relative vulnerability. Building on this perspective, [Huang et al., 2011] employed DEA at the regional level to evaluate vulnerability to natural hazards across Chinese provinces, highlighting spatial disparities in disaster preparedness and exposure. DEA has also been utilized at more disaggregated spatial scales to support disaster management and policy interventions. For example, [Saein and Saen, 2012] assessed site-effect vulnerability in urban regions of Tehran using DEA, providing a ranking of vulnerable areas and recommendations for disaster mitigation. More recent studies have expanded the methodological scope by incorporating different DEA specifications. [Gao et al., 2023b] applied both CCR and BCC DEA models at the county level in mainland China to evaluate earthquake vulnerability, decomposing it into technical and scale components, and identifying key factors influencing disaster impacts. In the context of Türkiye, [Üstün, 2016] evaluated the earthquake resilience capacity of Istanbul's districts using DEA combined with returns-to-scale analysis, distinguishing between efficient and inefficient districts and identifying improvement potentials. Advanced DEA frameworks have also been adopted in disaster resilience studies. [Liu et al., 2018] employed a three-stage super-efficiency DEA model to assess county-level resilience to moderate earthquakes in China, controlling for environmental factors and providing insights into determinants of resilience. Beyond earthquake-specific applications, DEA has been used to examine other disaster types and comparative settings. [Tanaka, 2005] conducted a cross-country comparison between Japan and the United States to evaluate the effectiveness of disaster education in earthquake preparedness, while [Sahrizan et al., 2018] applied DEA to assess regional flood vulnerability in Peninsular Malaysia. Complementary approaches have also been proposed to capture post-disaster economic dynamics; for instance, [Oliva and Lazzeretti, 2018] measured the economic resilience of Japanese prefectures to major earthquakes by constructing indices of resistance and recovery. Collectively, these studies demonstrate that DEA provides a flexible framework for evaluating vulnerability and resilience across different disaster contexts, spatial scales, and methodological settings.

Within the disaster literature, many studies have used Data Envelopment Analysis (DEA) to examine earthquake-related vulnerability, resilience, and preparedness. These studies generally focus on how efficiently regions, cities, or administrative units use available resources and preparedness measures to reduce earthquake impacts or improve resilience. Early research mainly concentrated on vulnerability assessment at different spatial levels. For example, [Saein and Saen, 2012] applied DEA to evaluate site-effect vulnerability in urban areas of Tehran, producing a relative ranking of earthquake-prone locations and offering useful guidance for mitigation planning. Later studies expanded this approach by considering scale effects and more advanced DEA models. [Gao et al., 2023b] used both CCR and BCC DEA models to assess earthquake-related vulnerability at the county level in mainland China, separating vulnerability into technical and scale components and identifying factors that influence inefficiency. Similarly, [Üstün, 2016] examined the earthquake-resilience capacity of Istanbul's districts using DEA and returns-to-scale analysis, identifying efficient and inefficient districts and highlighting areas for improvement.

More recent studies have applied advanced DEA frameworks to better account for environmental and contextual factors that affect earthquake outcomes. [Liu et al., 2018] employed a three-stage super-efficiency DEA model to evaluate county-level resilience to moderate earthquakes in China, allowing for a clearer assessment after controlling for external factors. Some studies have also adopted comparative perspectives. For instance, [Tanaka, 2005] compared Japan and the United States to evaluate the role of disaster education and public preparedness in reducing earthquake impacts. In addition to physical impacts, other research has focused on economic outcomes following earthquakes. [Oliva and Lazzeretti, 2018] analyzed the economic resilience of Japanese prefectures by examining resistance and recovery after major earthquakes, providing insights into regional employment dynamics.

2.7.1 Basic Concept of Data Envelopment Analysis

The central idea of DEA is to assess efficiency through comparison rather than absolute measurement, by constructing an empirical production frontier formed by the best-performing units in the observed sample [Charnes et al., 1978, ?].

The efficiency of a DMU is conceptually defined as the ratio of a weighted sum of outputs to a weighted sum of inputs. For a given DMU k, the relative efficiency score is expressed as

$$h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}, \tag{2.1}$$

where y_{rk} denotes the amount of output r produced by DMU k, x_{ik} denotes the amount of input i used by DMU k, and u_r and v_i are the weights assigned to outputs and inputs, respectively. These weights are decision variables determined endogenously by the model in a way that maximizes the efficiency score of the evaluated DMU.

To ensure meaningful comparison across all DMUs, the same set of weights must not allow any DMU to achieve an efficiency score greater than unity. This requirement leads to a fractional programming formulation in which the efficiency ratio of every DMU, evaluated under the chosen weights, is constrained to be less than or equal to one. While this formulation captures the intuitive notion of efficiency, its fractional structure prevents direct solution using standard linear programming techniques.

To overcome this limitation, the fractional DEA model is transformed into a linear programming problem using the Charnes–Cooper transformation [Charnes and Cooper, 1962]. Specifically, the weighted sum of inputs for the evaluated DMU is normalized to unity,

$$\sum_{i=1}^{m} v_i x_{ik} = 1, \tag{2.2}$$

which eliminates the denominator in Equation (2.1). As a result, the objective function becomes linear, yielding the multiplier form of the DEA model:

$$\max_{u,v} \quad \sum_{r=1}^{s} u_r y_{rk}, \tag{2.3}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, 2, \ldots, n, \tag{2.4}$$

$$u_r \geq \varepsilon, \quad r = 1, 2, \ldots, s,$$

$$v_i \geq \varepsilon, \quad i = 1, 2, \ldots, m.$$

This formulation is referred to as the multiplier model, as it explicitly determines the optimal weights assigned to each input and output. The multiplier model provides insight into the relative importance of inputs and outputs in achieving efficiency; however, it does not directly reveal how inefficient DMUs should improve their performance or which peers serve as benchmarks.

To obtain such information, the dual of the multiplier model is derived using linear programming duality. The resulting formulation is known as the envelopment model, which offers a geometric interpretation of efficiency by constructing a piecewise linear frontier that envelops all observed DMUs. In the input-oriented constant returns to scale (CCR) framework, the envelopment model is given by:

$$\min_{\theta,\lambda} \quad \theta, \tag{2.5}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} x_{ij}\lambda_j \leq \theta x_{ik}, \quad i = 1, 2, \ldots, m, \tag{2.6}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{rk}, \quad r = 1, 2, \ldots, s, \tag{2.7}$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n.$$

In this formulation, θ represents the proportional reduction in inputs required for DMU k to become efficient, while λ_j are intensity variables that define the reference combination of peer DMUs forming the efficient frontier. A value of $\theta = 1$ indicates that the DMU lies on the frontier and is considered technically efficient, whereas $\theta < 1$ implies inefficiency.

Overall, DEA proceeds from an intuitive ratio-based efficiency concept to a linear programming formulation that enables empirical estimation. Through duality, the analysis shifts from weight determination to frontier construction and benchmarking, providing both quantitative efficiency scores and qualitative insights into performance improvement and peer comparison.

2.7.2 Orientation of DEA Models

Input-Oriented Envelopment Model (CCR)

In the input-oriented framework, the objective is to determine the maximum proportional reduction in inputs while maintaining at least the observed level of outputs. The input-oriented CCR envelopment model is formulated as:

$$\min_{\theta,\lambda,s^-,s^+} \quad \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right), \tag{2.8}$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ik}, \quad i = 1, 2, \ldots, m, \tag{2.9}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}, \quad r = 1, 2, \ldots, s, \tag{2.10}$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n.$$

Here, θ represents the radial efficiency score of DMU k, indicating the proportion by which all inputs can be reduced simultaneously. The slack variables s_i^- and s_r^+ capture input excesses and output shortfalls that remain after proportional adjustment. The small positive constant ε ensures that slacks are minimized only after achieving the maximum radial efficiency.

If $\theta = 1$ and all slack variables are zero, DMU k lies on the efficient frontier and is considered technically efficient. If $\theta < 1$, the DMU is inefficient and can proportionally reduce its inputs while still producing the same level of outputs.

Output-Oriented Envelopment Model (CCR)

Alternatively, DEA can be formulated in an output-oriented manner, where the objective is to maximize outputs given fixed input levels. The output-oriented CCR envelopment model is given by:

$$\max_{\phi,\lambda,s^-,s^+} \quad \phi + \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right), \tag{2.11}$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{ik}, \quad i = 1, 2, \ldots, m, \tag{2.12}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{rk}, \quad r = 1, 2, \ldots, s, \tag{2.13}$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n.$$

In this formulation, ϕ denotes the proportional expansion factor applied to outputs. A value of $\phi = 1$ indicates efficiency, whereas $\phi > 1$ implies that outputs can be proportionally increased without requiring additional inputs.

The envelopment formulation provides a direct geometric interpretation of efficiency by enveloping all observed DMUs with a piecewise linear frontier. The intensity variables λ_j identify peer DMUs that serve as benchmarks for inefficient units. Consequently, the envelopment model not only yields efficiency scores but also offers practical guidance on performance improvement through reference comparisons [Cook and Zhu, 2014].

Output-Oriented BCC Model

Alternatively, the output-oriented BCC model maximizes output levels given fixed input quantities under variable returns to scale. The envelopment form of the output-oriented BCC model is expressed as:

$$\max_{\phi,\lambda,s^-,s^+} \quad \phi + \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right), \tag{2.14}$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{ik}, \quad i = 1, 2, \ldots, m, \tag{2.15}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{rk}, \quad r = 1, 2, \ldots, s, \tag{2.16}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{2.17}$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n.$$

In this formulation, ϕ denotes the proportional expansion factor applied to outputs. A value of $\phi = 1$ indicates efficiency, while $\phi > 1$ implies that outputs can be proportionally increased without additional inputs, conditional on the variable returns to scale assumption.

The BCC model generalizes the CCR framework by relaxing the constant returns to scale assumption. As a result, efficiency scores obtained from the BCC model are always greater than or equal to those from the CCR model. The ratio of CCR efficiency to BCC efficiency provides a measure of scale efficiency, indicating whether a DMU operates under increasing, constant, or decreasing returns to scale.

By incorporating the BCC model, DEA analysis is able to distinguish inefficiencies arising from managerial or technological shortcomings from those driven by suboptimal scale of operation, which is particularly relevant in cross-country and R&D-based performance evaluations.

2.7.3 Scale of DEA Models

Starting from the linear multiplier model, the application of linear programming duality yields the envelopment form of DEA. Unlike the multiplier model, which focuses on determining optimal input and output weights, the envelopment model directly assesses how far a DMU is from the efficient frontier and identifies the reference units that define it.

CCR Model (Constant Returns to Scale)

The CCR model, introduced by Charnes, Cooper, and Rhodes [Charnes et al., 1978], constitutes the foundational DEA framework under the constant returns to scale (CRS) assumption. This assumption implies that proportional changes in all inputs lead to proportional changes in all outputs, an appropriate characterization when decision-making units are assumed to operate at an optimal scale.

Within the CCR framework, efficiency can be evaluated using either an input-oriented or an output-oriented perspective. Furthermore, each orientation admits two mathematically equivalent representations: the multiplier form and the envelopment form. While the multiplier model emphasizes selecting optimal weights for inputs and outputs, the envelopment model provides a frontier-based interpretation and serves as the basis for benchmarking analysis.

Overall, the CCR model establishes the fundamental DEA structure by linking efficiency measurement to linear programming under constant returns to scale, serving as the basis for more advanced DEA extensions.

BCC Model (Variable Returns to Scale)

While the CCR model assumes constant returns to scale (CRS), this assumption may be restrictive in empirical applications where decision-making units do not necessarily operate at an optimal scale. In many real-world contexts, inefficiency may arise not only from poor management or technology, but also from scale-related effects. To address this limitation, Banker, Charnes, and Cooper [Banker et al., 1984] extended the CCR framework by introducing the BCC model, which allows for variable returns to scale (VRS).

The key distinction between the CCR and BCC models lies in how they treat scale effects. The BCC model decomposes overall technical inefficiency into two components: pure technical inefficiency and scale inefficiency. This is achieved by imposing an additional convexity constraint on the envelopment formulation, ensuring that each DMU is compared only with peers operating at a similar scale.

2.8 Research Gap and Contribution of the Thesis

The main contribution of this thesis is the application of an input–output oriented Data Envelopment Analysis (DEA) framework to evaluate earthquake-related research and innovation performance under varying levels of seismic risk. Unlike existing studies, the proposed framework explicitly links research inputs and outputs to earthquake risk by incorporating disaster magnitude and risk exposure into the performance assessment.

A further contribution of the study is the classification of research outputs according to the four phases of disaster management: preparedness, mitigation, response, and recovery. This phase-based structure enables countries to be grouped based on their dominant research focus, and allows for a systematic comparison of national research strategies in relation to earthquake risk.

The empirical analysis reveals that earthquake magnitude is positively related to scientific publication activity at the country level. This finding suggests that scientific research activity reacts strongly to seismic events and plays an important role in post-disaster knowledge production. In contrast, patent-based outputs do not exhibit a clear relationship with earthquake magnitude, indicating that technological innovation responds to seismic risk through different and more long-term mechanisms.

By jointly considering risk indicators, research inputs, and phase-specific outputs within a single DEA framework, the thesis provides a structured comparison of how efficiently countries allocate research resources under earthquake risk conditions. The results demonstrate that countries with similar levels of seismic exposure can display markedly different efficiency patterns, mainly due to differences in research focus, resource allocation, and strategic orientation.

The existing literature on earthquakes has provided valuable insights into disaster risk assessment, scientific knowledge production, technological innovation, and efficiency measurement methods. Studies on earthquake risk and disaster impacts emphasize the multidimensional nature of risk, highlighting the role of hazard exposure, vulnerability, and institutional capacity. Bibliometric research documents the growth and geographical concentration of earthquake-related scientific output, while patent-based studies examine technological responses to seismic risk. In parallel, Data Envelopment Analysis has been widely applied to evaluate efficiency in research, innovation, and disaster management contexts.

Despite these contributions, several important gaps remain in the literature. First, most studies examine earthquake risk, scientific research, and technological innovation as separate domains. Limited attention has been given to integrated frameworks that jointly analyze disaster risk conditions and research and innovation performance across countries.

Second, existing bibliometric and patent-based studies tend to focus either on single-country analyses over long time periods or on cross-country comparisons conducted over relatively short time horizons with a limited set of variables. While these approaches provide useful descriptive insights, they often fail to capture the combined effects of research inputs, resource availability, and national capacity in a comprehensive manner. As a result, many existing studies offer only partial assessments of research and innovation performance, which may limit the validity of cross-country comparisons.

Third, although DEA has been increasingly used in disaster and innovation research, its application to earthquake-related scientific and technological performance remains limited. In particular, few studies explicitly examine how countries exposed to different levels of earthquake risk transform research resources into disaster-related scientific knowledge and technological outputs within a unified efficiency framework.

In addition to these contributions, this thesis integrates composite disaster risk indices into the efficiency analysis to provide a more risk-sensitive interpretation of research and innovation performance. By incorporating long-term average measures of vulnerability, hazard and exposure, and coping capacity into the DEA framework, the analysis explicitly accounts for the structural risk conditions under which countries operate. The VRS-based target results further reveal that inefficiencies are not solely driven by insufficient research output, but are strongly associated with elevated risk components. Linking these efficiency outcomes to the underlying indicators of the disaster risk indices clarifies that institutional quality, socio-economic vulnerability, and exposure-related factors play a decisive role in shaping national research efficiency. This risk-integrated perspective extends existing DEA-based studies by moving beyond output-oriented assessments and offering a more contextualized and policy-relevant evaluation of earthquake-related research performance.

Overall, the findings highlight that efficiency in earthquake-related research and innovation should be evaluated not only in terms of output volume, but also in relation to risk exposure and the effective use of available resources. In this sense, the proposed DEA framework contributes to the literature by offering a risk-aware perspective on research efficiency that is directly relevant for disaster risk reduction and science policy.

Chapter 3

DESCRIPTIVE ASSESSMENT OF EARTHQUAKE IMPACTS, RESEARCH ACTIVITY, AND RISK PROFILES

This chapter presents the descriptive and statistical analysis of the variables employed in the study. The primary objective is to summarize the main characteristics of earthquake risk, earthquake impacts, scientific research output, and technological innovation across countries and over time. By examining distributions, variability, and group-based patterns, this chapter provides an empirical overview of the data and establishes the descriptive foundation for the model-based analyses conducted in subsequent chapters. The datasets used in the analysis, together with their sources, time coverage, and content, are summarized in Table 3.1. Detailed information on data retrieval procedures, including data acquisition dates, search strategies, selection criteria, and applied filters for all datasets, is provided in Appendix A.

Descriptive analysis of earthquake-related events requires a consistent conceptual framework for defining and classifying disasters and hazards. To ensure comparability across studies, the international scientific community has developed standardized hazard classification systems. One of the most widely recognized frameworks is the Peril Classification and Hazard Glossary, developed by the Integrated Research on Disaster Risk (IRDR) working group in collaboration with the Centre for Research on the Epidemiology of Disasters (CRED) [Integrated Research on Disaster Risk (IRDR), 2014]. This framework serves as the primary reference for classifying natural hazards in the EM-DAT database and provides a common terminology for disaster-related research.

Within this classification system, hazards are organized into six broad categories: geophysical, hydrological, meteorological, climatological, biological, and extraterrestrial. Each category is further subdivided into specific hazard types. For example, geophysical hazards include earthquakes and volcanic activity; hydrological hazards encompass floods and landslides; meteorological hazards cover storms and extreme temperatures; climatological hazards involve droughts and wildfires; biological hazards include epidemics and infestations; and extraterrestrial hazards refer to space weather and impact events [CRED, 2020]. This structured categorization facilitates systematic comparisons across hazard types and supports consistent descriptive assessments.

Conceptual clarity in disaster risk research also depends on a clear distinction between hazard and disaster. In this context, the United Nations Office for Disaster Risk Reduction (UNDRR) plays a central role by coordinating global disaster risk reduction efforts and providing internationally accepted terminology and definitions [United Nations Office for Disaster Risk Reduction, 2015]. According to this framework, a hazard refers to a potentially damaging physical event, phenomenon, or human activity that may result in loss of life, injury, property damage, or broader social, economic, and environmental disruption.

A disaster, by contrast, is defined as the outcome of hazardous events interacting with conditions of exposure, vulnerability, and capacity, leading to impacts that exceed the ability of affected communities to cope using their own resources [United Nations Office for Disaster Risk Reduction, 2015]. This situation highlights that disasters are not solely determined by the occurrence of hazardous events but rather by their interaction with societal conditions. Accordingly, the use of standardized classification frameworks is crucial for ensuring conceptual consistency and interpretability in the descriptive analysis of earthquake-related risks and impacts.

3.1 Earthquake Occurrence and Impact Analysis Based on EM-DAT

A detailed descriptive analysis of earthquake-related disasters requires an initial examination of how geophysical hazards are represented within global disaster databases. The EM-DAT database provides a systematic classification of disasters, enabling a comparative assessment of different geophysical hazard types within the broader disaster landscape. This structure allows researchers to identify dominant hazard categories and to contextualize earthquake-related events relative to other geophysical phenomena.

Within the EM-DAT framework, geophysical disasters comprise earthquakes, volcanic activity, and dry mass movements, each associated with distinct physical processes and impact pathways. Examining the relative frequency of these hazard types is an essential first step toward understanding overall disaster patterns and toward defining a focused analytical scope in earthquake research.

A closer inspection of earthquake-related records reveals that ground movement constitutes the dominant manifestation of earthquake disasters. Specifically, ground movement accounts for approximately 95.6% of all earthquake-related events recorded in EM-DAT, whereas tsunami-related earthquakes account for a comparatively small share of 4.4%. This distribution indicates that global earthquake disaster records are overwhelmingly characterized by ground shaking rather than secondary phenomena such as tsunamis. As a result, descriptive assessments of earthquake impacts using EM-DAT data are primarily driven by ground-movement-related events, as summarized in Table 3.2.

In contrast, volcanic activity and dry mass movements occur far less frequently. Volcanic disasters are dominated by ash fall events (approximately 79% of volcanic cases), whereas dry mass movement events are mainly associated with landslides (64%). Compared to earthquakes, however, these categories account for only a minor fraction of geophysical disasters in terms of frequency. As shown in Table 3.3, earthquakes account for the largest share of geophysical disaster records in the EM-DAT dataset during the study period. This empirical prevalence motivates the focus on earthquakes in the subsequent descriptive analysis.

Following the global overview of ground movement earthquakes, a more detailed examination at the country level provides insight into how these events are distributed across space and time. To capture temporal patterns and cross-country differences, ground movement earthquake events recorded in the EM-DAT database are aggregated into five-year periods. This approach enables a descriptive comparison of country-level trends, highlighting periods of relatively higher or lower earthquake activity. Table 3.4 presents the top 20 countries in terms of recorded ground movement earthquake events over the period 2000–2025. The distribution reveals substantial heterogeneity across countries and time periods. China consistently records the highest number of ground movement events across all sub-periods, indicating sustained earthquake activity throughout the study period. Indonesia and Iran (Islamic Republic of) also exhibit relatively high frequencies, though with more pronounced fluctuations across different time intervals.

Several countries, such as Türkiye, Japan, and the Philippines, show clear changes in the number of ground movement earthquakes over time, with some periods having more events and others having fewer. In contrast, countries like Italy, Greece, and the United States generally experience fewer ground movement earthquakes, and the number of events remains relatively stable across different periods. Overall, the table shows that ground movement earthquakes are not evenly distributed across countries or over time, underscoring the importance of country-level descriptive analysis for understanding global earthquake patterns.

From this perspective, Türkiye's earthquake activity can be viewed alongside other countries that frequently experience ground movement earthquakes, such as Japan, China, and Indonesia. Comparing these countries helps place Türkiye's earthquake record within the global context and shows how its earthquake patterns are similar to or different from those observed in other earthquake-prone countries.

The selection of countries analyzed in this study is guided by an established comparative framework in the earthquake research literature. Specifically, the country group follows the framework introduced by [Bae et al., 2021], who examined the efficiency of public research activities and knowledge spillovers in the context of earthquake-related R&D. This framework includes countries such as France, the United States, New Zealand, Iran, China, Japan, Türkiye, South Korea, Greece, Taiwan, India, and Italy, which together represent major centers of earthquake-related scientific activity and are characterized by varying levels of seismic exposure and research capacity. Adopting the same set of countries ensures consistency and comparability with prior studies while allowing for a structured cross-country assessment.

Figures 3.1 and 3.2 provide a descriptive overview of the global distribution of earthquakes with magnitude ≥ 4.5 recorded in the EM-DAT database during the period 2000–2025. The global distribution shows that earthquakes occur across countries, with a relatively small group accounting for a large share of recorded events. Countries such as China, Indonesia, Iran, Japan, Türkiye, and the Philippines appear among those most frequently affected. The countries highlighted in red correspond to the twelve high-exposure countries selected for this study, which are consistent with the country group analyzed by [Bae et al., 2021] in the context of country selection.

Focusing on this selected group, the Pareto distribution shows that these twelve countries experienced a total of 290 earthquake events, corresponding to 47.1% of all recorded global earthquakes with magnitude ≥ 4.5. The cumulative ranking presented in Table 3.5 further illustrates that a subset of countries—led by China, followed by Iran, Türkiye, and Japan—accounts for a substantial share of global earthquake activity. Together, these descriptive patterns indicate that the selected country group accounts for a significant share of global earthquake occurrences, providing a clear, data-driven basis for its use in subsequent country-level analyses.

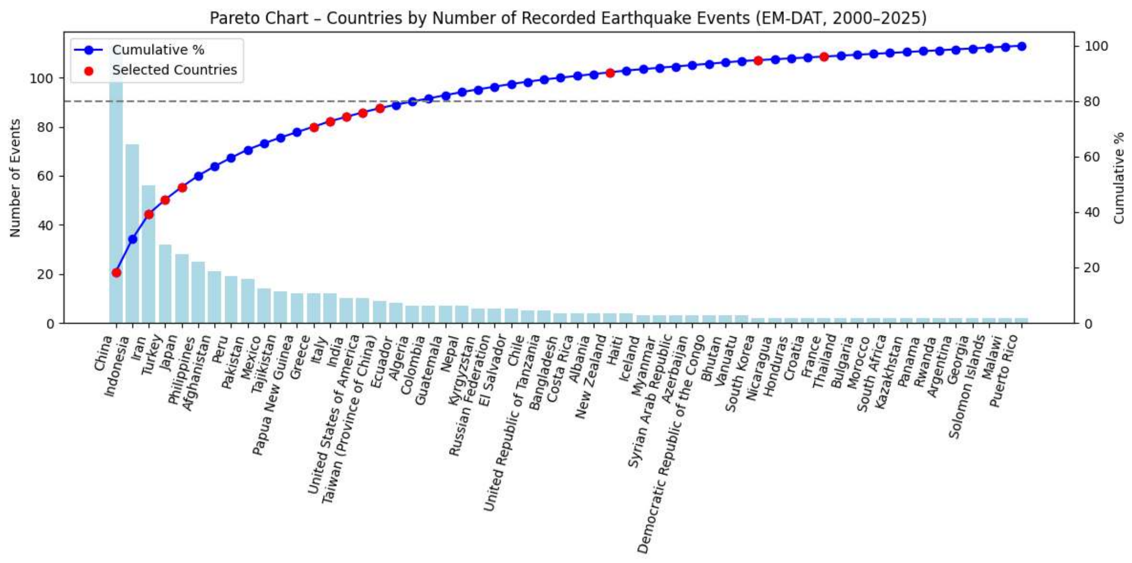

Figure 3.1: Global distribution of earthquakes with magnitude ≥ 4.5 recorded in the EM-DAT database and the contribution of the twelve selected high-exposure countries (2000–2025).

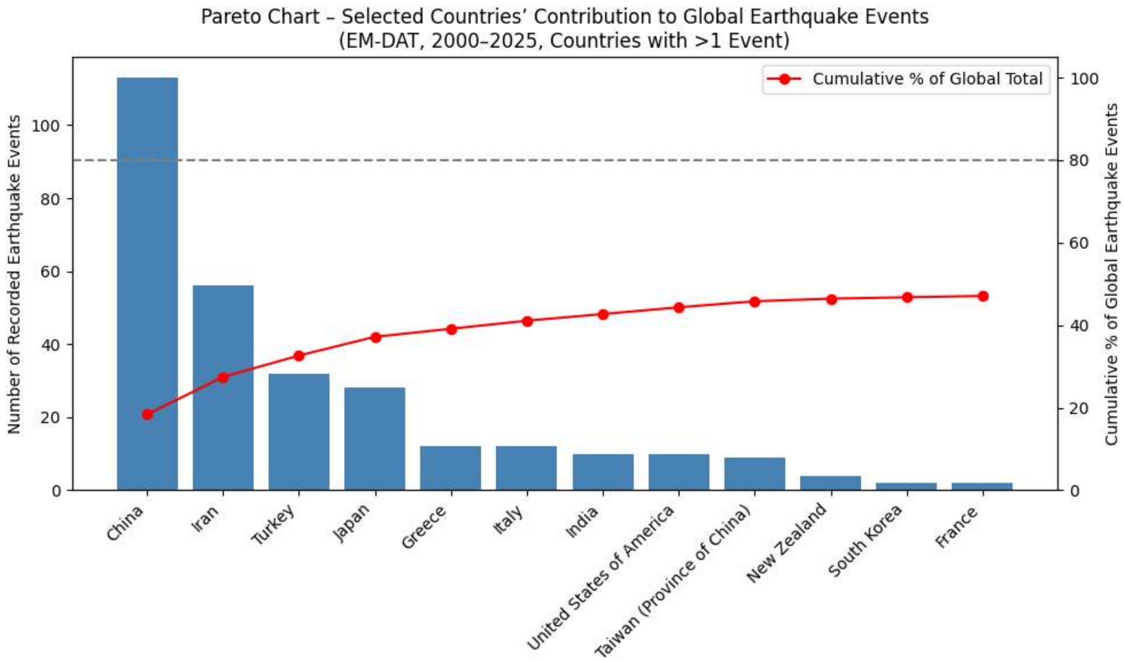

Figure 3.2: Pareto distribution of earthquakes with magnitude $\geq$ 4.5 across the twelve selected countries based on EM-DAT data (2000–2025).

3.1.1 Human and Economic Outcomes by Earthquake Magnitude

This subsection examines the human and economic consequences of earthquakes across countries, with a particular focus on differences by magnitude category. Table 3.6 summarizes earthquake frequency together with the affected population, injuries, and fatalities per million population, disaggregated by magnitude category for the period 2000–2024. Economic impacts are examined in Table 3.7, which reports total earthquake-related damage and damage per person by magnitude category. Taken together, these tables provide a comprehensive overview of how human and economic outcomes vary with earthquake magnitude.

(1) Human impacts are concentrated in high-magnitude earthquakes: Human impacts are largely concentrated in high-magnitude earthquakes. As shown in Table 3.6, earthquakes in the 4–5 and 5–6 magnitude ranges are associated with very limited fatalities and injuries across all countries, even in cases where a relatively large number of people are affected. In contrast, earthquakes with magnitudes be-

tween 6–7 and especially those exceeding magnitude 7 account for most deaths, injuries, and affected population per million. This pattern suggests that severe human losses are primarily driven by less frequent but stronger earthquakes, rather than by the overall number of seismic events.

(2) High exposure does not necessarily imply high mortality: The results further show that high earthquake exposure does not necessarily imply high mortality. Table 3.6 illustrates that some countries experience frequent and strong earthquakes while maintaining low levels of fatalities and injuries per million population. Conversely, countries such as Türkiye and Iran record considerably higher human losses during major earthquakes, despite having comparable or lower exposure levels. This divergence suggests that exposure alone is insufficient to explain observed human outcomes across countries.

(3) Economic losses and human losses follow different patterns: Economic losses follow a different pattern from human losses when examined across magnitude categories. As reported in Table 3.7, countries such as Japan and the United States incur substantial total and per-person economic damage in high-magnitude earthquakes while recording limited fatalities. In contrast, Türkiye and Iran experience sharp increases in both economic damage per person and human losses in the highest magnitude category. This comparison highlights that economic damage reflects the value of exposed assets, whereas human losses are more closely linked to vulnerability and protection levels.

(4) High-magnitude earthquakes amplify cross-country disparities:

Differences between countries become more visible as earthquake magnitude increases. Lower-magnitude earthquakes tend to produce relatively similar and limited impacts across countries. However, earthquakes above magnitude 7 lead to clearly different outcomes: some countries experience serious economic damage with low mortality, while others face significant human losses alongside economic damage. These patterns show that large earthquakes reveal differences in how countries are affected by severe seismic events; both Table 3.6 and Table 3.7 show that cross-country disparities become more pronounced as earthquake magnitude increases.

3.2 Scientific Research Output on Earthquakes: Evidence from Scopus

This section analyzes earthquake-related scientific research output using publication data retrieved from the Scopus database. The descriptive analysis examines the distribution of publication counts across countries and over time, highlighting differences in earthquake-related academic research activity. By comparing publication patterns across countries, this section aims to illustrate the heterogeneity in scientific responses to earthquake risk and to provide a descriptive overview of global and national trends in earthquake-related research production.

Earthquake-related publications were collected from Scopus based on a structured search strategy that applied clearly defined inclusion and exclusion criteria. The dataset covers the period 2000–2024 and includes only peer-reviewed journal articles written in English that explicitly address earthquake-related topics. Records such as review articles, conference papers, book chapters, and publications unrelated to earthquakes were excluded to ensure consistency and comparability across countries.

Following data retrieval, several preprocessing steps were implemented using Python. Publication records were cleaned and standardized to extract country affiliation information from author metadata. Countries were harmonized to ensure consistent naming conventions, and publications with multiple country affiliations were appropriately handled. The cleaned dataset was aggregated to obtain annual publication counts for each country, enabling a time-series representation of earthquake-related scientific output at the country level.

Before focusing on the twelve selected high-exposure countries, the analysis first presents a global overview of earthquake-related scientific publications to provide context for country-level comparisons. Examining publication trends among the leading publishing countries worldwide allows the relative position of the selected countries to be interpreted within the broader landscape of global earthquake research. Figure 3.3 presents the temporal evolution of earthquake-related scientific publications for the top fifteen publishing countries over the period 2000–2024, grouped according to their overall publication ranks. Across all country groups, a clear upward trend in earthquake-related research activity is observed from the early 2000s onward, indicating a growing scientific interest in these topics globally.

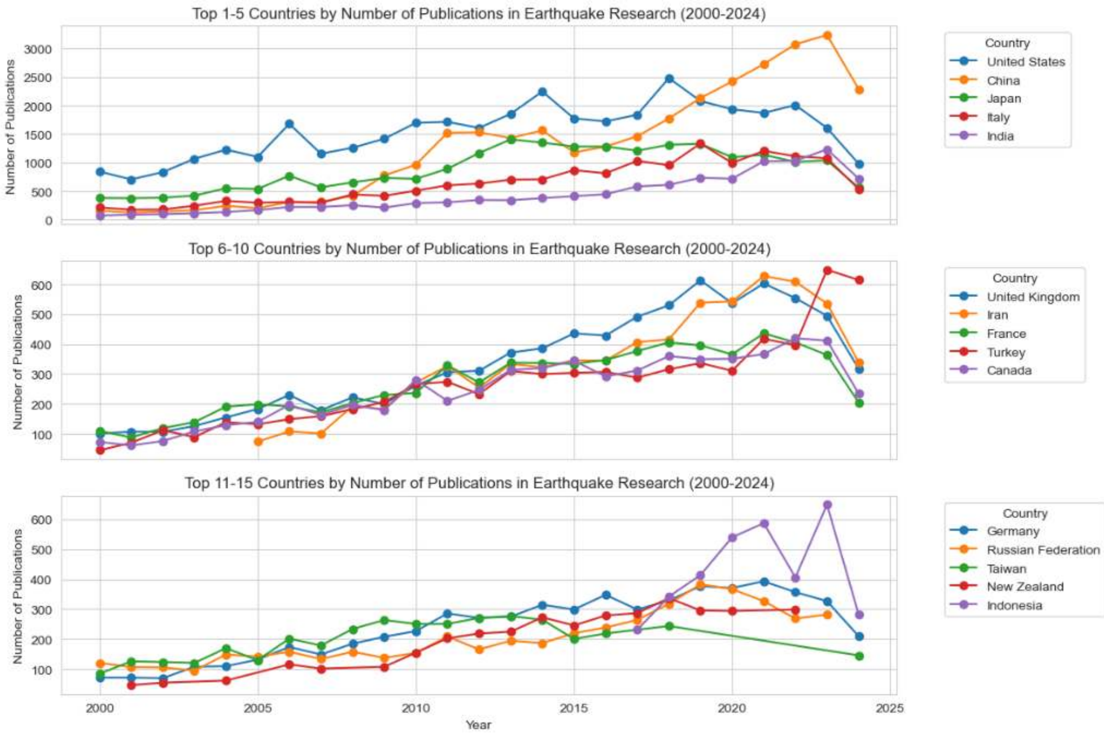

Figure 3.3: Temporal distribution of earthquake-related scientific publications for the top publishing countries worldwide (Scopus, 2000–2024).

Among the highest-publishing countries, the United States and China consistently dominate publication output throughout the period, although their trajectories differ in timing and intensity. Japan, Italy, and India also show sustained growth, with noticeable year-to-year fluctuations. Countries ranked between sixth and tenth, including Iran, France, and Türkiye, display more moderate but steadily increasing publication trends, particularly after the mid-2000s. In the lower-ranked group, publication volumes remain comparatively smaller, yet several countries exhibit pronounced increases in specific periods, reflecting changing levels of research engagement over time.

Overall, the figure highlights substantial heterogeneity in both the scale and temporal dynamics of earthquake-related scientific production across countries. This global overview provides a contextual benchmark for the subsequent analysis, which focuses on the selected high-exposure countries and examines their research activity in greater detail. This global overview is presented to identify the countries that dominate earthquake-related scientific publishing worldwide and to provide context for the selection of the twelve countries analyzed in the remainder of this chapter. The subsequent analysis, therefore, focuses exclusively on these selected countries, examining their publication patterns in greater detail.

Following the presentation of global publication trends, the analysis now focuses on the twelve selected high-exposure countries. Figure 3.4 and Table 3.8 summarize the distribution of unique earthquake-related scientific publications indexed in Scopus for these selected countries over the period 2000–2024. The Pareto representation illustrates each country's contribution to the total publication output of the selected group together with the cumulative share, while the table reports the corresponding publication counts and cumulative percentages.

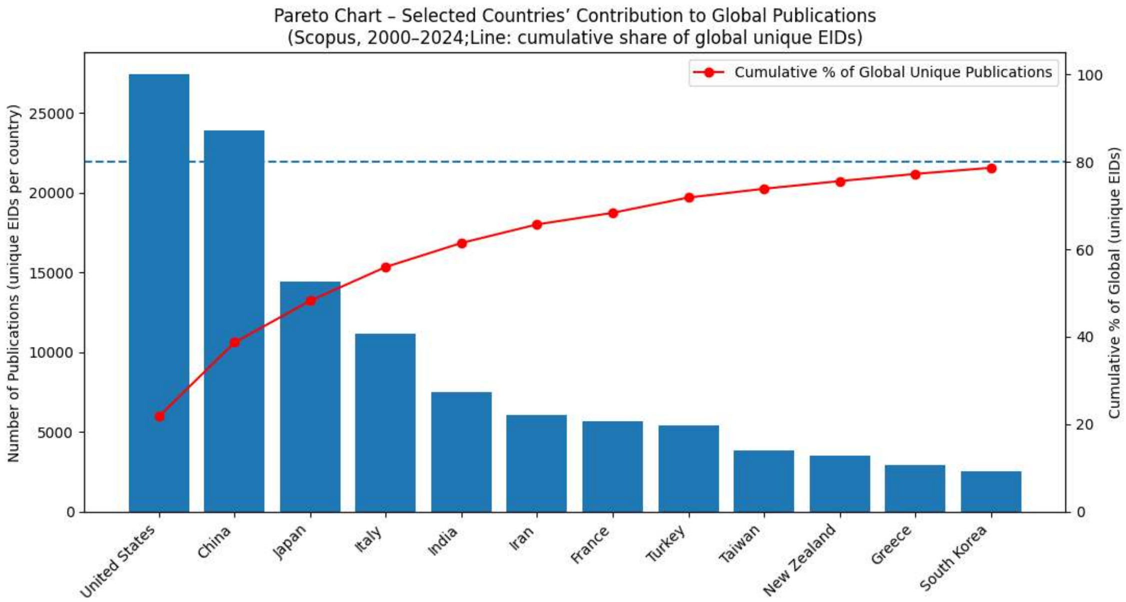

Figure 3.4: Pareto distribution of earthquake-related scientific publications across the selected countries indexed in Scopus (2000–2024). Bars represent the number of unique earthquake-related publications per country, while the cumulative line indicates the cumulative share of global publications.

The results indicate that earthquake-related scientific output is highly concentrated across countries. The United States and China together account for nearly

40% of all publications, followed by Japan and Italy, which further increase the cumulative share to over 50%. When all twelve selected countries are considered, they collectively produce 98,731 publications, accounting for 78.6% of the global earthquake-related research output during the study period.

This distribution highlights substantial heterogeneity in scientific research activity across countries. A small number of countries contribute a large share of global earthquake-related publications, while others exhibit more moderate research output.

3.2.1 Scientific Activity in Earthquake Research Over Time: An Activity Index Analysis

This subsection examines how scientific attention to earthquake-related research evolves over time across high-risk countries and assesses the extent to which this evolution reflects differences in national research priorities. Rather than focusing solely on absolute publication counts, the analysis adopts a relative perspective that accounts for each country's overall scientific output. This approach enables a more balanced comparison of research engagement across countries with varying publication capacities, providing insight into changes in thematic emphasis over time.

To evaluate countries' relative engagement in earthquake-related research, the Activity Index (AI) is used as a normalized indicator of thematic specialization. Originally introduced by [Schubert and Braun, 1986], the AI measures whether a country's publication share in a specific research field is higher or lower than its overall contribution to global scientific output. Subsequent studies by [Moed et al., 1991] and [Glänzel, 2000] refined and applied this measure to assess institutional and national research performance, while [Tijssen et al., 2002] highlighted its usefulness in cross-national comparisons and analyses of thematic focus.

In bibliometric research, AI is widely used to assess whether a country exhibits above-average specialization (AI $>$ 1), below-average specialization (AI $<$ 1), or alignment with the global average (AI $=$ 1) in a given research domain. By normalizing earthquake-related publication activity relative to total scientific output, AI enables the interpretation of differences in research intensity independent of country size or overall publication volume.

The Activity Index for country i in year t is defined as

$$AI_i^t = \frac{\frac{P_i^t}{\sum P^t}}{\frac{TP_i^t}{\sum TP^t}}, \tag{3.1}$$

where P_i^t denotes the number of earthquake-related publications produced by country i in year t, $\sum P^t$ represents the total number of earthquake-related publications worldwide in the same year, TP_i^t is the total number of publications by country i across all scientific fields in year t, and $\sum TP^t$ denotes the total number of scientific publications worldwide. This formulation expresses a country's relative research intensity in the earthquake domain compared to its overall scientific activity.

The Activity Index values reported in Table 3.9 are computed by the authors based on earthquake-related publication data retrieved from the Scopus database, following Equation 3.1. Countries are grouped by average AI level over the study period into three categories (AI: 0–1, 1–2, and 2–3). An AI value greater than one indicates above-average specialization in earthquake-related research relative to a country's overall scientific output, while values below one reflect lower relative specialization.

A longitudinal examination of Table 3.9 indicates that variations in the Activity Index (AI) are closely associated with the occurrence of major seismic events, revealing a distinct event–response dynamic in scientific output. For instance, New Zealand demonstrates a sharp rise in AI—from 1.8 in 2008 to above 2.7 after 2011—corresponding to the aftermath of the 2010–2011 Canterbury and Christchurch earthquakes [Potangaroa, 2011, Wilkinson and Chang-Richards, 2013].

Similarly, Türkiye experienced a gradual increase in AI during the 2010s, coinciding with a sequence of significant seismic events that heightened national research attention. Notably, the 2003 Bingöl [Emre et al., 2004], 2010 Elazığ [Ozalaybey et al., 2011], and 2011 Simav [Ozmen and Türkelli, 2013] earthquakes triggered heightened academic interest in seismic hazard assessment, structural resilience, and post-disaster management. This upward trajectory culminated in a pronounced surge after the 2023 Kahramanmaraş earthquakes, which prompted extensive research addressing urban vulnerability, infrastructure failure, and emergency coordination. These patterns underscore how major seismic events have historically acted as catalysts for increased earthquake-related scientific activity in Türkiye[Varolgüneş, 2025]

In conclusion, Table 3.9, which reports Activity Index (AI) values for selected countries over the period 2000–2024, shows that although the United States and China produce a very large number of scientific publications, their relative share of earthquake-related research remains low at the global level due to their highly diversified overall research output. In contrast, countries such as New Zealand and Greece consistently appear in higher AI ranges, indicating a stronger relative concentration on earthquake-related research despite producing fewer total publications. Türkiye occupies an intermediate position, with AI values reflecting a higher relative focus on earthquake-related research than in the United States, China, and South Korea, but a lower concentration than in New Zealand.

Overall, these results suggest that the Activity Index reflects a country's relative emphasis on earthquake-related research, rather than the total number of publications, highlighting cross-country differences in how earthquake research is prioritized within national research systems.

3.3 Technological Innovation Related to Earthquakes: Patent Evidence

This section examines technological innovation related to earthquakes using patent data obtained from the Espacenet database. The analysis focuses on the twelve selected countries and spans the period from 2000 to 2025. Patent activity is analyzed descriptively to assess how technological responses to earthquake risk vary across countries and over time.

For each country, the total number of earthquake-related patents is first identified on an annual basis. To enable meaningful cross-country comparison, earthquake-related patent counts are evaluated relative to each country's overall patenting activity. This approach accounts for differences in national patent systems and general innovation capacity, allowing the analysis to focus on the relative importance of earthquake-related technologies within national innovation portfolios.

Earthquake-related patent data were not available as a precompiled dataset and were therefore constructed manually for this study. Patent records were retrieved from the Espacenet database of the European Patent Office (EPO) through systematic country-by-country and year-by-year searches covering the period 2000–2024. Searches were conducted in English using the keyword "earthquake" in the title or abstract fields and were filtered by inventor country for the twelve selected countries. The retrieved patent records were subsequently processed in Python to organize the data by country and year, compute annual counts of earthquake-related patents, and merge these records with total national patent counts. Based on this processed dataset, a patent-based activity indicator was constructed to describe the relative intensity of earthquake-related technological innovation across countries and over time.

To further illustrate cross-country differences in earthquake-related technological activity, countries are grouped according to their overall patenting intensity in the earthquake domain. Based on the distribution of total earthquake-related patent counts over the study period, the twelve countries are divided into three groups representing the upper, middle, and lower thirds of the patent distribution. This grouping enables clearer visualization of temporal patterns by separating countries with persistently high patent activity from those with moderate and low levels of patenting.

Figure 3.5 presents the annual distribution of earthquake-related patent counts for the selected countries, grouped according to overall patenting intensity. Countries in the high-patent group, such as China, Japan, and the Republic of Korea, exhibit consistently higher patent counts over time, although noticeable year-to-year fluctuations are observed. These countries account for a substantial share of total earthquake-related patenting activity throughout the period.

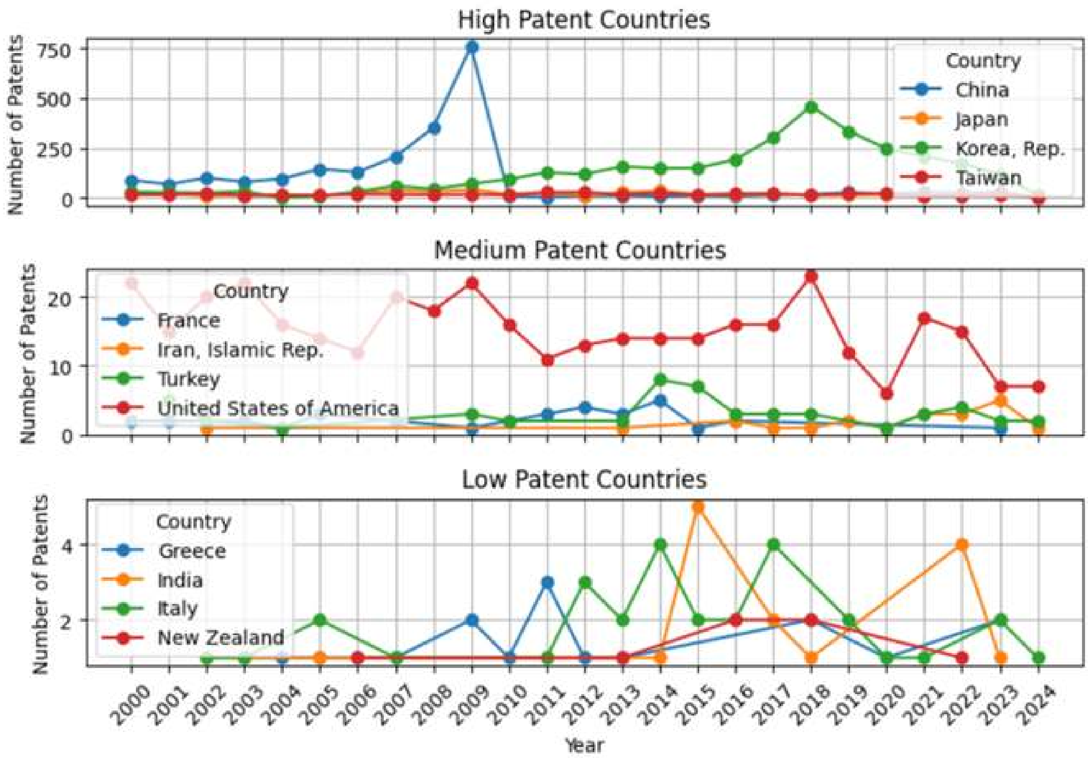

Figure 3.5: Distribution of earthquake-related patents over time by country groups. Countries are classified into high-, medium-, and low-patent groups based on their total earthquake-related patent counts during the study period (2000–2024).

The medium-patent group, including countries such as Türkiye, Iran, France, and the United States, displays more moderate patent counts with greater temporal variability. Patent activity in this group tends to fluctuate across years, suggesting less stable engagement in earthquake-related technological development than in the high-patent group.

In contrast, countries in the low-patent group exhibit relatively limited patenting activity, characterized by low annual counts and sporadic increases in certain years. Overall, the figure highlights pronounced heterogeneity across countries in both the level and temporal evolution of earthquake-related patent activity, providing a descriptive overview of how technological innovation related to earthquakes is distributed across national contexts.

3.3.1 Technological Activity in Earthquake-Related Innovation Over Time: A Patent Activity Index Analysis

Earthquake-related patent data were not available as a precompiled dataset and were therefore constructed manually for this study. Patent records were retrieved from the Espacenet database of the European Patent Office (EPO) through systematic country-by-country and year-by-year searches covering the period 2000–2024. The detailed search strategy, including query structure, filters, and country selection, is documented in Appendix 3.3.1. Searches were conducted in English using the keyword "earthquake" in the title or abstract fields and were filtered by inventor country for the twelve selected countries. The retrieved patent records were subsequently processed in Python to organize the data by country and year, compute annual counts of earthquake-related patents, and merge these records with total national patent counts. Based on this processed dataset, a patent-based activity indicator was constructed to describe the relative intensity of earthquake-related technological innovation across countries and over time.

Accordingly, a patent share indicator is constructed to measure the proportion of earthquake-related patents within total national patents. The patent share for country i in year t is calculated as follows:

$$\text{PatentShare}_i^t = \frac{\text{EarthquakePatentNumbers}_i^t}{\text{TotalPatentNumbers}_i^t} \times 100, \tag{3.2}$$

where $\text{EarthquakePatentNumbers}_i^t$ denotes the number of earthquake-related patent applications filed by country i in year t, and $\text{TotalPatentNumbers}_i^t$ represents the total number of patent applications filed by the same country in that year.

This indicator captures the relative emphasis placed on earthquake-related technological development, rather than overall patenting activity. By examining patent shares across countries and over time, the analysis identifies countries with comparatively higher engagement in earthquake-related innovation, highlights temporal changes in patenting behavior, and allows comparisons between countries with differing levels of overall patent output.

Table 3.10 presents the share of earthquake-related patents within total national patents for the selected countries over the period 2000–2025. The descriptive results provide insight into cross-country differences in technological responses to earthquake risk and complement the analysis of scientific research activity presented in the previous section.

When average patent shares are compared with publication-based Activity Index (AI) groupings, a clear divergence between technological and scientific specialization patterns emerges. Countries such as France, the United States, Italy, and India exhibit relatively low average shares of earthquake-related patents (below 0.05%) while also belonging to the lower- or mid-range AI groups, indicating modest or moderate thematic emphasis in their scientific output. In contrast, New Zealand, which forms the highest AI group (AI: 2–3), shows a comparatively higher patent share among the selected countries, suggesting stronger alignment between scientific focus and technological activity in the earthquake domain.

Similarly, countries including Türkiye, Greece, and Iran fall within the AI: 1–2 group for scientific publications, yet display heterogeneous patent shares, with Iran exhibiting the highest average patent share despite not belonging to the highest AI category. This comparison highlights that countries with stronger scientific specialization in earthquake research do not necessarily exhibit proportionally higher patent activity, underscoring differences in how scientific attention and technological development are translated within national systems.

Year-by-year patterns in the patent-based activity shares and the scientific Activity Index (AI) indicate that earthquake-related technological and scientific activity varies considerably across countries and over time. Patent shares remain generally low for most countries, with occasional increases in specific years, while AI values display noticeable temporal fluctuations, reflecting changes in the relative emphasis placed on earthquake-related research within national research systems

3.4 Disaster Risk Assessment Based on the INFORM Risk Index

In disaster management and earthquake-focused efficiency analysis, selecting risk-related input variables is a critical step, as it directly influences the interpretability and validity of subsequent empirical results. To capture country-level disaster risk in a structured, comparable, and internationally recognized manner, this analysis adopts the INFORM Risk Framework developed by the European Commission's Disaster Risk Management Knowledge Centre [INFORM Risk Index, 2025]. The INFORM framework conceptualizes disaster risk as the interaction of three core dimensions: Hazard and Exposure, Vulnerability, and Lack of Coping Capacity. Hazard and Exposure reflects the intensity, frequency, and spatial distribution of hazards as well as the exposure of populations and assets. Vulnerability captures socio-economic conditions that increase susceptibility to adverse impacts, while Lack of Coping Capacity represents institutional, infrastructural, and governance-related limitations that constrain a country's ability to anticipate, respond to, and recover from disasters. Each INFORM dimension is constructed from a set of underlying quantitative indicators. However, the contribution of individual indicators to their composite indices may vary across countries and over time.

Figure 3.6 visualizes the three-dimensional distribution of the selected countries based on their average INFORM component values. Each axis represents one dimension of the INFORM framework, enabling countries with similar risk profiles to be visually identified. The figure highlights clear clustering patterns, indicating that some countries share comparable combinations of hazard exposure, vulnerability, and coping capacity.

Countries such as Türkiye, Iran, and India appear in close proximity within the three-dimensional risk space, reflecting relatively high vulnerability and limited coping capacity alongside significant hazard exposure. In contrast, countries including Japan, South Korea, and New Zealand are positioned in regions characterized by lower vulnerability and stronger coping capacity, despite notable hazard exposure. Other countries, such as the United States and China, occupy intermediate positions, reflecting distinct balances between exposure and institutional capacity.

Figure 3.8 illustrates the evolution of the INFORM Risk Index for the selected countries over the period 2015–2024. The figure highlights clear cross-country differences in both risk levels and temporal dynamics. Countries such as India, Iran, and Türkiye consistently exhibit higher risk scores, reflecting the combined effect of substantial hazard exposure and comparatively higher vulnerability or limitations in

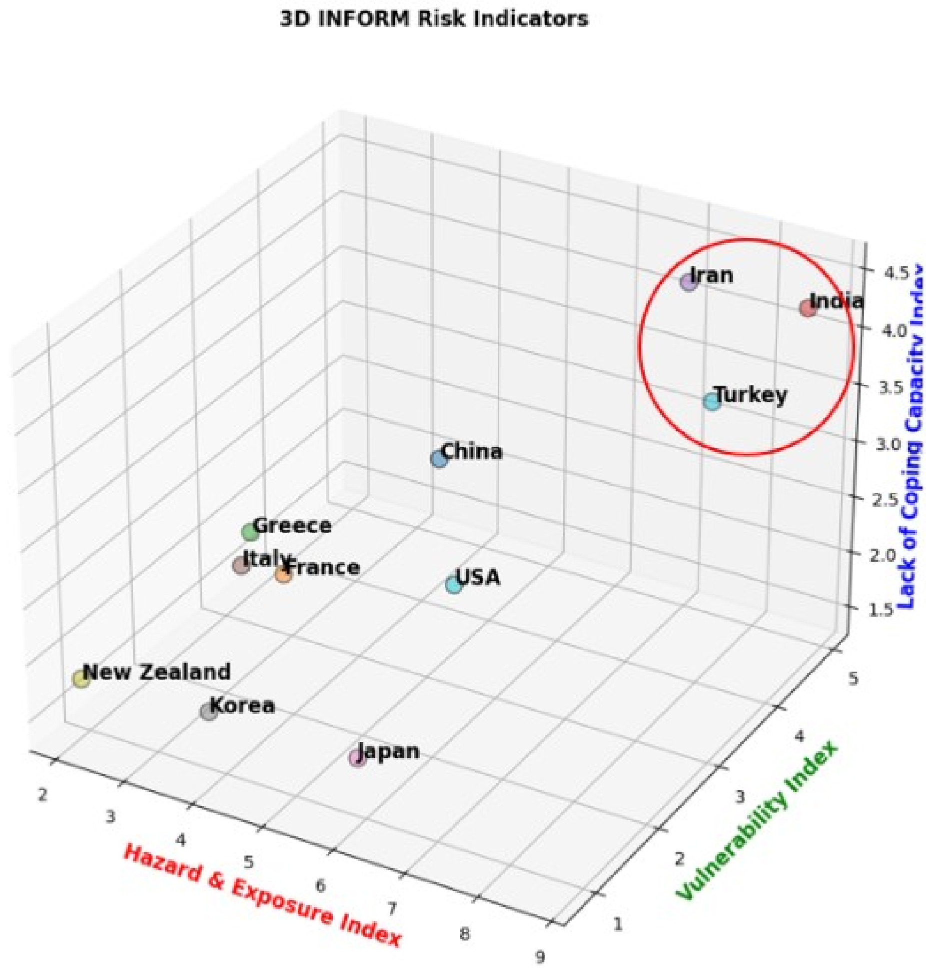

Figure 3.6: Three-dimensional distribution of selected countries based on average INFORM Risk Index components (2016–2025). The axes represent Hazard and Exposure, Vulnerability, and Lack of Coping Capacity. Countries that are closer together in three-dimensional space exhibit similar long-term disaster risk profiles.

coping capacity. In contrast, countries such as New Zealand, the Republic of Korea, and France consistently display lower risk levels, indicating stronger institutional capacity and lower overall vulnerability despite exposure to seismic hazards.

From a temporal perspective, INFORM risk scores remain relatively stable over time for most countries, suggesting that disaster risk is driven by structural conditions rather than short-term fluctuations. Moderate declines or plateaus observed in several countries reflect gradual improvements in vulnerability or coping capacity rather than abrupt changes in hazard exposure. The trends suggest that while hazard exposure may vary, long-term disaster risk profiles are primarily shaped by enduring socioeconomic and institutional factors.

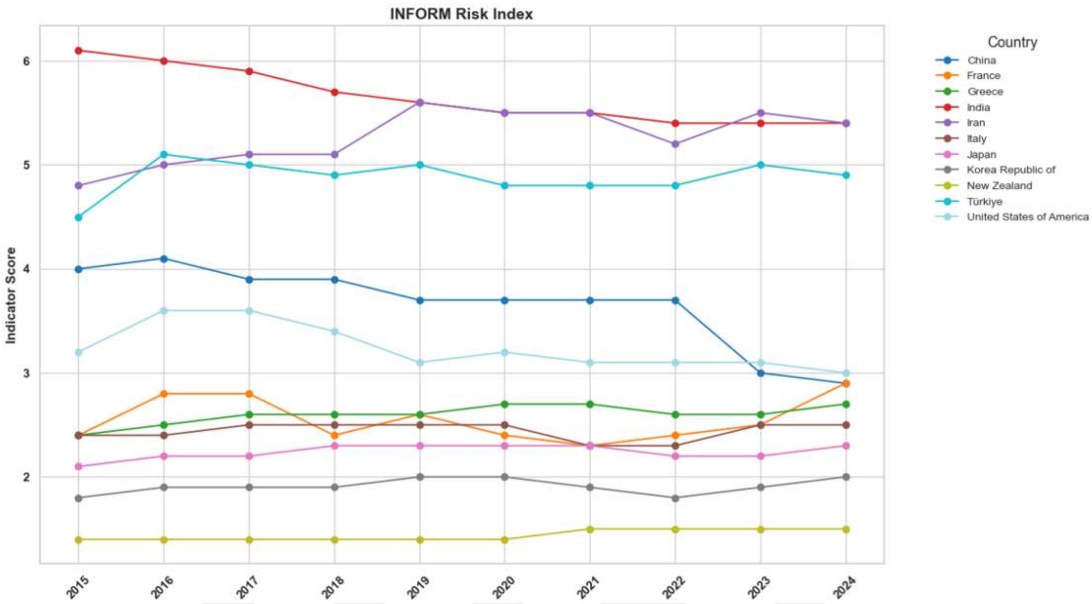

Figure 3.7: Trends in the INFORM Risk Index for selected earthquake-prone countries (2015–2024).

Figure 3.8 provides a more detailed view of the INFORM Risk Index by decomposing overall risk into its three core components—Hazard & Exposure, Vulnerability, and Lack of Coping Capacity—over the period 2015–2024. The figure shows that cross-country differences in overall risk are driven by distinct combinations of these components rather than a single dominant factor. For instance, India and Iran consistently exhibit high overall risk scores, primarily reflecting very high Hazard & Exposure levels combined with elevated Vulnerability and relatively limited Coping Capacity. Türkiye also displays a persistently high risk, with notable contributions from both Hazard & Exposure and Vulnerability. In contrast, countries such as New Zealand and the Republic of Korea maintain low overall risk levels, characterized by low Vulnerability and strong Coping Capacity, even when exposed to seismic hazards. The United States and China occupy intermediate positions, where moderate-to-high Hazard & Exposure is partially offset by comparatively stronger coping capacity and lower vulnerability.

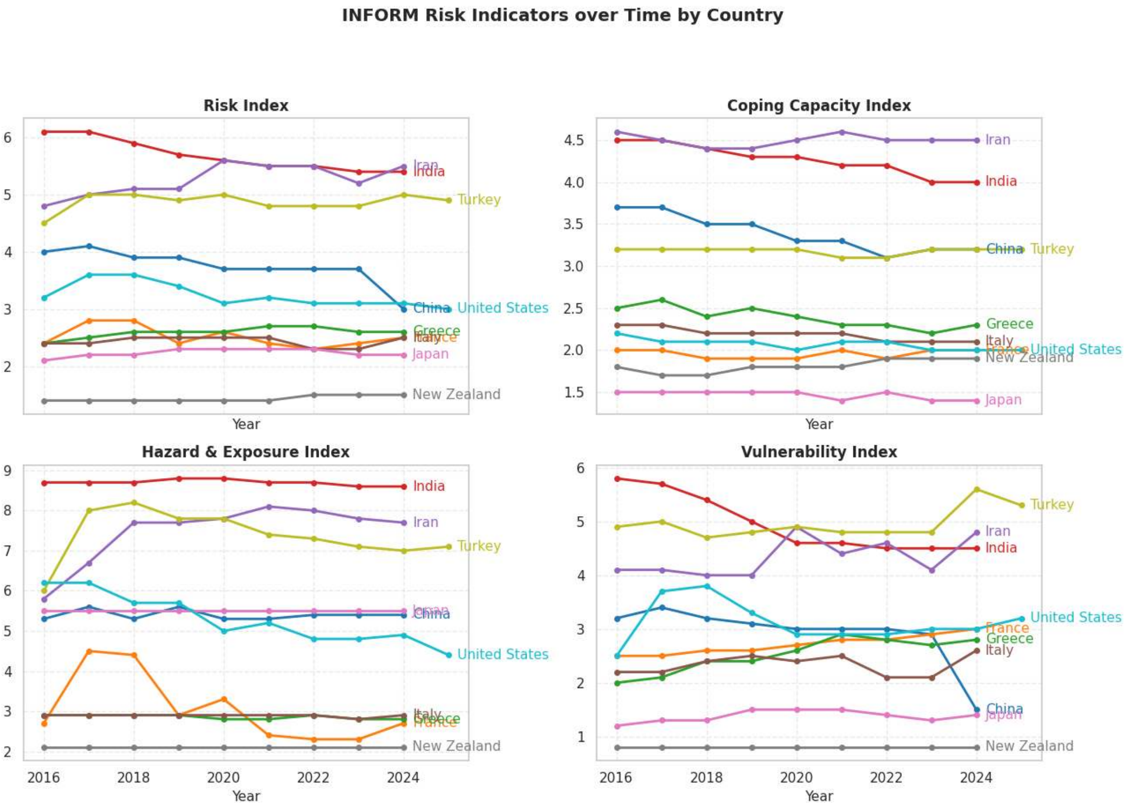

Figure 3.8: Trends in the INFORM Risk Index for selected earthquake-prone countries (2015–2024).

Overall, this descriptive visualization provides a comparative perspective on disaster risk conditions across countries and establishes a foundation for subsequent analyses. This component-level perspective illustrates that disaster risk emerges from the interaction of physical exposure, socio-economic conditions, and institutional capacity, underscoring the importance of considering all three dimensions when interpreting cross-country risk profiles. By situating scientific and technological activity within these risk profiles, the following section examines how the three INFORM risk components are characterized by their underlying indicators, focusing on correlation-based analysis to identify which variables most strongly explain each risk dimension

3.4.1 Indicator-Level Assessment of Hazard, Vulnerability, and Coping Capacity Components

The INFORM Risk Index and its sub-dimensions are constructed from a wide range of quantitative indicators that capture different aspects of disaster risk. While these indicators are not directly included as explanatory variables in the empirical regression models, understanding their structure is important for interpreting the role of the composite risk indices in the subsequent analyses.

The purpose of this indicator-level assessment is therefore not variable selection for model estimation but rather to provide an explanatory background on what each INFORM dimension represents in practice. By examining the correlations between composite indices and their underlying indicators, this analysis clarifies which socio-economic, institutional, and hazard-related factors are most strongly reflected in the INFORM framework. This information supports a more informed interpretation of the regression results presented in Chapter 4.

Tables 3.11, 3.12, and 3.13 report the correlations between each composite index and its underlying indicators for the Vulnerability, Lack of Coping Capacity, and Hazard & Exposure dimensions, respectively. For the Vulnerability dimension, the strongest correlations are observed for indicators related to multidimensional poverty, gender inequality, child health, and human development. These results indicate that the vulnerability index primarily reflects structural socio-economic conditions that increase countries' susceptibility to disaster impacts.

For the Lack of Coping Capacity dimension, institutional and infrastructure-related indicators such as government effectiveness, access to improved water and sanitation, and adult literacy exhibit strong associations with the composite index. Indicators capturing higher governance quality and technological development, including internet usage and corruption perception, display negative correlations. This pattern suggests that stronger institutions and infrastructure play a protective role by enhancing countries' ability to cope with disasters.

Within the Hazard & Exposure dimension, the highest correlations are associated with conflict-related indicators and measures of physical exposure to major hazards, including earthquakes and droughts. The strong link between conflict intensity and hazard exposure highlights that disaster risk is often amplified by socio-political instability alongside natural hazards.

Table 3.14 summarizes the indicators that show a strong association with the overall INFORM Risk Index based on a correlation threshold of $|\rho| \geq 0.7$. The results indicate that overall disaster risk is closely connected to socio-economic vulnerability, institutional capacity, and conflict dynamics. Indicators related to poverty, inequality, child mortality, and conflict intensity display strong positive correlations, while governance- and infrastructure-related indicators exhibit strong negative correlations, reflecting their risk-reducing effects.

Finally, Table 3.15 presents the distribution of strongly correlated indicators across the three INFORM dimensions. The relatively balanced representation across Hazard & Exposure, Vulnerability, and Lack of Coping Capacity confirms that disaster risk emerges from the interaction of physical hazard exposure, socio-economic fragility, and institutional constraints. This multidimensional structure provides important contextual insight for interpreting why disaster risk indicators show different relationships with scientific publications, human losses, economic losses, and patent activity in the empirical models.

3.4.2 Summary of Descriptive Findings

This chapter presents a descriptive overview of the analyses conducted in this study, providing a consolidated summary of earthquake occurrence, associated human and economic impacts, scientific research activity, patent-based innovation, and disaster risk profiles among the selected countries.

Tables 3.5, 3.6, and 3.7 together summarize the distribution of earthquake events and their associated human and economic impacts among the selected countries based on EM-DAT data. Table 3.5 shows that earthquake events are concentrated in a small number of countries. China accounts for the largest share of events, followed by Iran, Türkiye, and Japan. Together, these countries represent more than one-third of all recorded earthquakes within the selected sample, while the 12 countries as a whole account for approximately 47% of global earthquake events recorded in EM-DAT over the study period. Table 3.6 shows that human impacts increase with earthquake magnitude, particularly for the 6–7 and 7+ categories. However, countries with similar numbers of earthquakes often experience very different levels of affected population, injuries, and deaths per million population. Türkiye and Iran report relatively high injury and fatality levels in mid- to high-magnitude earthquakes, whereas Japan experiences lower human losses despite a relatively large number of events. New Zealand displays a different pattern, with few earthquakes but very high affected population and injury levels in higher magnitude categories, reflecting the impact of infrequent but severe events. In contrast, the United States, South Korea, and France report both fewer earthquakes and consistently low human impacts across all magnitude ranges. Therefore, these tables show that earthquake frequency and magnitude alone do not fully describe observed human impacts. Similar earthquake event exposure can be associated with different human outcomes across countries, highlighting the relevance of country-specific conditions that are examined in the subsequent analyses.

Tables 3.8 and 3.9 summarize earthquake-related scientific research activity among the selected countries using Scopus data for the period 2000–2024. Table 3.8 shows that publication output is concentrated in a small number of countries. The United States, China, and Japan together account for nearly half of all earthquake-related publications in the sample, while the 12 selected countries represent about 79% of global publications indexed in Scopus. Table 3.9 focuses on research intensity using the Activity Index (AI). The AI compares a country's share of earthquake-related publications with its share of total scientific publications at the global level, allowing research focus to be evaluated in relative terms. The results show clear differences among countries and over time. Some countries, such as New Zealand and Greece, have consistently high AI values, indicating a strong focus on earthquake research even with relatively low total publication numbers. In contrast, countries with large publication volumes, such as the United States and China, often have AI values close to or below one, suggesting a broader research focus. Regarding the distinction between absolute publication volume and relative research intensity, these tables show that producing a large number of earthquake-related publications does not necessarily imply a strong research focus on this topic. Based on a 25-year period (2000–2024), the Activity Index evaluates earthquake-related publications relative to total global scientific output. Countries such as the United States and China produce a high number of earthquake-related publications in absolute terms; however, because earthquake research represents a relatively small share of their overall scientific production, their AI values are close to or below one. In contrast, countries such as New Zealand and Greece produce fewer publications overall but exhibit consistently higher AI values, indicating a stronger relative focus on earthquake research within their national publication portfolios. A similar pattern is observed for technological innovation. Table 3.10 shows that the share of earthquake-related patents within total national patent applications are generally low, but vary across countries. Figure 3.5 further shows that countries with high absolute patent counts are not necessarily those with the highest relative specialization in earthquake-related innovation. Taken together, the publication and patent results indicate that high absolute output does not automatically correspond to a strong relative focus on earthquake-related research and innovation. The differences between absolute volume and relative intensity among countries highlight the importance of jointly considering scientific publications and patents when assessing the performance of research and innovation in subsequent analyses.

Table 3.1: Summary of datasets used in the descriptive and statistical analysis.

Dataset	Description	Reference
EM-DAT	Global earthquake disaster database providing information on earthquake events, magnitude, total deaths, total injuries, total affected population, and economic damage. Time coverage: 2000–2024.	[CRED, 2020]
NOAA	Event-level earthquake data, including magnitude, date, and location, were obtained from the National Centers for Environmental Information (NCEI). Time coverage: 2000–2024.	[NOAA, 2025]
Scopus	Earthquake-related scientific publications retrieved using TITLE-ABS-KEY search queries. Time coverage: 2000–2024.	[Elsevier Scopus, 2025]
Espacenet	Earthquake-related patent documents identified through title and abstract keyword searches. Time coverage: 2000–2024.	[European Patent Office (EPO), 2025]
INFORM Risk Index	Composite earthquake risk indicators include hazard and exposure, vulnerability, and lack of coping capacity. Time coverage: 2015–2024.	[INFORM Risk Index, 2025]
World Development Indicators (WDI)	Socio-economic indicators, including R&D expenditure, researchers, technicians, and population. Time coverage: 2000–2024.	[World Bank, 2025]

Table 3.2: Classification of disasters according to IRDR and CRED [CRED, 2020].

Disaster Category	**Examples of Subtypes**
Geophysical	Earthquake, Mass Movement (dry), Volcanic activity
Hydrological	Flood, Landslide, Wave action
Meteorological	Storm, Extreme temperature, Fog
Climatological	Drought, Glacial lake outburst, Wildfire
Biological	Animal accident, Epidemic, Insect infestation
Extra-terrestrial	Impact, Space weather

Table 3.3: Frequency distribution of geophysical disaster subtypes (2000–2025) based on EM-DAT data

Disaster Sub-type	**Category Details**	**Frequency**	**Percentage (%)**
Volcanic Activity	Ash fall	104	79.39
	Lava flow	11	8.39
	Pyroclastic flow	4	3.05
	Lahar	1	0.76
	Total	**131**	**100.00**
Earthquake	Ground movement	645	95.56
	Tsunami	30	4.44
	Total	**675**	**100.00**
Mass Movement (Dry)	Landslide	9	64.29
	Rockfall	4	28.57
	Avalanche	1	7.14
	Total	**14**	**100.00**

Table 3.4: Top 20 countries by ground movement earthquake events across five-year periods (2000–2025), based on EM-DAT data [CRED, 2020].

Country	**2000–2004**	**2005–2009**	**2010–2014**	**2015–2019**	**2020–2025**
China	28	18	34	17	16
Indonesia	18	17	17	14	7
Iran (Islamic Republic of)	14	10	14	8	10
Türkiye	12	3	5	2	10
Japan	7	7	3	6	5
Philippines	1	1	5	11	7
Afghanistan	7	4	3	2	5
Peru	3	2	4	3	3
Pakistan	5	2	4	4	3
Mexico	2	0	5	3	4
Tajikistan	4	2	3	2	2
Papua New Guinea	4	1	0	4	3
Italy	4	1	2	5	0
Greece	4	1	2	2	0
United States of America	3	2	2	2	1
India	2	1	2	4	1
Taiwan (Province of China)	1	1	3	2	2
Ecuador	3	0	1	2	3
Colombia	3	2	1	1	0
Algeria	4	1	1	0	1

Table 3.5: Cumulative distribution of significant earthquake events (magnitude ≥ 4.5) recorded in the EM-DAT database for the selected countries (2000–2025).

Country	Earthquake Events	Cumulative Share (%)
China	113	18.3
Iran	56	27.4
Türkiye	32	32.6
Japan	28	37.2
Greece	12	39.1
Italy	12	41.1
India	10	42.7
United States	10	44.3
Taiwan	9	45.8
New Zealand	4	46.4
South Korea	2	46.8
France	2	47.1
Total (12 countries)	**290**	**47.1**

Table 3.6: Earthquake frequency and human impact indicators per million population by magnitude category (2000–2024).

Country	All	Affected (per million)				Injured (per million)				Total deaths (per million)			
		4–5	5–6	6–7	7+	4–5	5–6	6–7	7+	4–5	5–6	6–7	7+
China	113	323	5828	5475	34094	0	41	29	273	0	0	3	65
Iran	56	26	8568	9525	2558	0	74	401	115	0	1	359	6
Türkiye	32	17	648	7541	213907	0	12	50	1499	0	1	4	718
Japan	28	0	371	1764	3548	0	9	62	35	0	0	1	4
Greece	12	0	69	7539	83	0	3	43	2	0	0	1	0
Italy	12	44	4	689	0	1	7	42	0	0	0	10	0
India	10	0	47	407	3456	0	0	0	138	0	0	0	17
United States	10	1	7	23	0	0	0	2	0	0	0	0	0
Taiwan	9	0	0	65	51	0	4	46	60	0	0	9	1
New Zealand	4	0	0	71486	68334	0	10	343	0	0	0	41	0
South Korea	2	0	678	0	0	0	2	0	0	0	0	0	0
France	2	11	11	0	0	0	0	0	0	0	0	0	0

Table 3.7: Total earthquake damage and per-person damage by magnitude category (2000–2024).

Country	**Total damage ('000 US$)**	**Damage per person ('000 US$), by magnitude**			
	Total	4–5	5–6	6–7	7+
China	152,204,542	0.00	0.01	0.02	0.09
Iran	5,037,962	0.00	0.01	0.05	0.01
Türkiye	37,729,086	0.00	0.01	0.01	0.49
Japan	166,329,509	0.00	0.04	0.36	0.09
Greece	853,275	0.00	0.00	0.08	0.00
Italy	34,522,531	0.00	0.00	0.54	0.00
India	6,326,151	0.00	0.04	0.00	0.00
United States	5,530,611	0.00	0.00	0.02	0.00
Taiwan	2,504,544	0.00	0.00	0.11	0.00
New Zealand	33,530,956	0.00	0.93	4.64	2.07
South Korea	26,661	0.00	0.00	0.00	0.00
France	445,000	0.01	0.00	0.00	0.00

Table 3.8: Earthquake-related scientific publications indexed in Scopus by country (2000–2024).

Country	**Publications**	**Cumulative Share (%)**
United States	27,440	21.9
China	23,914	38.7
Japan	14,426	48.3
Italy	11,169	56.0
India	7,505	61.4
Iran	6,066	65.7
France	5,672	68.3
Türkiye	5,426	71.8
Taiwan	3,829	73.8
New Zealand	3,503	75.6
Greece	2,913	77.2
South Korea	2,513	78.6
Total (12 countries)	**98,731**	**78.6**

Table 3.9: Activity Index (AI) values for earthquake-related scientific publications across selected countries (2000–2024), grouped by average AI levels and sorted in ascending order of mean AI.

Year	**AI: 0–1**					**AI: 1–2**						**AI: 2–3**
	South Korea	United States	China	India	France	Taiwan	Japan	Italy	Iran	Türkiye	Greece	New Zealand
2000	0.29	0.51	1.18	0.67	0.48	1.40	0.79	1.24	1.37	1.24	2.52	1.45
2001	0.28	0.50	0.87	0.75	0.43	2.01	0.90	1.09	1.66	1.75	2.06	2.04
2002	0.29	0.51	0.69	0.75	0.58	1.77	0.81	0.98	0.89	2.11	2.06	2.14
2003	0.27	0.53	0.64	0.70	0.57	1.29	0.79	1.14	1.58	1.36	2.02	1.60
2004	0.32	0.52	0.45	0.67	0.64	1.58	0.87	1.27	0.97	1.29	1.78	1.52
2005	0.34	0.47	0.44	0.81	0.71	1.03	0.89	1.22	1.38	1.16	1.60	1.88
2006	0.33	0.52	0.41	0.77	0.59	1.03	1.00	0.95	1.13	1.04	1.95	2.01
2007	0.27	0.50	0.47	0.91	0.55	1.30	0.89	0.96	1.35	1.34	1.78	1.80
2008	0.26	0.45	0.43	0.79	0.57	1.23	0.97	1.09	1.28	1.19	1.87	1.62
2009	0.31	0.46	0.66	0.60	0.58	1.41	1.11	1.10	1.37	1.20	1.37	1.83
2010	0.27	0.49	0.60	0.62	0.56	1.14	0.89	1.01	1.33	1.45	1.79	2.56
2011	0.18	0.48	0.55	0.55	0.63	1.01	1.09	1.20	1.12	1.29	1.53	2.79
2012	0.22	0.46	0.53	0.58	0.55	1.19	1.30	1.28	0.98	1.11	1.71	2.71
2013	0.29	0.52	0.58	0.22	0.68	1.15	1.62	1.29	1.36	1.35	2.29	3.06
2014	0.27	0.49	0.51	0.47	0.61	0.94	1.44	1.13	1.15	1.15	1.54	2.76
2015	0.32	0.56	0.58	0.18	0.61	0.91	1.57	1.36	1.39	1.28	2.15	3.39
2016	0.25	0.47	0.47	0.51	0.60	0.97	1.44	1.14	1.07	1.04	1.58	2.61
2017	0.28	0.46	0.49	0.65	0.50	0.85	1.35	1.34	1.15	0.90	1.59	2.90
2018	0.35	0.46	0.51	0.54	0.61	0.89	1.24	1.27	1.08	1.00	1.81	2.86
2019	0.34	0.46	0.53	0.49	0.58	0.89	1.34	1.27	1.32	0.97	1.43	2.26
2020	0.42	0.45	0.55	0.46	0.56	0.83	1.14	1.15	1.24	0.83	1.62	2.68
2021	0.41	0.44	0.55	0.53	0.62	0.69	1.15	1.16	1.05	0.95	1.52	2.07
2022	0.43	0.46	0.58	0.54	0.56	0.76	1.15	1.10	1.38	0.91	1.53	2.40
2023	0.40	0.40	0.60	0.53	0.57	0.74	1.19	1.06	1.24	1.37	1.38	2.25
2024	0.42	0.40	0.58	0.56	0.52	0.82	1.16	0.99	1.18	2.13	1.27	2.22

Table 3.10: Share of earthquake-related patents within total national patents (%), 2000–2025.

Year	France	United States	Italy	India	Japan	Taiwan	New Zealand	China	Türkiye	South Korea	Greece	Iran
2000	0.01	0.02	0.04	0.00	0.04	0.06	0.22	0.20	0.00	0.03	0.00	0.00
2001	0.01	0.02	0.02	0.12	0.04	0.06	0.00	0.13	0.58	0.05	0.00	0.00
2002	0.01	0.02	0.00	0.04	0.02	0.08	0.00	0.15	0.18	0.04	0.00	2.47
2003	0.02	0.02	0.01	0.10	0.02	0.04	0.00	0.13	0.00	0.05	0.21	0.00
2004	0.00	0.01	0.01	0.02	0.02	0.04	0.00	0.10	0.05	0.01	0.17	0.00
2005	0.02	0.02	0.02	0.01	0.02	0.03	0.05	0.14	0.00	0.02	0.00	0.00
2006	0.02	0.01	0.00	0.00	0.02	0.03	0.14	0.11	0.06	0.03	0.12	0.00
2007	0.03	0.02	0.01	0.03	0.04	0.04	0.00	0.11	0.00	0.05	0.00	0.00
2008	0.01	0.02	0.01	0.00	0.05	0.02	0.18	0.12	0.05	0.07	0.29	0.83
2009	0.00	0.02	0.01	0.01	0.06	0.03	0.04	0.23	0.14	0.10	0.59	0.86
2010	0.01	0.01	0.01	0.00	0.03	0.05	0.10	0.05	0.10	0.11	0.30	0.00
2011	0.01	0.01	0.03	0.01	0.02	0.06	0.00	0.06	0.05	0.14	0.28	0.00
2012	0.02	0.02	0.03	0.00	0.02	0.05	0.00	0.02	0.12	0.12	0.14	0.00
2013	0.02	0.02	0.04	0.02	0.04	0.07	0.10	0.03	0.11	0.15	0.22	1.15
2014	0.01	0.02	0.06	0.04	0.03	0.04	0.00	0.04	0.31	0.13	0.00	0.00
2015	0.01	0.02	0.03	0.05	0.04	0.04	0.00	0.03	0.28	0.12	0.00	0.00
2016	0.03	0.01	0.05	0.00	0.03	0.04	0.16	0.02	0.11	0.14	0.08	0.50
2017	0.01	0.01	0.02	0.04	0.03	0.06	0.00	0.04	0.09	0.19	0.28	0.18
2018	0.00	0.02	0.03	0.05	0.03	0.04	0.18	0.03	0.04	0.30	0.13	0.00
2019	0.00	0.02	0.03	0.01	0.02	0.07	0.05	0.04	0.04	0.32	0.06	0.65
2020	0.00	0.02	0.03	0.01	0.03	0.05	0.22	0.05	0.05	0.28	0.12	0.35
2021	0.01	0.02	0.02	0.02	0.03	0.05	0.09	0.04	0.02	0.27	0.00	0.37
2022	0.00	0.02	0.02	0.04	0.04	0.05	0.08	0.03	0.03	0.23	0.06	0.70
2023	0.00	0.02	0.02	0.02	0.02	0.07	0.05	0.03	0.17	0.20	0.37	1.03
2024	0.01	0.02	0.02	0.02	0.02	0.06	0.05	0.04	0.16	0.18	0.13	0.66
2025	0.01	0.01	0.03	0.03	0.03	0.04	0.00	0.04	0.23	0.14	0.16	0.37
Mean (%)	0.01	0.02	0.02	0.03	0.03	0.05	0.06	0.08	0.11	0.13	0.14	0.39

Table 3.11: Correlation between the Vulnerability Index and its underlying indicators.

Indicator	Correlation
Multidimensional Poverty Index	0.853
Gender Inequality Index	0.815
Under-five mortality rate	0.696
Total Persons of Concern (absolute)	0.677
Human Development Index	0.676
Total ODA (% YEARREF| – 2%)	0.634
Net ODA received (% of GNI)	0.595
Prevalence of undernourishment	0.579
Total Persons of Concern (relative)	0.568
Food Utilization	0.549
Malaria death rate	0.519
Income Gini coefficient	0.517
Children underweight	0.481
Population affected by disasters (last 3 years)	0.472
Public aid per capita	0.417
Tuberculosis prevalence	0.399
Food availability	0.238
Adult HIV prevalence	0.206
Average dietary supply adequacy	-0.232

Table 3.12: Correlation between the Lack of Coping Capacity Index and its underlying indicators.

Indicator	Correlation
Government effectiveness	0.846
Access to improved water source	0.785
Adult literacy rate	0.764
Access to improved sanitation	0.762
Measles	-0.028
Access to electricity	-0.408
Hyogo Framework for Action	-0.411
Mobile cellular subscriptions	-0.420
Physicians density	-0.510
Road density	-0.632
Health expenditure per capita	-0.645
Internet users	-0.753
Corruption Perception Index	-0.840

Table 3.13: Correlation between the Hazard & Exposure Index and its underlying indicators.

Indicator	Correlation
Highly Violent Conflict Probability	0.888
Violent Conflict Probability Score	0.887
Current Conflict Intensity (UCDP)	0.832
Earthquake exposure MMI VI (absolute)	0.729
People affected by droughts (relative)	0.698
People affected by droughts (absolute)	0.642
River flood exposure (absolute)	0.637
Earthquake exposure MMI VIII (absolute)	0.586
Agricultural drought probability	0.567
River flood exposure (relative)	0.477
Tsunami exposure (absolute)	0.461
Cyclone exposure category 3 (absolute)	0.382
Cyclone exposure category 1 (absolute)	0.320
Coastal flood exposure	0.310
Cyclone exposure category 3 (relative)	0.291
Drought frequency	0.189
Earthquake exposure MMI VIII (relative)	0.166
Earthquake exposure MMI VI (relative)	0.041
Cyclone exposure category 1 (relative)	-0.045
Tsunami exposure (relative)	-0.076

Table 3.14: Indicators strongly correlated with the INFORM Risk Index ($r \geq 0.7$).

Indicator	Correlation
Multidimensional Poverty Index	0.951
Highly Violent Conflict Probability	0.933
Violent Conflict Probability Score	0.933
Gender Inequality Index	0.930
Current Conflict Intensity (UCDP)	0.865
Human Development Index	0.822
Access to improved water source	0.800
Under-five mortality rate	0.789
Government effectiveness	0.771
Adult literacy rate	0.762
People affected by droughts (relative)	0.760
Access to improved sanitation	0.730
Agricultural drought probability	0.728
People affected by droughts (absolute)	0.714
Prevalence of undernourishment	0.712
Internet users	-0.713
Corruption Perception Index	-0.791

Table 3.15: Distribution of strongly correlated indicators across INFORM risk dimensions.

Risk Dimension	Number of Indicators
Hazard & Exposure	20
Vulnerability	19
Lack of Coping Capacity	13

Chapter 4

EMPIRICAL ANALYSIS AND MODEL RESULTS

This chapter presents the empirical findings and model results from the Data Envelopment Analysis and complementary hypothesis-testing analyses. The DEA framework is implemented under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions using an input oriented approach, with the aim of evaluating the relative efficiency of selected countries in minimizing disaster risk inputs while maintaining comparable levels of earthquake related scientific publication output across the preparedness, mitigation, response, and recovery phases of disaster management.

In addition to the DEA-based efficiency assessment, this chapter reports the results of several empirical and hypothesis-driven analyses examining the relationships among disaster risk indicators, knowledge production, and disaster outcomes. These analyses include publication-based, human-loss-based, economic-loss-based, and patent-based evaluations, providing a multidimensional perspective on cross-country differences in disaster risk management performance. By jointly considering efficiency scores, benchmarking results, and hypothesis testing outcomes, this chapter offers a comprehensive assessment of how countries differ in their ability to manage disaster risk in relation to scientific and innovative activity.

The decision-making units (DMUs) considered in the analysis are China, France, Greece, India, Iran, Italy, Japan, New Zealand, South Korea, Türkiye, and the United States. Disaster risk is represented by three key input indicators: the Vulnerability Index, which measures social and economic susceptibility to earthquake impacts; the Hazard and Exposure Index, which reflects the degree of physical exposure to seismic hazards; and the Lack of Coping Capacity Index, which represents limitations in institutional, economic, and infrastructural capacity to manage and respond to disasters.

Using a comparative DEA framework, countries with similar risk profiles are benchmarked against one another on both disaster risk indicators and scientific publication outputs. This approach enables the identification of relatively efficient and inefficient countries, highlighting differences in how disaster risk is managed given comparable levels of earthquake-related scientific research output. The results provide insights into cross-country variations in risk management efficiency and form the basis for the efficiency scores, reference sets, and benchmarking interpretations discussed in the subsequent sections.

4.1 Input-Oriented DEA Results under CRS and VRS Assumptions

This section presents the results of the input-oriented Data Envelopment Analysis conducted under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions, with the aim of evaluating the relative efficiency of selected countries in minimizing disaster risk inputs while maintaining comparable levels of earthquake-related scientific publication output across the preparedness, mitigation, response, and recovery phases of disaster management.

Within this framework, disaster-related risk conditions are treated as inputs, represented by vulnerability, hazard, exposure, and lack of coping capacity, while earthquake-related scientific publications constitute the output. Under the input-oriented specification, the analysis examines whether countries can sustain their existing levels of knowledge production while operating with reduced levels of disaster risk inputs. Accordingly, higher efficiency scores indicate a stronger capacity to manage disaster risk while maintaining comparable levels of scientific output.

Both CRS and VRS DEA models are employed to account for potential scale effects across countries with differing sizes and structural characteristics. The CRS model captures overall efficiency by jointly reflecting technical and scale efficiency, while the VRS model isolates pure technical efficiency by controlling for scale-related influences. Comparing efficiency scores obtained under these two assumptions allows for an assessment of whether observed inefficiencies are primarily attributable to scale effects or to differences in technical performance.

Table 4.1 presents a comparative overview of efficiency scores derived from the CRS and VRS input-oriented DEA models, providing a basis for benchmarking countries with similar levels of earthquake-related scientific publication output but differing disaster risk profiles.

Table 4.1: Comparison of CRS and VRS input-oriented DEA efficiency scores.

Country	**CRS Efficiency**	**VRS Efficiency**
China	1.000	1.000
France	0.214	0.886
Greece	0.230	0.761
India	0.218	0.413
Iran	0.231	0.409
Italy	0.911	1.000
Japan	1.000	1.000
New Zealand	0.990	1.000
South Korea	0.285	1.000
Türkiye	0.232	0.513
United States	1.000	1.000

The comparison between CRS and VRS efficiency scores highlights how countries' disaster risk profiles shape their ability to sustain earthquake-related scientific production. Under the CRS specification, efficiency reflects how well countries transform their overall risk environment into scientific output. The low CRS efficiency observed for many countries suggests that high levels of vulnerability, hazard exposure, and limited coping capacity place substantial constraints on sustained research production.

When these risk conditions are assessed under the VRS framework, which controls for differences in country characteristics, several countries exhibit markedly higher efficiency. This pattern indicates that, despite operating under challenging disaster risk conditions, some countries are able to organize and utilize their research systems effectively. For instance, France and Greece display relatively strong performance once country-specific risk contexts are taken into account, suggesting that their research output is not inherently inefficient but is influenced by broader structural and risk-related constraints.

In contrast, countries such as India, Iran, and Türkiye remain inefficient under both specifications. This finding implies that elevated disaster risk alone does not explain their lower performance; rather, limitations in how risk conditions are translated into scientific knowledge—particularly across the different phases of disaster management—play a more decisive role. Overall, the comparison underscores that efficiency in earthquake-related research is closely linked to how effectively countries manage risk and vulnerability while sustaining scientific production, rather than to the sheer volume of resources or exposure levels.

Beyond efficiency scores, slack values provide additional insight into the sources of inefficiency by identifying non-radial adjustments required in both inputs and outputs. In the context of this study, input slacks indicate excess disaster-related risk conditions that could be reduced without lowering scientific output, while output slacks reveal unrealized publication potential across the different phases of disaster management. Examining slack values under both CRS and VRS specifications allows for a deeper comparison of how risk conditions and research output interact under different modeling assumptions.

Table 4.2: Input and Output Slack Values under VRS Specification

Country	**LCC**	**H&E**	**Vulnerability**	**Response**	**Recovery**	**Mitigation**	**Preparedness**
France	0.000	0.000	1.476	2.716	5.925	0.000	1.876
Greece	0.000	0.000	1.122	0.733	10.462	0.867	3.320
India	0.000	0.000	0.695	4.757	16.934	0.000	3.613
Iran	0.000	0.000	0.457	0.000	14.853	3.885	2.600
Türkiye	0.000	0.000	1.416	4.201	10.701	1.821	0.000

Note: The first three variables represent input slacks, where LCC denotes *Lack of Coping Capacity*, H&E refers to the *Hazard and Exposure Index*, and Vulnerability corresponds to the vulnerability index. The remaining four variables represent output slacks associated with earthquake-related scientific publication performance across the disaster management phases of *response*, *recovery*, *mitigation*, and *preparedness*.

Table 4.3: Input and Output Slack Values under CRS Specification

Country	**LCC**	**H&E**	**Vulnerability**	**Response**	**Recovery**	**Mitigation**	**Preparedness**
France	0.096	0.000	0.211	0.000	1.068	0.124	0.000
Greece	0.171	0.000	0.240	0.000	2.712	1.232	0.000
India	0.003	0.000	0.010	15.783	8.721	0.000	0.000
Iran	0.299	0.000	0.017	0.000	8.015	3.714	0.000
Italy	0.502	0.000	0.750	30.866	7.743	0.000	0.000
New Zealand	1.148	0.000	0.000	34.352	0.000	5.059	0.381
South Korea	0.115	0.408	0.000	0.000	1.572	1.216	0.000
Türkiye	0.069	0.000	0.142	40.204	8.163	4.240	0.000

Note: LCC denotes *Lack of Coping Capacity*, while H&E refers to the *Hazard and Exposure Index*. These abbreviations are used due to space limitations.

A comparison of slack values under CRS and VRS specifications reveals notable differences in how disaster-related risk conditions and scientific output interact. Under the VRS model, input slacks are concentrated almost exclusively in the Vulnerability Index, while no slack is observed for hazard exposure or lack of coping capacity. This pattern suggests that, once country-specific risk contexts are accounted for, vulnerability emerges as the primary structural constraint limiting efficiency.

In contrast, the CRS results display input slacks across multiple risk dimensions, including lack of coping capacity and, in some cases, hazard exposure. This indicates that under the CRS assumption, excess risk conditions impose broader constraints on scientific production. Furthermore, output slacks under CRS are substantially larger, particularly in the response and recovery phases, implying that overall inefficiency is driven not only by risk conditions but also by limitations in sustaining publication output at the aggregate level.

Taken together, these findings suggest that while vulnerability plays a central role in shaping pure technical efficiency, broader risk conditions exert stronger constraints on scientific production when overall efficiency is considered. This distinction highlights the importance of addressing vulnerability-specific challenges while simultaneously improving the capacity to translate disaster risk into sustained research output across all phases of disaster management.

To further investigate the sources of inefficiency, reference (benchmark) countries are examined under the input-oriented VRS DEA model. Unlike the CRS specification, the VRS framework accounts for country-specific characteristics and isolates pure technical efficiency. The reference sets, therefore, identify countries that effectively transform disaster-related risk conditions into earthquake-related scientific output within their own national contexts.

Table 4.4: Lambda (reference) coefficients under the input-oriented CRS DEA model.

DMU	**China**	**Japan**	**United States**
China	1.000	0.000	0.000
France	0.048	0.000	0.078
Greece	0.095	0.000	0.027
India	0.142	0.000	0.213
Iran	0.053	0.000	0.272
Italy	0.360	0.000	0.131
Japan	0.000	1.000	0.000
New Zealand	0.000	0.230	0.154
South Korea	0.086	0.000	0.030
Türkiye	0.000	0.000	0.323
United States	0.000	0.000	1.000

The VRS reference structure highlights a diverse and context-sensitive benchmarking pattern. Japan, New Zealand, South Korea, and the United States emerge as the main reference countries, indicating that they are able to efficiently convert disaster-related risk conditions into earthquake-related scientific output.

The prominence of New Zealand and South Korea as benchmarks is particularly noteworthy, as it suggests that efficient performance is not solely driven by the scale of scientific production. Instead, these countries demonstrate effective organization and prioritization of earthquake- related research under their specific risk environments.

For countries such as France, Greece, India, Iran, and Türkiye, the reliance on convex combinations of multiple reference countries indicates that inefficiency is not linked to a single dominant benchmark. Rather, it reflects the need for balanced improvements in how vulnerability, exposure, and coping capacity are translated into scientific output across the different phases of disaster management.

Table 4.5: Lambda (reference) coefficients under the input-oriented VRS DEA model.

DMU	**Japan**	**New Zealand**	**South Korea**	**United States**
China	0.000	0.000	0.000	0.000
France	0.043	0.600	0.356	0.000
Greece	0.000	0.954	0.046	0.000
India	0.297	0.553	0.000	0.151
Iran	0.088	0.708	0.000	0.204
Italy	0.000	0.000	0.000	0.000
Japan	1.000	0.000	0.000	0.000
New Zealand	0.000	1.000	0.000	0.000
South Korea	0.000	0.000	1.000	0.000
Türkiye	0.359	0.333	0.308	0.000
United States	0.000	0.000	0.000	1.000

As shown in Figure 4.1, inefficient countries are benchmarked against a small set of efficient DMUs that define the best-practice frontier under the VRS specification.

Figure 4.1 and Table 4.5 jointly illustrate the reference structure of inefficient countries under the input-oriented VRS DEA model. The results show that Japan, New Zealand, South Korea, and the United States act as dominant benchmark countries, indicating that inefficiency is primarily driven by structural and institutional differences rather than scale effects.

In DEA, overall technical efficiency (TE) obtained under the CRS assumption can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE).

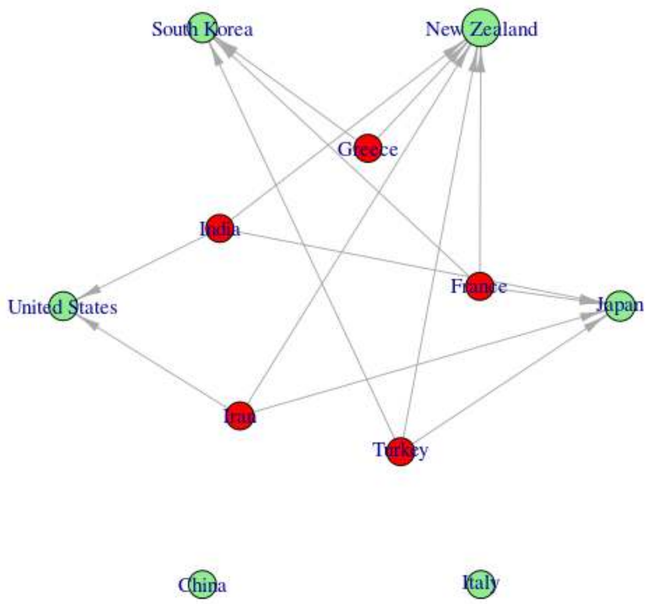

Figure 4.1: Reference network derived from the input-oriented VRS DEA model, illustrating benchmark relationships between inefficient countries and efficient DMUs based on lambda coefficients.

Pure technical efficiency is measured under the VRS specification and reflects how efficiently a country transforms its inputs into outputs given its specific operating conditions. Scale efficiency captures the extent to which a country operates at an optimal scale.

$$SE_k = \frac{TE_k}{PTE_k}, \tag{4.1}$$

where TE_k denotes the CRS efficiency score and PTE_k denotes the VRS efficiency score for country k. A value of $SE_k = 1$ indicates scale-efficient operation, whereas $SE_k < 1$ suggests that inefficiency is partly driven by scale-related factors.

As shown in Table 4.1, several countries exhibit substantially higher VRS efficiency than CRS efficiency, implying scale inefficiency. This finding suggests that while some countries manage disaster-related risk relatively well in sustaining earthquake-related scientific output, overall efficiency remains constrained when broader production conditions are considered. These results indicate that excess risk-related inputs are not the sole source of inefficiency; differences in how countries organize and scale their research activity also play a role.

Table 4.6: Mean Disaster Risk Input Indices (INFORM, 15-Year Average) and VRS DEA Efficiency Status

Country	Lack of Coping Capacity Index	Hazard & Exposure Index	Vulnerability Index	VRS Efficiency Status
France	1.96	3.14	2.75	Inefficient
Greece	2.38	2.85	2.56	Inefficient
India	4.24	8.69	4.91	Inefficient
Iran	4.50	7.46	4.38	Inefficient
Türkiye	3.18	7.37	4.96	Inefficient
China	3.37	5.39	2.78	Efficient
Italy	2.18	2.89	2.37	Efficient
Japan	1.46	5.50	1.40	Efficient
New Zealand	1.82	2.10	0.81	Efficient
South Korea	1.63	3.60	1.16	Efficient
United States	2.07	5.29	3.12	Efficient

Table 4.6 reports the mean values of disaster-related risk input indices derived from the INFORM framework, calculated as 15-year averages. Based on these inputs, the input-oriented basic radial DEA model with variable returns to scale (VRS) classifies France, Greece, India, Iran, and Türkiye as inefficient, while the remaining countries operate on the VRS efficiency frontier.

Table 4.7: Target Input Values for Inefficient Countries under Input-Oriented VRS DEA

Country	Lack of Coping Capacity Index	Hazard & Exposure Index	Vulnerability Index
France	1.7367	2.7822	0.9603
Greece	1.8113	2.1690	0.8261
India	1.7509	3.5885	1.3327
Iran	1.8396	3.0496	1.3337
Türkiye	1.6322	3.7828	1.1297

The target input values reported in Table 4.7 represent the projected disaster risk levels required for inefficient countries to operate on the VRS efficiency frontier while maintaining their existing levels of earthquake-related scientific output. The interpretation of the VRS input-oriented target results should be conducted in conjunction with the underlying structure of the INFORM disaster risk indices. As documented in Tables 3.12, 3.11, and 3.14, each composite risk component is strongly represented by a specific set of highly correlated indicators, which clarifies the primary drivers of inefficiency observed at the country level.

The Lack of Coping Capacity Index is most strongly correlated with indicators related to institutional quality and basic service provision, particularly government effectiveness, access to improved water and sanitation, adult literacy, and corruption perception. Negative correlations with variables such as internet usage, health expenditure per capita, and physician density further indicate that higher coping capacity is closely associated with stronger institutional and infrastructural development. Consequently, inefficiencies observed for countries such as India, Iran, and Türkiye largely reflect structural limitations in governance effectiveness, public service accessibility, and institutional preparedness rather than short-term response failures.

The Vulnerability Index is predominantly driven by socio-economic and human development factors, with particularly strong correlations with the Multidimensional Poverty Index, Gender Inequality Index, under-five mortality rate, and Human Development Index. These relationships suggest that vulnerability-related inefficiencies primarily capture long-standing socio-economic inequalities and development constraints. Therefore, the elevated vulnerability targets identified for India, Iran, and Türkiye point to deep-rooted social and demographic pressures that limit the efficiency of disaster risk management, even in the presence of scientific knowledge production.

The Hazard and Exposure Index is most strongly associated with indicators capturing conflict intensity and population exposure, including highly violent conflict probability, conflict intensity measures, and absolute earthquake exposure. Additional correlations with drought- and flood-related exposure indicators highlight the multidimensional nature of hazard exposure. As a result, inefficiencies observed for countries such as France and Greece, where coping capacity is relatively stronger, are instead driven by exposure-related factors, including population concentration in hazard-prone areas and exposure to multiple natural and socio-political hazards.

4.2 Analysis of Earthquake Magnitude Effects

4.2.1 Earthquake Magnitude and Knowledge Production

This section provides a general assessment of the relationship between earthquake magnitude and disaster-related knowledge production using data from two key sources. Scientific knowledge production is measured through earthquake-related publications indexed in Scopus, covering the period from 2000 to 2025, while technological knowledge production is captured using earthquake-related patent data obtained from Espacenet. These two sources are widely used in the literature to represent complementary dimensions of knowledge creation, where scientific publications reflect codified research output and patents capture applied and technological innovation [Griliches, 1990, Narin et al., 1997, OECD, 2009]. Together, they provide critical insights into how countries respond to seismic events through research and innovation over time.

Earthquake exposure is measured using observed earthquake magnitude, while knowledge production is captured through two complementary dimensions: earthquake-related scientific publications indexed in Scopus and earthquake-related patent activity. To ensure comparability across observations and to explicitly account for heterogeneity in seismic intensity, country–year records are grouped into three earthquake magnitude categories reflecting increasing levels of seismic exposure. These categories correspond to low-magnitude events ($M < 5$), medium-magnitude events ($5 \leq M < 6$), and high-magnitude events ($M \geq 6$). This classification enables systematic comparison of knowledge-production patterns across different levels of seismic stress.

The analysis investigates whether disaster-related knowledge production differs across earthquake magnitude groups. Specifically, two sets of hypotheses are considered. First, it is tested whether earthquake-related scientific publication activity varies systematically across magnitude categories. Second, the analysis examines whether the likelihood of generating earthquake-related patents varies with the severity of seismic exposure.

Table 4.8 reports descriptive statistics for earthquake-related scientific publications across the three magnitude groups. The results indicate that publication activity is not monotonically increasing with earthquake magnitude. Countries exposed to medium-magnitude earthquakes exhibit the highest average publication output, with a mean of 547.63 publications, followed by those exposed to high-magnitude events, which display an average of 480.12 publications. In contrast, country–year observations characterized by low-magnitude earthquakes exhibit the lowest average publication activity, with a mean of 378.87 publications. This pattern suggests that moderate seismic exposure may be associated with more intensive scientific engagement, whereas extreme seismic events do not necessarily correspond to proportionally higher levels of academic output.

Table 4.8: Earthquake-Related Scientific Publications by Magnitude Group.

Magnitude Group	**Observations**	**Min**	**Max**	**Mean**
Low ($M < 5$)	39	10	1594	378.87
Medium ($5 \leq M < 6$)	139	10	3222	547.63
High ($M \geq 6$)	111	11	2695	480.12

Complementary evidence for technological knowledge production is presented in Table 4.9, which summarizes earthquake-related patent activity across magnitude groups. In contrast to the publication patterns, average patent counts decline as earthquake magnitude increases. The highest mean patent activity is observed in the low-magnitude group, while the lowest average patent output characterizes country–year observations exposed to high-magnitude earthquakes. This finding suggests that stronger seismic events do not systematically translate into higher levels of technological innovation and may instead impose constraints on inventive activity.

Overall, the descriptive evidence indicates that higher seismic intensity does not automatically lead to higher levels of disaster-related knowledge production. While

Table 4.9: Earthquake-Related Patent Activity by Magnitude Group.

Magnitude Group	**Observations**	**Min**	**Max**	**Mean**
Low ($M < 5$)	39	0	521	86.82
Medium ($5 \leq M < 6$)	138	0	1091	77.31
High ($M \geq 6$)	103	0	521	50.63

moderate earthquake exposure appears to be associated with increased scientific publication activity, technological innovation, as proxied by patent counts, tends to decline with increasing earthquake magnitude. These non-monotonic patterns motivate the subsequent regression and DEA-based analyses, which aim to control for country-specific characteristics and assess the efficiency with which countries transform seismic exposure into scientific and technological outputs.

The first hypothesis examines whether earthquake-related scientific publication activity varies across different earthquake magnitude groups. The null hypothesis, denoted as $H_0^{(1)}$, states that earthquake-related publication activity does not differ across earthquake magnitude categories. The alternative hypothesis, $H_1^{(1)}$, asserts that earthquake-related publication activity differs across earthquake magnitude groups.

The second hypothesis focuses on technological knowledge production measured through earthquake-related patent activity. The null hypothesis, $H_0^{(2)}$, states that the likelihood of producing earthquake-related patents does not differ across earthquake magnitude groups. In contrast, the alternative hypothesis, $H_1^{(2)}$, proposes that the likelihood of producing earthquake-related patents differs across earthquake magnitude categories.

To formally examine whether disaster-related knowledge production differs across earthquake magnitude groups, Pearson Chi-square tests are employed. This test is particularly suitable in the present context because the analysis focuses on categorical group comparisons rather than continuous linear relationships, and because both publication and patent indicators exhibit highly skewed distributions with substantial dispersion across country–year observations [Agresti, 2018].

For scientific knowledge production, the Chi-square test rejects the null hypothesis of independence at the 5% significance level ($p = 0.021$), indicating that earthquake-related publication activity differs across magnitude groups. This result suggests that seismic exposure is statistically associated with variations in research output. However, the observed differences do not follow a linear or monotonic pattern with respect to earthquake magnitude. Countries experiencing medium-magnitude earthquakes display higher average publication activity than those exposed to either low- or high-magnitude events, implying that knowledge production is influenced not only by hazard intensity but also by institutional capacity, research infrastructure, and prior experience [Gao et al., 2023a, Guan and Zuo, 2014].

In contrast, technological knowledge production does not exhibit a statistically significant association with earthquake magnitude. When patent activity is analyzed using a binary indicator capturing the presence of earthquake-related patenting, the Chi-square test fails to reject the null hypothesis of independence ($p = 0.963$). This finding reflects the sparse and zero-inflated nature of disaster-related patent data, which has been widely documented in the innovation literature [Hall and Rosenberg, 2010, Popp, 2019]. The absence of a significant association suggests that exposure to stronger earthquakes does not automatically translate into increased technological innovation, as patenting typically requires long-term R&D investment, stable institutional frameworks, and market-oriented incentives rather than short-term disaster shocks [Kahn, 2005].

Table 4.10 compares the Chi-square test results for scientific publications and patent activity across earthquake magnitude groups. The results indicate a statistically significant association between earthquake magnitude groups and scientific publication activity ($\chi^2 = 282.03$, $p = 0.02$). Moreover, the effect size, measured by Cramér's V, is 0.70, indicating a strong association. This finding suggests that countries exposed to higher earthquake magnitudes tend to exhibit systematically different publication patterns compared to those experiencing lower seismic intensity.

Accordingly, Hypothesis H1, which states that earthquake magnitude is associated with scientific publication activity, is strongly supported by the empirical evidence.

Table 4.10: Chi-square test results for earthquake magnitude groups: comparison of scientific publications and patent activity.

Academic Publications		**Patents**	
Statistic	Value	Statistic	Value
Chi-square (χ^2)	282.03	Chi-square (χ^2)	0.08
Degrees of Freedom (df)	236	Degrees of Freedom (df)	2
p-value	0.02	p-value	0.96
Cramér's V	0.70	Cramér's V	0.02
Sample Size (N)	289	Sample Size (N)	289

The divergent results observed for publications and patents highlight a critical distinction between knowledge production and knowledge application in the context of disaster-related research systems. While exposure to stronger seismic events appears to stimulate scientific knowledge production, this effect does not extend to technological innovation as measured by patent activity.

This gap suggests that the generation of academic knowledge following high-magnitude earthquakes does not automatically translate into applied technological outputs. Such a discrepancy may reflect structural barriers in innovation systems, including limited commercialization mechanisms, weak university–industry collaboration, or insufficient policy incentives for translating research findings into patented technologies.

From a policy perspective, these findings imply that disaster exposure alone is insufficient to drive technological innovation. Targeted policy interventions are required to bridge the gap between scientific research and practical technological solutions, particularly in earthquake-prone countries where the societal benefits of innovation are substantial.

Overall, the results provide empirical support for the argument that disaster-driven research systems are more effective in generating scientific output than in fostering technological applications, underscoring the importance of integrated research and innovation policies.

4.2.2 Magnitude-Based Differences in Human and Economic Loss Outcomes

This section examines whether earthquake magnitude is associated with differences in human and economic losses across countries. The analysis focuses on identifying magnitude-related patterns while accounting for the heterogeneous nature of disaster impacts.

Human losses are primarily measured as deaths per million population, which reflects the most severe and irreversible consequences of earthquakes. This indicator is selected due to its robustness, cross-country comparability, and reduced sensitivity to reporting inconsistencies relative to other human loss measures such as the number of injured or affected individuals. Economic losses are captured by damage per person (in thousand USD), reflecting the intensity of material destruction relative to population size.

Earthquakes are classified into three magnitude groups: $5 \leq M < 6$, $6 \leq M < 7$, and $M \geq 7$. Preliminary inspection of the data reveals highly skewed distributions and the presence of extreme values in both human and economic loss variables. Consequently, non-parametric statistical tests are employed to avoid distributional assumptions.

The Kruskal–Wallis test is preferred due to the highly skewed distribution of disaster-related mortality data and the presence of extreme values, which violate the normality assumptions required for parametric tests [Field, 2013, Conover, 1999]. The test assesses whether the median level of human loss differs across the three earthquake magnitude groups.

To evaluate whether human losses differ across earthquake magnitude levels, a Kruskal–Wallis test is applied to deaths per million population. Deaths are employed as the primary indicator of human loss, as mortality represents the most severe and irreversible consequence of earthquakes and provides a more robust and comparable measure across countries than the number of injured or affected individuals [Kahn, 2005, Toya and Skidmore, 2007].

The results indicate a Kruskal–Wallis test statistic of $H = 5.83$ with a corresponding p-value of 0.054. This finding suggests a marginally significant difference in human losses across magnitude levels at the 10% significance level. Similar studies in the disaster economics literature report that earthquake magnitude alone explains human losses only partially, while institutional capacity, preparedness, and socio-economic vulnerability play a decisive role in shaping mortality outcomes [Kahn, 2005, Noy, 2009].

Hypothesis (H2): Economic losses differ significantly across earthquake magnitude levels.

To examine whether economic losses vary across earthquake magnitude levels, a Mann–Whitney U test is applied to damage per person (000 USD), comparing the $5 \leq M < 6$ and $6 \leq M < 7$ magnitude groups. Damage per person is selected as the indicator of economic loss in order to normalize total damage by population size and ensure cross-country comparability.

Given the highly skewed distribution of economic loss data and the presence of extreme values, a non-parametric test is employed. The Mann–Whitney U test assesses whether the distributions of economic losses differ between the two magnitude groups without assuming normality.

The results indicate a Mann–Whitney U statistic of $U = 42.5$ with a corresponding p-value of 0.085. This finding suggests a marginally significant difference in economic losses between the two magnitude groups at the 10% significance level.

Hypothesis (H3): Human and economic loss indicators are weakly correlated, indicating heterogeneous loss profiles across countries.

To examine the relationship between human and economic losses, a Spearman rank correlation analysis is conducted between the Human Loss Index and damage per person (in thousands of USD). The Human Loss Index is constructed as a composite measure based on standardized values of the affected population, injuries, and deaths, while economic loss is represented by damage normalized by population size. Given the non-normal distribution of disaster loss variables and the presence of extreme observations, Spearman's rank correlation is employed to assess the strength and direction of the association without assuming linearity or normality. The results indicate a Spearman correlation coefficient of $\rho = 0.67$ with a corresponding p-value of 7.14×10^{-6}. This result reveals a statistically significant and moderately strong positive association between human and economic losses.

Building on the correlation results, a comprehensive classification of countries is constructed to jointly assess human and economic loss outcomes across earthquake magnitude levels. Rather than evaluating human and economic losses separately, this approach integrates both dimensions into a unified framework to capture heterogeneous loss profiles among countries exposed to similar seismic intensities. Table 4.11 presents the integrated human–economic loss classification by magnitude level. The table highlights substantial cross-country heterogeneity, showing that countries exposed to similar earthquake magnitudes may experience fundamentally different combinations of human and economic losses. While countries such as China, Iran, and Türkiye increasingly appear in the high human–high economic loss category as magnitude rises, others, including France, Greece, Italy, South Korea, and the United States, remain predominantly in the low human–low economic loss group. This contrast underscores the decisive role of preparedness, coping capacity, and disaster governance in mitigating both human and economic impacts.

Table 4.11: Integrated Human and Economic Loss Classification by Earthquake Magnitude Level

Magnitude Level	**Human Loss**	**High Economic Loss**	**Low Economic Loss**
5–6	High Human	China, Iran, Türkiye	–
5–6	Low Human	India, Japan, New Zealand	France, Greece, Italy, South Korea, Taiwan, United States
6–7	High Human	China, Greece, Iran, Italy, Japan, New Zealand, Taiwan, Türkiye	–
6–7	Low Human	United States	France, India, South Korea
≥7	High Human	China, Iran, Japan, New Zealand, Türkiye	India, Taiwan
≥7	Low Human	–	France, Greece, Italy, South Korea, United States

4.3 Regression-Based Analysis and Hypothesis Testing Results

4.3.1 Publication-Based Analysis: Model Results

This section analyzes the relationship between disaster risk indicators, earthquake magnitude levels, research capacity, and scientific publication activity. The dependent variable is the logarithm of earthquake-related publication counts. An OLS regression model with robust standard errors is used.

Table 4.12 reports the regression coefficients, while Table 4.13 presents the model fit statistics. The results show that the model explains a large part of the variation in publication activity. The adjusted R^2 value is 0.663, and the overall model is statistically significant according to the F-test. Regarding disaster risk indicators, the Hazard & Exposure Index is not statistically significant. However, both the Vulnerability Index and the Lack of Coping Capacity Index have negative, statistically significant coefficients. This indicates that countries with higher vulnerability and weaker coping capacity tend to produce fewer earthquake-related publications. Earthquake magnitude indicators are not statistically significant. This suggests that the number of earthquakes at different magnitude levels does not directly affect scientific publication activity. In contrast, research capacity variables are strongly related to publication output. Higher R&D expenditure is associated with a higher number of publications, while the number of researchers in R&D also shows a strong relationship with publication activity.

Overall, the results indicate that scientific publication activity is mainly driven by research capacity rather than disaster risk or earthquake occurrence. These findings provide a basis for the following analyses of human loss, economic loss, and technological outcomes. Additional descriptive evidence supporting these relationships is provided in Appendix B.

4.3.2 Human Loss-Based Analysis: Model Results

This section examines the relationship between disaster risk indicators, earthquake magnitude levels, and human loss outcomes. The dependent variable is the logarithm of total human losses, and an OLS regression model with robust standard errors is

Table 4.12: OLS regression results: Disaster risk components, earthquake magnitude, research capacity, and scientific publication activity

Variable	**Dependent variable: Log Publication Count**			
	Coefficient	**Std. Error**	**z-statistic**	**P-value**
Constant	8.168	0.342	23.854	0.000
Hazard & Exposure Index	0.040	0.041	0.967	0.334
Vulnerability Index	-0.178	0.069	-2.585	0.010
Lack of Coping Capacity Index	-0.391	0.143	-2.740	0.006
EQ_Count_M4_5	0.125	0.189	0.663	0.508
EQ_Count_M5_6	0.093	0.088	1.054	0.292
EQ_Count_M6_7	-0.040	0.073	-0.542	0.588
EQ_Count_M7p	-0.044	0.105	-0.418	0.676
R&D Expenditure (% of GDP)	0.710	0.084	8.442	0.000
Researchers in R&D (per million people)	-0.001	0.000	-11.594	0.000

employed. Table 4.14 presents the estimated regression coefficients, while Table 4.15 reports the model fit statistics. The model explains a substantial share of the variation in human losses, with an adjusted R^2 value of 0.569, and the overall model is statistically significant according to the F-test. The results show that disaster risk indicators are not statistically significant once earthquake magnitude is taken into account. In contrast, all earthquake magnitude indicators exhibit positive and statistically significant coefficients. The magnitude of the coefficients increases with earthquake intensity, indicating that higher-magnitude earthquakes are associated with significantly greater human losses.

Overall, the findings suggest that human loss outcomes are primarily driven by the physical severity of earthquakes rather than by underlying disaster risk or coping capacity indicators. This result contrasts with the publication-based analysis, where research capacity played a more prominent role.

Table 4.13: Model fit and diagnostic statistics for the publication-based analysis

Statistic	**Value**
Dependent variable	Log Publication Count
Number of observations	110
Degrees of freedom (model)	9
Degrees of freedom (residuals)	100
R^2	0.691
Adjusted R^2	0.663
F-statistic	45.63
Prob (F-statistic)	1.65×10^{-31}
Log-Likelihood	-68.307
AIC	156.6
BIC	183.6
Covariance type	HC3 (robust)
Condition number	3.40×10^4

Table 4.14: OLS regression results: Disaster risk components, earthquake magnitude, and human loss outcomes

Variable	**Dependent variable: Log Human Loss**			
	Coefficient	**Std. Error**	**z-statistic**	**P-value**
Constant	0.004	0.265	0.014	0.989
Hazard & Exposure Index	0.048	0.106	0.456	0.648
Vulnerability Index	0.069	0.305	0.226	0.822
Lack of Coping Capacity Index	-0.177	0.314	-0.562	0.574
EQ_Count_M4_5	1.594	0.781	2.042	0.041
EQ_Count_M5_6	0.726	0.232	3.129	0.002
EQ_Count_M6_7	1.155	0.347	3.326	0.001
EQ_Count_M7p	1.649	0.490	3.368	0.001

Table 4.15: Model fit and diagnostic statistics for the human loss-based analysis

Statistic	**Value**
Dependent variable	Log Human Loss
Number of observations	110
Degrees of freedom (model)	7
Degrees of freedom (residuals)	102
R^2	0.597
Adjusted R^2	0.569
F-statistic	9.063
Prob (F-statistic)	1.16×10^{-8}
Log-Likelihood	-170.54
AIC	357.1
BIC	378.7
Durbin–Watson	2.048
Covariance type	HC3 (robust)
Condition number	31.4

4.3.3 Economic Loss-Based Analysis: Model Results

This model focuses on the determinants of economic losses caused by earthquakes. The dependent variable is the logarithm of inflation-adjusted economic damage. An OLS regression model with robust standard errors is employed. Table 4.16 presents the estimated coefficients, and Table 4.17 reports the model fit statistics. Compared to the publication- and human-loss-based models, this model's explanatory power is more limited. The adjusted R^2 is 0.198, indicating that the included variables capture only a partial portion of the economic losses. Disaster risk indicators do not show statistically significant effects on economic losses. This suggests that vulnerability and coping capacity alone are not sufficient to explain cross-country differences in economic damage once earthquake occurrence is taken into account. Earthquake magnitude indicators, however, play a selective role. Earthquakes in the 4–5, 5–6, and 6–7 magnitude ranges are positively and significantly associated with economic losses, while the effect of very large earthquakes (7+) is not statistically significant. This pattern suggests that cumulative damage from moderate-to-strong earthquakes contributes more consistently to economic losses than rare extreme events. The CPI variable is not statistically significant, suggesting that price-level differences do not substantially affect the estimated economic losses in this model.

Therefore, the results indicate that economic losses are influenced by earthquake magnitude, but less systematically than human losses. Unlike publication activity, which is driven by research capacity, and human losses, which are strongly magnitude-driven, economic losses appear to be shaped by a combination of event frequency and context-specific factors that the model does not fully capture.

Table 4.16: OLS regression results: Disaster risk components, earthquake magnitude, and economic loss outcomes

Variable	**Dependent variable: Log Economic Loss**			
	Coefficient	**Std. Error**	**z-statistic**	**P-value**
Constant	-6.031	8.911	-0.677	0.499
Hazard & Exposure Index	0.347	0.719	0.482	0.630
Vulnerability Index	-0.612	0.886	-0.691	0.490
Lack of Coping Capacity Index	-0.822	1.151	-0.714	0.475
EQ_Count_M4_5	4.230	1.396	3.030	0.002
EQ_Count_M5_6	1.594	0.619	2.577	0.010
EQ_Count_M6_7	1.959	0.945	2.073	0.038
EQ_Count_M7p	2.049	1.565	1.309	0.190
CPI	0.124	0.100	1.238	0.216

4.3.4 Patent-Based Analysis: Model Results

The patent-based analysis examines earthquake-related technological innovation using patent activity as the outcome measure. The dependent variable is the logarithm of earthquake-related patent counts. Table 4.18 presents the regression coefficients,

Table 4.17: Model fit and diagnostic statistics for the economic loss-based analysis

Statistic	**Value**
Dependent variable	Log Economic Loss
Number of observations	43
Degrees of freedom (model)	8
Degrees of freedom (residuals)	34
R^2	0.351
Adjusted R^2	0.198
F-statistic	2.499
Prob (F-statistic)	0.0298
Log-Likelihood	-113.33
AIC	244.7
BIC	260.5
Durbin–Watson	2.349
Covariance type	HC3 (robust)
Condition number	1.14×10^3

while Table 4.19 reports the model fit statistics. The model exhibits strong explanatory power, with an adjusted R^2 value of 0.847, indicating that a large share of the variation in patent activity is explained by the included variables. Disaster risk indicators show limited influence on patent activity. Among these variables, only the Vulnerability Index is statistically significant and negatively associated with patent production. Earthquake magnitude indicators are not statistically significant, suggesting that the frequency of earthquakes at different magnitude levels does not directly stimulate technological innovation.

In contrast, research capacity variables play a dominant role. R&D expenditure has a strong positive association with patent activity, while the number of researchers in R&D is also highly significant. These results indicate that earthquake-related technological innovation is primarily driven by research investment and human capital rather than by disaster occurrence or exposure. Therefore, the patent-based analysis reinforces the findings of the publication-based model, highlighting the central role of research capacity in shaping knowledge creation, while disaster risk and earthquake magnitude play a secondary role.

Table 4.18: OLS regression results: Disaster risk components, earthquake magnitude, research capacity, and earthquake-related patent activity

Variable	**Dependent variable: Log Patent Count**			
	Coefficient	**Std. Error**	**z-statistic**	**P-value**
Constant	0.582	0.477	1.220	0.223
Hazard & Exposure Index	0.090	0.073	1.229	0.219
Vulnerability Index	-0.254	0.107	-2.364	0.018
Lack of Coping Capacity Index	0.152	0.178	0.855	0.393
EQ_Count_M4_5	-0.449	0.302	-1.485	0.138
EQ_Count_M5_6	-0.019	0.096	-0.199	0.842
EQ_Count_M6_7	-0.084	0.161	-0.518	0.605
EQ_Count_M7p	0.121	0.196	0.615	0.539
R&D Expenditure (% of GDP)	1.680	0.107	15.647	0.000
Researchers in R&D (per million people)	-0.0004	0.00006	-5.946	0.000

Table 4.19: Model fit and diagnostic statistics for the patent-based analysis

Statistic	**Value**
Dependent variable	Log Patent Count
Number of observations	110
Degrees of freedom (model)	9
Degrees of freedom (residuals)	100
R^2	0.860
Adjusted R^2	0.847
F-statistic	61.50
Prob (F-statistic)	8.68×10^{-37}
Log-Likelihood	-108.07
AIC	236.1
BIC	263.1
Durbin–Watson	1.147
Covariance type	HC3 (robust)
Condition number	3.40×10^4

Chapter 5

CONCLUSION

This thesis examined the relationship between earthquake-related risk conditions, scientific knowledge production, and technological innovation across high-seismicity countries using a combination of descriptive statistics, statistical hypothesis testing, and Data Envelopment Analysis (DEA). By integrating multidimensional disaster risk indicators with bibliometric and patent data, the study provides a comprehensive assessment of how countries transform seismic exposure into scientific and technological outputs.

The empirical findings reveal that disaster-related knowledge production does not increase monotonically with earthquake magnitude. Descriptive statistics and Chi-square test results indicate that scientific publication activity is significantly associated with earthquake magnitude groups, with medium-magnitude events corresponding to the highest average publication output. In contrast, technological innovation, measured through earthquake-related patent activity, does not exhibit a statistically significant relationship with seismic intensity. This divergence highlights a critical distinction between knowledge generation and knowledge application in disaster-related research systems.

DEA results further demonstrate that inefficiency is driven by both risk-related conditions and structural characteristics of national research systems. Under the variable returns to scale (VRS) specification, inefficiency is primarily associated with vulnerability, indicating that pure technical efficiency is constrained by structural weaknesses rather than by hazard exposure alone. In contrast, constant returns to scale (CRS) results reveal broader inefficiencies across multiple risk dimensions, suggesting that overall efficiency is affected by both scale-related and institutional factors.

The analysis of reference (benchmark) countries under the input-oriented VRS model identifies Japan, New Zealand, South Korea, and the United States as dominant benchmarks. Importantly, the prominence of countries such as New Zealand and South Korea underscores that efficient performance is not solely determined by the scale of scientific production. Instead, organizational capacity, prioritization of earthquake-related research, and effective translation of risk into sustained research activity play a decisive role.

The decomposition of overall technical efficiency into pure technical efficiency and scale efficiency provides additional insights into the sources of inefficiency. Several countries exhibit substantially higher VRS efficiency than CRS efficiency, indicating the presence of scale inefficiencies. This finding suggests that while some countries manage disaster-related risk effectively within their institutional contexts, inefficiencies persist when research systems operate at suboptimal scales.

The second main conclusion of this study is derived from the regression analyses examining the relationships between disaster risk, earthquake characteristics, research capacity, and different outcome dimensions. The results demonstrate that the effects of disaster risk and seismic activity vary substantially across outcome types.The publication-based and patent-based analyses reveal that scientific knowledge production and technological innovation are primarily driven by research capacity rather than by disaster risk or earthquake occurrence. Variables related to R&D investment and human capital consistently exhibit strong and statistically significant effects, whereas most disaster risk indicators and earthquake magnitude measures do not show direct influence on knowledge-related outcomes. This finding suggests that exposure to seismic risk alone is insufficient to stimulate sustained scientific or technological responses without adequate institutional and research capacity. In contrast, the human loss and economic loss models highlight the dominant role of earthquake magnitude. Human losses are strongly and systematically associated with earthquake intensity, indicating that physical characteristics of seismic events remain the primary drivers of mortality and injury outcomes. Economic losses also respond to earthquake magnitude, though the relationship is less uniform, reflecting the more complex, context-dependent nature of economic damage. Taken together, these results underscore a clear distinction between impact-driven and capacity-driven outcomes. While human and economic losses are largely shaped by the physical severity of earthquakes, scientific and technological outputs depend mainly on a country's ability to mobilize research resources. This distinction provides important insight into why countries facing similar levels of seismic risk may experience very different patterns of loss, knowledge production, and innovation.

From a policy perspective, the results show that disaster exposure alone is not enough to promote effective scientific and technological progress in earthquake-related research. Although high disaster risk may increase research activity, the VRS DEA results indicate that several countries remain inefficient because of high vulnerability levels and limited coping capacity. As shown in Table 4.7, improving efficiency primarily requires reducing disaster-related risk conditions rather than increasing scientific output. This finding suggests that disaster research policies should focus not only on hazard-driven incentives but also on strengthening institutions, reducing socio-economic vulnerability, and improving governance capacity.

The interpretation of these results is further supported by the structure of the INFORM risk components. Tables 3.12 and 3.11 show that coping capacity and vulnerability are strongly linked to indicators such as government effectiveness, access to basic services, poverty, inequality, and human development. In addition, Table 3.14 indicates that the hazard and exposure component is mainly driven by conflict intensity and population exposure to natural hazards. Together, these findings explain why inefficiencies are closely related to long-term institutional and socio-economic conditions rather than short-term disaster events.

From a methodological perspective, this study demonstrates the value of combining Data Envelopment Analysis with a structured disaster risk framework and correlation analysis. The use of CRS, VRS, and returns-to-scale models allows for a clearer understanding of efficiency differences, scale effects, and structural constraints across countries with different risk profiles. Linking DEA target values to the underlying risk components also makes the efficiency results easier to interpret and more useful for policy analysis.

A country-level analysis provides clearer insight into the sources of inefficiency identified by the VRS input-oriented DEA model and highlights why these findings are important for disaster research and policy design.

France and Greece are identified as inefficient primarily because of elevated levels of hazard and exposure, rather than weak coping capacity or high vulnerability. As indicated by the target values in Table 4.7, efficiency improvements for these countries would mainly require reductions in exposure-related risks, such as population concentration in hazard-prone areas and exposure to multiple natural and socio-political hazards. This finding is consistent with Table 3.14, which shows that the hazard and exposure component is strongly driven by conflict intensity and absolute exposure indicators. The result is important because it shows that even countries with relatively strong institutions may face efficiency losses if exposure risks are not adequately managed.

For India and Iran, inefficiency is driven by a combination of high vulnerability and high hazard exposure. The target input values suggest that substantial reductions across all risk dimensions are needed to reach the VRS efficiency frontier. Tables 3.11 and 3.12 indicate that vulnerability and coping capacity are strongly linked to poverty, inequality, health outcomes, and governance quality. This implies that inefficiency in these countries reflects long-term structural and socio-economic challenges rather than a lack of scientific knowledge production. The importance of this finding lies in highlighting that disaster-related research efficiency cannot be improved without addressing broader development and institutional constraints.

In the case of Türkiye, the results indicate that inefficiency is mainly associated with hazard, exposure, and vulnerability, while coping capacity is relatively close to efficient benchmark levels. According to Table 4.7, the largest efficiency gains would come from reducing exposure-related risks and socio-economic vulnerability. This finding is particularly important because it suggests that policy efforts focused on land-use planning, exposure control, and vulnerability reduction may be more effective than policies that only aim to expand research output.

By contrast, countries such as China, Italy, Japan, New Zealand, South Korea, and the United States operate on the VRS efficiency frontier. Despite differences in their absolute risk levels, these countries achieve a better balance between disaster-related risk conditions and scientific knowledge production. This result underscores that efficiency is not determined solely by low risk, but by how effectively countries manage risk while sustaining research activity.

Taken together, the country-level results demonstrate that inefficiency in disaster-related research systems is closely linked to specific risk components rather than overall disaster exposure. The integration of DEA target values with the underlying INFORM risk structure shows that different countries face different efficiency constraints, ranging from exposure-driven inefficiencies to vulnerability- and governance-related limitations. This distinction is crucial for policy design, as it implies that uniform disaster research policies are unlikely to be effective. Instead, efficiency-oriented policies should be tailored to national risk profiles, focusing on exposure management, vulnerability reduction, or institutional strengthening depending on the dominant source of inefficiency.

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Appendix A

DATA SOURCES AND SEARCH STRATEGIES

The datasets used in this study are derived from publicly available sources and processed by the author. Processed data and analysis files are available from the author upon reasonable request.

Table A.1: Summary of the EM-DAT disaster dataset used in this study.

Attribute	**Description**
Database	EM-DAT (CRED / UCLouvain)
Hazard type	Earthquakes
Geographical coverage	Selected earthquake-prone countries
Time period	2000–2024
Data type	Disaster occurrence and impact records
File type	Public EM-DAT custom request
Number of records	820
File creation date	March 13, 2025

Table A.2: Search strategy and inclusion criteria for the Scopus earthquake dataset.

Attribute	Description
Database	Scopus
Time period	2000–2024
Subject area	Earthquake-related research
Document type	Articles only
Language	English
Search field	TITLE-ABS-KEY
Search keyword	"earthquake"
Publication year filter	PUBYEAR > 1999 and PUBYEAR < 2025
Access date	January 2, 2025

Table A.3: Search strategy for earthquake-related patents retrieved from Espacenet.

Attribute	Description
Database	Espacenet (European Patent Office)
Search field	Title and Abstract
Search keyword	"EARTHQUAKE"
Document type	Patent documents
Publication period	2000–2024
Query language	English
Inventor country filter	China, India, Türkiye, Iran, USA, Italy, Japan, South Korea, New Zealand, France, Greece, Taiwan

Table A.4: Key indicators retrieved from the World Development Indicators (WDI) database.

Indicator	Description
R&D expenditure (% of GDP)	National research and development intensity
Researchers in R&D	Number of researchers per million people
Technicians in R&D	Number of technicians per million people
Population (total)	Normalization and per-capita calculations
Time period	2000–2024

Table A.5: Structure of the INFORM Risk Index used in the analysis.

Indicator	Description
Hazard & Exposure	Natural and human-induced hazards
Vulnerability	Socio-economic conditions and vulnerable groups
Lack of Coping Capacity	Institutional and infrastructure capacity
Time period	2015–2024
Countries	China, India, Türkiye, Iran, United States, Italy, Japan, South Korea, New Zealand, France, Greece, Taiwan

Appendix B

SUPPLEMENTARY DESCRIPTIVE FIGURES

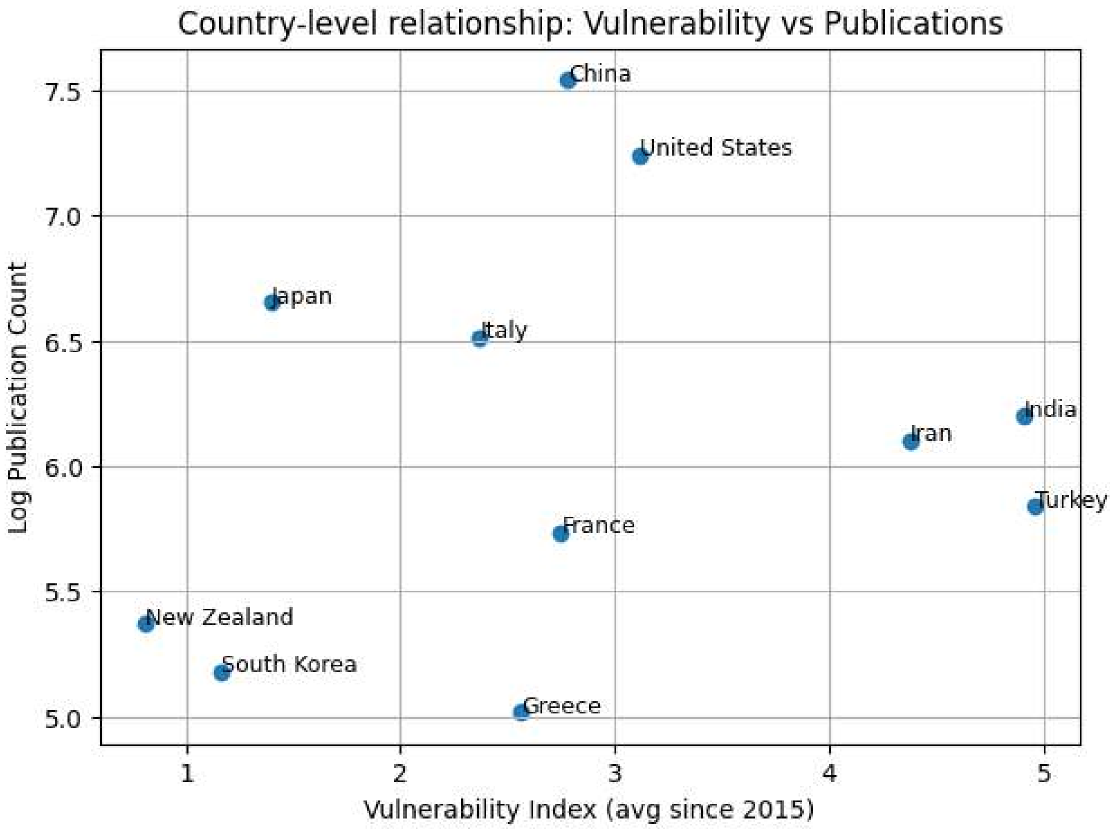

Figure B.1: Country-level relationship between the Vulnerability Index and scientific publication activity.

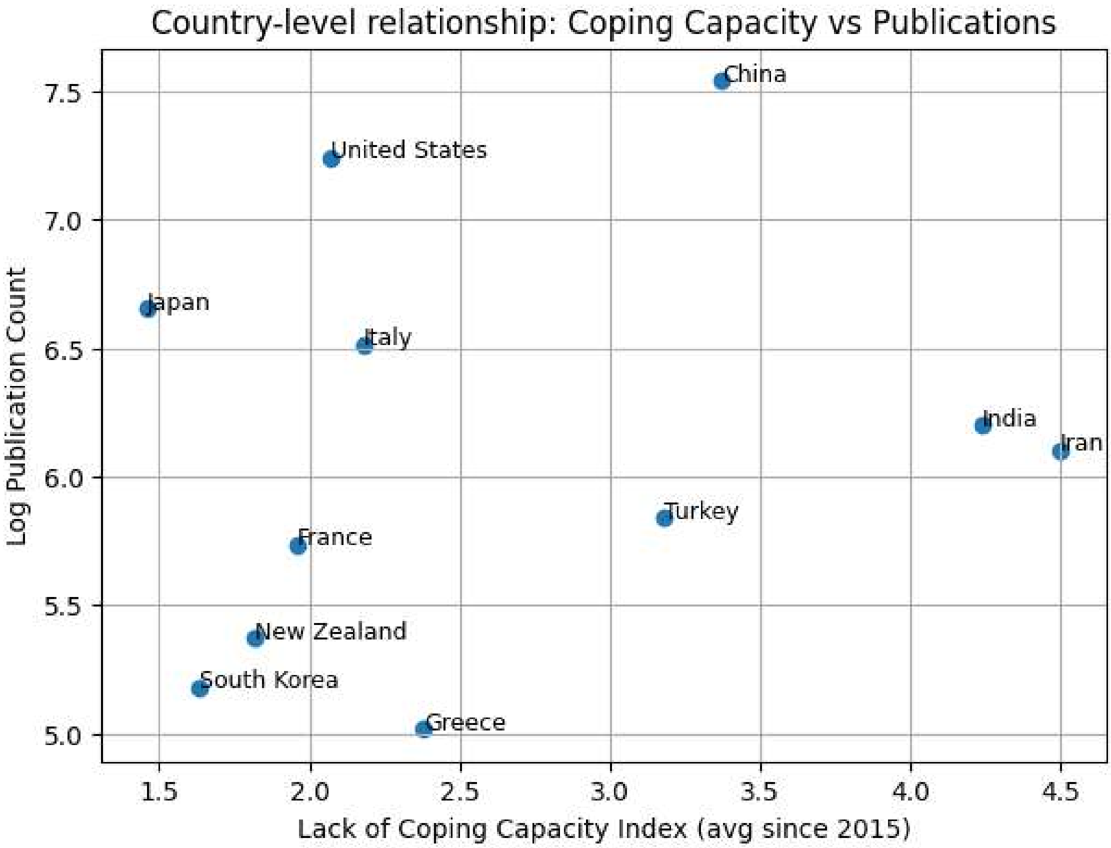

Figure B.2: Country-level relationship between the Lack of Coping Capacity Index and scientific publication activity.

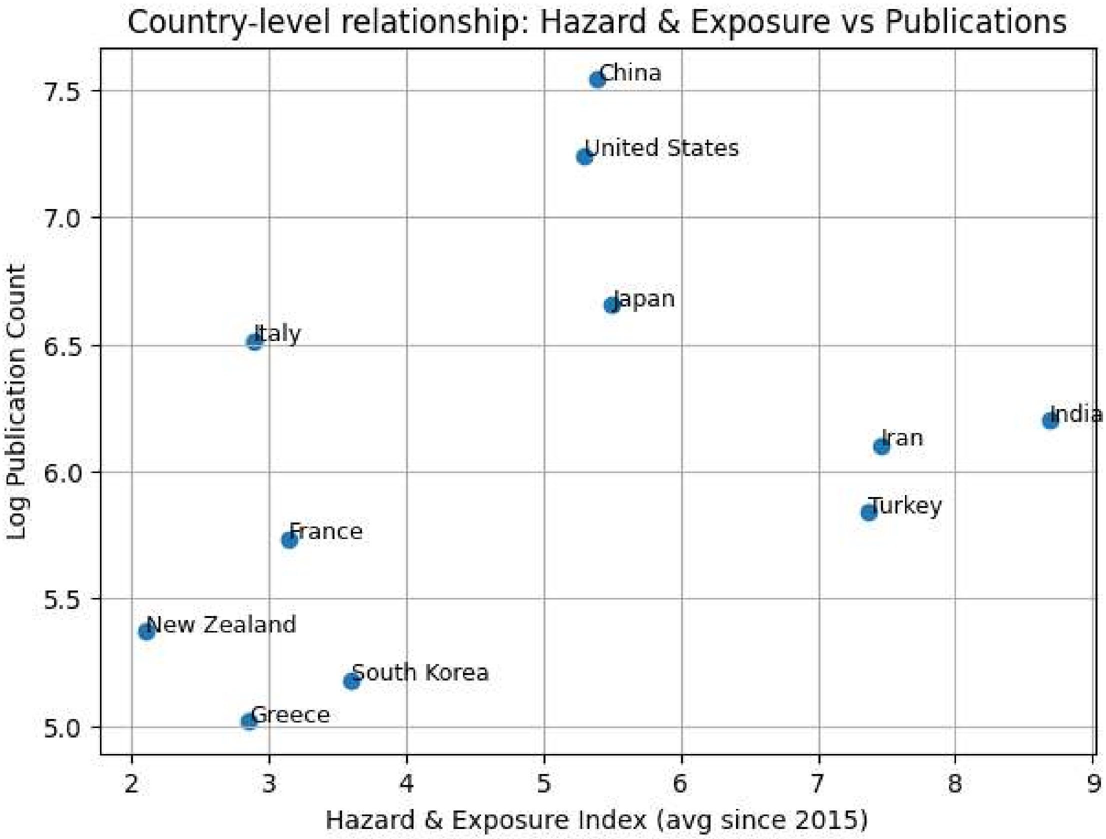

Figure B.3: Country-level relationship between the Hazard & Exposure Index and scientific publication activity.