A System Dynamics Framework for Resource Allocation in Disaster Vulnerability Analysis

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Abstract: This paper addresses a transdisciplinary application area that uses systems thinking to concord disaster vulnerability, sustainability, and resilience. Through a System Dynamics framework, the study connects Sustainable Development Goals (SDGs) with the dynamic interactions among societal, economic, and environmental factors influencing preparedness and recovery. It illustrates how systems modeling can capture interdependencies and resource flows, supporting more effective strategies for sustainable and resilient disaster risk reduction, based on seven critical factors. A Vulnerability Index is introduced to explore the allocation of resources among these interconnected factors. From a practical point of view, this approach allows to connect SDGs targets with the analytical rigor of systems modeling, demonstrating the essential role of System Dynamics in understanding and managing complex, interdependent systems that underpin societal resilience, advancing complex decision support systems.

Keywords: systems thinking; system dynamics; sustainability; resilience; simulation

1. INTRODUCTION

Sustainability and resilience are often used as complementary concepts. Both concepts align to promote dynamic capabilities that ensure system longevity and robustness under changing conditions (Drăgoicea et al. (2020)). *Sustainability* use cases are formulated for a wide range of global challenges, such as education, healthcare, poverty, water, garbage, climate action, and airline recovery, to name but a few, and the Sustainable Development Goals (SDGs) of the United Nations (UN (May 2024)) provide a set of universally accepted targets for global evaluation. *Resilience* is related to the availability of resources and requires a multi-contextual design of services (Drăgoicea et al. (2020)). Knowledge co-production activities for public services are needed, thus improving emergency preparedness through the integration of resources across multiple contexts (Drăgoicea et al. (2020)), while pursuing multiple goals simultaneously. Education, including knowledge and skills, and values are operant resources that are integrated in the value co-creation processes (Walletzký et al. (2024), Vargo et al. (2020)).

The growing impact of natural disasters on urban environments has triggered great interest in research on *earthquake resilience* (Zhai et al. (2023), Kodag et al. (2022)) and *sustainability* (Di Ludovico et al. (2020), Pribadi et al. (2021)). *Earthquake resilience* refers to the ability of a community to prepare for, respond to, and recover from earthquakes, minimizing adverse impacts on social, economic, and physical structures (NSTC (2005)). Unlike *seismic resilience*, which focuses primarily on the structural integrity of buildings and infrastructure (Kassem et al. (2022)), earthquake resilience encompasses a broader spectrum, including *community participation*, preparedness, and recovery strategies.

Despite the significant advances achieved in understanding earthquake resilience, few studies have thoroughly investigated how resilience objectives could be matched with the SDGs. SDG 11 (Sustainable Cities), SDG 9 (Resilient Infrastructure), and SDG 13 (Climate Action) are only a few of the sustainability goals that are partially addressed by researchers. However, the SDGs are inherently interconnected and should not be addressed in isolation, they should be viewed as an *integrated system*, not as separate targets (Luchian et al. (2025), Spaiser et al. (2017)).

Within this line of thought, this paper seeks to unravel the complex relationship between earthquake resilience and sustainability taking the lens of resource availability and allocation integrated in a System Dynamics modeling approach, ultimately identifying and validating the critical factors that foster synergies in resource allocation in *earthquake-prone regions*. It is explored how communities can be better prepared for natural disasters, with a particular focus on earthquakes. To address this, the study identifies clusters of activities that simultaneously advance resilience and sustainability objectives, linking them explicitly to relevant targets of the SDGs. As a main contribution, a Vulnerability Index is introduced that quantifies systemic exposure to earthquake hazards and evaluates a community's capacity to anticipate, withstand, and recover from disasters.

The study adopts a *systems thinking* perspective grounded in Von Bertalanffy (1968) General Systems Theory. Such an approach enables the analysis of dynamic relationships and feedback loops across social, economic, and environmental domains, offering a holistic understanding of how progress in one area can influence resilience and sustainability in others. System Dynamics (Forrester (1997)) has emerged as a valuable tool in modeling complex social systems, enabling researchers to simulate feedback loops and predict long-term trends in public behavior (Hirsch et al. (2016)) and business (Rezvany and Kashani (2022)). System Dynamics models are developed in various domains, such as guiding the transition to sustainable activities across production areas (Pérez-Pérez et al. (2021)), improving urban sustainability performance (Sutley and Hamideh (2018)), evaluate sustainable development problems (Honti et al. (2019)), achieving sustainable management of water supply and demand (Naeem et al. (2023)) or investigate the sustainability of food systems (Amiri et al. (2020)).

The remainder of the paper is structured as follows. Section 2 provides a brief review of the literature connecting resilience and sustainability. Section 3 describes the research methodology based on the PRISMA approach, used along with topic modeling, to identify key topics that illustrate the synergies among the UN SDGs. A proposed framework for preparedness, recovery, and long-term development is introduced, which integrates the seven-factor model of resilience and sustainability, *emphasizing resource availability and allocation*. Section 4 presents the System Dynamics model that incorporates these critical factors, along with the simulation results. In Section 5, the study evaluates the proposed Vulnerability Index. Finally, Section 6 summarizes the main contributions, discusses the limitations of the current research, and offers directions for future studies.

2. LITERATURE REVIEW

The scientific literature demonstrates that earthquake resilience and sustainability are not mutually exclusive but rather deeply interconnected and mutually reinforcing concepts in various aspects, such as:

- *Prioritize key concepts*: Identify crucial areas of focus for research and mitigation efforts (Sadia et al. (2024));
- *Increase public awareness*: Educate citizens about seismic risks and encourage preparedness (Dagatan et al. (2024));
- *Promote sustainable practices*: Foster the adoption of sustainable building codes and land-use planning in high-risk zones (Ding et al. (2024));
- *Inform resilience and mitigation strategies*: Provide data-driven insights for developing effective disaster response and recovery plans (Qin et al. (2024), Jianu and Dragoicea (2024));
- *Support sustainable urban planning*: Guide policy decisions that improve urban resilience and minimize the impact of future earthquakes (Zhai et al. (2023)).

Addressing gaps in reconstruction and community needs, a new model, validated during recovery from the Changning Ms 6.0 earthquake in Sichuan, China, has been proposed by (Shi et al. (2021)). By analyzing diverse community and family needs, the model effectively guides policy by integrating decision-making methods to enhance resilience and recovery outcomes.

A sustainable recovery framework that incorporates the needs of citizens, addressing a gap in the disaster recovery literature has been proposed by (Zhou et al. (2022)). Using *system theory*, the framework identifies key factors influencing recovery and provides recommendations to improve disaster recovery management, with potential for global application in developing regions.

The intersection of earthquake resilience with healthcare infrastructure has been the focus of some studies, aligning to the SDG 3. A new approach presented in (Hassan and Mahmoud (2020)) provides an estimate of how well a community's healthcare services would function and recover after an earthquake. As a result of earthquake damage, effective planning for patient transfers and the distribution of ambulances and mobile operating rooms can be created using a different suggested methodology (Ceferino et al. (2020)).

Earthquake events can severely disrupt energy systems, particularly in regions that rely on centralized power grids (Mate et al. (2021)) or fossil fuels (Cong et al. (2022)), according to SDG 7. In (Wu et al. (2022)) a post-disaster power supply recovery strategy has been proposed, due to the increasing frequency of natural disasters, such as earthquakes, which led to frequent power outages in urban distribution networks.

To save more lives and mitigate economic disruptions caused by infrastructure damage, (Pribadi et al. (2021)) advocates for the creation of a knowledge management system for earthquake-resistant infrastructure in Indonesia that reaches its sustainable development goals. Infrastructure resilience is a key focus of SDG 9.

Urban safety and sustainability are seriously threatened by earthquakes, as they are unpredictable and often catastrophic natural disasters, especially in highly populated areas. (Assarkhaniki et al. (2023)) has proposed to organize the SDGs into five categories based on their coverage of each resilience dimension, and a guideline has been developed to demonstrate the goals related to each resilience dimension. (Malhotra et al. (2020)) proposed a systematic framework of resilience indicators to incorporate previously ignored resilience features into the UN 2030 Agenda. (Tiwari and Shukla (2022)) proposed an SDG-aligned framework to assess well-being recovery and guide post-disaster reconstruction for greater future resilience. These research directions align with the targets of SDG 11, which seeks to make cities and human settlements inclusive, safe, resilient, and sustainable, thereby directly connecting urban resilience with sustainability.

The need for comprehensive disaster resilience strategies is highlighted by the increasing number and severity of natural disasters, especially those caused by climate change. Although earthquakes are not caused by climate change, the aftermath of earthquakes often intersects with the effects of climate-related events such as floods (Quigley and Duffy (2020)) and storms (Chmiel et al. (2022)). This line of research aligns with the targets of SDG 13, which primarily focuses on climate change mitigation and adaptation.

Thus, initiatives to understand and increase earthquake resilience (Kassem et al. (2022), Jianu and Drăgoicea

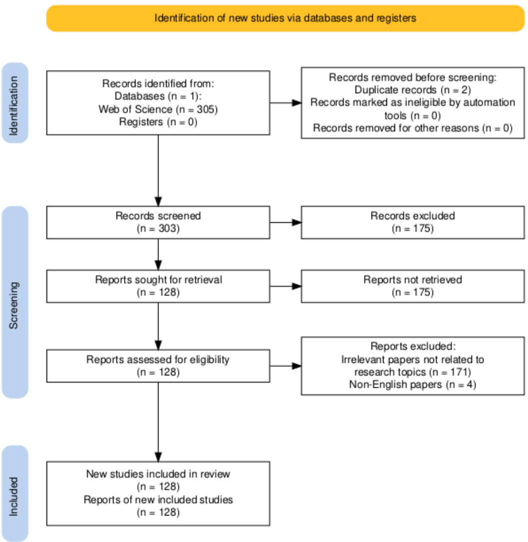

Fig. 1. Systematic literature review and reporting - PRISMA Flow Diagram

(2024)) can advance the goals of *global sustainability* (Luchian et al. (2025), Govindarajan and Sukanya (2023)), e.g. in the domains of areas of infrastructure, urban planning, and community resilience (Hu et al. (2024), Zhang et al. (2022)).

However, *the achievement of sustainable development targets in earthquake-prone regions* requires a holistic and integrated approach that acknowledges and addresses the physical, social, economic, and environmental dimensions of resilience.

3. RESEARCH METHODOLOGY

The methodology adopted in this study is based on a multistage approach. Initially, a systematic literature review was conducted using the PRISMA[1] method, aimed at identifying relevant articles that illustrate the synergies between the SDGs and resilience (Fig. 1). Following established inclusion criteria, only peer-reviewed scientific papers published in English and indexed in the Web of Science (WoS) database were considered. The selection process involved applying specific filters to ensure relevance and quality:

TS=((”*earthquake**” OR ”*seismic**” OR ”*seismo**”) AND (”*awareness*” OR ”*preparation*” OR ”*preparedness*” OR ”*resilient*” OR ”*resilience*” OR ”*recovery*” OR ”*mitigation*” OR ”*urban planning*” OR ”*policy development*” OR ”*education*” OR ”*policies*” or ”*plans*”) AND (”*sustainable*” OR ”*sustainability*” OR ”*SDG*”))

NOT TS=(”*buildings**” OR ”*coping*” OR ”*water**” OR ”*bridge**” OR ”*slope*” OR ”*supply chain**” OR ”*rail**” OR ”*rural**” OR ”*material**” OR ”*gas**” OR ”*tourism**” OR ”*housing**” OR ”*COVID**”) AND PY=(2019-2024)

A total of 305 scientific papers have initially been identified. After removing duplicates and screening for relevance, 128 scientific papers have been selected for inclusion in this study. These comprised journal articles (89.07%), conference proceedings (7.81%), and books and book chapters (3.12%), all published between 2019 and 2024.

The next stage of the methodology addressed the creation of a *text analysis modeling pipeline*, focusing on the extraction of specific topics that characterize the synergies among the SDGs and highlighting resilience aspects. Topic modeling stage revealed seven different topics (Fig. 2) based on which the potential synergies between the clusters and the SDGs have been formulated as follows:

Cluster 1: Education and preparedness aligns with SDG 4 (Quality Education) and SDG 11 (Sustainable Cities and Communities) by promoting a culture of safety and empowering students to respond effectively to disasters.

Cluster 2: It focuses on hospital infrastructure and seismic frameworks, supports SDG 3 (Good Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure) by ensuring that healthcare systems remain operational during crises.

Cluster 3: Health recovery strategies improve community resilience, contributing to SDG 3 and SDG 16 (Peace, Justice, and Strong Institutions).

Cluster 4: Urban vulnerability assessments help reduce risks in cities, advancing SDG 11 and SDG 13 (Climate Action).

Cluster 5: Coastal hazard mitigation ensures the protection of coastal ecosystems, aligning with SDG 14 (Life Below Water) and SDG 15 (Life on Land).

Cluster 6: Post-disaster reconstruction focuses on emphasizing sustainable rebuilding practices, supporting SDG 9 and SDG 11;

Cluster 7: Economic models and evacuation planning ensures the integration of social and economic factors in disaster response, contributing to SDG 1 (No Poverty) and SDG 8 (Decent Work and Economic Growth).

In the next step, a *seven-factors T1-T7 framework of resilience and sustainability* has been proposed (Fig. 3), with the aim of constructing a more comprehensive approach to preparedness, recovery, and long-term development.

T1. Education and Preparedness: to develop comprehensive educational programs on earthquake preparedness targeting students and schools and to implement regular drills and provide *operant resources* (*knowledge and skills*) Vargo et al. (2020) for emergency response. By promoting continuous education that adapts to evolving risks, this theme supports safer, more resilient communities and advances the goals of SDG 4 and SDG 11.

T2. Healthcare Infrastructure and Systems to strengthen hospital infrastructure to withstand seismic events; to develop robust response frameworks and retrofit hospital buildings for seismic resilience, implement emergency response systems, and train healthcare workers in disaster response. This theme supports SDG 3 and SDG 9 by emphasizing the long-term resilience of healthcare systems, ensuring that today's infrastructure investments remain effective during future disasters.

T3. Health Recovery and Community Involvement to enhance health recovery programs and involve local

[1] https://www.prisma-statement.org/, https://estech.shinyapps.io/prisma_flowdiagram/

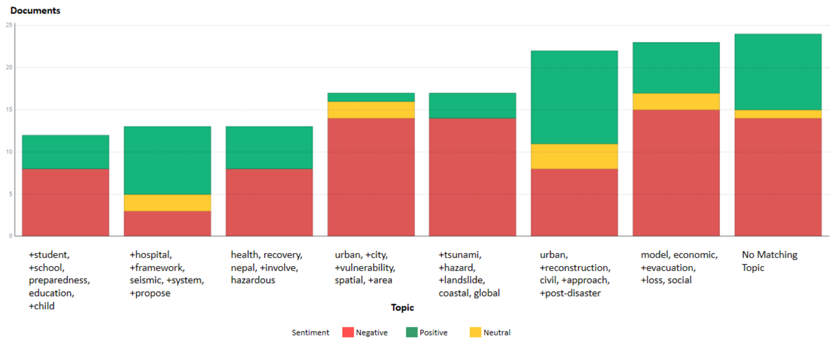

Fig. 2. Identified topics in relevant literature and the number of scientific papers (documents) per topic

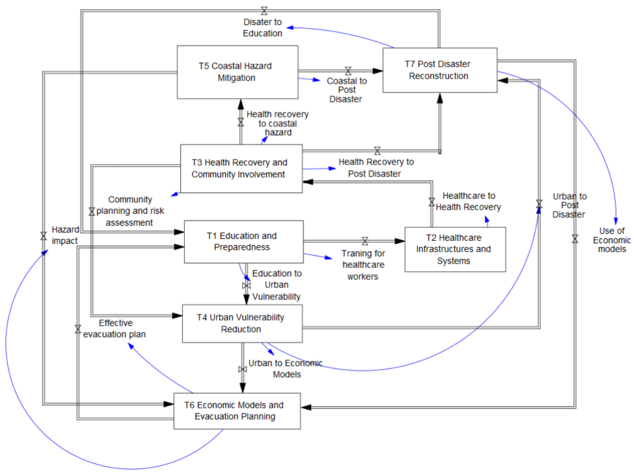

Fig. 3. The seven-factors framework of resilience and sustainability

communities in recovery efforts; to engage local communities in recovery planning; to develop mitigation strategies for hazardous conditions. This theme supports SDG 3 and SDG 16 by fostering community participation in recovery processes, enhancing social resilience, and promoting long-term well-being after seismic events.

T4. Urban Vulnerability Reduction to assess urban vulnerabilities and implement spatial planning to reduce risk. Urban vulnerability assessments align with SDG 11 and SDG 13 by promoting seismic risk–aware planning that supports sustainable development and reduces future recovery costs and losses.

T5. Coastal Hazard Mitigation to implement comprehensive coastal hazard mitigation strategies to protect against tsunamis and landslides, develop early warning systems, build protective coastal infrastructure, and educate coastal communities about response to hazards. This theme supports SDG 14 and SDG 15 by promoting sustainable mitigation of coastal hazards that protects human life, preserves ecosystems, and strengthens long-term resilience.

T6. Post-Disaster Reconstruction to plan and execute sustainable urban reconstruction projects using civil engineering and community-based approaches; to develop reconstruction master plans, engage local communities in reconstruction efforts, and utilize sustainable building materials and techniques. This theme advances SDG 9 and SDG 11 by reducing the environmental footprint of rebuilding efforts and provides long-term social and economic benefits to affected communities.

T7. Economic Models and Evacuation Planning to develop robust economic models to assess and mitigate losses and improve evacuation strategies, create economic impact models for disaster scenarios, plan and simulate evacuation strategies, and incorporate social considerations into economic and evacuation planning. Economic Models and Evacuation Planning. This theme supports SDG 8 by fostering inclusive and sustainable economic growth, and SDG 1 by contributing to poverty reduction.

These identified synergies highlight the *need to pursue multiple goals simultaneously* to align resilience and sustainability goals.

4. RESULTS

To validate this seven factors framework, the System Dynamics (SD) lens (Forrester (1997)) has been applied to highlight the relationships and feedback loops that arise when pursuing multiple goals simultaneously Karunathilake et al. (2020), and to take into account *resource availability and allocation*. A SD model simulates intricate feedback processes found in socio-ecological systems by using stocks (accumulated quantities), flows (rates of change), and causal connections to show dynamic interactions over time.

4.1 System modeling

The SD model (Fig. 4) has been developed and simulated using Vensim (`https://vensim.com/`) as described in Subsection 4.2. The stocks composing the model correspond to the seven identified factors: T1 - Response Capacity (RC), T2 - Healthcare Capacity (HC), T3 - Community Health (CH), T4 - Urban Resilience (UR), T5 - Coastal Protection Capacity (CPC), T6 - Economic Resilience (ER), and T7 - Reconstruction Progress (RP).

Stocks are modeled using the differential equation defined by (1) Forrester (1994):

$$\frac{dS(t)}{dt} = Inflows(t) - Outflows(t) \quad (1)$$

where $S(t)$ is the value of the stock at time t; $Inflows(t)$ is the total rate of inflows into the stock at time t;

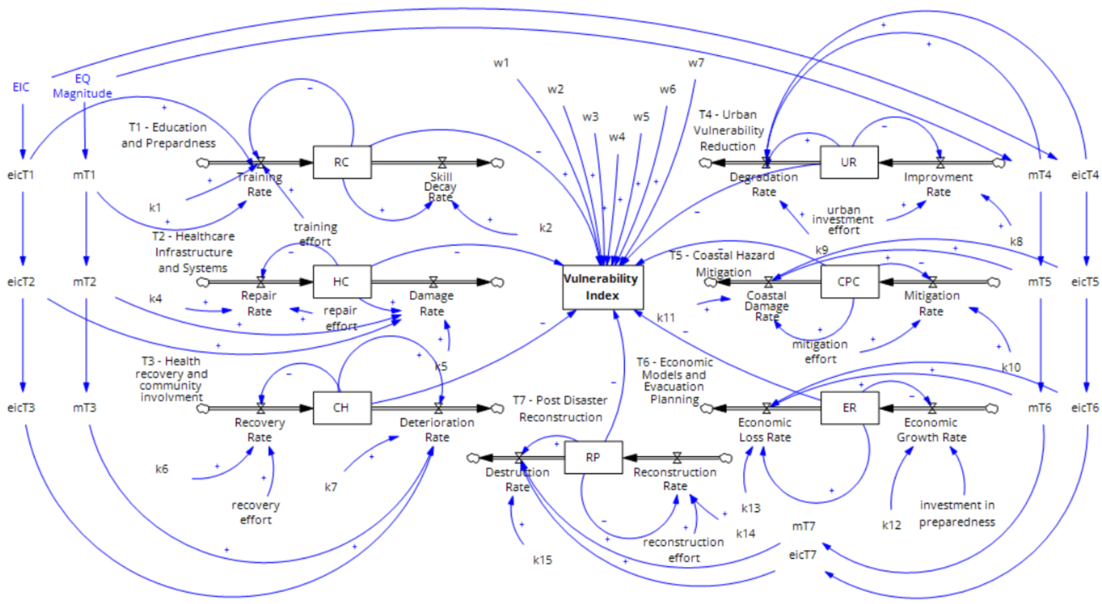

Fig. 4. System Dynamics model of key resilience factors in earthquake preparedness (T1–T7)

$Outflows(t)$ is the total rate of outflows from the stock at time t.

The **global behavior** of the SD model is governed by two global parameters: a generic earthquake magnitude (`EQ Magnitude`, in Equation (2)), and the earthquake sensitivity coefficient (`EIC`), a global parameter defined in the model that shows how strongly an earthquake affects different parts of the system (Table 1).

$$EQMagnitude = PULSE(10,1) \cdot 4 + \\ + PULSE(20,1) \cdot 5 + \\ + PULSE(30,1) \cdot 7 + PULSE(40,1) \cdot 5 \quad (2)$$

Table 1. SD global parameters

Variable name	Type	Equation	Generic units	Description	Value
EQ Magnitude	global parameter	(2)	magnitude	Magnitude of the earthquake	-
EIC	global parameter	-	1 / magnitude	Earthquake sensitivity coefficient	0.5

`EQ Magnitude` was set using PULSE functions to show earthquakes happening at certain times: at year 10 with magnitude 4, at year 20 with magnitude 5, at year 30 with magnitude 7, and at year 40 with magnitude 5.

The **local behavior** of the components of the model, corresponding to the seven resilience factors, has been defined as follows.

T1 subsystem captures the role of the community in reducing the vulnerability. It is represented by the stock *RC* (`Response Capacity` in Equation (3)). It increases through a `Training Rate` (from Equation (4)) and decreases due to `Skill Decay Rate` (from Equation (5)):

$$\frac{dRC}{dt} = TrainingRate(t) - SkillDecayRate(t) \quad (3)$$

$$TrainingRate(t) = k_1 \cdot trainingeffort \\ \cdot (1 - \frac{RC(t)}{100} \cdot (1 + eicT_1 \cdot mT_1)) \quad (4)$$

$$SkillDecayRate(t) = k_2 \cdot RC(t) \quad (5)$$

where k_1 is the defined as the effectiveness of each training session, *trainingeffort* is the effort of the training, $eicT_1$ is the earthquake sensitivity coefficient, mT_1 is the magnitude of the earthquake, and k_2 is the skill decay rate sensitivity (Table 2).

Table 2. T1: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
RC	Stock	(3)	percent	Response Capacity	20
Training Rate	Inflow	(4)	percent / Year	Training rate	-
Skill Decay Rate	Outflow	(5)	percent / Year	Skill decay rate	-
training effort	parameter	-	session / Year	# training sessions per year	5
k_1	parameter	-	1 / session	effectiveness of training rate	0.9
k_2	parameter	-	1 / Year	skill decay rate sensitivity	0.01
$eicT_1 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_1 = EQ\ Magnitude$	parameter	(2)	magnitude	magnitude of the earthquake	-

T2 subsystem models the condition and functionality of healthcare infrastructure during and after disasters. The *HC* (`Healthcare Capacity` stock in Equation (6)) is increased by a `Repair Rate` (from Equation (7)), and decreased by a `Damage Rate` (from Equation (8)). Both of them are influenced by repair efforts and external input, such as earthquake magnitude.

$$\frac{dHC}{dt} = RepairRate(t) - DamageRate(t) \quad (6)$$

$$RepairRate(t) = k_4 \cdot repaireffort \cdot (1 - \frac{HC(t)}{100}) \quad (7)$$

$$DamageRate(t) = k_5 \cdot HC(t) \cdot (1 + eicT_2 \cdot mT_2) \quad (8)$$

where k_4 is the defined as the effectiveness of the *repair-effort*, $eicT_2$ is the earthquake sensitivity coefficient, mT_2 is the magnitude of the earthquake, and k_5 is the damage sensitivity coefficient (Table 3).

Table 3. T2: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
HC	Stock	(6)	percent	Healthcare Capacity	70
Repair Rate	Inflow	(7)	percent / Year	Repair rate	-
Damage Rate	Outflow	(8)	percent / Year	Damage rate	-
repair effort	parameter	-	effortunits / Year	# effort units per year	15
k_4	parameter	-	1 / effortunits	effectiveness of the repair effort	0.99
k_5	parameter	-	1 / Year	damage rate sensitivity coefficient	0.04
$eicT_2 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_2 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

T3 subsystem focuses on psychological and social dimensions of post-disaster recovery. It is represented by CH (`Community Health`) stock, defined by the Equation (9) and it evolves based on `Recovery Rate`, defined by Equation (10), and `Deterioration Rate`, defined by Equation (11), both affected by community-level recovery efforts:

$$\frac{dCH}{dt} = RecoveryRate(t) - DeteriorationRate(t) \quad (9)$$

$$RecoveryRate(t) = k_6 \cdot recoveryeffort \cdot (1 - \frac{CH(t)}{100}) \quad (10)$$

$$DeteriorationRate(t) = k_7 \cdot CH(t) \cdot (1 + eicT_3 \cdot mT_3) \quad (11)$$

where k_6 is the defined as the effectiveness of the *recoveryeffort*, $eicT_3$ is the earthquake sensitivity coefficient, mT_3 is the magnitude of the earthquake, and k_7 is the deterioration sensitivity coefficient (Table 4).

T4 subsystem focuses on the physical infrastructure resilience within urban areas. The UR (`Urban Resilience` stock in Equation (12)), increases via an `Improvement Rate`, defined by Equation (13), driven by urban investment efforts and declines due to `Degradation Rate`, defined by Equation (14):

$$\frac{dUR}{dt} = ImprovmentRate(t) - DegradationRate(t) \quad (12)$$

$$ImprovmentRate(t) = k_8 \cdot \cdot urbaninvestmenteffort \cdot (1 - \frac{UR(t)}{100}) \quad (13)$$

Table 4. T3: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
CH	Stock	(9)	percent	Community Health	95
Recovery Rate	Inflow	(10)	percent / Year	Recovery rate	-
Deterioration Rate	Outflow	(11)	percent / Year	Deterioration rate	-
recovery effort	parameter	-	effortunits / Year	# recovery efforts per year	65
k_6	parameter	-	1 / effortunits	effectiveness of the recovery effort	0.99
k_7	parameter	-	1 / Year	deterioration sensitivity	0.06
$eicT_3 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_3 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

$$DegradationRate(t) = k_9 \cdot UR(t) \cdot (1 + eicT_4 \cdot mT_4) \quad (14)$$

where k_8 is the defined as the urban investment effectiveness coefficient of the *urbaninvestmenteffort*, $eicT_4$ is the earthquake sensitivity coefficient, mT_4 is the magnitude of the earthquake, and k_9 is the degradation sensitivity coefficient (Table 5).

Table 5. T4: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
UR	Stock	(12)	percent	Urban Reduction	45
Improvment Rate	Inflow	(13)	percent / Year	Improvment rate	-
Degradation Rate	Outflow	(14)	percent / Year	Degradation rate	-
urban investment effort	parameter	-	investmentunits / Year	# urban investment efforts per year	10
k_8	parameter	-	1 / investmentunits	investment effectiveness coefficient	0.9
k_9	parameter	-	1 / Year	degradation sensitivity coefficient	0.03
$eicT_4 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_4 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

T5 subsystem focuses on actions that may protect coastal areas from natural disasters. It is represented by the stock CPC (`Coastal Protection Capacity` in Equation (15)), which is increased by `Mitigation Rate`, defined in Equation (16), and reduced by `Coastal Damage Rate`, defined by the Equation (17):

$$\frac{dCPC}{dt} = MitigationRate(t) - -CoastalDamageRate(t) \quad (15)$$

$$MitigationRate(t) = k_{10} \cdot mittigationeffort \cdot \cdot (1 - \frac{CPC(t)}{100}) \quad (16)$$

$$CoastalDamageRate(t) = k_{11} \cdot CPC(t) \cdot \cdot (1 + eicT_5 \cdot mT_5) \quad (17)$$

where k_{10} is the defined as the mitigation effectiveness coefficient of the *mittigationeffort*, $eicT_5$ is the earthquake sensitivity coefficient, mT_5 is the magnitude of the earthquake, and k_{11} is the coastal damage sensitivity coefficient (Table 6).

Table 6. T5: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
CPC	Stock	(15)	percent	Coastal Protection Capacity	80
Mitigation Rate	Inflow	(16)	percent / Year	Mitigation rate	-
Coastal Damage Rate	Outflow	(17)	percent / Year	Coastal damage rate	-
mitigation effort	parameter	-	effortunits / Year	# effort units per year	20
k_{10}	parameter	-	1 / effortunits	investment effectiveness coefficient	0.99
k_{11}	parameter	-	1 / Year	coastal damage sensitivity coefficient	0.04
$eicT_5 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_5 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

T6 subsystem focuses on economic resilience and emergency management. It is represented by the stock ER (`Economic Resilience`), Equation (18), which is shaped by `Economic Growth Rate`, defined by the Equation (19), and `Economic Loss Rate`, Equation (20):

$$\frac{dER}{dt} = EconomicGrowthRate(t) - \\ - EconomicLossRate(t) \tag{18}$$

$$EconomicGrowthRate(t) = k_{12} \cdot \\ \cdot investmentinpreparedness \cdot (1 - \frac{ER(t)}{100}) \tag{19}$$

$$EconomicLossRate(t) = k_{13} \cdot ER(t) \cdot (1 + eicT_6 \cdot mT_6) \tag{20}$$

where k_{12} is the economic investment effectiveness coefficient of the *investmentinpreparedness*, $eicT_6$ is the earthquake sensitivity coefficient, mT_6 is the magnitude of the earthquake, and k_{13} is the economic damage sensitivity (Table 7).

T7 subsystem represents the process of rebuilding after a disaster. The RP (`Reconstruction Progress`) stock, defined by Equation (21), accumulates through `Reconstruction Rate`, defined by the Equation (22), and diminishes due to `Destruction Rate`, defined by the Equation (23), both sensitive to reconstruction effort.

$$\frac{dRP}{dt} = ReconstructionRate(t) - \\ - DestructionRate(t) \tag{21}$$

$$ReconstructionRate(t) = k_{14} \cdot \\ \cdot reconstructioneffort \cdot (1 - \frac{RP(t)}{100}) \tag{22}$$

Table 7. T6: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
ER	Stock	(18)	percent	Economic resilience capacity	50
Economic Growth Rate	Inflow	(19)	percent / Year	Economic growth rate	-
Economic Loss Rate	Outflow	(20)	percent / Year	Economic loss rate	-
investment in preparedness	parameter	-	effortunits / Year	# investment in preparedness effort units per year	15
k_{12}	parameter	-	1 / effortunits	economic investment effectiveness coefficient	0.9
k_{13}	parameter	-	1 / Year	economic damage sensitivity coefficient	0.04
$eicT_6 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_6 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

$$DestructionRate(t) = k_{15} \cdot RP(t) \cdot (1 + eicT_7 \cdot mT_7) \tag{23}$$

where k_{14} is the reconstruction effectiveness coefficient of *reconstructioneffort*, $eicT_7$ is the earthquake sensitivity coefficient, mT_7 is the magnitude of the earthquake, and k_{15} is the damage sensitivity coefficient (Table 8).

Table 8. T7: Stocks, flows and parameters

Variable name	Type	Equation	Generic units	Description	Initial value
RP	Stock	(21)	percent	Reconstruction Progress	15
Reconstruction Rate	Inflow	(22)	percent / Year	Reconstruction rate	-
Destruction Rate	Outflow	(23)	percent / Year	Destruction rate	-
reconstruction effort	parameter	-	effortunits / Year	# reconstruction effort units per year	10
k_{14}	parameter	-	1 / effortunits	reconstruction effectiveness coefficient	0.99
k_{15}	parameter	-	1 / Year	damage sensitivity coefficient	0.04
$eicT_7 = EIC$	parameter	-	1 / magnitude	earthquake sensitivity coefficient	0.5
$mT_7 =$ *EQ Magnitude*	parameter	(2)	magnitude	magnitude of the earthquake	-

Vulnerability Index. It is a global variable defined in the model (from Equation (24)) that is being used to measure how exposed the overall system is to earthquake hazards. It concentrates the effect of each of the seven resilience factors and quantifies the overall susceptibility of the community to the impacts of disasters. In this way, one can determine how well the community can anticipate, respond to, and recover from natural disasters.

$$VI = \sum_{i=1}^{7} w_i \cdot R_{T_i} \tag{24}$$

where w_i represents the weights of the model, where $\sum_{i=1}^{7} w_i = 1$, $w_i \in [0, 1]$, and R_{T_i} represents the stocks of each of the Ti subsystem ($i = \overline{1,7}$), i.e. $R_{T_1} = RC$, $R_{T_2} = HC$, $R_{T_3} = CH$, $R_{T_4} = UR$, $R_{T_5} = CPC$, $R_{T_6} = ER$, and $R_{T_7} = RP$.

It combines seven important weights of the system: education and preparedness weight (w_1), healthcare infrastructure weight (w_2), health recovery and community involvement weight (w_3), urban vulnerability reduction weight (w_4), coastal hazard mitigation weight (w_5), economic models and evacuation planning weight (w_6), and post-disaster reconstruction weight (w_7).

Compact state-space model. To explicitly integrate the proposed modeling approach using the developed SD model within a formal system-theoretic framework, the following representation of the state-space model is presented (Equation (25)):

$$\dot{\mathbf{x}}(t) = \mathbf{f}\big(\mathbf{x}(t), \mathbf{u}(t), \mathbf{p}\big) \tag{25}$$

where the state vector, defined by Equation (26), includes the main stocks of subsystems T1-T7 as state variables, representing the dynamic level of a critical factor in the system,

$$\mathbf{x}(t) = \begin{bmatrix} RC(t) \\ HC(t) \\ CH(t) \\ UR(t) \\ CPC(t) \\ ER(t) \\ RP(t) \end{bmatrix} \tag{26}$$

and $\mathbf{u}(t)$ represents the external inputs, such as earthquake magnitude and resource allocation efforts, and $\mathbf{p}$ represents the vector of model parameters. The nonlinear function $\mathbf{f}(\cdot)$ is derived from the stock–flow equations defined in Equations (1)–(23), capturing the feedback mechanisms and interconnections among the subsystems.

4.2 Model Simulation

The model simulates over a 50-year time horizon to capture the long-term behavior and dynamic evolution of community resilience, with a time step of one year and the Euler integration method. These scenarios have been constructed taking into consideration the pulsed behavior of the `EQ Magnitude` parameter, defined by Equation (2).

A higher value of `EIC` means that the system is more sensitive, so earthquakes can negatively impact preparedness, healthcare or infrastructure aspects. Higher values of `EQ Magnitude` may lead to more stress and damage. These two parameters have been initialized with plausible baseline values to ensure realistic behavior of the model and to allow comparisons between different scenarios (Table 1).

T1 subsystem. The model parameters for T1 have been defined as follows: $k_1 = 0.9$ represents the effectiveness of each training session, $k_2 = 0.01$ represents the rate at which skills are lost over time, and $eicT_1 = 0.5$ represents the earthquake sensitivity coefficient.

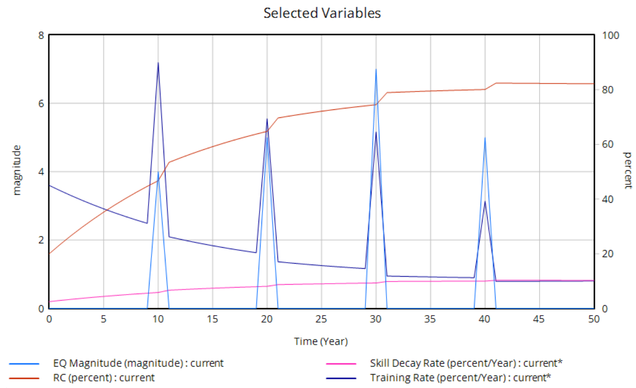

Fig. 5. Response Capacity (RC)

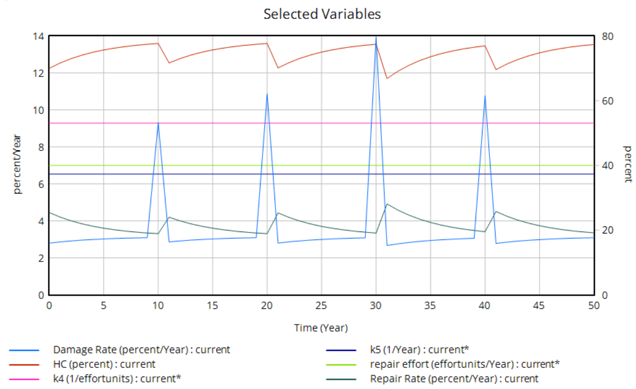

Fig. 6. Healthcare Capacity (HC)

Under current defined conditions, RC increases from 20% to 82.18% (Fig. 5). This suggests that despite earthquakes and the natural decline in skills, constant preparedness efforts improve the community's ability to deal with disasters. Continuing education and practical exercises can improve the resilience of the community in the face of earthquakes. Although the impact of large earthquakes (such as the one in the year 30) temporarily reduces the response capacity, the system recovers due to sustained efforts.

T2 subsystem. The model parameters for T2 have been defined as follows: $k_4 = 0.99$ represents the effectiveness of repair effort in restoring the HC, $k_5 = 0.04$ represents the damage sensitivity coefficient of the HC, and $eicT_2 = 0.5$ represents the sensitivity of the earthquake.

HC is increasing from 70% to 77.38% (Fig. 6). This suggests that despite the damage caused by the earthquake, the repair processes and efforts (determined by factors such as effectiveness and repair effort) were robust enough to partially compensate for the losses and to progressively improve the health system as a whole. Thus, the T2 subsystem becomes more resilient over time, ensuring better preparedness and response capacity for future disasters.

T3 subsystem. The model parameters for T3 have been defined as follows: $k_6 = 0.99$ represents the effectiveness of recovery effort in restoring the CH, $k_7 = 0.06$ represents the deterioration sensitivity coefficient of the CH, and $eicT_3 = 0.5$ represents the sensitivity of the earthquake.

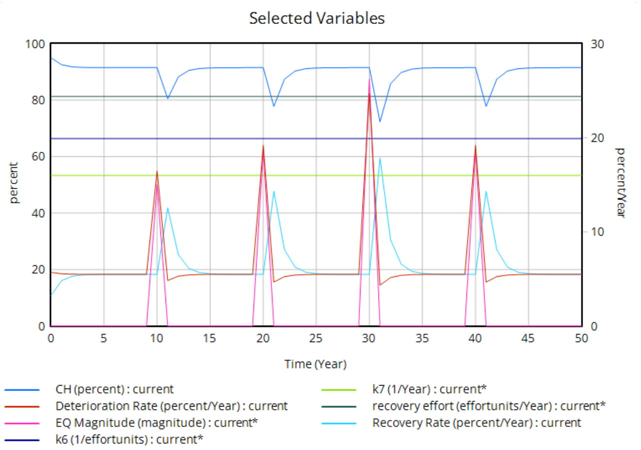

Fig. 7. Community Health (CH)

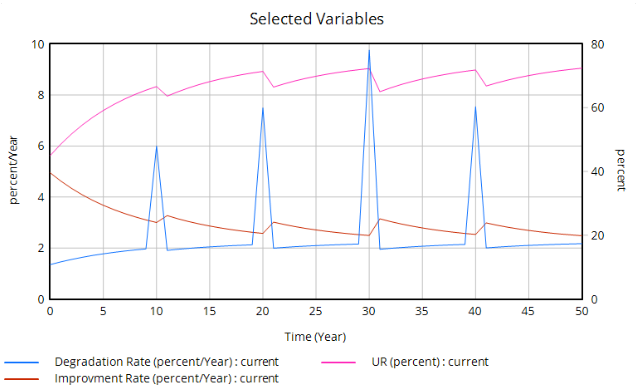

Fig. 8. Urban Resilience (UR)

With the defined parameters, CH is slightly decreasing from 95% to 91.47% over the 50-year period (Fig. 7). This indicates that recovery efforts and community involvement helped, but they were not strong enough to completely balance the damage caused by earthquakes. The drop is small, so the system stays fairly stable, but it also shows that if recovery or community action were stronger, the community's health could stay higher over time.

T4 subsystem. The model parameters for T4 have been defined as follows: $k_8 = 0.9$ is the urban investment effectiveness coefficient, $k_9 = 0.03$ is the degradation sensitivity coefficient, and $eicT_4 = 0.5$ is the defined sensitivity coefficient of the earthquake.

In the current scenario, UR increases from 45% to 72.42% (Fig. 8), indicating that due to continuous investments, upgrades, or good urban planning, the city becomes much stronger and able to handle natural disasters.

T5 subsystem. The model parameters for T5 have been defined as follows: $k_{10} = 0.99$ is the mitigation effectiveness coefficient, $k_{11} = 0.04$ is the coastal damage sensitivity coefficient, and $eicT_5 = 0.5$ is the sensitivity of the earthquake.

CPC is slightly increasing from 80% to 82.41% (Fig. 9), suggesting that mitigation efforts, such as building defenses and involving the community, are helping the coastal system improve over time. Continuous effort is needed to keep coastal areas safer against natural hazards.

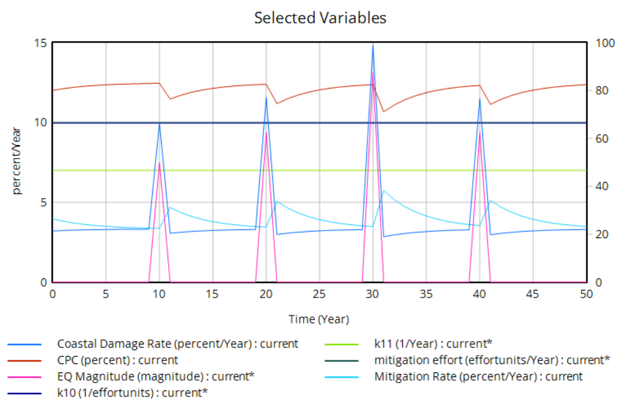

Fig. 9. Coastal Protection Capacity (CPC)

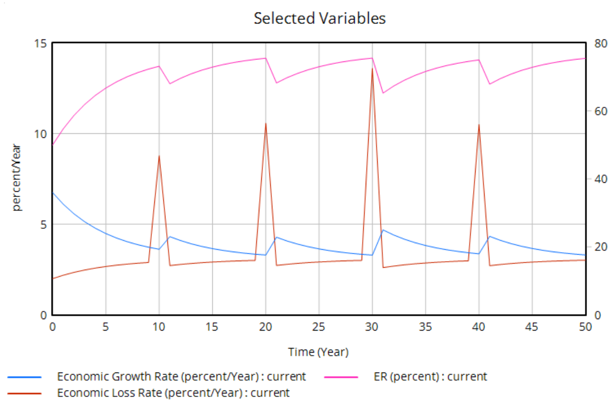

Fig. 10. Economic Resilience (ER)

T6 subsystem. The model parameters for T6 have been defined as follows: $k_{12} = 0.9$ is the coefficient of the economic investment effectiveness, $k_{13} = 0.04$ is the economic damage sensitivity, and $eicT_6 = 0.5$ is the sensitivity of the earthquake.

Under the defined conditions, ER increases from 50% to 75.51% (Fig. 10). This suggests that ER becomes much stronger over time and the community becomes better at handling disasters and bouncing back, due to stronger planning and economic stability.

T7 subsystem. The model parameters for T7 have been defined as follows: $k_{14} = 0.99$ is the reconstruction effectiveness coefficient, $k_{15} = 0.04$ is the damage sensitivity coefficient, and $eicT_7 = 0.5$ is the earthquake sensitivity.

The simulation shows that RP is increasing from 15% to 68.76% (Fig. 11), indicating that RP improved a lot over time and communities are able to rebuild much more over time, moving from very little progress at the start to more than two thirds of the necessary reconstruction effort after 50 years.

5. DISCUSSION

This study employs the System Dynamics approach not as a full empirical validation, but as a conceptual proof-of-consistency aimed at demonstrating the internal coherence and plausibility of the identified synergies. At this stage, model parameters were assigned heuristically (Silver (2004)) to emphasize the causal logic among factors and to

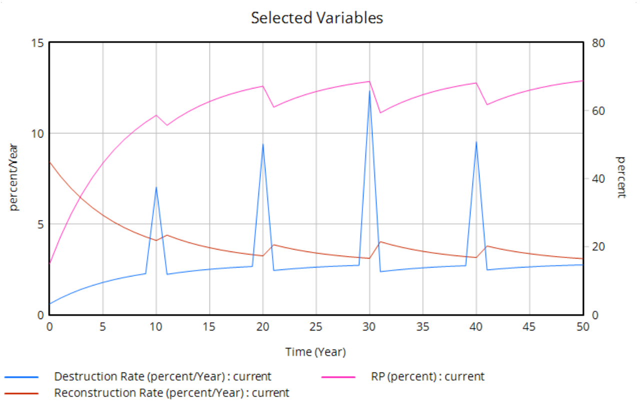

Fig. 11. Reconstruction Progress (RP)

test whether the framework generates consistent dynamic behavior under the defined structural conditions (Tables 2–8).

The weights assigned to each subsystem contributing to the `Vulnerability Index` (VI) were initially chosen to reflect equal contribution across all components, with a slight adjustment applied to the reconstruction factor. Specifically, the initial values of the weights were set as follows: $w_1 = w_2 = w_3 = w_4 = w_5 = w_6 = 0.14$ and $w_7 = 0.16$. This distribution reflects the equal influence of the first six subsystems (T1–T6), while assigning a slightly higher weight to T7 (Post-Disaster Reconstruction), acknowledging its critical role in long-term recovery and resilience building (Fig. 12). Each of the weights shows how important that part is in reducing the total vulnerability. In this way, VI reflects the strength or weakness of the whole system.

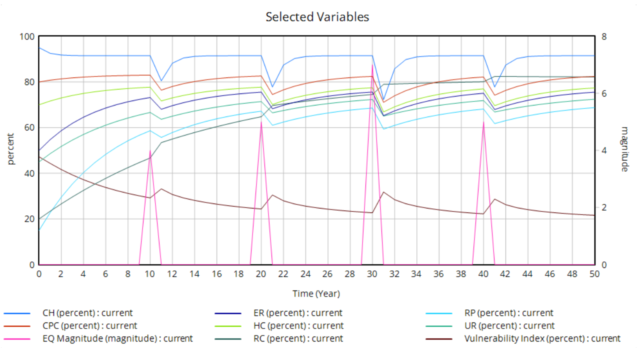

Fig. 12. Vulnerability Index

In this simulation scenario, the initial calculated value of VI was 47.2%, which means that the system was almost half vulnerable, with many weaknesses that could cause high risks during a strong earthquake. During the 50-year period, VI dropped to 21.61%, showing a clear improvement in resilience. This happened because of steady improvements in training, healthcare, recovery, urban safety, coastal protection, economic preparedness, and post-disaster recovery. The `Vulnerability Index` resulting at the end of the simulation ($VI = 21.61\%$) indicates that the system has been able to withstand shocks and recover faster after an event.

At the T1 subcomponent level, external inputs, such as `EQ Magnitude`, modulate the training rate, thus influencing the rate at which preparedness improves. A higher level of RC contributes negatively to the `Vulnerability Index`, indicating that better education and awareness reduce social vulnerability. For T2, investments in healthcare infrastructure strengthen recovery capacity, directly lowering `Vulnerability Index`. This component highlights how strong health systems and population survival rates during emergencies are related and how poor access to healthcare can exacerbate the effects of natural disasters. Analyzing the T3 subcomponent, it can be seen how a better response of CH reduces the `Vulnerability Index`. It shows the important role of community trust, cooperation and participation, which are sometimes overlooked, in helping communities stay strong and recover after natural disasters. A higher response of CPC decreases the `Vulnerability Index` (the T5 subcomponent). This part of the model indicates that effective disaster risk reduction must be adapted to the local environment, especially in low, flat, or densely populated coastal areas. A higher response of ER lowers the `Vulnerability Index` of the model (T6 subcomponent), revealing how economic strength and strategic planning influence long-term recovery strategies. RP also decreases the `Vulnerability Index` of the model. This indicates that fast and effective rebuilding reduces long-term vulnerability and may help communities return to normal.

The weights assigned to each subsystem ($w_i, i = \overline{1,7}$) may be optimized using specific methods, such as sensitivity analysis Castillo et al. (2008) and calibration techniques using Monte Carlo simulation Mikhailov and Sabelfeld (1992). By comparing model outputs with empirical data from past earthquake events, the relative importance of each component can be refined to better reflect real-world dynamics. This optimization may improve the precision and relevance of VI, supporting more targeted and effective resilience building strategies.

6. CONCLUSION

Although the current case study emphasizes earthquakes, the proposed model offers a flexible framework that can be easily extended to other types of natural hazards, supporting integrated decision-making for disaster risk reduction and sustainable community development. This study illustrates how systems thinking, viewed through a System Dynamics lens, can enhance understanding and improvement of earthquake readiness. The proposed System Dynamics (SD) model incorporates seven critical factors related to sustainability and resilience, illustrating how decisions and actions can either strengthen or weaken the system during an earthquake. By adjusting parameters such as training effectiveness, skill decay, seismic sensitivity, and reconstruction efficiency, various scenarios can be tested to reveal system behavior across different conditions — from vulnerable to resilient outcomes — highlighting both improvement potential and associated risks.

The proposed `Vulnerability Index` (VI) aggregates the influence of all seven factors (T1–T7) into a single measure. VI indicates how the entire system changes over time by comparing different scenarios. The decrease in VI demonstrates how long-term investments and planning can make critical sectors more sustainable. A lower VI

means less fragility and better preparedness for future disasters, proving the sustainability of the system. The VI may also be used at the level of individual cities. Each city may have its own values for preparedness, healthcare, recovery, urban safety, coastal protection, economy, and reconstruction. Calculating VI at the local conditions level may show how vulnerable or resilient a city is compared to others. This may help local governments and communities identify their weaknesses, set priorities, and plan targeted actions. In this way, VI works not only as a general measure for the whole system but also as a practical tool to guide how to build resilience at the city level.

This study has several limitations that merit consideration. The developed System Dynamics model represents a simplified abstraction of reality, relying on assumptions about training, healthcare, urban safety, and economic factors that may not fully capture regional variations or contextual nuances. Key influences such as geographical differences, cultural aspects, and policy frameworks were not explicitly modeled, which may limit the real-world applicability of the results. Furthermore, parameter values were estimated heuristically rather than derived from observed data.

Each disaster may have different impacts, but the same approach of using subsystems like preparedness, healthcare, recovery, urban safety, economic planning, or post-disaster reconstruction can still be useful. By adjusting certain parameters, the model can be adapted to the unique challenges of each hazard. This could make the model flexible and valuable for improving resilience and sustainability in a wider range of disaster situations.

Future research can extend this work to strengthen the robustness and validity of the results. The System Dynamics model should be further developed using complex real datasets and advanced analytical techniques to enable data-driven calibration and validation, making the model more realistic and easier to apply in practice. A wider picture of earthquake readiness could be obtained by including additional subsystems such as communication networks, political decision-making, or environmental impacts. To further validate and refine the equations proposed in this study, an important next step would be to test the model against real-world case studies by comparing simulation outcomes with observed earthquake events. This validation would position the model as a *decision-support tool* for designing policies that enhance preparedness, response, resilience, and sustainability.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors have not used any AI-assisted technologies in the writing process. The text was edited using Overleaf Latex editor with Writefull grammar check.

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