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Modelling and quantifying tomorrow's risks from natural hazards

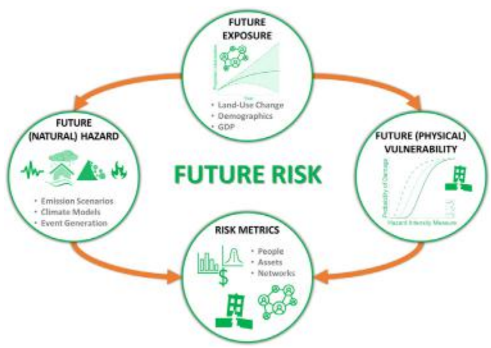
Gemma Cremen [a,*], Carmine Galasso [a,b], John McCloskey [c]

[a] Department of Civil, Environmental and Geomatic Engineering, University College London (UCL), London, UK
[b] Scuola Universitaria Superiore (IUSS) Pavia, Pavia, Italy
[c] School of GeoSciences, The University of Edinburgh, Edinburgh, UK

HIGHLIGHTS

- We explore work that has modelled and quantified future risks from natural hazards.
- We focus on individual components of risk (hazard, exposure, and vulnerability).
- We discuss risk-modelling challenges, and their effect on relevant decision making.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding and modelling future risks from natural hazards is becoming increasingly crucial as the climate changes, human population grows, asset wealth accumulates, and societies become more urbanised and interconnected. This need is recognised by the 2015–2030 Sendai Framework for Disaster Risk Reduction, which emphasises the importance of preparing for the disasters that our world may face tomorrow through strategies/policies that aim to minimise uncontrolled development in hazardous areas. While the vast majority of natural-hazard risk-assessment frameworks have so far focused on static impacts associated with current conditions and/or are influenced by historical context, some authors have sought to provide decision makers with risk-quantification approaches that can be used to cultivate a sustainable future. This Review documents these latter efforts, explicitly examining work that has modelled and quantified the individual components that comprise tomorrow's risk, i.e., future natural hazards affected by climate change, future exposure (e.g., in terms of population, land use, and the built environment), and the evolving physical vulnerabilities of the world's infrastructure. We end with a discussion on the challenges faced by modellers in determining the risks that tomorrow's world may face from natural hazards, and the constraints these place on the decision-making abilities of relevant stakeholders.

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* Corresponding author.
E-mail address: g.cremen@ucl.ac.uk (G. Cremen).

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1. Introduction

Global population is projected to increase to almost 11 billion by 2100 (United Nations, 2019). By this time, 75% or more of people are expected to be living in cities (Angel et al., 2012) and there is general consensus in the scientific community that climactic conditions will be significantly different from those currently experienced (Hallegatte, 2009). Even by 2030, the total amount of urban land located in high-frequency flood zones is predicted to increase by 33% compared to 2015 (Güneralp et al., 2015). These changes are set against a backdrop of ever-increasing wealth disparities between the world's rich and poor (Brian, 2015), which can act to either amplify or mitigate the impacts of natural-hazard disasters. All of these facts point to the critical importance of evaluating risks to natural hazards through a future-focused lens, so that properly informed decisions are taken today on the spatial planning and risk-prevention measures/policies that will shape the coming decades (e.g., Neumann et al., 2015; Lavell et al., 2012; Burby et al., 2000; Ferrier and Haque, 2003; Huppert and Sparks, 2006).

The need to consider the long-term implications of natural hazards is recognised by well-established intergovernmental organisations, such as the United Nations (UN), the European Union (EU), and the World Bank, among others. The UN Sendai Framework for Disaster Risk Reduction (UNISDR, 2015) inherently focuses on the future, through its aim to substantially reduce disaster loss by 2030; the goal to mitigate forthcoming disasters is further underscored by Article 8 of the UN Framework Convention on Climate Change "Paris Agreement" (Savaresi, 2016). The EU encourages a forward-looking approach to assessing disaster risks, particularly highlighting the importance of accounting for climate change impacts (European Commission, 2020). The World Bank underlines the obligation of disaster risk managers to "move instead towards risk assessments that can guide decision makers towards a resilient future" (Fraser et al., 2016). Furthermore, the Intergovernmental Panel on Climate Change (IPCC) state that "effective risk reduction and adaptation strategies consider the dynamics of vulnerability and exposure and their linkages with socioeconomic processes, sustainable development, and climate change" (IPCC, 2014).

Despite the evident necessity, most studies of natural-hazard risks do not consider its long-term evolutionary nature, relying instead on past or static observations of society within current environmental conditions (Gallina et al., 2016). A somewhat recent examination of 80 open-source risk assessment tools for natural hazards (GFDRR, 2014) found that none accounted for future risk in an explicit sense. Even catastrophe loss models used by the insurance industry tend to disregard the dynamic relationship between built-environment portfolios and the natural hazards that affect them (Fraser et al., 2016).

The primary purpose of this paper is to provide an overview of state-of-practice methods and approaches that feature in efforts of the literature to quantify and model risk from natural hazards in tomorrow's world – rather than to conduct a systematic review of all work that has been published on future natural-hazard risk; interested readers are referred to Ward et al. (2020) for the latter type of assessment at the global scale. We define the term 'risk' as the convolution of hazard, exposure, and vulnerability, in line with many previous studies of natural hazards like flooding and earthquakes (e.g., Birkmann and Welle, 2015; Erdik, 2017). All three of these components are changing over time under natural and human influences and impacting future risk estimates. We explicitly examine attempts to model each of these separate components into the future, primarily from a physical sciences and engineering perspective (this means that social vulnerability is broadly outside the scope of this study, for example). We also review the metrics that are used to define future risk, and end with a discussion on the challenges associated with realising and leveraging future natural-hazard risk assessments.

2. Future (natural) hazard

A hazard is defined according to the UN General Assembly as "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation" (UNDRR, 2020). Natural hazards are classified under a number of categories (IFRC, 2020), 1) geophysical (which covers earthquakes, landslides, tsunamis, and volcanic eruptions); (2) hydrological (which includes avalanches and floods); (3) climatological (which accounts for extreme temperatures, drought, and wildfires); (4) meteorological (which incorporates cyclones/hurricanes and storm surges); and (5) biological (consisting of disease epidemics and insect/animal plagues). They may also be categorised as (i) rapid onset (e.g., earthquakes, flash floods, and landslides); or (ii) slow onset (e.g., sea level rise, increasing temperatures, and droughts) (Tosun and Howlett, 2021). This Review specifically relates to the aforementioned classifications (1) to (4).

2.1. Climate modelling

The quantification of tomorrow's natural hazards commonly involves accounting for future climactic conditions (see Fig. 1). Climate change raises sea levels globally, affects the intensity/frequency of the strongest storms, increases extreme temperatures, and modifies precipitation patterns (e.g., Dessler, 2021). Therefore, climate change projections are frequently used as input to models for heat-, drought-, wind-, fire-, and flood-related risk assessments (e.g., Zscheischler et al., 2018; Kwadijk et al., 2010; Dowdy et al., 2019). These data are derived from so-called climate models that are combined with information on possible future scenarios of emissions. Note that the term climate model used here incorporates a variety of approaches for quantifying climate dynamics (in line with Van

Fig. 1. A typical methodological approach to modelling future climate-related hazards. Adapted from Fig. 8 of Salman and Li (2018). Information on possible scenarios of future emissions are combined with climate models that are then appropriately downscaled to provide finer resolution data for hazard analysis in the region of interest. The downscaled climate models are used to simulate values for dynamic weather variables, from which hazardous events can be derived. Then, local intensities associated with these events are calculated. The last three steps of the process can be repeated for many temporal instants in the future, to generate frequency exceedance curves for the hazard intensity measures of interest.

Vuuren et al., 2011) including (in order of increasing complexity) Simple Climate Models (SCMs), Earth-System Models of Intermediate Complexity (ESMIC), and Atmosphere-Ocean General Circulation Models (AOGCMs). SCMs (such as the Model for the Assessment of Greenhouse-Gas Induced Climate Change; e.g., Wigley and Raper, 2001) describe the ocean-atmosphere system as a collection of global or hemispherical boxes, and may be used to provide dynamic estimates of global mean temperature and sea-level rise. AOGCMs are the main tool used for climate projections, and comprehensively capture dynamics of the atmosphere-ocean system as well as other physical phenomena (e.g., land-surface processes). Examples of commonly used AOGCMs include the HadCM3 (Hadley Centre Coupled Model version 3; e.g., Gordon et al., 2000) and the HadGEM2-ES (Hadley Centre Global Environment Model version 2 - Earth-System; e.g., Bellouin et al., 2011), which were developed by the UK Met Office. ESMIC operate at a lower spatial resolution than AOGCMs, but account for some dynamics of ocean-atmosphere circulations and can be leveraged to measure continental-scale climate change. Frequently used ESMIC include CLIMBER-2 (CLIMate-BiosphERe model; Petoukhov et al., 2000). More details on each of the climate model categories is available in IPCC (2007).

It is important to note that, due to recognised biases, the outputs of these large-scale climate models should be appropriately downscaled to a higher resolution for the context of interest (unless it is of global scale), before they are directly integrated into risk assessments (Fowler et al., 2007). This can be achieved in two main ways, i.e., empirical (statistical) or dynamic downscaling (Fowler et al., 2007). Statistical downscaling relies on empirical relationships between global and regional climate models. It may involve the use of scaling factors (e.g., Arnell, 2003), regression models (e.g., Salathé, 2005), weather generators (i.e., stochastic models that combine historical data and the outputs of large-scale climate models; e.g., Eum et al., 2011), or weather typing (whereby particular weather classes are related with local weather conditions; e.g., Bermúdez et al., 2020). Dynamic downscaling refers to the development of higher resolution regional climate models that leverage boundary conditions from the larger scale models (e.g., Ozturk et al., 2017). Further correction of biases may also be necessary at fine resolutions, to account for residual discrepancies between simulations and observations (e.g., Hempel et al., 2013; Chen et al., 2021). Numerous bias-correction techniques have been proposed in the literature, including the linear scaling of mean simulated values and non-linear adjustments that also address variance inaccuracies. A detailed review of these and other approaches can be found in Teutschbein and Seibert (2012).

Uncertainties are typically incorporated in climate change predictions via ensemble modelling (Stewart et al., 2014), to provide more informative risk assessments than those that are produced using discrete scenarios (New et al., 2007). Ensemble modelling may consist of using a series of data from a variety of climate models (e.g., Mortin et al., 2014), simulating data from sets of different internal parameters of a single climate model (e.g., Murphy et al., 2007) or generating data using a range of input parameters for the same model (e.g., Murphy et al., 2004). The first two methods capture modelling uncertainty, while the latter is used to quantify climate variability (which can be natural or otherwise, depending on the range of input parameters used). Examples of future risk modelling efforts that have leveraged climate ensemble modelling include Rojas et al. (2013), Ward et al. (2014), and Muis et al. (2015).

2.2. Emission scenarios

Information on future emissions can be obtained from scenario storylines, such as those provided in the Special Report on Emission Scenarios (Nakicenovic et al., 2000, SRES; see "Future exposure" section for more details). For example, emission data from the SRES storylines scenarios were combined with a set of climate models to determine a series of future sea-level rise (SLR) scenarios in the IPCC Fourth Assessment Report (IPCC, 2007). These SLR scenarios have been used to quantify future flooding risk in a number of subsequent studies, including Hallegatte et al. (2011) and Hinkel et al. (2012). Further future risk assessments that have integrated SRES emissions data with various climate models include Pardaens et al. (2011), Nicholls and Tol (2006), Rojas et al. (2013), Te Linde et al. (2011), Schuster et al. (2012), and Balbi et al. (2013). SRES emission information was replaced with emission data from the Representative Concentration Pathways (RCPs) in the IPCC Fifth Assessment report (Pachauri et al., 2015). RCPs consist of four future pathways on emissions and land use (Van Vuuren et al., 2011) that are consistent with a large set of scenarios provided by the literature. Examples of future risk studies that have incorporated emission-related information from RCPs include Hinkel et al. (2014), who combined these data with four AOGCMs to determine coastal flooding damage in the 21st century on a global scale. Additional risk quantification work that has used RCPs include Huang et al. (2019), Dottori et al. (2018), Winsemius et al. (2015), and Arnell and Lloyd-Hughes (2014). Emission scenarios are usually treated in a discrete manner, such that climate change predictions are produced for each one individually. However, some recent work has leveraged variance-based sensitivity analysis to quantify their uncertainties (Xu et al., 2019).

2.3. Additional dynamic hazard features

The impact-model used to represent the physical process that directly results in the hazard may also have dynamic features, to align with the previously discussed climate projections. For example, the annual maximum discharges and windspeeds that are respectively used to compute future flood and storm hazards may be non-stationary (e.g., Rojas et al., 2013; Byun and Hamlet, 2020; Li and Stewart, 2011; Condon et al., 2015; Xu et al., 2020). In addition, dynamic modelling of ground-cover change (e.g., replacement of natural ground with impermeable surfaces, changes to drainage or irrigation systems, and deforestation) can influence future projections of flooding and landslide hazards (e.g., Fraser et al., 2016; Guo et al., 2020; Avand et al., 2021; Pisano et al., 2017).

2.4. Modelling of future non-climate-related hazards

Time-dependent approaches are also available for projecting future hazards that are not directly related to climate change, such as earthquakes. In this case, long-term time-dependent hazard assessment procedures condition the expected duration until a fault's next event on the amount of time that has elapsed since its last earthquake (or the occurrence of an event on a neighbouring fault), to account for changes in elastic strain energy. A comprehensive review of these methods is provided in Iacoletti et al. (2021). Short-term time-dependent seismic hazard assessments account for the spatial and temporal clustering of aftershock events that follow the occurrence of a mainshock earthquake (e.g., Papadopoulos et al., 2020).

3. Future exposure

Exposure is defined as "the people, property, systems, or other elements present in hazard zones that are thereby subject to potential losses" (UNISDR, 2009). Future exposure to natural hazards will be driven by increases in population (such as urbanisation, i.e., the movement of people from rural to urban areas), socioeconomic growth (e.g., Angel et al., 2011), as well as choices on land use (e.g., Santini and Valentini, 2011) (Fig. 2).

3.1. Modelling population and socioeconomic growth

Future population and economic growth are commonly modelled on the basis of socioeconomic scenario storylines (e.g., Hammond, 1998; De Vries et al., 1994). These narratives detail alternative characterisations of how the world may evolve, depending on political, economic, technical and social developments at global and regional levels. The first set of socioeconomic scenario storylines adopted for widespread use in research were presented in SRES, which were developed based on an extensive review of the literature. SRES comprises four scenario families for describing future emission-driven impacts on the world, based on population, economy, technology, energy, land use and agriculture. For example, one of these storylines (A1) describes a future of rapid economic growth, global population that is maximised in the middle of the 21st century and decreases afterward, and the rapid introduction of new technologies. Six different emission modelling approaches are used to quantify each storyline in a number of scenarios, which are designed to capture the full range of (known) uncertainties in the underlying factors. Studies that have adopted the socioeconomic component of the SRES scenarios at the global scale include Nicholls (2004), who examined changes in flooding by storm surges and Nicholls and Tol (2006), who quantified the impacts of sea-level rise. Rojas et al. (2013), which examined the future risk of flooding in Europe, is an example of a continent-level study that has leveraged socioeconomic data from the SRES scenarios. Socioeconomic information from SRES scenarios has also been incorporated into smaller-scale analyses at country or regional level (e.g., Hall et al., 2005; Kebede et al., 2012; Penning-Rowsell et al., 2013).

O'Neill et al. (2014) developed the shared socioeconomic pathways (SSPs) framework as an update to the SRES storylines. This contains five alternative plausible means by which society and ecosystems will evolve in the 21st century (in both narrative form and using a quantified set of socioeconomic metrics that define scenarios), and is more focused on the challenges of climate change than SRES. Examples of studies that have leveraged SSPs are Arnell and Lloyd-Hughes (2014); Dottori et al. (2018); Huang et al. (2019), as well as the most recent IPCC report (IPCC, 2021). Other socioeconomic storylines include the UN Environment Programme's Global Environmental Outlook, the Millenium Ecosystem Assessment, and the World Energy Outlook; a comprehensive review of these and other scenario families is provided by Van Vuuren et al. (2012).

Socioeconomic scenario storylines are presented in a highly aggregated manner and are therefore often downscaled to obtain finer resolution data. Various downscaling approaches have been applied in the literature. Population and economic growth forecasts can be proportionally downscaled to national or regional level, which assumes that the growth rates are consistent at both scales (e.g., Gaffin et al., 2004; van Vuuren et al., 2007). Other methods for population downscaling explicitly account for urbanisation trends, prioritizing growth in urban regions (e.g., Grübler et al., 2007; Nicholls, 2004). Economic growth downscaling can also be determined based on convergence approaches, which ensure consistency with local average values (e.g., van Vuuren et al., 2007), and more finer downscaling may differentiate between urban and rural gross domestic product (GDP) (e.g., Grübler et al., 2007) or involve stakeholder input (e.g., Carter et al., 2004). The aforementioned methods may be broadly categorised as top-down downscaling approaches; a comprehensive review of these types of procedures is provided in van Vuuren et al. (2010). Bottom-up approaches to downscaling have additionally been developed in the literature, which leverage participatory input on site-specific conditions (e.g., Nilsson et al., 2017) or are based on shared policy assumptions for the local context (e.g., Frame et al., 2018). While socioeconomic storylines are typically implemented in future risk assessments as discrete (deterministic) scenarios, some work has translated their GDP information into probabilistic distributions (Güneralp and Seto, 2013).

Population projections can also be quantified or obtained in other ways. Single "best-guess" forecasts of country-wide populations are available from agencies such as the World Bank and the Population Reference Bureau, for example (Lutz and KC, 2010). The UN produces high, medium, and low scenarios of future population at national and international scale (United Nations, 2019), which are characterised by corresponding variations in fertility, mortality, and migration. These scenarios can be combined with uncertainty estimates produced by the U.S. National Research Council (Councile and Population, 2000), to construct future population probability distribution functions (Seto et al., 2012; Muis et al., 2015). Fully probabilistic population projections may also be obtained for 13 regions of the world from modelling work of the International Institute for Applied Systems Analysis (Lutz et al., 1997, 2001, 2008).

3.2. Land-use change and urbanisation

It is important to note that the term land-use change can cover a multitude of transitions, such as the abandonment or adaptation of agricultural land (Acosta et al., 2014; Acosta-Michlik and Espaldon, 2008). For the purposes of natural-hazard risk assessments, land-use change is typically interpreted as urban growth (e.g., Penning-Rowsell et al., 2013), which has been modelled in the literature in a variety of ways. Bottom-up procedures can include the use of cellular automata (CA) or agent-based modelling (ABM). An example of this kind of approach is the SLEUTH (Slope, Land cover, Excluded regions, Urban land cover, Transportation, and Hillshade) model (Chaudhuri and Clarke, 2013). SLEUTH uses previous

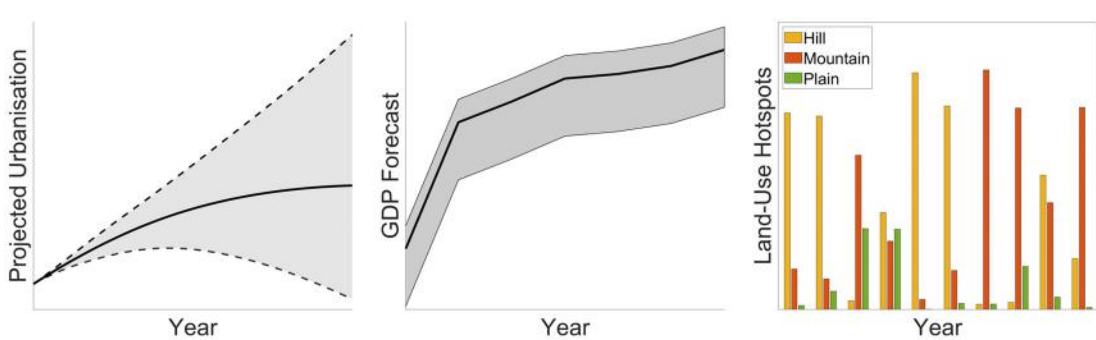

Fig. 2. Future exposure to natural hazards will be influenced by increases in urbanisation, socioeconomic growth, and fluctuations in land-use choices.

maps of historical growth (containing the first five features of its acronym) to probabilistically determine future land use according to relatively simple simulation rules that are founded on spatial auto-correlation and neighbourhood effects. It has recently been applied to simulate urban growth in the city of Istanbul (e.g., Sarica et al., 2020), the state of California (Clarke and Johnson, 2020), and at a global scale (Zhou et al., 2019). ABM and CA approaches are sometimes integrated with other tools to model urban growth. For example, ABM (or multi-agent systems) has been coupled with weighted geographical regression (Calderón and Silva, 2021), logistic regression (Pandey and Joshi, 2015), and Bayesian networks (Kocabas and Dragicevic, 2013), whereas CA has been combined with Markov chain methods (Lallemant, 2015; Rimal et al., 2019). Urban growth may also be simulated using empirical (e.g., Hu and Lo, 2007) or semi-empirical (e.g., Santini and Valentini, 2011) methods, landscape metrics (e.g., Taubenböck et al., 2009), machine learning approaches (such as artificial neural networks, e.g., Tayyebi et al., 2011), coupled Markov chain-genetic algorithm models (e.g., Tang et al., 2007), weight of evidence (Soares-Filho et al., 2004), socioeconomic storylines (e.g., Te Linde et al., 2011), as well as integrated top-down, bottom-up approaches that capture interactions at various scales (Verburg and Overmars, 2009; Promper et al., 2014).

Some work has leveraged population and economic growth projections to better constrain urban expansion models. For example, Seto et al. (2012) and Muis et al. (2015) informed their urban growth model with per capita land approximations, which were empirically computed from per capita GDP estimates (that were determined based on forecasted population and economic growth values). Calderón and Silva (2021) adjusted their pre-calibrated land-use model based on estimates of built-up area, which were empirically derived from future population projections. On a smaller scale, population increases have been used as a proxy for estimating annual increases in housing number (Bjarnadottir et al., 2014; Stewart and Li, 2010).

4. Future (physical) vulnerability

Vulnerability is broadly defined as “the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard” (UNISDR, 2009). We particularly focus on physical vulnerability in this Review, which may be interpreted in this context as the tendency of exposed elements (assets) to suffer adverse effects when impacted by natural hazards (Cardona et al., 2012). Risk assessment methods account for the future vulnerability of physical infrastructure to natural hazards from two main perspectives. The first of these outlooks assumes that vulnerability will increase in time as a result of unplanned/informal modifications or maintenance/degradation challenges, whereas the second focuses on the reduction in vulnerability that can be achieved by adapting infrastructure to future conditions (see Fig. 3). These divergent standpoints reflect the two main drivers of vulnerability, i.e., socioeconomic conditions and policy decisions (Fraser et al., 2016).

4.1. Assessing increasing vulnerability

One of the foremost attempts to quantify dynamically increasing building-level physical vulnerability is the work of Lallemant et al. (2017). This study developed a framework for modelling the time-dependent earthquake fragility (i.e., the probability of collapse) of incrementally expanding construction, which is a commonly adopted strategy for accommodating ever-increasing urban growth in developing countries (e.g., Amoako and Boamah, 2017). Markov chains were leveraged to quantify the probability of residential buildings transitioning to a new state with more stories, and the framework was demonstrated by quantifying dynamic projections of building collapses in Kathmandu valley, Nepal. Other work has characterised the short-term increase in physical vulnerability that may occur after or during a series of natural-hazard events. For instance, attempts have been made to model the accumulation of damage in structures that takes place after a mainshock earthquake and during the subsequent

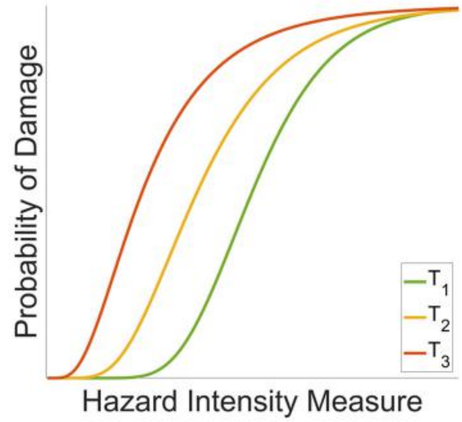

Fig. 3. Sample changes in the vulnerability of a structure through time, from T_1 to T_3. Dynamic increases in structural vulnerability (as shown in the figure) may be driven by informal structural modifications, environment-induced deterioration, and accumulation of damage due to cascading hazard events (e.g., aftershocks). These increases can be offset by vulnerability adaptation measures (shifting the vulnerability curves to the right), many of which may be broadly categorised as “climate adaptation engineering” approaches.

aftershock sequence; very recent examples include Aljawhari et al. (2020), Gentile and Galasso (2020), and Papadopoulos et al. (2020).

A vast array of studies have focused on modelling the time-dependent environment-induced deteriorating vulnerability of infrastructure. We only discuss here the most timely advances in the field for brevity, but we note that several reviews on approaches for modelling/quantifying the environmental degradation of physical assets have been released in recent times (e.g., Kashani et al., 2019; Amaya-Gómez et al., 2019; Guo et al., 2019). Most recent state-of-the-art developments in the field include (1) the study of Zamanian et al. (2020), which simulated the impacts of corrosion on buried concrete sewer pipes using a novel high-fidelity finite element model that captured the nonlinear behaviours of concrete, soil, and combined pipe-soil interactions; (2) the work of Soltani et al. (2021), which developed a new statistical (multiple linear regression) model for quantifying the reduced shear capacity of corroded reinforced concrete beams; and (3) research by Zanini et al. (2020), which leveraged systems reliability theory to compute original time-dependent fragility functions and corresponding dynamic seismic reliability profiles for environmentally degraded reinforced concrete bridges.

Research on the effects of environmentally-driven deterioration to the built environment is beginning to account for future climactic conditions (Bastidas-Arteaga and Stewart, 2015, 2016; Wang et al., 2012; Stewart et al., 2012; El Hassan et al., 2010; Yang and Frangopol, 2020; Sevieri and Galasso, 2021). This is important, given that rising carbon dioxide levels associated with global warming will increase the likelihood of carbonation-induced corrosion (Stewart et al., 2011). One of the first attempts to incorporate future weather in the assessment of corrosion was the work of Bastidas-Arteaga et al. (2010), which specifically focused on reinforced concrete structures. This study leveraged a model that coupled the effects of convection, chloride binding, and concrete ageing with temperature and humidity data that were informed by three scenarios of global warming. Stewart et al. (2011) provided a probabilistic and reliability-based approach for predicting the probability of corrosion initiation and damage to concrete infrastructure, deriving temperature and humidity information from nine AOGCMs combined with three emission scenarios. Peng and Stewart (2016) used a series of climate projections to probabilistically determine future carbonation-induced damage to reinforced concrete structures in different Chinese cities. Lately, the work of Yang and Frangopol (2019a) leveraged various general circulation models to determine future scour-induced failure probabilities of bridges (and the associated long-term risks).

4.2. Accounting for adapted vulnerability

Work that has focused on a potential reduction in the future vulnerability of the built environment is often framed within the context of dynamically increasing climate risks and termed "climate adaptation engineering" (Stewart et al., 2014; Stewart and Deng, 2015; Mondoro et al., 2018). A significant motivation for this body of research is that the changing climate is generally likely to inflict more damage on engineering assets in the future, even if design standards remain unchanged (e.g., Stewart, 2015). Many of these studies have particularly focused on Australia. For example, Stewart (2015) assessed the risk, costs, and benefits of climate adaptation strategies for reducing the vulnerability of new housing to evolving wind-induced risk for three cities in Australia, under three emission scenarios. Li and Stewart et al. (2011) studied the economic viability of various mitigation strategies (such as building retrofitting and an improvement in new building design) against future cyclone hazards in Northern Australia. Qin and Stewart (2020) probabilistically examined two adaptation options for reducing the vulnerability of Australian housing to non-cyclonic windstorms in a changing climate, i.e., reinforcing the building envelope or increasing the water resistance of the building interior. In addition, Ryan et al. (2016); Ryan and Stewart (2017, 2020) considered the feasibility of reducing the vulnerability of Australian power distribution networks to future climate impacts. Further important contributions to the field of climate adaptation engineering are the work of Dong and Frangopol (2017), which proposed a genetic algorithm-based optimisation approach for the process of adapting residential buildings to the future impacts of hurricanes; the study of Liu et al. (2020), which presented optimal adaptation schedules for bridge networks vulnerable to abutment scour that considered the cost of both adaptation and network-level failure; and the investigation by Du et al. (2020) of various building vulnerability adaptation strategies (including dry-proofing, wet-proofing, and the construction of raised floors) on the effect of future flood risk in Shanghai.

Other studies have examined the potential implementation of physical or natural protective measures to reduce the vulnerability of regions to future flooding events. For example, the study of Dawson et al. (2005) quantified the reduction in inundation area associated with raising the Thames Estuary flood defences and installing additional tidal flood barriers in London, under different sea-level rise scenarios. The construction of dikes has been assessed as an alternative flood-related vulnerability reduction measure in a number of studies (e.g., Hinkel et al., 2013; Tol, 2007), including the work of Ward et al. (2017), which demonstrated that dyke investment could reduce flood risk below current levels in some areas of the world (despite climate change and dynamic economic conditions). The level of future flood-vulnerability mitigation offered by various nature-based solutions (i.e., actions inspired and supported by nature; e.g., Faivre et al., 2017) is an active area of research. For example, Zölch et al. (2017) measured the reduction in future urban surface runoff due to trees and green roofs in Munich, while Reguero et al. (2014) investigated the effectiveness of wetland restoration/conservation, beach nourishment, and oyster reef restoration in lowering flood vulnerability along the U.S. Gulf Coast. Additional research (Prudhomme et al., 2010) has taken a more conceptual, reliability-based approach to the concept of future flood vulnerability by developing an analytical framework for quantifying the fraction of climate model scenarios that would be facilitated by a prescribed adaptation measure.

4.3. Non-physical vulnerability

While quantitative natural-hazard risk assessments centre predominantly on the future vulnerability of the built environment, we briefly mention here efforts that have focused elsewhere. In fact, socioeconomic vulnerability also changes over time, impacted by the occurrence of disasters (disrupting lives and livelihoods) and by the effects of climate change. Bjarnadottir et al. (2011) quantified social vulnerability dynamics due to climate change, using a time-dependent index that accounted for the most relevant factors (e.g., race, age, gender and socioeconomic status) (Cutter et al., 2008). A weighted socioeconomic vulnerability index for climate-change-affected regions in Bangladesh was developed in Ahsan and Warner (2014), to guide future adaptation policies, while adapted vulnerability to floods was defined in terms of expected annual fatalities by Jongman et al. (2015). Finally, some work on future drought events (Naumann et al., 2021) has accounted for adapted socioeconomic vulnerability on the basis of GDP growth, using pre-determined empirical relations (Formetta and Feyen, 2019).

5. Risk metrics

Risk metrics act as a crucial bridge between the quantitative risk assessment and the decision-making process that they are used to inform (Johansen and Rausand, 2014). High-level preliminary assessments have used relative risk indices to identify potential future natural-hazard risk hotspots (e.g., Hawchar et al., 2020). Most future-focused approaches to quantifying natural-hazard risk have concentrated on measuring risk in terms of conventional asset losses. For example, Stewart et al. (2018) examined the consequences of climate-induced extreme wind loading on residential roofs in terms of its percentage of house value. Both Forzieri et al. (2018) and Dawson et al. (2009) quantified the effects of future natural-hazard events as the expected annual cost of damage to physical infrastructure and/or agricultural land, while Schuster et al. (2012) expressed the impacts of flooding to a facility as the expected cumulative damage cost over its lifetime. Salmanidou et al. (2021) measured risks from future tsunamis in terms of their effect on the value of household-level assets. Other authors (e.g., Gaslikova et al., 2011; Schwierz et al., 2010) have focused exclusively on insured property losses.

Tomorrow's risk from natural hazards may also be presented in terms of its direct effect on the human population. For example, Maaskant et al. (2009), Nagai et al. (2020), and Stone et al. (2014) examined the potential mortality associated with different future natural-hazard events, while Nicholls (2004) measured the number of people likely to be affected by sea-level rise. The study of Darwin and Tol (2001) explicitly accounted for welfare changes associated with sea-level rise, using the equivalent variation metric to express losses.

Wider perspectives on risk have been offered by some authors, who have quantified the impacts of future natural-hazard events in terms of multiple metrics and/or based on a broader network-level perspective. Stewart (2016) examined structural, non-structural and business interruption losses associated with roof cover damage to industrial and commercial buildings in future wind events. Stewart et al. (2014) considered both the direct and indirect losses (in the form of, for example, residential clean-up, alternative household accommodation, disaster response and relief, injuries and fatalities, and business and economic disruption) associated with projected wind-related damage to residential buildings. Yang and Frangopol (2019b) quantified the societal risk of the impacts of climate change on transportation networks, which accounted for the costs incurred by users due to necessary detours and the loss of time. Both Liu et al. (2020) and Yang and Frangopol (2019a) considered the societal risk metric in addition to the direct economic cost associated with transportation-network bridge failure. Verschuur et al. (2020) measured the risk associated with future Bangladesh flooding events using a Composite Development Index, which incorporated information on welfare losses, the relative extent to which policy interventions reduce these losses for poor households, and resilience (i.e., the ratio of asset to welfare losses).

The Dynamic Interactive Vulnerability Assessment (DIVA) tool has been leveraged to determine future risk in a number of studies (e.g., Hinkel et al., 2013, 2012; Mcleod et al., 2010). In addition to quantifying direct economic losses, this model describes the consequences of sea-level rise in terms of three socially-focused indicators (Hinkel et al., 2010), 1) the number of people who live in the coastal floodplain (i.e., below the 1000-year storm-surge level); (2) the expected annual number of people subjected to flooding; and (3) the number of people forced to migrate as a result of erosion. The work of Bosello et al. (2012) used DIVA in combination with GTAP (Global Trade Analysis Project) – EF, a computable general equilibrium model for Europe, to also quantify wider indirect economic effects of sea-level rise (e.g., impacts on GDP, investment, and international trade flows).

6. Modelling future risk

6.1. Challenges

Decision makers of today have a notable opportunity to positively influence the risks of tomorrow, through their choices on implementing strategies/policies that control future risk drivers. However, the selection of appropriate risk-management interventions strongly relies on our ability to model tomorrow's risks from natural hazards, explicitly accounting for the dynamic nature of hazard, exposure, and vulnerability. One of the main challenges to modelling future risk that has been identified in the literature is the significant inherent uncertainty in each of these components of tomorrow's risk (e.g., Hemmati et al., 2020). Some of the unknowns related to future risk, such as natural climate variability, cannot be (completely) reduced with new knowledge. Epistemic (i.e., modelling) uncertainties are captured by leveraging a combination (ensemble) of different models in a given risk assessment, which poses its own difficulties. For example, while general circulation models for climate have different levels of skill in modelling climate variables, there is no generally accepted protocol for ranking/aggregating models (e.g., Stewart et al., 2011). This means that current best practice is to average climate projections across all models in an ensemble, which may not be optimal (Gleckler et al., 2008). In addition, these ensembles may not capture all potential versions of the future. For instance, it has recently been argued that the IPCC scenarios for global sea-level rise under strong warming are concentrated on merely the lower end of possible outcomes (Siegert et al., 2020). Furthermore, the necessary downscaling of climate projections amplifies their uncertainties because subgrid parameterisations (i.e., submodels) are only approximate, idealistic representations of complex physical phenomena (Hourdin et al., 2017). Even if climate projections were well constrained, quantifying their impact on future hazard would be hampered by a lack of data on extreme events (Hallegatte, 2007). We have focused our discussion here on hazard uncertainty in particular, but note that this is even further exacerbated by comparable unknowns in terms of future population (Cohen, 2004), the point in time at which an updated vulnerability measure may be introduced (Kwadijk et al., 2010), and the eventual success of any adopted adaptation measures (Dilling et al., 2015), for example. The combined effects of these uncertainties can inhibit the utility of future risk assessments in decision-making processes (e.g., Wilby and Dessai, 2010), which may help to explain why disaster risk managers tend to frame their risk perceptions in terms of today's - rather than tomorrow's - hazards (Dilling et al., 2015).

Despite clear and numerous efforts to model individual risk components associated with future natural-hazard events, there remains a lack of a commonly accepted analytical framework for complete end-to-end risk quantification. This is reflected in the wide range of inconsistent approaches found in the literature for calculating future loss projections, which incorporate various degrees of complexity (e.g., Jurgilevich et al., 2017). To illustrate this point, we take risk modelling for future tropical cyclones (hurricanes) as an example. Some work in this area (e.g., Webersik et al., 2010) quantified cyclone losses under the assumption that population distribution, economic growth, and vulnerability remain unchanged from 2010 conditions. Other studies (e.g., Bjarnadottir et al., 2014) accounted for the dynamic variability of both hazard and exposure, but leveraged a static representation of vulnerability. A more comprehensive approach was taken by Mendelsohn et al. (2012), who incorporated projected changes to all components of risk (hazard, exposure, and vulnerability) into their predictions of future tropical cyclone damage. Robust methodological frameworks and protocols are required to overcome these types of modelling inconsistencies (Bouwer, 2013).

Some work related to this need has already been accomplished. For example, Bouwer (2013) presented a framework for modelling future natural-hazard risk (see Fig. 4), which accounted for the dynamic nature of hazard (via climate change and natural weather variability), vulnerability (via socioeconomic change and adaptation measures), and exposure (via temporal adjustments to population and economic growth). Muis et al. (2015) developed a similarly structured framework with a specific focus on flood hazard and the corresponding expected annual damage. Verschuur et al. (2020) provided a more detailed framework for specifically analysing future welfare risks that accompany asset losses caused by Bangladesh flooding

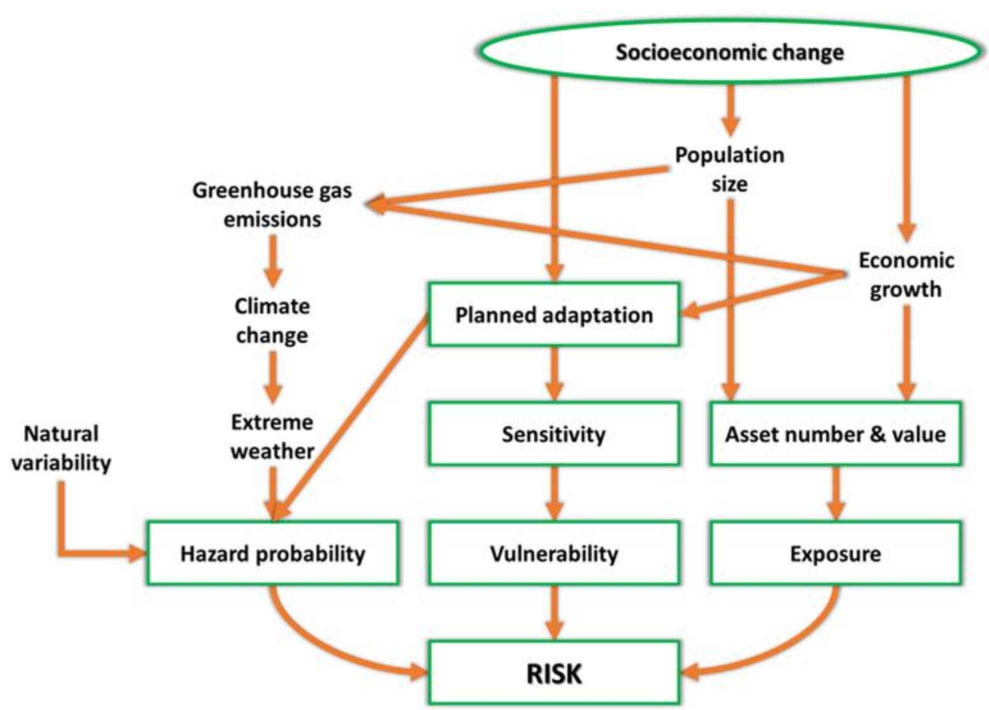

Fig. 4. End-to-end framework for quantifying future natural-hazard risk, as proposed by Bouwer (2013). Note that the term "sensitivity" in this context refers to the empirical relationship between the hazard and the loss. Adapted from Fig. 1 of the aforementioned paper.

events, through a pro-poor lens. Finally, Lee et al. (2018) proposed an adaptive decision-making methodology to determine optimal strategies for mitigating seismic risks in the face of evolving hazard, exposure, and vulnerability.

6.2. Perspectives

While the aforementioned frameworks help to facilitate comprehensive assessments of future risk, they have some limitations that may hinder decision-making related to tomorrow's natural hazards. Firstly, each centres on just one hazard. This narrow-focused approach may lead to increased risks from other overlooked hazards (Gill and Malamud, 2016) as part of a failure to account for “asynergies” in disaster risk management (de Ruiter et al., 2021), is not effective for spatial planning purposes (Greiving et al., 2006), and is not aligned with the “all-hazards” perspective adopted in conventional emergency management (Ferrier and Haque, 2003). A multi-hazard (or multi-risk) outlook would significantly improve the risk-reduction potential of these frameworks (Gill and Malamud, 2014; Kappes et al., 2012). This could be achieved by making use of the multi-risk mathematical environment developed by Selva (2013), for example, which accounts for interactions between hazardous events across all three components of risk. However, it is important to mention here that modelling these interactions can currently be inhibited by shortages in computational and storage capacities (Bevacqua et al., 2019), data constraints that can further exacerbate the uncertainties associated with single-hazard assessments (Ciscar et al., 2019), and a lack of innovative risk assessment methods that capture the complexity of joint hazard occurrences within a single unifying framework (Mignan et al., 2014).

Secondly, these frameworks incorporate a limited set of risk metrics (e.g., direct economic costs and household resilience) that do not explicitly account for disruptions to socio-economic and technical networks, such as supply-chain interruption (e.g., Jabbarzadeh et al., 2016) and accessibility reduction (e.g., Miller and Baker, 2016). Interconnected risks often form the main source of crisis in the aftermath of a natural-hazard event (Pescaroli and Alexander, 2018), thus consideration of their effect should play a central role in future risk models. Quantification of these types of risks could benefit from more detailed datasets of future socio-economic projections than those typically leveraged in current models. For instance, many studies measure the effects of future natural hazards using aggregated population predictions (Lutz and KC, 2010), whereas more refined age-based projections could be useful for deriving time-dependent estimates of user numbers in a transportation network or predicting the perceived habitability of a neighbourhood after an event.

A further disadvantage of the aforementioned approaches is that they do not explicitly facilitate formal decision-making processes on future risk-management and mitigation measures. Cost-benefit analyses (CBA), which have already been successfully leveraged to appraise different climate adaptation policies (Ryan and Stewart, 2017) could be integrated into risk assessment procedures to overcome this issue. However, CBA methodologies fail to account for the different risk perspectives of various stakeholders, which are crucial for effective risk governance (Komendantova et al., 2014) and the successful adoption of any risk-management strategies (Carpignano et al., 2009). While the Composite Development Index metric output of the framework developed in Verschuur et al. (2020) allows for differently weighted policy objectives to reflect diverse priorities and preferences, the considered objectives (reducing disaster losses, increasing resilience, and promoting pro-poor solutions) are specifically tailored to the Bangladesh case study carried out and the framework is only demonstrated for the scenario of equal weights. One way of better promoting a participatory approach to future natural-hazard risk quantification would be to explicitly include an additional decision-making (or impact assessment) module in the future risk-assessment framework (see Fig. 5), representing a process in which the stakeholder would rank the importance of various risk metrics of interest and a final evaluation of the weighted risk (or impact) would be carried out. This could be achieved using a similar methodology to that developed for selecting optimal earthquake early warning actions in Cremen and Galasso (2021), where risk outputs of a traditional framework would act as an input to a multi-criteria decision-making process that accounted for stakeholder preferences. Note that the impact assessment module could also feed back to the risk calculations (including the exposure inputs - which may also affect the multi-hazard simulations - and the vulnerability component), to allow stakeholder perspectives, management plans, and priorities to be accounted for in the final quantification and selection of risk metrics.

7. Conclusions

Modelling and quantifying tomorrow's risks from natural hazards is becoming ever more critical as we face an uncertain future of increasing human populations, relentless urbanisation, and significantly different climactic conditions. This paper has reviewed state-of-the-art approaches to future natural-hazard risk quantification, including various methodologies that have been developed to model tomorrow's hazards, exposure, and (physical) vulnerability. We have also documented diverse ways in which future risk has been measured, such as in terms of asset damage, business interruption, welfare losses, and travel-time delays.

Our Review has revealed that while there have been numerous efforts to model the individual components of future natural-hazard risk, some significant obstacles to quantifying this risk for management and mitigation purposes still remain. These include the substantial uncertainty associated with future risk projections, some of which (including natural climate variability) cannot be (completely) reduced with new information. There is also a clear lack of a standard framework for end-to-end future risk modelling that (1) captures multiple hazards; (2) accounts for network-level disruptions in our increasingly interconnected societies; (3) incorporates a broad set of risk metrics that, for instance, account for socioeconomic disparities; and (4) facilitates the diverse perspectives of a wide set of stakeholders involved in risk governance.

In summary, it is clear that there is some work to do before future risks from natural hazards can be quantified in a manner that is meaningful for the important decisions that need to be made as our world keeps changing. Our efforts will inevitably be enhanced as more data becomes available to constrain our models, but we first need to develop consistent risk-quantification procedures. It is also important to remember that we can readily improve our current assessments of tomorrow's natural-hazard risks, by leveraging existing tools (e.g., related to multi-criteria decision-making and multi-hazard theories) that have been successfully adopted for risk quantification in other contexts. The Tomorrow's Cities Hub of the United Kingdom Research and Innovation (UKRI) Global Challenge Research Fund (GCRF), which is aiming to develop a comprehensive methodology for facilitating the risk-sensitive design of future cities that is co-produced with local stakeholders, accounts for multiple hazards, and incorporates both social and physical vulnerabilities (Galasso et al., 2021), represents a promising step in the right direction towards addressing some of the current challenges.

Data availability

No data are created or directly analysed as part of this review.

Declaration of competing interest

The authors declare no competing interests.

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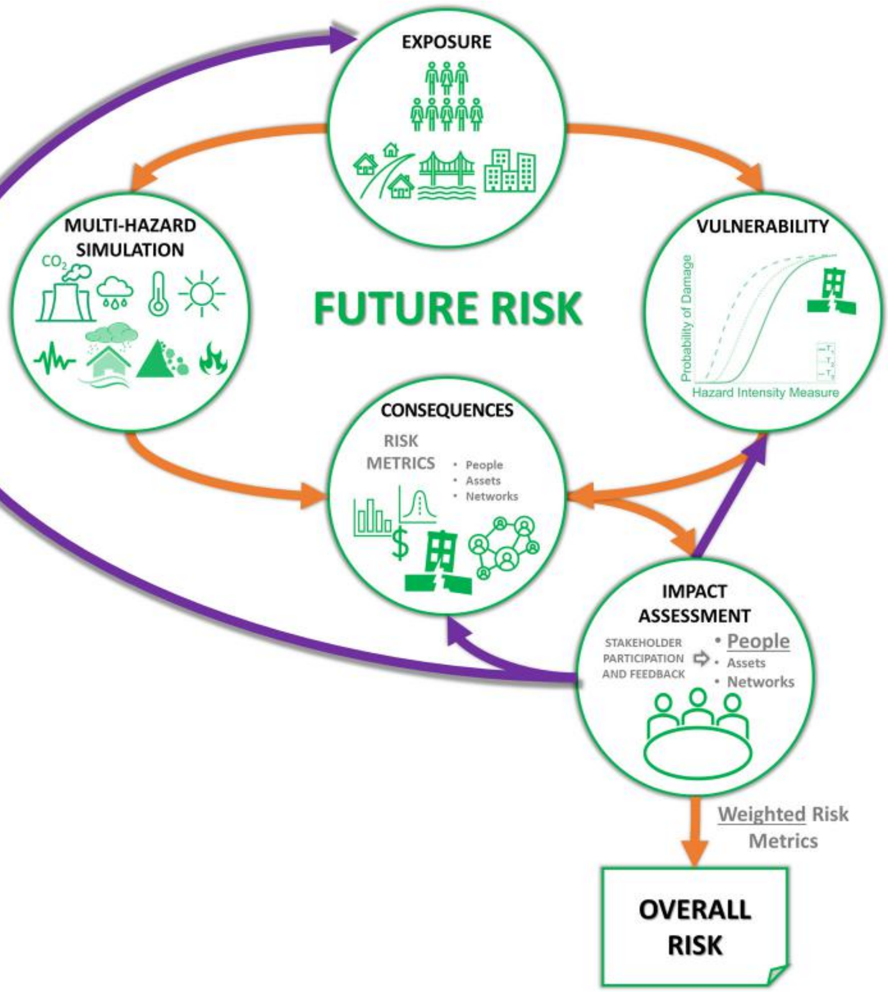

Fig. 5. Outline of a proposed idealised stakeholder-centred end-to-end risk modelling framework for future natural hazards. The conventional risk assessment approach (that consists of combining a single hazard, exposure, and vulnerability to produce consequence values typically related to economic and/or building-level loss) is advanced to account for: (1) multiple hazards; (2) a flexible suite of risk metrics that can account for both socio-economic and technical networks; and (3) stakeholder perspectives and priorities towards different dimensions of risk. Feedback loops to the risk calculations (including exposure inputs and the vulnerability component) enable stakeholder perspectives, plans, and priorities to be accounted for in the final quantification and selection of risk metrics.

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