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Integrated modeling for managing catastrophic risks: vulnerability analysis and systemic risks management

Nadejda Komendantova komendan@iiasa.ac.at
Tatiana Ermolieva ermol@iiasa.ac.at
Taher Zobeydi zobeyditaher@gmail.com
Iuliana Armas iulia_armas@geo.unibuc.ro
Dragos Toma-Danila toma_drag@yahoo.com
Marcel Hürlimann marcel.hurlimann@upc.edu

Corresponding author: Tatiana Y. Ermolieva, ermol@iiasa.ac.at

Abstract

Catastrophic dependent systemic losses have analytically intractable multidimensional probability distributions dependent on exogenous shocks, interactions among goals and constraints of the involved actors and systems, activities of economic sectors, structural and environmental standards, critical infrastructure in place, feasible mitigation and adaptation structural and financial measures, investment potentials, etc. For the analysis of the systemic risks we argue for the design of proper Decision Support Systems (DSSs) and integrated catastrophe analysis and management modeling approaches similar to ISCRiMM model of IIASA. We discuss several important aspects and components of the ISCRiMM. This includes considerations of systemic risks, safety and security constraints, the necessity of robust mitigation and adaptation (structural and financial) measures, the need for stochastic catastrophe models (scenario generators), and proper stochastic optimization solution procedures to enable the decision-support regarding coherent systemic ex-ante and ex-post preventing and coping actions for dealing with catastrophes. The diversion of capital from ex-post measures to ex-ante investments into structural loss reduction measures can essentially reduce the dependencies among losses and, hence, decrease overall vulnerability, stabilize insurance mechanisms, and reduce the demand for ex-post risk sharing and restoration efforts. One of the ISCRiMM submodels is Vulnerability assessment model. In the paper we discuss different methodologies and models for vulnerabilities analysis and how they can be effectively integrated within ISCRiMM. In particular, vulnerability models can be based on AI, statistical and machine learning principles, which provide an effective means of incorporating them into ISCRiMM and designing optimal robust interdependent ex-ate and ex-post mitigation and adaptation options decreasing overall vulnerabilities relying on risk-based scenario evaluations.

Key words: Systemic risks, Integrated Catastrophe risk modeling and management model, ISCRiMM, two-stage STO, safety constraints, interdependent ex-ante precautionary and ex-post adaptive measures, vulnerability analysis, statistical and machine learning

3.1. Introduction

The increasing vulnerability of the modern society is an alarming tendency. Losses from natural and human-made catastrophes are rapidly increasing. Catastrophes destroy communication systems, electricity supply and irrigation, affect agricultural and energy production and provision systems.

One of the main reasons for the increasing losses due to natural and man-made catastrophes is the ignorance of risks and the lack of risk-based planning leading to the concentration of industries, infrastructure, wealth, people in risk prone areas as well as the creation of new risk prone areas. The trend becomes alarming especially because of the growing interdependencies among economic sectors and regions, introduction of new policies and technologies, growing demands, increasing frequency and severity of floods, hurricanes, storms, droughts, landslides, prolonged heatwaves.

Continued urbanization and development in hazardous areas have been putting more people and wealth in harm’s way. Urbanization and population concentration magnify impacts of hurricanes, windstorms, floods, heatwaves, epidemics, and other natural catastrophes, exacerbated by the systemic risks within socio-economic and environmental systems.

The alarming tendency of increasing losses due to the combination of natural and human-induced risks calls for risk-based approaches to economic developments and catastrophe management, for the design of robust interdependent ex-ante mitigation and ex-post adaptation options, to deal with the risks of all kinds.

Robust measures aim to decrease societal vulnerabilities. For the analysis of the systemic risks, we argue for the design of Decision Support Systems (DSSs) and integrated catastrophe analysis and management modeling approaches similar to ISCRiMM model of IIASA (Amendola and Ermolieva *et al.* 2013; Ermoliev et al., 1997; Ermolieva et al. 1997; Ermoliev et al. 2000; Ermoliev et al. 2008; Ermoliev et al. 2018; Ermoliev et al. 2003; Ermolieva *et al.* 2016; Ermolieva *et al.* 2023). In section 3.2.1 we discuss several important aspects and components of the ISCRiMM. This includes considerations of systemic risks, safety and security constraints, robust interdependent ex-ante and ex-post (strategic and operational) mitigation and adaptation, structural and financial measures, the need for stochastic catastrophe models (scenario generators), and proper stochastic optimization solution procedures to enable the decision-support for dealing with catastrophes. Section 3.2.2 summarizes main features of systemic risks as a new type of risks which depend on the whole structure of systemic interdependencies (see, e.g., Ermoliev and von Winterfeldt 2012; Ermolieva *et al.* 2016a,b; Ermolieva *et al.* 2021; Ermolieva *et al.* 2023). These risks are analytically intractable. They can be triggered by a combination of exogenous and endogenous shocks, i.e., by natural hazards in combination with decisions of intelligent agents and, therefore, they cannot be described by a single probability distribution. In section 3.2.3 we outline Impact Chains (ICs) approach as one of the existing ways to describing systemic interdependencies. However, ICs can mislead systemic risks management as they may not include the critical elements because of uncertainties and ambiguities.

Management of systemic risks requires approaches incorporating individual and joint systemic safety and security constraints as it is discussed in section 3.2.4. The model can be revised and tuned to address specifics of case studies under investigation. For example, catastrophe funds (risk reserves) can be used for sufficient capital accumulation and further investments into structural retrofitting ex-ante and reconstruction ex-post, as well as for loss compensation after disaster event.

Systemic risks depend on socio-economic and structural vulnerabilities, reliability and resilience of infrastructures. Section 3.3 makes an overview of different vulnerabilities, as well as the existing approaches to vulnerabilities modeling. As alternative or supplementing the traditional modeling methods, section 3.4 outlines statistical and machine learning approaches, the methodology and selected results. The section presents also Risk&Vulnerability Scenario generator software being developed at International Institute for Applied Systems Analysis Cooperation and Transformative Governance group (CAT at IIASA), in particular, for PARATUS project (Promoting disaster preparedness and resilience by co-developing stakeholder support tools for managing the systemic risk of compounding disasters, https://www.paratus-project.eu/). The software aims to visualizing socio-economic and structural vulnerability scenarios simulated under alternative assumptions (projections) of vulnerability drivers, e.g., population density, level of education, dependency ratios, population by age groups, buildings' codes/taxonomy, structural safety requirements, etc. The software enables to test various mitigation preparedness and post-event reconstruction measures, which are briefly summarized in sections 3.5. Conclusions are presented in section 3.6.

3.2. Management of endogenous systemic risks: safety indicators and robust measures

3.2.1. *Structure of Integrated Catastrophe risk management model*

In this section we briefly outline the structure of the Integrated Spatially-explicit Catastrophe Risk Management Model (ISCRiMM). More details can be found in (Amendola and Ermolieva *et al.* 2013; Ermoliev et al., 1997; Ermolieva et al. 1997; Ermoliev et al. 2000; Ermoliev et al. 2008; Ermoliev et al. 2018; Ermoliev et al. 2003; Ermolieva *et al.* 2016; Ermolieva *et al.* 2023). The model consists, in principle, of three major submodels or modules: a catastrophe module, an engineering vulnerability module, and an economic multi-agent module.

A catastrophe module simulates (or takes into account the available) stochastic scenarios of natural hazards based on the knowledge of the event and scientific equations and variables describing it. The catastrophe models used in IIASA's case studies are based on Monte Carlo dynamic simulations of geographically explicit catastrophe patterns in selected regions.

The vulnerability module is used to estimate damages that may result from catastrophes. These can be direct and indirect damages depending on the goals of a case study. Shaking intensities, duration of standing water, water discharge speed or wind speeds, and other characteristics of the natural hazard are the variables, which vulnerability modules can take from the catastrophe modules to calculate potential damages. The vulnerability module accounts for engineering principles. To calculate damages to buildings, e.g., it can use structural vulnerability (or fragility) curves based on the buildings taxonomy. It can also incorporate reduced forms of "damage" ("vulnerabilities") scenario generators using statistical and machine learning principles as it is discussed in section 3.4. The vulnerabilities can be reduced through improvements of buildings codes and infrastructure safety requirements, construction of shelters, population relocation, loss compensation and reconstruction programs, etc. The level and location of implemented measures depend on the overall goals of the ISCRiMM model incorporating safety constraints for systemic risks management (see discussion in section 3.2.4).

The economic multi-agent model is a stochastic dynamic welfare growth model. This model maps spatial economic losses/damages into gains and losses of the involved agents, i.e., those who are affected by the disaster and those who are responsible for the implementation of preparedness, emergency response, and recovery measures: central and local governments, infrastructure administration, water and energy systems authorities, private or/and public mandatory catastrophe insurance (catastrophe funds), investors, "individuals" (cells or regions), producers (farmers), etc., depending on implemented loss mitigating and sharing policy options.

GIS-based modeling of catastrophes and vulnerability coupled with multi-agent models, though still limited in use, is becoming increasingly important: to governments and legislative authorities for better comprehension, negotiation and management of risks; to insurance companies for making decisions on the allocation and values of contracts, premiums, reinsurance arrangements, and the effects of mitigation measures; to households, industries, farmers for risk-based allocation of properties and values.

However, a scenario-by-scenario approach leads to different scenario-dependent strategies. The number of alternative decisions can be very large. The exploding dimensionality of the "if-then" analysis can be bypassed. The search for "robust" optimal combination of interdependent ex-ante preparedness and ex-post adaptative decisions can be done by incorporating the two-stage stochastic optimization and the Spatial Adaptive Monte Carlo optimization procedure (based on stochastic Quasi-gradient procedure, SQG (Ermoliev and Wets 1988; Ermoliev 2009a,b,c)) into catastrophe modeling. The adaptive Monte Carlo search procedure enables the design of desirable robust solutions without evaluating all possible alternatives. The capacity of a region to deal with disaster losses ex-post is built ex-post.

Schematically, the model with an embedded optimization procedure is presented in Figure 1. Starting with some initial setting, policy variables are input into the "Catastrophe Model". The "Catastrophe Model" generates (or picks up) stochastic catastrophe scenarios and induced direct and indirect damages. The efficiency of the policies is evaluated with respect to safety and security performance indicators (block “Indicators”) of the agents, e.g., insurers, insured, governments, etc. If these do not fulfill the requirements, i.e., the goals and constraints (e.g., cause imbalances, or failures or business interruption), they are further adjusted in the block “Adaptive Feedbacks”. In this manner it is possible to take into account complex interdependencies between damages in different locations, available decisions, resulting damage reductions, reconstruction demand, compensations, etc.

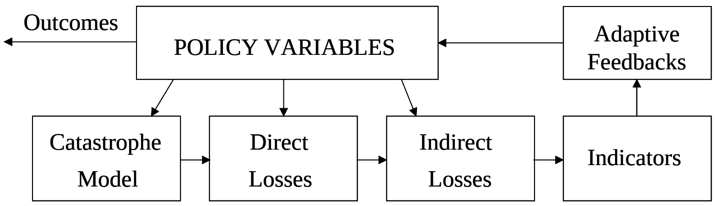

Figure 1. Schematic representation of the models: Adaptive Monte Carlo.

A crucial aspect is the use of appropriate risk indicators and safety constraints, e.g., to avoid “bankruptcies” or “ruins” of agents.

3.2.2. Systemic risks

Systemic risks and security analysis include risks (threats), which are generated in interdependent food, energy, water, environmental, social (FEWES) and other systems due to failures in the systems, shortfalls of supply-demand relationships among the systems, exceedances of critical thresholds (e.g., lack of water for hydropower generation or electricity power station cooling), etc. Examples of systemic risks are floods which are often triggered by rains, hurricanes, and earthquakes in combination with inappropriate land use planning, maintenance of flood protection systems and behavior of various agents. The construction of levees, dikes, and dams may create an illusion of safety. However, in the absence of proper maintenance and further developments in the neighboring areas, these constructions can create potential catastrophic events of high consequences. Other examples include systemic risks in social, financial, economic, energy, food and water, and systems security management, e.g., due to inadequate infrastructures (buildings codes), not satisfying the safety requirements.

Systemic risks in interdependent FEWES systems can be defined as the risks of a subsystem (a part of the system) threatening the sustainable performance of the whole system and the achievement of FEWES security goals. Thus, a shock in a peripheral subsystem induced (intentionally or unintentionally) by an endogenous or exogenous event, can trigger systemic risks propagation with impacts, i.e. instability or even a collapse, at various levels. The risks may have quite different policy-driven dependent spatial and temporal patterns. While standard risks analysis and assessment can rely on historical data, systemic cascading risks in FEWE systems are implicitly defined by the whole structure and the interactions among the systems, in particular costs, production and processing technologies, prices, trade flows, supply-demand balances, risk exposure, FEWE security requirements, risk measures, decisions of agents

The notion of systemic risks was introduced in relation to financial systems. The definition has been adopted for other natural and anthropogenic systems, e.g. power grids and critical infrastructures, biodiversity, financial and insurance systems [8-10], and other natural and anthropogenic systems.

Prediction of systemic risks in integrated natural and anthropogenic policy-driven FEWE systems is a rather tedious task. The main issue in this case is robust management of the risks, which can be achieved by equipping the systems with precautionary (risk prevention and mitigation) and adaptive (emergency and post disaster recovery) strategies enabling the systems sufficient flexibility and robustness to maintain sustainable performance and fulfill joint FEWES security goals independently of what systemic shock occurs (Ermoliev and Winterfeldt, 2012; Ermolieva et al. 2016b, 2021).

In front of uncertainties, the strategies (decisions) can be of the two main types: the ex-ante strategic precautionary anticipative actions (engineering design, building codes, shelters, resource allocation, technological investments, water and grain reserves) and the ex-post adaptive adjustments (inventory control, subsidies, prices, costs, reconstruction and BBB) that are made after the event occurance.

A portfolio of robust interdependent ex-ante and ex-post strategies can be designed by using a two-stage stochastic optimization (STO) approach incorporating both types of decisions (see e.g., (Ermoliev 2009a,c; Ermoliev *et al.* 2000; Ermolieva *et al.* 2003, 2016, 2023 and references therein). The two-stage STO has been also applied in studies for dealing with systemic interdependent risks, e.g., for agricultural risks management (Borodina *et al.* 2012, 2020), for energy security management (Cano *et al.* 2014; Ermoliev, Komendantova, Ermolieva 2023), for robust operation of multipurpose reservoirs (Ortiz-Partida *et al.* 2019), for climate change risk analysis (Ermolieva and Obersteiner 2005; O''Neil, Ermoliev, Ermolieva 2006).

The management of systemic risks and security strongly depends on the individual and systemic safety and reliability regulations (standards, requirements) imposed on the systems' relationships and policies (measures) in place. Depending on the risks (earthquake, heavy precipitation, windstorm, heat wave), structural measures have to withstand the required earthquake shaking; shelters have to protect population; dams, dikes, levees have to confirm safety requirements; they have to be well operated, maintained, and regularly monitored; water retention areas and channels have to be designed and maintained to protect against overtopping and/or flooding; policy of a better land-use planning to preserve forests protecting areas against hurricanes, strong winds and precipitation runoff; discourage building in areas prone to catastrophes, etc.

Structural measures can considerably reshape the risks, which calls for their thorough evaluation. They can induce additional benefits. For example, construction of a dike motivates additional regional developments. On the other hand, without proper evaluation and safety requirements, the measures can transform the risks to more severe and compound.

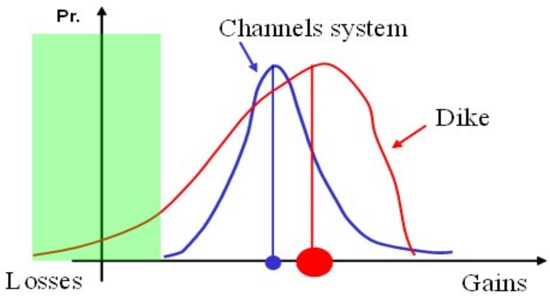

Figure 2: Loss distribution dependents on policies regarding dike or channel flood protection system: what risk is better? A dike can protect larger region and stimulate economic growth nearby, however if it breaks, the losses can be much heavier than from a natural disaster. Channel system can inspire less growth and would result in less average benefits, however it is safer in the sense that it cannot cause extreme losses as in case of dike break. Investments into new and reinforcement of old structural measures can be effectively supplemented by insurance, which would provide an ex-ante financial solution to cover or transfer the losses further to financial markets.

3.2.3. *Management of dependent systemic risks*

Natural disaster can cause direct and indirect structural damages. Houses can be knocked off their foundations, buildings can collapse, thereby causing roads blockage. Roads and bridges can be damaged or collapse either due to an earthquake or due to post-events like landslides or floods. Landslides can block roads and knock down energy utility poles or, more generally, energy infrastructure, taking out power in large areas. Power, gas, internet lines can rupture preventing sustainable businesses functioning. The interdependence, risks associated with each element and the systemic damage can be to a certain extent captured by ICs, for example, in Figure 2.

ICs are being developed to explore cause and effect relationships to provide insights into the trigger events, systemic interdependencies and risks. They can show

how one event leads to another. This is essential for understanding how the events are linked together. However, uncertainties and ambiguity among the interdependent systems related, e.g., to the inclusion of the relevant systems and their dependencies, the spatio-temporal resolutions of the case study area, the directions of the causual relations (cause vs consequences), the imbalances and threshold risks, all these important features of systemic risks cannot be included in IC and, therefore, ICs can mislead the analysis and management of the risks. For example, a flood can be triggered by expansive deforestation in a region upstream beyond the IC diagram. Another example is a flooding upstream due to a bridge blockage preventing river flow downstream.

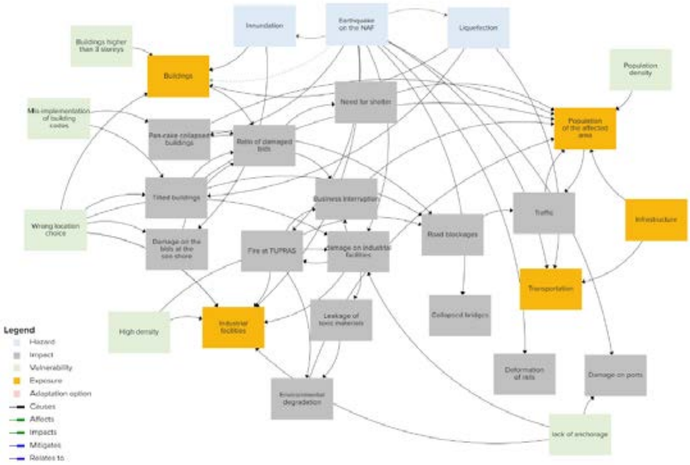

Figure 3. Example of an IC for a region prone to earthquake risks

Systemic risks can be addressed by safety regulations in combination with robust and interdependent precautionary and adaptive measures through building-up the resilience with ex-ante measures minimizing occurrences of systemic failures and by expanding adaptive capacities to cope with the consequences ex-post.

3.2.4. *Safety constraints for systemic risks management*

This section presents an example of how safety constraints for systemic risks management are integrated within the ISCRiMM model. To account for multiple risk exposed stakeholders and respective risk management options, the study region is subdivided into sub-regions or locations $j = \overline{1:m}$. Locations (or regions) can be characterized by a collection of households, a segment of a gas pipe-line, flood-protection zone, municipality, etc. For example, in the flood-risk case study in the Netherlands (Ermolieva et al. 2016) the locations corresponded to dike-protected areas. We assume that for each location j an estimation W_j of the property value (corresponding to elements-at-risk, EAR) or "wealth" of this location exists, which includes values of houses, lands, factories, etc.

Assume that the risks are mitigated and covered by a joint loss sharing and (re)construction program, and there are n agents, $i = \overline{1:n}$, (insurers, governments, re-insurers, funds, individuals, energy and water authorities), contributing to this program. They may have obligations (contracts in the case of insurers) with locations to cover losses, or, more generally, to finance retrofitting and post-event recovery projects. Each agent i has an initial fund, stock of money, or a risk reserve R_i^0 that in general depends on magnitudes of catastrophic events, loss-reduction measures in place, socio-economic and structural vulnerabilities.

Assume that the planning horizon covers $t = 0,1. ..$ time intervals. The risk reserve (reconstruction fund) R_i^t at each t is calculated according to the following formula:

$$R_i^{t+1} = R_i^t + \sum_{j=1}^{m} (\pi_{ij}^t - c_{ij}^t(q_{ij}^t)) - \sum_{j=1}^{m} L_j^t(\omega_t) q_{ij}^t, \qquad (1)$$

where q_{ij}^t is the loss coverage or reconstruction financing of a company (insurer, fund) i in location j at time t, $\sum_{i=1}^{n} q_{ij}^t \leq 1$, π_{ij}^t is the premium (tax) paid into a company i in location j at time t, $c_{ij}^t(q_{ij}^t)$ are transaction costs or administrative, running or other costs. $L_j^t(\omega_t)$ is the loss (damage) in location j caused by a catastrophe ω_t at time t.

Catastrophic events $\omega = (\omega_0, \omega_1, \dots)$ may affect a random number of different locations. In general, a catastrophic event at time t is modeled by a random subset of affected locations j and its magnitude in each j. The losses $L_j^t(\omega_t)$ depend on the event ω_t, mitigation measures (e.g., dikes against flooding) and vulnerability of structural values in j (e.g., building codes, structural reliability requirements).

Decision variables q_{ij}^t and π_{ij}^t allow to characterize the differences in risks at different locations. It is assumed that all agents can cover different fractions of catastrophic losses from the same location. In the case of a catastrophe, a location j faces losses (damages) $L_j^t(\omega_t)$. Individuals at this location receive compensation $L_j^t(\omega_t) q_{ij}^t$ from a company i when such a loss occurs, and pay insurance premiums (taxes) π_{ij}^t.

If W_j^0 is the initial wealth (property value) in location j, then the location's j wealth at time $t+1$ equals

$$W_j^{t+1} = W_j^t + \sum_{i=1}^{n} (L_j^t(\omega_t) q_{ij}^t - \pi_{ij}^t) - L_j^t(\omega_t)\ t = 0,1, \dots \qquad (2)$$

Let us note that random variables R_i^t and W_j^t implicitly depend on decision variables $x^k = (q^k, \pi^k)$, $q^k = \{ q_{ij}^k,\ i = \overline{1:n}, j = \overline{1:m}\}$, $\pi^k = \{ \pi_{ij}^k,\ i = \overline{1:n}, j =$

$\overline{1{:}m}\}$, and random event ω_k, where $k = 0,1,\ldots,t-1$. For the sake of simplicity we indicate in the following these path-dependencies of R_i^t and W_j^t as $R_i^t(x,\omega)$ and $W_j^t(x,\omega)$.

The robustness of the loss sharing and reconstruction program depends on whether the accumulated risk reserve $R_i^t(x,\omega)$ at a random time $t = \tau(\omega)$ of a first catastrophic event avoids, in a probabilistic sense, the individual insolvency defined by events $E_{1i} = \left\{\omega : R_i^{\tau(\omega)}(x,\omega) < 0\right\},\ i = \overline{1{:}n}$,

and the joint insolvency defined by the combination of events

$$E_1 = E_{11} \cup E_{22} \cup \ldots \cup E_{1n}. \tag{3}$$

Individuals (locations, firms) are concerned with their wealth, which depends on whether the amount of taxes or premiums that they pay into the insurers or cat risk funds do not exceed the compensation of losses at time $\tau(\omega)$, i.e., with the joint event E:

$$E_2 = E_{21} \cup E_{22} \cup \ldots \cup E_{2m} \tag{4}$$

where

$$E_{2j} = \left\{\omega : W_j^{\tau(\omega)}(x,\omega) < 0\right\} \text{ for } j = \overline{1{:}m},$$

are individual events.

Stability of the interdependent insurers, governments, households, firms, businesses, etc., depend on the joint fulfillment of constraints (3-4), i.e., the events (3-4) determine the stability (resilience) of the regional program for protection against systemic risks, which can occur if one of the safety requirements is not fulfilled.

Therefore, a critical issue is to avoid these events with the highest possible probability. For example, by minimizing the expected uncovered losses $E\sum_j (1 - q_j)L_j^{\tau(\omega)}$ under a probabilistic safety constraint of the type

$$Pr\,o\,b[E_1, E_2] \le \overline{p}, \tag{5}$$

where $\overline{p}$ is a critical probability threshold of the program's systemic insolvency (failure, default) that may occur, say, only once in 100 years.

The notation $Pr\,o\,b[E_1, E_2]$ is used to denote a probability of insolvency as a general function of E_1, E_2. Another, more relaxing example of constraints (5), may be constraints $Pr\,o\,b[E_1\ or\ E_2] \le \overline{p}$.

Probabilistic constraints (5) in the ISCRiMM can be reformulated to define a convex STO problem with specific non-smooth risk (penalty) functions enabling to derive optimal and robust interdependent ex-ante and ex-post solutions. This problem is effectively solved by the linear programming methods. The safety and reliability constraints are central for large-scale integrated interdependent risk management problems.

3.3. Types of vulnerability and vulnerability analysis approaches

Direct and indirect damages and losses due to catastrophes depend on vulnerabilities of agents and structures. In what follows we discuss different aspects of vulnerabilities and ways of their analysis and modeling as one of the components of the ISCRiMM model.

The concept of vulnerability is addressed in many different disciplines. The definition depends on the area of research, such as disaster management, economics, finance, sociology, environmental sciences, and engineering (Cutter, 1996). Among the definitions is, for example, the following: “the quality or state of being exposed to the possibility of being attacked or harmed, either physically or emotionally. The understanding of social and environmental vulnerability, as a methodological approach, involves the analysis of the risks and assets of disadvantaged groups, such as the elderly.”

In relation to hazards and disasters, "… the concept of vulnerability expresses the multi-dimensionality of disasters by focusing attention on the totality of relationships in a given social situation which constitute a condition that, in combination with environmental forces, produces a disaster" (Oliver-Smith, 2003). It is also the extent to which changes could harm a system, or to which the community can be affected by the impact of a hazard or exposed to the possibility of being attacked or harmed, either physically or emotionally. According to UNISDR's terminology, vulnerability is “the conditions determined by physical, social, economic, and environmental factors or processes which increase the susceptibility of an individual, a community, assets, or systems to the impacts of hazards” (UNISDR, 2009).

Liverman (1990) distinguishes between vulnerability as a biophysical condition and vulnerability as defined by political, social and economic conditions of society. Kasperson et al. (1990) defines vulnerability as the differential capacity of groups and individuals to deal with hazards, based on their position within physical and social world. Cutter (1993) identifies vulnerability as the likelihood that an individual or group will be exposed to and adversely affected by a hazard. It is the interaction of the hazards of place (risk and mitigation) with social profile of communities. Blaikie et al. (Blaikie et al., 1994) formulates the definition of vulnerability as the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard. It involves a combination of factors that determine the degree to which someones life and livelihood are put at risk by a discrete and identifiebale event in nature or in society.

The methodologies and models for analysing and assessing vulnerability indicators are among the major research areas. These include the analysis and assessment of external exogenous factors - sudden shocks and continued stresses, and internal endogenous factors such as dependencies, low incomes, unemployment, inability to cope with incapacities, inadequate infrustructures, etc. Vulnerability research covers a complex, multidisciplinary field including development and poverty studies, public health, climate studies, security studies, engineering, geography, political ecology, and disaster risk management (as well as risk management).

Measurement of vulnerability follows the advancements of the vulnerability concept (Cutter et al., 2003). One of the approaches is the 'Vulnerability Hazards-of-Place Model' by Cutter (Cutter, 1996; Cutter et al., 2000). This model focuses on describing the place-based interaction between biophysical vulnerability and social vulnerability. In this approach, it is explained how the vulnerability of a place is determined by factors such as socioeconomic status, urbanization status, and demography. Another model, the Earthquake Disaster Risk Index (EDRI), defines vulnerability and hazard as a component in the context of risk.

Different disciplines develop different vulnerability frameworks. In relation to natural disasters and the systemic risks, researchers are currently working to refine the definitions of vulnerability, measurement and assessment methods accordingly. In the presence of possible systemic dependent chain risks, which are typical for densely populated areas with developed infrastructures (energy, water, transportation, etc.), the vulnerabilities account for multiple socio-economic, demographic, environmental vulnerability components along with the vulnerabilities of critical physical infrastructure.

In urban areas “in addition to natural disasters, the entire possible loss and damage that may occur due to reasons such as general layout of a city, urban texture, usage areas, existing housing, transportation systems and infrastructure, planning and management weaknesses in a city” (Erdogan and Terzi, 2022 ; ISMEP, 2014b, p.12). Urban vulnerability indicators can be divided into social, economic, environmental, physical, and systemic vulnerability criteria. Cardona et al. (2012) grouped vulnerability under four different main criteria: environmental, social, economic, and other criteria that interact and intersect. The methods for the improvement of vulnerability assessment in the European Union (MOVE) framework are discussed under six main criteria, such as physical, economic, social, cultural, environmental, and institutional (European-Union, 2015). Some of the main vulnerability types can be defined as follows:

For structural (physical) vulnerability analysis, safety of buildings, roads, and infrastructure systems are being evaluated to define weak infrustructure elements and areas (ISMEP, 2014b), (Karimzadeh et al., 2014). The safety and reliability of infrastructure during a disaster directly determines the injury or loss of life. FEMA definition of the social vulnerability "… is the susceptibility of social groups to the adverse impacts of natural hazards, including disproportionate death, injury, loss, or disruption of livelihood." As adopted by FEMA for US, the SVI (Social Vulnerability Index) is a location-specific assessment of social vulnerability that utilizes 16 socioeconomic variables determining a community's ability to prepare for, respond to, and recover from hazards: below 150% poverty, unemployed, housing costs, no high school diploma, no health insurance, aged 65 and older, aged 17 and younger, civilian with a disability, racial and ethnic minority status, multi-unit structures, mobile homes, crowding, no vehicle, group quarters, single-parent households, english language proficiency (FEMA).

Systemic vulnerability (also referred to as critical vulnerability) is the damage of subsystems in the urban system, rendering other systems inoperable (ISMEP, 2014). The infrastructure elements that could be damaged and trigger further damages in the event of a disaster are the following: electric power supplies, gas and oil, telecommunications, banking and finance, transportation, water supply systems, emergency services.

3.3.1. *Social vulnerability in urban areas, Bucharest (Romania) and Istanbul (Turkey)*

A vulnerability analysis approach in urban areas of Bucharest, Romania, has been proposed in Armas et al., 2017. The socio-economic vulnerability included "four social vulnerability dimensions - social, education, housing, and social dependence ...". These indicators "explained over 88% of the variance among relevant variables as estimated from the Principle Component Analysis and deriving a middling value for Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy. The four dimensions were further integrated into a criteria tree using the SMCE (Spatial Multi-Criteria Evaluation) module of the Ilwis software (ITC 2001) and weighted according to expert judgment and scenario testing", which allowed to distinguish areas (tracts) in Bucharest, Romania, by the level of their socio-economic vulnerabilities. The four criteria were constructed based on the following subcriteria data: social – dwelling population density, widows female population in total population, elderly (e.g., over 65 years), female population in total population, room occupancy per household; educational – minimum level of education, unemployed population (inactive population), women with more than 3 children (in total women who gave birth); housing – housing density, average room area per person on census tract, average household room area on census tract, average no. of private/owned houses, number of rooms, etc.

In Istanbul urban area (Erdogan and Terzi, 2022), the vulnerability assessmeent by neighbouhoods of Istanbul, Turkey, four main criteria (critical urban services, infrastructure facilities, structural, socioeconomic) were identified and further subdivided into subcriteria. For example, the “socioeconomic” criterion comprised population density, daytime density, average household size, education status, average household income, population over 65, child population ratio, women population ratio. The “critical urban services” consisted of road blockage, distance to fuel stations, accessibility to fire stations (in m), accessibility to police stations (in m), accessibility to open spaces (in m); criterion “infrastructure” included damaged electricity line length (in km), damage distribution of water pipelines (Rm (PGV): damage ration (points per km), damage distribution of natural gas pipelines (Rm (PGV):damage ration (points/km); and structural criteria included such subcriteria as building age, building construction type, building density (building/ha), Peak Ground Acceleration (PGA-gal). After the data on criteria-subcriteria were collected, the data was reclassified into 1-5 scale. After reclassification, each class was scored using 1-5 rating scale, the highest score is assigned to the class that models affects the seismic vulnerability. After the classes are scored, the Analytical Hierarchy Process (AHP) method identified the weights of the criteria according to experts opinion. In this process, experts determined the order of the importance among criteria in the pairwise comparison matrices score scale from 1 to 9 and weights of the criteria and subcriteria are calculated for urban earthquake vulnerability analysis.

In real studies, the data at required resolutions (e.g., tracts, neighborhoods, households) can be difficult and costly to obtain. Therefore, the dynamic revision of vulnerability indices in the context on newly introduced risk mitigation measures can become not possible. In some cases, missing historical data and indicator values can be substituted by expert estimates. For the development of future vulnerability scenarios when the necessary data can depend on multiple uncertain global and local drivers and trends, the analysis can rely on statistical and machine learning models (section 3.3.3).

3.3.2. *Structural (physical) vulnerability, building codes*

The overall vulnerability significantly depends on structural vulnerability, which is characterised by the compliance with infrustructure reliability norms, buildings codes, buildings density, magnitudes of the disasters, e.g., of earthquakes. In the context of urban vulnerability assessment, the buildings vulnerability is especially important. In Armas et al. (Armas *et al.* 2017) as well as in other studies (Erdogan and Terzi, 2022) residential buildings vulnerability was introduced as a separate criterion in the vulnerability analysis.

Building codes ensure buildings safety in cases of certain magnitudes disasters. They are introduced to limit the damages in exposed regions. The incompliance with building codes can trigger systemic losses in urban areas. There is an often-repeated saying, "earthquakes don't kill people, buildings do" (FEMA). For example, in Istanbul, geoscientist Okan Tüysüz from Istanbul Technical University reminded that “… approximately 1.2 million houses are located in the metropole. Some 70 percent of them are not earthquake resistant … nearly 90,000 buildings in the city should be either demolished and rebuilt, or strengthened. The first rule in earthquake is to reduce the risk. If even only one person resides in each of these buildings, 90,000 lives can be saved with this step" (https://www1.wsrb.com/blog/turkey-building-codes-and-the-importance-of-regulation).

The analysis of the structural vulnerability can start with the analysis of individual buildings. Especially in urban regions, it is very important to determine which areas of the city have the greatest residential building vulnerability. For example, in "... Bucharest, only 855 buildings (located mostly in the city center) could be classified according to their vulnerability by the Bucharest General Municipality (2016), although the total number of residential buildings in Bucharest is 131,875. Approximately 40,000 of these structures are older than 1963; they date from a construction period when no seismic design regulations were available. In other words, reliable information about building vulnerability can only be found for 0.65% of the city's buildings" (Armas *et al.* 2017; Toma-Danila *et al.* 2015, 2017).

Because of data shortage, Toma-Danila (Toma-Danila *et al.* 2015, 2017) adopted a more generalized approach relying on analytical methods of Improved Displacement Coefficient Method (IDCM), as well as statistical data such as the number of buildings per construction period, building material, and structure height. The buildings were classified into building typologies accounting for construction materials (such as adobe, reinforced or unreinforced masonry, wood, and reinforced concrete), building height classes, and construction periods representative for Romania. The typologies were customised and reclassified to reflect the specific of buildings in Bucharest. Vulnerability (also called fragility) functions, were developed and adapted from the literature for each building typology, to associate with each identified building typology. To address the question on which urban areas are more endangered, three seismic scenarios were used to calculate the respective damages to different buildings typologies. Two of these scenarios are based on real recorded values (for the 1990 and 1977 Vrancea earthquakes with moment-magnitudes of 6.9 and 7.4, respectively) and one (for the maximum possible Vrancea earthquake, with moment-magnitude of 7.8).

3.4. Statistical and machine learning approaches to predict future vulnerabilities

Vulnerability analysis and assessment through regular collecting, updating, and processing all the relevant data and indicators can be both time and cost consuming. The required data can be missing at the required resolutions, e.g., households level.

The development of future socio-economic vulnerability scenarios can be restricted by data and projections availability, e.g., projections of population by age and income groups or unemployment. For projecting structural (physical) damage and vulnerability, e.g., the seismic fragility functions require large amounts of data, which are also not always available. Large uncertainties in the application of fragility curves stem from earthquake characteristics as well as variability in building attributes. Data scenarios, i.e., number of buildings by typology, population, incomes, etc., can depend on multiple uncertain global and local drivers and trends.

Alternatively or supplementing the traditional methods described in previous section, the vulnerability analysis and prediction can rely on AI, statistical and machine learning (ML) methods. Machine learning is an expansion of statistical learning theory (Vapnik, 1995), which is regarded as one of the most developed branches of artificial intelligence. It provides the theoretical basis for many of today's AI machine learning algorithms.

Statistical and ML approaches are becoming popular for the vulnerability analysis. Mangalathu et al. (2019) uses machine learning to classify building damage for the 2014 South Napa earthquake. Nateghi et al. (Nateghi *et al*., 2011) develops statistical methods for predicting indirect damages from natural hazards, in particular, hurricanes.

Approach based on statistical and machine learning can be developed and applied to estimate and predict future socio-economic vulnerability based on vulnerability drivers. For example, (Kalaycıoglu *et al*., 2023) develops a predictive model that allows to identify households with high social vulnerability. A ML social vulnerability model can rely on previously constructed social vulnerability indexes and relevant variables (as, e.g., Armas *et al.* 2017; Toma-Danila *et al*., 2015, 2017).

Thus, the trained ML model can serve as a scenario generator of plausible future structural and socio-economic vulnerability scenarios accounting for changing new conditions and scenarios of relevant covariates, for testing feasible mitigation precautionary and reconstruction BBB measures. The approach can reduce the time and costs for new data collection and revision of social vulnerability indexes (Kalaycıoglu *et al*., 2023).

3.4.1. *The choice of covariates for statistical and machine learning model*

3.4.1.1. *Socio-economic vulnerability predictors*

As presented in section 3. 3.1, the predictors of socio-economic vulnerabilities can be classified into four main indicator groups: social, educational, housing, and social dependence. The drivers of these indicators are: social – dwelling population density, widows female population in total population, elderly (e.g., over 65 years), female population in total population, room occupancy per household; educational – minimum level of education, unemployed population (inactive population), women with more than 3 children (in total women who gave birth); housing – housing density, average room area per person on census tract, average household room area on census tract, average no. of private/owned houses, number of rooms, etc. The ML model can be trained based on a pre-calculated SVI and relevant covariates. Then, it can be used to predict socio-economic vulnerability for different scenarios of predictors.

3.4.1.2. *Structural vulnerability predictors*

Selection of predictors (also, independent variables, covariates, or drivers) is essential for explaining and predicting the target (dependent) variable. For modeling and predicting structural vulnerability, the number of building stories, building material, distance to epicentre, and other variable characterizing structural and physical properties of buildings and earthquakes can be used in statistical methods to explain the damage volume. In some regions, also foundation type, land type, roof type, ground floor type, and superstructure type based on construction materials are considered as predictor variables.

The data for structural (physical) vulnerability (or damage) assessment can be compiled from the historical earthquake data or come from simulation models. Detailed information about earthquake characteristics, building typology, position, foundation, floor, and roof type, and site condition can be incorporated as input features in machine learning models to estimate the dependencies between, e.g., damages and buildings typology. The methods can be used to predict the damages and the need for new type of buildings, buildings retrofitting and rehabilitation intervention.

3.4.2. *Methodology and selected results*

The truly integrative developments planning, foremost in urban areas, benefits from incorporating the statistical and machine learning methods into ISCRiMM model (as discussed in section 3.2) for designing interdependent robust ex-ante mitigation and ex-post adaptive risk management options. Informed decisions based on the safety norms and a disaster-resistant systemic urban planning would decrease the damages and vulnerabilities of all types. The development of statistical and machine learning models for the analysis and prediction of future vulnerabilities can shed the light on the role of decisions, their contribution to the vulnerability decrease, increase of resilience and BBB capacity.

The development of the statistical and machine learning models aims to analyze the correlation between exploratory variables and the drivers. Machine learning models are gaining popularity for the analysis of vulnerability to natural hazards, including random forest, neural networks, convolutional neural networks, recurrent neural networks, classification and regression tree, support vector machine, naïve Bayes, k-nearest neighbours. Because many of these models have a black-box nature, the tractability of the results is not straightforward. Also, the prediction accuracy is sensitive to model structure and parameter calibration, and it can be difficult to explain the accuracy or inaccuracy of the derived results.

In this study we develop a linear regression model which enables easy tractability of individual independent variable's contributions to the total vulnerability indicator. Furthermore, the linear regression can be extended to the quantile (linear) regression to identify the quantiles of vulnerabilities based on various combinations of the drivers.

3.4.2.1. *Multivariate linear regression model*

Multivariate regression analysis has been extensively used in earthquake-related studies, including predictions, damage reduction strategies through various indicators, vulnerability detection, and the development of more resilient structures and cities. Researchers such as Godschalk et al. (Godschalk et al., 1998 ; Bostenaru Dan and Armas (Bostenaru Dan and Armas, 2014, 2015), Rahman et al. (Rahman et al., 2023) and Mitsova et al. (Mitsova et al., 2018) have emphasized the use of multivariate regression analysis to enhance the design and policy-making processes in urban planning related to natural disasters. They have demonstrated the relationships between disaster-resilient urban infrastructure, superstructure development, and earthquake damage using this method. The multiple regression analysis has been ustilized in Jia and Yan (2015), Bostenaru Dan and Armaş (2014, 2015), Yariyan et al. (2020), and Saputra et al. (2017) to identify the factors influencing earthquake damage and to create earthquake vulnerability indices.

A (multiple) linear regression (MLR) can be considered as one of the machine learning algorithms, which is in fact one of the most popular models in machine learning. It is widely used because it is simple and tractable. The simplicity means it is easy to understand the responses of the dependent variables to each covariate, i.e., the regression coefficient of an independent variable reflects the change in the dependent variable as a result of a unit-change in the respective independent variables.

On the other hand, the MLR assumes that the residuals are normally distributed. The linear regression model for calculating the mean responce takes the form

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_m x_{im}, \tag{6}$$

where $i = 1, \dots n$ is a number of observations and m is a number of covariates. Coefficients of the MLR are found by minimizing the Mean Square Error "Goodness-of-Fit" function

$$MSE = (y_i - (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \cdots + \beta_m x_{im}))^2,$$

which gives the "best regression line".

To distinguish vulnerability by classes, i.e., very high, high, moderate, low, very low, in response to various combinations of drivers, a quantile-based criteria instead of the mathematical expectation can be used. Quantile regression is an extension of linear regression that is used when the conditions of linear regression are not met (i.e., linearity, homoscedasticity, independence, or normality).

For the quantile regression it is assumed, that the τth quantile is given as a linear function of the explanatory variables. Taking a similar structure to the linear regression model, the "best" quantile regression model equation for the τth quantile is

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau) x_{i1} + \beta_2(\tau) x_{i2} + \beta_3(\tau) x_{i3} + \cdots + \beta_m(\tau) x_{im},$$

where $i = 1, \dots n$ is a number of observations and m is a number of covariates (independent variables). Coefficients $\beta_m(\tau)$ are functions of the required quantile τ. They are defined as

$$\beta(\tau) = argmin_{\beta \in R^m} \{ \textstyle\sum_{i|Y_i \geq \beta'(\tau) X_i} \tau |Y_i - \beta'(\tau) X_i| + (1-\tau) \sum_{i|Y_i < \beta'(\tau) X_i} |Y_i - \beta'(\tau) X_i| \}, \quad (11)$$

where Y_i are observations of dependent variables, X_i is a vector of independent variables $X_i = (x_{i1}, \dots, x_{im})$, and $\beta(\tau)$ is a vector of coefficients $\beta(\tau) = (\beta_1(\tau), \dots, \beta_m(\tau))$, and m is a number of observations.

3.4.2.2. *Socio-economic vulnerability*

The dataset utilized for this study is based on studies in (Armas *et al*. 2017; Toma-Danila *et al*. 2015). For the socio-economic vulnerabilities, we establish a relationship between pre-computed in Armas *et al*., 2017 human vulnerability indicators and the indicators reflecting social dependency, education, housing conditions. That is, the vulnerabilities computed for Bucharest (Romania) by Armas *et al*. (2017) are used to train the regression model.

The LR dependence between, e.g., human vulnerability and the other four indices (social dependence, housing, education, social factor) is measured by R^2=0.95. From the 4 explanatory variables, most contribution to human vulnerability is due to social and social dependence factors comprised of such variables as share of dependents, share of children in total population, population density, share of widows in total population, population over 65 years old, share of women in total population, room occupancy per household.

In Figure 4, the human vulnerability indice is visualized with a Risk&Vulnerability Scenario (RVS) generator (see Zobeydi, Komendantova, Ermolieva forthcoming), the software being developed by Cooperation and Transformative Governance group of Advanced Systems Analysis Program (CAT-ASA, IIASA) for PARATUS project. Figure 5 displays the front page of the software enabling a short introduction into the PARATUS project.

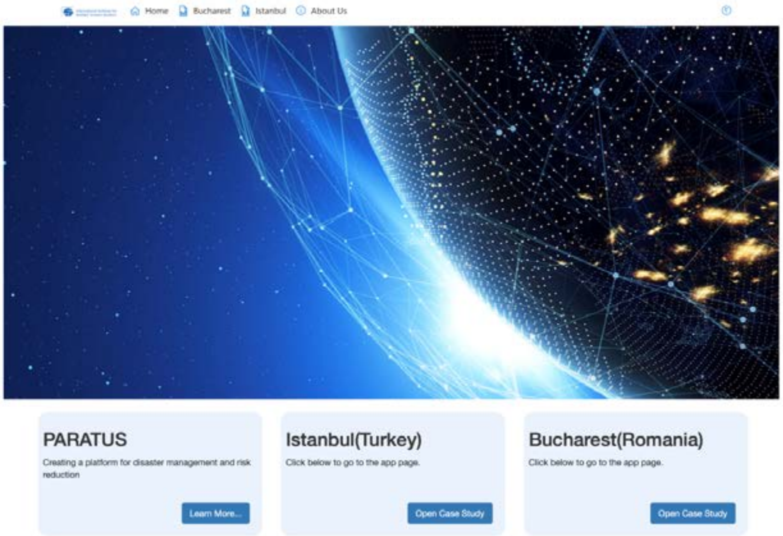

Figure 4: Front page of the Risk&Vulnerability Scenario (RVS) generator, the software being developed by CAT group of ASA Program, IIASA.

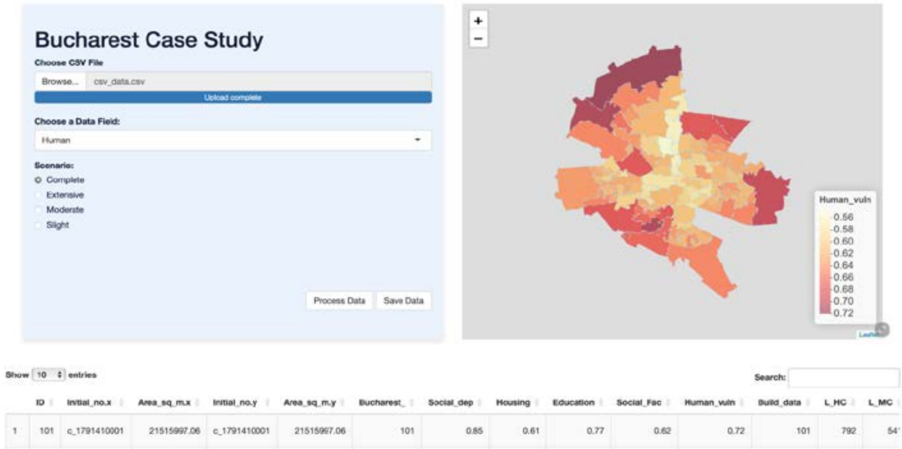

Figure 5: Human vulnerability indice (Armas et al., 2017).

The RVS allows for the interactive update of the covariates (vulnerability drivers) and recalculation of the vulnerability indices according to plausible alternative scenarios of population density, buildings typologies, buildings codes, etc. Thus, it allows for testing outcomes of implementing vulnerability reduction decisions regarding retrofitting, population relocation, building shelters, etc,

3.5. Application of the ML regression model to future vulnerability scenarios testing

Using the developed ML regression models for the assessment of the vulnerabilities and damages based on historical data and previous model-based results reflecting socio-economic, demographic, structural indicators, several scenario combinations of vulnerability drivers for the analysis of future vulnerabilities can be designed and estimated.

3.5.1. *Buildings upgrading and retrofitting*

In urban areas, centers of large cities, with higher percentage of dependent and elderly population residing in old houses, the human vulnerability is rather high. The human vulnerability can be decreased by decreasing structural vulnerability, which can be assessed from the available data on structural damages. For example, several dynamic scenarios of buildings' upgrading and retrofitting can be considered in areas of Bucharest (Romania) and Istanbul (Turkey), which are most vulnerable to structural damages :

1. Do nothing scenario: No taxes/insurance premiums will be accumulated and, therefore, no retrofitting will be done.
2. Flat scenario: Average annual losses from the previous events will be collected as taxes or premiums and invested equally in retrofitting.
3. Risk-based scenario: Average annual losses from the previous events will be collected as taxes or premiums and invested on risk-based principle.

The retrofitting can be financed through tax (insurance premiums) collection into a catastrophe fund, loss coverage can be provided by local and national government(s), administrative authorities, private and state companies, insurance companies. The optimal retrofiting scenario (Risk-based scenario 3) can be designed with ISCRiMM model (see section 3.2). The accumulation of catastrophe fund and the the contributions from the population into the fund are constraint by incomes, prices, running costs, etc., as it is also outlined in section 3.2.

3.5.2. *Construction of shelters*

The building of earthquake evacuation shelters is an effective way to reduce earthquake disaster risk and protect lives. The shelters can be built in areas with highest population and infrastructure density and, e.g., with high risk of structural damages. Urban earthquake evacuation shelters are safe places that provide evacuation protection and basic life support services after an earthquake. They can be classified into three categories: emergency shelter, fixed shelter and central shelter. Facility location models can address assessment of optimal places for locating earthquake evacuation shelters. The evacuation shelter location models are effective and suitable tools to assist in risk-based urban planning (Lomer et al., 2023; Qiu et al., 2024 ; Xu et al., 2016).

3.5.3. *Population relocation*

Millions of people have been forced by natural disasters to move away from their native places. One of such events is Hurricane Irma, which has brought devastation on the islands of the Caribbean as well as South Florida. In Indonesian, on Ruang island, government plans focused on permanently relocate almost 10,000 residents after a series of explosive eruptions of the Ruang volcano.

On Caribbean islands, the island of Montserrat, has been completed destroyed by a volcano and it required population relocation. On the morning of 9th of April 2021, the La Soufrière Volcano on the main island of St. Vincent and the Grenadines erupted -filling the sky with ash and transforming the lives, livelihoods and landscape of this small Southern Caribbean nation. More than 22,000 people were displaced from their homes, buildings including schools and businesses were damaged, livestock was destroyed and almost an entire population was cut off from clean drinking water and other basic necessities for five months. In total the damage amounted to more than $ 234 million; the impact of which was felt well beyond the main island to communities across the archipelago. Two years later, the ash from La Soufrière has settled, but the aftermath of the eruption continues to shape ordinary life and the development trajectory of this Small Island Developing State.

Governments have a responsibility to protect their people, including from disasters and the effects of climate change. While efforts are underway to reduce the risks of disasters, sometimes these measures are insufficient. A landslide or earthquake can destroy a village and people cannot return home. Sea-level rise may also make it impossible for people to remain on their coastal land and they need to move – or be moved – to safer areas.

Relocating people and communities is a complex undertaking and should be used only as a last resort – after all other alternatives have been explored. No one wants to be forced to leave their homes, only when it is absolutely necessary people should be relocated.

3.6. Conclusions

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