A Bespoke Approach to Quantifying the Impacts of Disasters, Using Stakeholder-relevant Metrics

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Abstract

Disaster impact metrics (DIMs) are key outputs of natural-hazard risk models/assessments that provide a tangible way of communicating risk. However, typical DIMs are limited in that they tend to capture only direct damage/economic losses, be specifically designed for developed countries, account for just one snapshot in time, and be characterised for individual assets rather than systems. These shortcomings somewhat stem from a lack of understanding around the bespoke requirements of different stakeholders concerning disaster impact/risk assessments. Addressing these limitations, we propose a toolbox for characterising context-specific DIMs that capture relevant stakeholder priorities/requirements. The toolbox includes: (1) a comprehensive, holistic pool of DIMs developed from a literature review and a conceptual representation of societal dependencies; and (2) a stakeholder-centred framework for facilitating the appropriate selection of DIMs from this pool. We demonstrate the framework for Kathmandu, Nepal, revealing that the relative importance of a given disaster impact can change for different stakeholder groups and spatio-temporal dimensions. Impacts related to direct damage/economic losses are not the most crucial concern of the considered stakeholders. Higher priority is placed on characterising accessibility impacts around utilities and social networks, for instance. This work contributes to advancing the usefulness of natural-hazard risk assessments for important decision-making.

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Abstract

Disaster impact metrics (DIMs) are key outputs of natural-hazard risk models/assessments that provide a tangible way of communicating risk. However, typical DIMs are limited in that they tend to capture only direct damage/economic losses, be specifically designed for developed countries, account for just one snapshot in time, and be characterised for individual assets rather than systems. These shortcomings somewhat stem from a lack of understanding around the bespoke requirements of different stakeholders concerning disaster impact/risk assessments. Addressing these limitations, we propose a toolbox for characterising context-specific DIMs that capture relevant stakeholder priorities/requirements. The toolbox includes: (1) a comprehensive, holistic pool of DIMs developed from a literature review and a conceptual representation of societal dependencies; and (2) a stakeholder-centred framework for facilitating the appropriate selection of DIMs from this pool. We demonstrate the framework for Kathmandu, Nepal, revealing that the relative importance of a given disaster impact can change for different stakeholder groups and spatio-temporal dimensions. Impacts related to direct damage/economic losses are not the most crucial concern of the considered stakeholders. Higher priority is placed on characterising accessibility impacts around utilities and social networks, for instance. This work contributes to advancing the usefulness of natural-hazard risk assessments for important decision-making.

Keywords: disaster impact metrics; natural-hazard risk; stakeholder-relevant; questionnaire; Kathmandu

1 INTRODUCTION

Disaster impact metrics (DIMs) are key outputs of disaster risk models that summarise various estimated consequences of modelled hazard events, e.g., earthquakes, floods, hurricanes, and wildfires. They can include the number of damaged or collapsed buildings and/or infrastructure components (e.g., bridges), casualties, the resulting direct economic losses, and business downtime (e.g., Kibboua et al., 2014; Ceferino et al., 2018; Hulsey et al., 2022; Cremen et al., 2020). DIMs could be represented as a summary statistic or in a fully probabilistic manner. Furthermore, they could be computed for one hazard event scenario or a series of stochastically modelled events. DIMs provide a tangible way of communicating potential hazard event consequences that could occur to an urban system in a specific period of time to various stakeholders (e.g., residents, insurers, government officials, and disaster planning authorities; UNDRR, 2015). For example, potential casualties from hypothetical or ongoing disasters represent a direct and prompt means of conveying their severity to the general public, especially residents (Hiroi et al., 1985).

DIMs also inform important policy-related decision-making. For instance, they can be used to guide the emergency response phase efforts of humanitarian organisations or government authorities to appropriately allocate food, rescue crews, and rescue equipment (e.g., Caunhye et al., 2012; Goldschmidt and Kumar, 2019; Cook et al., 2018; Yulianto et al., 2021). In the longer term, they can be leveraged by relevant government agencies to inform the appropriation of disaster relief funds and devise reconstruction programs (e.g., Costa and Baker, 2023; Lallemant et al., 2017; Opabola and Galasso, 2024; Opabola et al., 2023). They can also be used for comparing the sensitivity of urban plans to future disaster risk (Cremen et al., 2023).

However, the existing array of commonly used DIMs is limited in many ways. First, DIMs typically capture only direct physical damage and economic losses (e.g., Silva et al., 2014, 2020; Ellingwood, 2006), neglecting the well-being implications of hazard events on affected communities and the unique challenges that different social groups may face due to such events (Markhvida et al., 2020; Walsh and Hallegatte, 2020; Cremen et al., 2023). This limitation impedes the consideration of equity in disaster impact assessment, obscuring disparities in the distribution of disaster risk for diverse groups and leading to equity-unaware disaster risk reduction (DRR) policies and disaster risk management (DRM) practises (Soden et al., 2023). For example, the Nepal Housing Reconstruction Project (NHRP) provided a fixed-amount reconstruction funding ($3,000; which covered only 30 to 50% of the typical rebuilding cost, Rawal et al., 2021; Galasso and Opabola, 2024) for damaged residences exclusively based on direct physical damage, which impeded the recovery of socially vulnerable communities (Starr, 2018; Platt et al., 2020; Amnesty International, 2017) that could not secure (low-interest) loans or use their savings to fund shortfalls in the repair financing.

DIMs have been predominantly characterised for individual assets (mainly buildings) rather than broader physical and social infrastructure systems and networks (e.g., Erdik, 2017; Erdik et al., 2003; Pitilakis et al., 2006; Khatakho et al., 2021), neglecting the dynamic interdependencies and interactions among people and various infrastructure systems within the built environment (Zimmerman, 2001). In addition, conventional DIMs tend to capture circumstances at just one specific point in time, for instance, the immediate aftermath of a hazard event (e.g., National Planning Commission, 2015; Subedi and Chhetri, 2019; Potter et al., 2015; Yuan, 2008), overlooking the evolving recovery phase across (potentially many) years that is important to consider for long-term planning. Nuances in how various disaster impacts can be tolerated across different time periods (Murphy and Gardoni, 2008; Esmalian et al., 2019; Wiboonratr and Kosavisutte, 2009) as well as spatial scales (Esmalian et al., 2021; Hong et al., 2021; Cetinkaya et al., 2013) are also lost.

Furthermore, existing DIMs are primarily tailored for application to developed countries, for instance for (re-) insurance purposes (e.g., Mitchell-Wallace et al., 2017). This means that they potentially lack relevance for stakeholders in the Global South, where there can be distinct challenges related to disaster impact assessment.

For example, Global South regions can experience disaster-related disruptions to types of infrastructure not typically observed in the Global North, e.g., floating markets (Wattanacharoensil and Sakdiyakorn, 2016). Unique land policies may also lead to very context-specific disaster impacts in the Global South. For instance, the feudal and informal land tenure system of Nepal (Chhatkuli et al., 2019) meant that many people without a land ownership certificate were ineligible for the government reconstruction grant after the 2015 Gorkha earthquakes, and forced to live with the consequences of having to self-fund housing repairs (Amnesty International, 2017).

In general, the shortcomings of DIMs can at least partially be attributed to a lack of research effort on - and therefore, understanding of - the bespoke requirements of different stakeholders concerning disaster impact assessment. Although some studies address multi-stakeholder engagement in disaster risk management (e.g., Chang et al., 2008; Bostick et al., 2017; Gregory et al., 2012; Yang and Zou, 2014; Ellingwood and Kinali, 2009), there is no definitive list of stakeholders that use or rely on the outputs of disaster risk models (i.e., DIMs). Furthermore, there is a lack of quantitative research on stakeholder priorities or perceptions related to these outputs, which are clearly not homogeneous. Pathak et al. (2020) conducted semi-structured interviews with 51 stakeholders in Florida, USA and found that while public sector agencies and non-governmental organisations (NGOs) typically prioritise disaster-related components relevant to their responsibilities (e.g., infrastructure restoration and environmental preservation), private stakeholders (e.g., construction firms, tourism businesses, and financial institutions) and residents tend to value those directly related to their immediate needs or concerns, such as safety and business activities. Differences in priorities exist even within the same category of stakeholders and may result from their diverse capacities to cope with disaster impacts (Dong et al., 2021; Levac et al., 2012). For example, high-income households are likely to be equipped with resources like standby generators, drinking water, food, and an emergency fund for procuring essential services (Costa et al., 2022b; Dong et al., 2021), which - compared to households with less coping capacity - make them more tolerant of (or less interested in understanding) some types of disaster impacts (e.g., drinking water supply and electricity supply; Esmalian et al., 2021).

To address these limitations, we propose a toolbox for characterising context-specific DIMs that meet relevant stakeholder needs. The DIMs toolbox (see Figure 1) includes 1) a pool of representative DIMs developed from a comprehensive literature review of disaster impacts across various contexts and a conceptual representation of how society functions, capturing holistic disaster consequences that extend far beyond direct physical damage or financial losses (e.g., loss of access to food over a period of time, impacts on well being, forced relocation, etc.); 2) a framework to facilitate the appropriate selection of DIMs from this pool (or the development of novel DIMs) for 3) application to a prescribed testbed of interest, by quantitatively assessing stakeholders' disaster-impact perspectives obtained through targeted questionnaires. The results from these targeted questionnaires are analysed through a set of statistical tests integrated within user-friendly web applications. We demonstrate the toolbox using the testbed of Kathmandu, Nepal, considering various stakeholders such as residents (especially those from vulnerable communities at risk and traditionally excluded from decision making), utility companies, consulting firms, non-governmental organisations, construction companies, researchers, government officials, insurers, etc.

We structure this paper as follows. We present the DIMs toolbox in Section 2. We then describe the details and results of the case-study application to Kathmandu, Nepal, in Section 3. We offer some concluding remarks in Section 4.

2 DIMS TOOLBOX

The DIMs toolbox is initially shaped by a stakeholder mapping process, to ensure it comprehensively reflects the breadth of different stakeholders' requirements and priorities concerning disaster impact assessment (e.g., Gregory et al., 2012; Pathak et al., 2020). The toolbox comprises three interconnected modules (see Figure 1). The pool of representative DIMs in module #1 is first developed from a comprehensive literature review of disaster impacts across various contexts and a conceptual representation of how society functions (as summarised in the DIMs pyramid, to be described later). This pool is used to develop the questionnaires of module #2, which are structured in line with the DIMs pyramid. These questionnaires are then deployed in module #3 to capture the context-specific DIMs-related perspectives of various stakeholder groups defined in the mapping process. The stakeholders' responses are analysed using a data processing package (integrated in user-friendly web applications; see supplementary materials) contained in module #2. The outputs of the data processing package include the most relevant DIMs for each targeted stakeholder group. They may also identify the importance of additional context-specific DIMs that were not covered by the original questionnaire, which would be subsequently added to the DIMs pool of module #1, for input to module #2 and further applications in module #3.

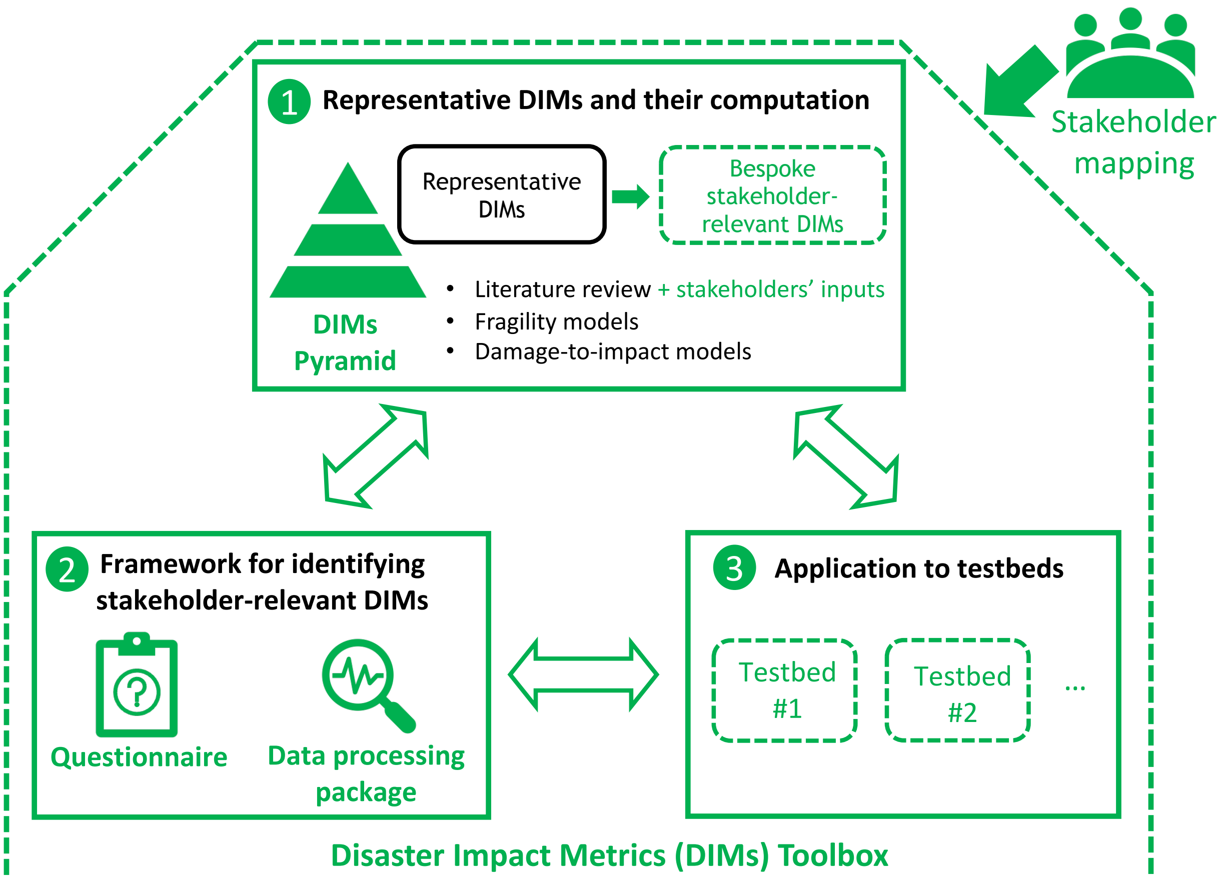

Figure 1. An illustration of the proposed disaster impact metrics (DIMs) toolbox.

2.1 Stakeholder mapping

Stakeholder mapping exercises involve identifying parties interested in the subject under investigation and understanding their specific needs (Walker et al., 2008). We use the stakeholders identified by Chang et al. (2008), Pelling et al. (2023), and Arlikatti et al. (2007) as a basis for the initial mapping process of this work. Chang et al. (2008) identified a wide range of stakeholders that represent public voices on the topic of community disaster resilience, including researchers, local and national government officials (including policymakers and emergency response staff), residents, property/business owners, and industry representatives. Pelling et al. (2023) identified a wide array of stakeholders for normative future visioning exercises (that surface aspirations for future urban environments) in Istanbul, Kathmandu, Nairobi and Quito, including civil society groups representing the urban poor, government officials at the municipal and ward (local) levels, private sector representatives (such as Chambers of Commerce), experts, academics, and journalists. Arlikatti et al. (2007) defined various stakeholder groups related to seismic risk management within the context of the USA, including federal, state and local government authorities, experts (i.e., scientists, professionals, educational institutions), watchdogs (e.g., news media, citizens' and environmental groups), industry/employers of the private sector, and households. We expand the lists of Chang et al. (2008), Pelling et al. (2023), and Arlikatti et al. (2007) through an additional investigation of further literature sources (details to follow). Our mapping process ultimately results in six representative stakeholder groups with a vested interest in disaster impact assessment (see Figure 2; note that the examples provided for each stakeholder group are non-exhaustive): residents, professionals or experts, regulatory bodies (including related agencies), utility companies, industry, and additional stakeholders that serve the public interest.

Residents are directly affected by the disaster and DRR policies informed by disaster impact assessment (e.g., Taeby and Zhang, 2019; Scolobig et al., 2015; Ikeda and Nagasaka, 2011; Egbelakin et al., 2011). Involving residents in the assessment of DIMs constitutes a people-centred approach (Cremen et al., 2023; Scolobig et al., 2015; Marchezini, 2020) that allows the voices of communities potentially at risk to be heard (e.g., Chang et al., 2008; Scolobig et al., 2015; Han et al., 2021; Cremen et al., 2023; Galasso et al., 2021). Residents may be further disaggregated into subgroups (see Figure 2) to better capture potentially diverse perspectives within this heterogeneous set of people, and to facilitate the design of policies that target a specific group (e.g., the urban poor, Wang et al., 2023b).

The other identified stakeholder groups assume various roles in DRM. For example, professionals or experts use relevant information in their practice to evaluate disaster risk and/or make policy recommendations (e.g., Ellingwood and Kinali, 2009; Sechi et al., 2022; Arlikatti et al., 2007; Yang and Zou, 2014). Regulatory bodies (and/or other related agencies) are usually in charge of policy-related decision-making on disaster risk management (e.g., Pathak et al., 2020; Peng et al., 2014; Djalante, 2012; Ellingwood and Kinali, 2009; Yang and Zou, 2014; Langenbruch et al., 2020; Dastous et al., 2008; Bostick et al., 2017; Solarino et al., 2021; Scheer et al., 2014; Markmann et al., 2013). Utility companies provide essential services (e.g., water and wastewater, electricity, telecommunication) crucial for the normal operation and post-disaster recovery of society (e.g., Esmalian et al., 2019; Guidry et al., 2015; Román et al., 2019; Guikema and Quiring, 2012; Kwasinski et al., 2009), which makes them an important stakeholder group in disaster impact assessment (e.g., Chang et al., 2008; Sapapthai et al., 2020; Baroudi and Rapp, 2014). The industry stakeholder group is liable for economic losses from disasters, which may be their own (e.g., in the case of business owners) or those transferred to them from others (in the case of insurers and reinsurers)(e.g., Pathak et al., 2020; Dastous et al., 2008; Scheer et al., 2014; Chang et al., 2008; Peng et al., 2014; Ellingwood and Kinali, 2009; Markmann et al., 2013). Additional stakeholders that serve the public interest include watchdogs for disaster risk management and those that disseminate relevant knowledge to communities (e.g., media and educational institutions; Hiroi et al., 1985; Yang and Zou, 2014; Arlikatti et al., 2007; Yamori, 2008; Solarino et al., 2021; Chang et al., 2008; Markmann et al., 2013) as well as organisations that invest in disaster risk reduction and/or participate in post-disaster rehabilitation (e.g., non-governmental organisations, international organisations, and development banks; Yang and Zou, 2014; RISK, 2003; Clarke and Dercon, 2019; Aniens and Benson, 1999; Pathak et al., 2020).

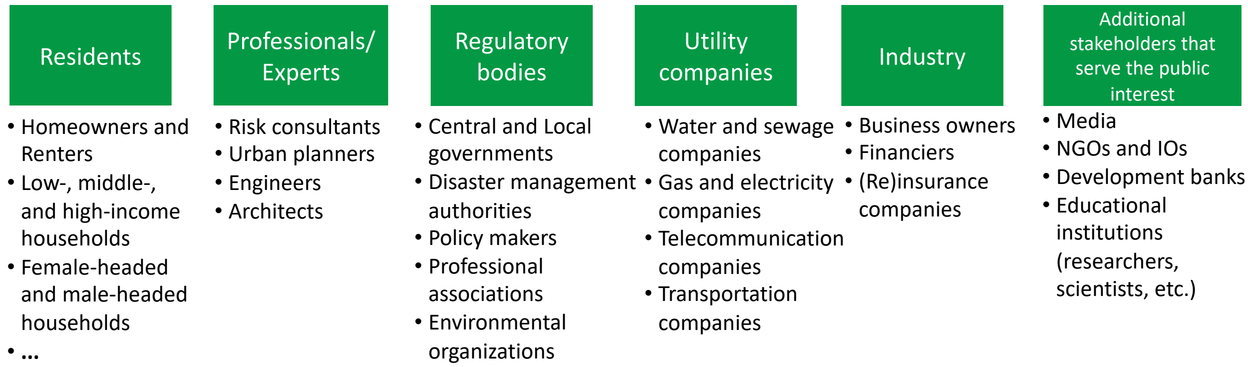

Figure 2. The results of the stakeholder mapping process. NGOs refer to non-governmental organisations and IOs refer to intergovernmental organisations. The term "regulatory bodies" also encompasses other related agencies. Note that the examples provided for each stakeholder group are non-exhaustive.

2.2 Characterising and computing representative DIMs

In line with the requirements of DRM, we define a disaster impact metric as a quantitative measurement of a specific disaster (or more general hazard-related) consequence associated with a specific spatial scale at a prescribed time instance. An example is loss of access to drinking water at the household level two weeks after a hazard event. In this case, the disaster impact of interest is loss of access to drinking water, and the specific spatial scale and temporal instance considered are, respectively, the household level and two weeks after the event. Explicitly accounting for the spatial scale helps to capture variations in disaster impacts and stakeholder requirements across the disaster-affected region (Chang and Tanner, 2022; Frazier et al., 2013) and facilitates the communication of disaster impacts to various levels of stakeholders (e.g., local businesses or national and international businesses, local government or central government; Mardian, 2022). Recognising the temporal dimension of disaster impacts acknowledges the dynamic nature of stakeholders' priorities, e.g., the longer a disaster impact persists, the less tolerable it may become (Murphy and Gardoni, 2008; Esmalian et al., 2019; Wiboonratr and Kosavisutte, 2009; Cremen, 2023). Note that some DIMs may only include a description of a specific spatial scale or a temporal instance, and the extent of space or time considered could be restricted. For example, economic losses caused by building damage at the household level are implicitly associated with the immediate aftermath of a disaster, and reduced air quality two weeks after a hazard event is only relevant at regional or broader-level spatial scales.

The list of representative DIMs is based on a conceptual representation of how society functions, which is depicted using a pyramid (herein referred to as the "DIMs pyramid"; see Figure 3). Components on the lowest level of the DIMs pyramid represent physical infrastructure (including transportation, utilities, buildings, telecommunications) and the natural environment that collectively underpin societal functions. Components on the middle level of the DIMs pyramid encompass the essential services and activities of society that are supported by the infrastructure and environment of the bottom layer. The DIMs pyramid is hierarchical by nature, i.e., each level relies on the presence of the previous one, analogous to Maslow's hierarchy of needs (Maslow and Lewis, 1987).

The structure of the DIMs pyramid is based on an extensive literature review. It exhaustively captures the nine so-called critical functions associated with coastal disaster resilience planning that were identified in Bostick et al. (2017): telecommunication, electricity, housing, transportation, port/shipping industry, clean water, tourism industry, ecosystem health, community and culture. It also reflects the four categories of "Minimum Standards for Disaster Response" proposed by Bayram et al. (2012) (i.e., health, shelter, food and nutrition, and water and sanitation) as well as the basic worldwide needs defined by Sachs (2012) (i.e., access to safe and sustainable water and sanitation, adequate nutrition, primary health services, and basic infrastructure, including electricity, roads, and connectivity to the global information network). Moreover, the DIMs pyramid shares a similar structure to the Built Environment Model proposed by Infrastructure and Projects Authority (2021), in which interconnected infrastructure systems provide the foundation for the services on which society depends, all of which are ultimately built upon the natural environment.

The DIMs pyramid conceptualises the pathway for realising disaster impacts on society, serving as a theoretical basis for the characterisation (and computation) of DIMs. In essence, DIMs are characterised by disruptions to the middle-level social and economic infrastructure, which result from damage to physical infrastructure and the natural environment on the lowest level. This damage is estimated using broadly defined ‘fragility’ models (e.g., Scawthorn et al., 2006; Kircher et al., 2006; Vickery et al., 2006, among many others). Note that the fragility of the natural environment could relate to disaster-induced changes in species abundance and composition (Nilsson and Grelsson, 1995; Meisner et al., 1987; Nilsson et al., 1991; Franz and Bazzaz, 1977). The damage information produced by fragility models is translated into disruption to (middle-level) social and economic infrastructure using models generally termed as ‘damage-to-impact’ (or ‘consequence’) (Gentile et al., 2022). For example, the damage-to-impact model in Wang et al. (2023a) estimates the number of households who relocate after an earthquake, considering damage to workplace and residential buildings as well as socio-economic factors such as household-level place satisfaction and household demographics. The damage-to-impact model proposed by Logan et al. (2023) estimates the number of people with lack of access to essential services due to physical infrastructural damage resulting from inundation caused by sea-level rise. The damage-to-impact model in Reed et al. (1984) estimates environmental disturbances resulting from oil spills on fisheries. Table 1 summarises definitions related to the lowest level of the DIMs pyramid and provides examples of associated fragility models. Table 2 provides definitions related to the middle level of the DIMs pyramid and examples of associated damage-to-impact models. For DIMs that depend on multiple middle-level components, a judgment-driven or empirical function is required to translate the outputs of damage-to-impact models into the final outcome (details to follow). This function could be, for example, the minimum or multiplication of damage-to-impact model outputs. Both the spatial scale and temporal instance of interest can influence the components of each layer considered in the conceptualisation of a DIM, as well as the types of models deployed at each calculation stage. Note that vulnerability (“hazard-to-impact”) models (e.g., Gentile et al., 2022; Yepes-Estrada et al., 2016) could be used to provide a direct path from the lowest level of the pyramid to the top, with only implicit reference to the middle level. We do not discuss these types of models further however, because this paper aims to characterise DIMs in a more fundamental sense.

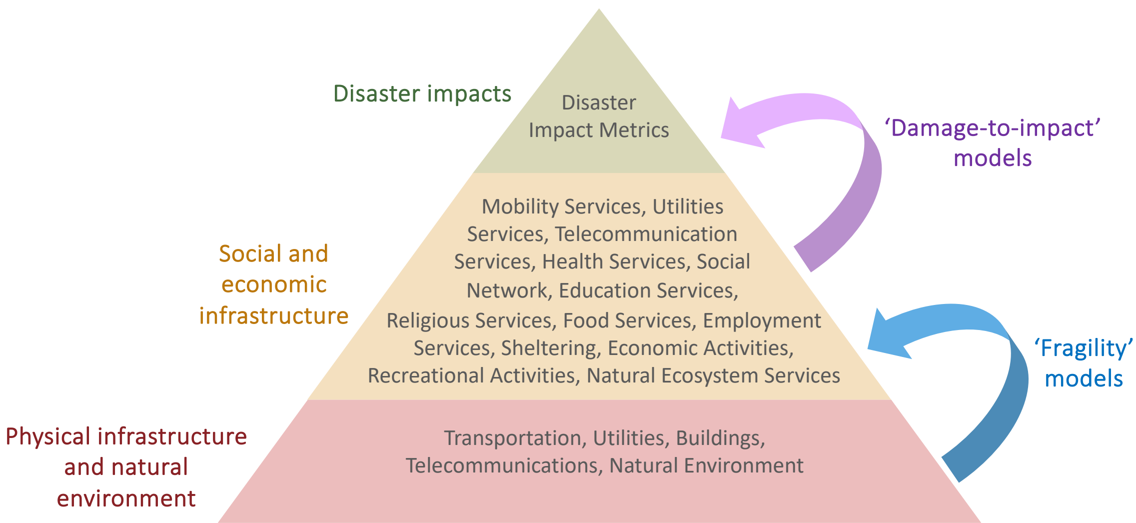

Figure 3. The proposed hierarchical DIMs pyramid for characterising and computing disaster impact metrics.

Table 1. Definition of components in the lowest level of the DIMs pyramid that represent physical infrastructure and the natural environment. Also provided are examples of fragility models for estimating associated damage. The definition of components is derived from Britannica Dictionary (2024) and Vocabulary (2024) unless otherwise specified.

Component	Definition	Example fragility models
Transportation	Various systems and/or associated infrastructure components (e.g., roads, tunnels, bridges, airports, railways, etc.) by which the movement of persons and goods from place to place is accomplished.	Nocera et al. (2018); Cantillo et al. (2019); Freckleton et al. (2012); Chen et al. (2015); Guo et al. (2017); Matini et al. (2022)
Utilities	Infrastructure systems supporting public services related to electricity, water, gas, sewage, etc.	Iannacone et al. (2022); Zhang et al. (2020, 2022); Costa et al. (2019); Mohagheghi and Javanbakht (2015); Hou et al. (2019); Kwasinski et al. (2009); Hossain et al. (2021); Mazumder et al. (2022)
Buildings	All types of structural assets (e.g., a house, hospital, school, etc.) with a roof and walls that are used as a place for people to live, work, do activities, store things, etc.	Kircher et al. (2006); Vickery et al. (2006); Scawthorn et al. (2006)
Telecommunication	Infrastructure systems supporting communication over a distance by cable, telegraph, telephone, or satellite.	Kwasinski et al. (2009); Patricelli et al. (2009); Parajuli and Haynes (2016); Cardoni et al. (2022); De Iuliis et al. (2021)

Natural environment	Natural resources, natural habitats, natural ecosystems that exist within nature as well as green infrastructure. It provides food, water, fuel, clean air and other services crucial for sustaining life and well-being (The Chartered Institution of Water and Environmental Management, 2024).	Nilsson and Grelsson (1995); Meisner et al. (1987); Nilsson et al. (1991); Dosi (2001); King et al. (2005); Sun et al. (2015)

Table 2. Definition of components in the middle-level of the DIMs pyramid that represent social and economic infrastructure. Also provided are examples of damage-to-impact models for estimating the disruption to each component. The definition of components is derived from Britannica Dictionary (2024) and Vocabulary (2024) unless otherwise specified.

Component	Definition	Associated physical infrastructure and/or natural environment	Example damage-to-impact models
Mobility services	Services that are supported by transportation systems, and transport passengers from place to place via one or more transport modes, e.g., private car, car sharing and rental, underground, rail, bus, bike, motorbikes, taxi, etc.	Transportation	Aschenbruck et al. (2007); Chang and Tanner (2022); Bhattacharjee and Baker (2023); Boakye et al. (2022); Silva-Lopez et al. (2022); Horner and Widener (2011); Wei and Mukherjee (2022); Zamanifar and Hartmann (2021); Horner and Widener (2011)
Utility services	Services supported by utility systems. For example, the provision of water and wastewater services, electricity, natural gas, etc.	Utilities	Costa et al. (2022b); Balaei et al. (2021); Brozović et al. (2007); Opabola and Galasso (2023); Purwar et al. (2020); Chambers et al. (2021); Mitra et al. (2021); Romero et al. (2010); Tabucchi et al. (2010)
Telecommunication services	Services supported by telecommunication systems. For example, the provision of a landline service, cellular services, broadcast services, and internet services.	Telecommunication	Jrad et al. (2004); Van Wyk and Starbird (2020); O'Reilly et al. (2006); Marshall et al. (2023); Mohamadi et al. (2019)
Health services	The provision of medical care by doctors, dentists, and psychologists via hospitals, clinics, remote consultation, etc.	Transportation, Utilities, Buildings, Telecommunication	Alisjahbana et al. (2022a); Ceferino et al. (2020); Jacques et al. (2014); Hu et al. (2015); Friedman et al. (2022); Suk et al. (2020)

Social network	The inherent social fabric of communities bonded via community assets and social ties, e.g., family, neighbours, friends, co-workers (Wellman and Wortley, 1990).	Transportation, Utilities, Buildings, Telecommunication	Costa et al. (2022c); Wang et al. (2023a); Costa et al. (2022a); Nejat et al. (2020); Miles and Chang (2011)
Education services	The provision of systematic instruction, especially at a school, college, or university (in-person and online).	Transportation, Utilities, Buildings, Telecommunication	Alisjahbana et al. (2022b); Nouri et al. (2011); Esnard et al. (2018); Shiwaku and Shaw (2016); Shiwaku et al. (2016); Anelli et al. (2019)
Religious services	Services supporting the act of public worship following prescribed rules.	Utilities, Buildings, Telecommunication	Ngwacho (2020); Aten and Topping (2010); Strader et al. (2019)
Food services	The provision of nutritious substances that people eat or drink to maintain life and growth (including drinking water).	All	Horner and Widener (2011); Rathore et al. (2021); Altay and Ramirez (2010); Nozhati et al. (2019); Zeuli et al. (2018)
Employment services	The provision of jobs and stable sources of livelihood.	All	Hulsey et al. (2022); Sarnosky et al. (2022); Nocera and Gardoni (2019); Cremen et al. (2020); Liu et al. (2020); Qiu et al. (2018)
Sheltering	The provision of housing (place to live) on different timescales, including permanent homes, temporary housing, and public shelters.	Utilities, Buildings	Wang et al. (2022); Costa et al. (2022a); Nappi et al. (2019); Zhao et al. (2017); Vecere et al. (2017); Chen et al. (2013)
Economic activities	Processes that lead to the manufacture of goods or the provision of services (Eurostat, 2024). Disaster impacts on economic activities can lead to direct economic loss to business owners (as well as relevant employees) and wider indirect economic loss. The economic loss due to direct property or infrastructure damage (e.g., replacement cost of a house) is also included.	All	Cremen et al. (2020); Costa and Baker (2021); Markhvida and Baker (2023); Markhvida et al. (2020); Nocera and Gardoni (2019); Wu et al. (2012); Mao et al. (2020); Hallegatte (2008); Chiou et al. (2013); Martins et al. (2016)

Recreational activities	Discretionary activities that people do to refresh their bodies and minds and make their leisure time enjoyable. Examples of recreational activities are hiking, swimming, camping, meditation, reading, playing games and dancing (National Center for Biotechnology Information, 2024).	All	Sandifer et al. (2017); Gertler et al. (2015); Whitworth and May (2006); Faaui et al. (2017); Zhu et al. (2019); Kauppila and Karjalainen (2012); Thomas et al. (2013)
Natural ecosystem services	Conditions and processes through which the natural environment (ecosystems, and the species that comprise them) sustain and fulfil life. Natural ecosystem services regulate and support the functioning of built environments. These services include, e.g., provision of clean air, flood management, water purification, provision of natural habitats for wildlife (Scotland's Nature Agency, 2023).	Natural environment	Ascott et al. (2016); Rui et al. (2018); Sandifer et al. (2017); Dang et al. (2018); Yang et al. (2015); Chiang et al. (2014); Nelson et al. (2013); Reed et al. (1984)

Figure 4 provides an example of how the DIMs pyramid facilitates the characterisation and computation of a DIM, which is loss of access to food at the household level two weeks after an event of interest. A household's access to food at this time instance primarily relates to food services, but is simultaneously dependent on mobility services (which enable the household to reach a grocery store; Nozhati et al., 2019; Smith and Frankenberger, 2018), utility services (that facilitate food preservation; Nozhati et al., 2019), employment services (that enable food to be affordable; Naqvi and Monasterolo, 2021), telecommunication services (that allow households to receive information on the availability of food retailers and disaster relief goods; Zhong et al., 2022; Swanson and Guikema, 2023), and sheltering (that facilitate food preparation; Kim et al., 2021). These services ultimately depend on different physical infrastructure and/or the natural environment. For example, food services are supported by buildings (e.g., food retailers, factories), the natural environment (that creates the conditions necessary for avoiding food-related contamination and for crop and livestock farming; Zeuli et al., 2018), transportation, utilities, and telecommunication (e.g., for the smooth running of, and coordination with, the food supply chain; Reddy et al., 2016; Okumura, 2012). Once the pathway for characterising the DIM of interest has been identified, its calculation can be performed using a bottom-up approach. Physical damage is first calculated using appropriate fragility models for buildings (e.g., those related to food retailers, residential buildings, workplaces; Baker et al., 2021), transportation infrastructure (e.g., Nocera et al., 2018; Cantillo et al., 2019), utility infrastructure (e.g., Iannacone et al., 2022; Zhang et al., 2020; Costa et al., 2019; Hossain et al., 2021), telecommunication infrastructure (e.g., Kwasinski et al., 2009; Cardoni et al., 2022), and the natural environment (e.g., Meisner et al., 1987; Sun et al., 2015). These damages are then translated, using damage-to-impact models, into two-week disruptive effects on food services (e.g., Horner and Widener, 2011; Rathore et al., 2021), mobility services (e.g., Horner and Widener, 2011; Silva-Lopez et al., 2022), utility services (e.g., Costa et al., 2022b; Opabola and Galasso, 2023; Brozović et al., 2007), telecommunication services (e.g., O'Reilly et al., 2006; Van Wyk and Starbird, 2020), employment services (e.g., Nocera and Gardoni, 2019; Hulsey et al., 2022; Sarnosky et al., 2022), and sheltering (e.g., Wang et al., 2022; Zhao et al., 2017; Vecere et al., 2017). These disruptions are finally synthesised into the DIM using some judgment-driven or empirical function. For example, Nozhati et al. (2019) considered food security (i.e., the opposite of loss of access to food) as the intersection (∩) of food availability (relying on the functionality of a household's home and a food retailer), accessibility (relying on the functionality of mobility services between households and food retailers), and affordability (relying on the functionality of employment services).

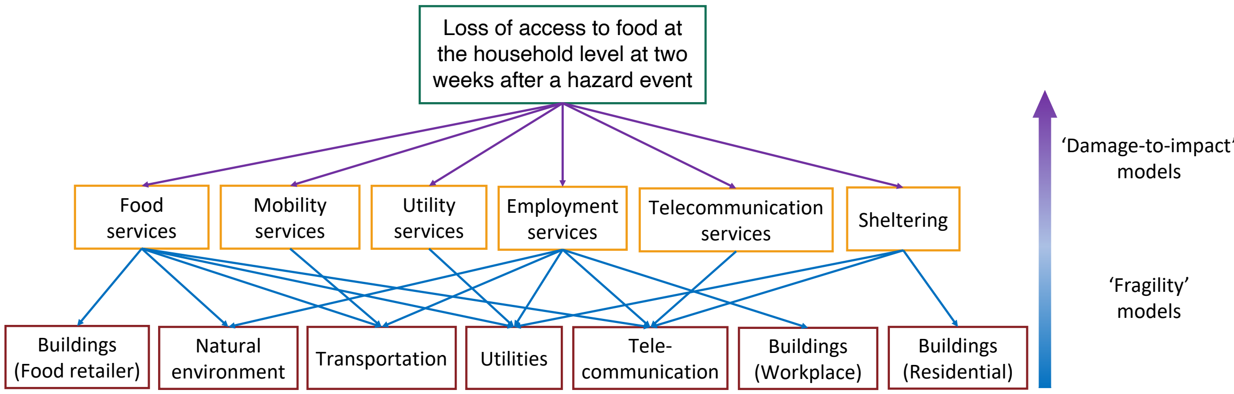

Figure 4. Using the DIMs pyramid to facilitate the characterisation and computation of a specific DIM, which is loss of access to food at the household level, two weeks after a hazard event.

2.3 Framework for identifying stakeholder-relevant disaster impact metrics

The second module of the DIMs toolbox contains questionnaires that are developed and structured based on the contents of module #1. These questionnaires are used to collect quantitative disaster-impact perspectives of different stakeholder groups identified in the stakeholder mapping process. Module #2 also contains a data processing package (integrated within web applications in *R Shiny* - see supplementary material; Chang et al., 2023) to perform various statistical analyses on the questionnaire responses. These statistical analyses are used to understand the perceived importance of characterising and computing different DIMs over varying spatial scales and temporal instances across stakeholder groups.

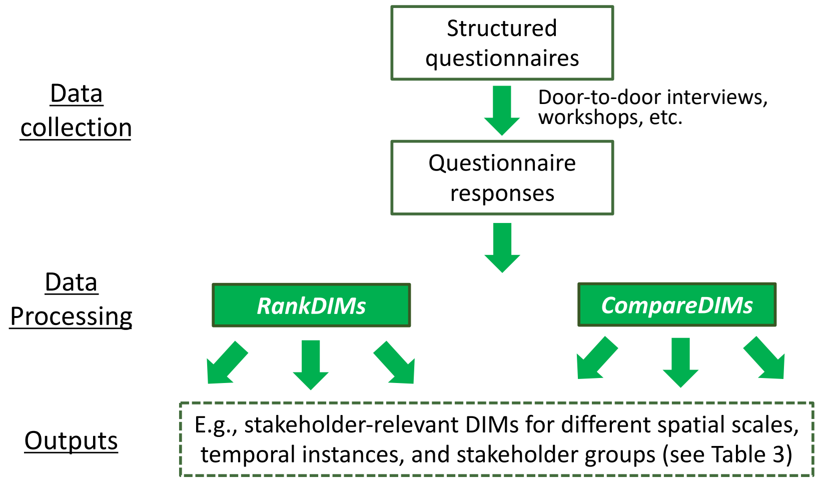

Figure 5. A framework for identifying stakeholder-relevant DIMs. The framework leverages structured questionnaires and *R*-based web applications developed for statistical analyses: ***'RankDIMs'*** and ***'CompareDIMs'***.

2.3.1 Structured questionnaire

The questionnaire consists of three sections (see supplementary materials). Section A records socioeconomic and demographic information on respondents as well as their households (for residential stakeholders) or background information on the associated organisation or company, its staff, or its beneficiaries (for all other stakeholders). This information includes, for example, the area in which the respondent resides in or serves (rural or urban areas; Mitsova et al., 2018), household income bracket (Cutter et al., 2003), the age group of household members or staff (Paul and Routray, 2011), the gender of the household head (Cutter et al., 2003; Flatø et al., 2017), the size of the household or the organisation/company (Cutter et al., 2003; Ivancevich et al., 1998), and the number of persons with special needs within the household or the organisation/company (Cutter et al., 2003). Section A is included because it provides information that can lead to the definition of more precise subgroups within the broad groups of stakeholders defined as part of the mapping process (see Figure 2).

Section B asks respondents to provide their perspectives on (i.e., importance scores for) each DIM, using a scale from -1 to 4 (see Table 3), with higher values indicating higher importance and -1 indicating irrelevance. This scale has proven useful for attitude and perspective measurement (Oppenheim, 2000; Boynton and Greenhalgh, 2004). Section B is divided into two parts, in line with the DIMs pyramid (see Figure 3). Part I contains questions about disaster impacts on the natural environment (whereas damage to physical infrastructure is implicitly captured via questions related to the resultant economic loss in Part II), corresponding to the lowest level of the DIMs pyramid. Part II includes questions about disaster impacts on social and economic infrastructure, corresponding to the middle level of the DIMs pyramid. Section B questions are based on the list of representative DIMs formulated in module #1. They currently capture 59 disaster impacts, three spatial scales of analyses (household, neighbourhood, i.e., a geographically localised community within a larger city, town, suburb or rural area, and region, i.e., a city-size area) and two temporal instances (two weeks and six months, corresponding to short-term emergency response and intermediate recovery phases, respectively; Department of Homeland Security, 2016). The questionnaire also allows respondents to specify the maximum duration for which different disaster impacts can be tolerated, if the respondents do not consider the disaster impacts to be relevant at the specified temporal instances. Section C invites respondents to define and provide an importance score for additional DIMs not considered in

Section B. The questionnaire is adaptable to the specific context of interest; ideally, a unique version of the questionnaire should be developed for each stakeholder group and the specific lens of interest (e.g., whether an organisation is providing perspectives in relation to its employees or those that it serves).

Table 3. Different opinions on disaster impact metrics and the associated importance score.

Not relevant	Unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Important
-1	0	1	2	3	4

2.3.2 Data processing package

Module #2 integrates two interactive web applications (using the *Shiny* package in *R*) that can be leveraged to perform statistical analyses on questionnaire responses. ***RankDIMs*** produces relative measurements of importance and can be used to understand stakeholders' priorities at different spatial scales and temporal instances. ***CompareDIMs*** then determines whether absolute changes in importance across different spatial scales, temporal instances, and stakeholder groups are statistically significant. Table 4 summarises examples of outputs produced by the data processing package.

Table 4. Examples of outputs produced by the data processing package. Note that n_{cus} and n_{sub} are end-user defined integers.

Examples of output	Description
Q1	At a specific temporal instance after a hazard event, what are the top n_{cus} most important disaster impacts for a specific spatial scale of analysis, and how do these results change when varying emphasis is placed on the perspectives of different stakeholder groups.
Q2	How does the importance of a specific disaster impact change across different considered spatial scales and temporal instances.
Q3	How much collective importance is captured by a subset of DIMs (containing n_{sub} entries).
Q4	For a specific disaster impact and temporal instance, is there a statistically significant difference in the importance at different spatial scales.
Q5	For a specific disaster impact and spatial scale, is there a statistically significant difference in the importance at different temporal instances.
Q6	What is the sample size (i.e., number of responses) necessary to draw conclusive results from the previous outputs with a specified confidence level for a given statistical hypothesis test.

RankDIMs determines the rankings of all DIMs included in the questionnaire according to the average weighted importance score, S_{DIM_i}, given by:

$$S_{DIM_i} = \sum_{j=1}^{N_g}[w_j \cdot \sum_{l=1}^{n_j}(w_{j,l} \cdot \frac{\sum_{p=1}^{n_{j,l}} S_{DIM_{i,j,l,p}}}{n_{j,l}})] \quad (1)$$

where DIM$_i$ is the ith DIM considered, w_j is the weight placed on the jth stakeholder group ($\sum_{j=1}^{N_g} w_j = 1$), N_g is the number of stakeholder groups ($1 \leq N_g \leq 6$; this number should be determined for the specific context of interest), n_j is the number of subgroups in the jth stakeholder group (see Figure 2 for examples of subgroups within each stakeholder group), $w_{j,l}$ is the weight placed on the lth subgroup within the jth stakeholder group ($\sum_{l=1}^{n_j} w_{j,l} = 1$), $n_{j,l}$ is the number of participants in the lth subgroup within the jth stakeholder group, $S_{DIM_{i,j,l,p}}$ is the importance score for the ith DIM given by the pth participant in the lth subgroup within the jth stakeholder group. w_j and $w_{j,l}$ reflect how much the end user values the perspectives of each stakeholder group (and corresponding subgroups) in a relative sense. The weights could be determined using, for example, the Analytic Hierarchy Process (Saaty, 1988). This procedure requires the end users to perform a series of pairwise comparisons for each stakeholder group (as well as any subgroups within it), based on qualitative descriptions of relative importance that are measured on a numeric scale. S_{DIM_i} is therefore determined from all stakeholder groups (and subgroups) in line with how many stakes they hold. ***RankDIMs*** creates separate ranking lists for each combination of spatial scale and temporal resolution, to ensure meaningful and fair comparisons between DIMs.

RankDIMs produces two other metrics: the positive importance ratio, I_{pos}, and the total importance ratio, I_{tot}, which quantify how much importance is captured by a specific subset of DIMs (analogous to the percentage of variance or information represented by each principle component in principle component analysis, Ringnér, 2008). I_{pos} captures only positive perceptions of importance, whereas I_{tot} accounts for all perceptions of importance. Both metrics exclude irrelevant DIMs (i.e., with $S_{DIM_i} < 0$). They can be written as

$$I_{pos} = \begin{cases} \frac{\sum_{k=1}^{n_{sub,pos}} (S_{DIM_k} - 2)}{\sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2)} & if \sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2) > 0 \\ 0 & if \sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2) = 0 \end{cases} \tag{2}$$

$$I_{tot} = \begin{cases} \frac{\sum_{k=1}^{n_{sub,rel}} S_{DIM_k}}{\sum_{i=1}^{n_{tot,rel}} S_{DIM_i}} & if \sum_{i=1}^{n_{tot,rel}} S_{DIM_i} > 0 \\ 0 & if \sum_{i=1}^{n_{tot,rel}} S_{DIM_i} = 0 \end{cases} \tag{3}$$

where $n_{sub,pos}$ is the number of DIMs in the customised subset with $S_{DIM_i} > 2$ (since 2 indicates "neither important nor unimportant"; see Table 3), $n_{sub,rel}$ is the number of DIMs in the customised subset with $S_{DIM_i} \geq 0$ (and n_{sub} is the total number of DIMs in this subset), $n_{tot,pos}$ is the total number of DIMs considered with $S_{DIM_i} > 2$, $n_{tot,rel}$ is the total number of DIMs considered with $S_{DIM_i} \geq 0$ (and n_{tot} is the total number of DIMs considered), and S_{DIM_k} is as previously defined. The outputs of ***RankDIMs*** can shed light on the disaster impacts that should be prioritised in future DRR policy making, for instance. They ultimately help to inform the level of computational resources required for modelling DIMs (Nocera and Gardoni, 2022; Ujjwal et al., 2019).

CompareDIMs performs two statistical hypothesis tests - Welch's Analysis of Variance (ANOVA; Liu, 2015) and Welch's two-sample t-test (Derrick et al., 2016) - on varying numbers of S_{DIM_i} values. These values can correspond to two separate DIMs or the same DIM for two different stakeholder groups; in the former case, w_j in equation 1 is quantified to reflect the number of participants per stakeholder group and in the latter case, it is set to 1. Welch's ANOVA is used to test whether three or more S_{DIM_i} values are different with statistical significance. A common threshold for statistical significance is 0.05 (Greenland et al., 2016). Welch's two-sample t-test is used to test whether two S_{DIM_i} are different with statistical significance. This test assumes that the sample S_{DIM_i} values being compared are normally distributed but does not require equal variances. The implementation of this test within the ***CompareDIMs*** application also includes power analyses that determine the extent to which the sample sizes are large enough to produce the correct test outcome (Cohen, 1992). The common threshold for power analyses is 0.80 when a 0.05 significance level is used (Greenland et al., 2016).

The hypothesis test outputs of ***CompareDIMs*** help end users to better understand the spatial resolution and temporal instances for which disaster impacts and associated policies should be modelled/designed and whether opinions on these differ across stakeholder groups. The power analyses can be used to estimate how many samples (questionnaire responses) are required to reach a certain confidence level in the test results.

3 APPLICATION TO A TESTBED: KATHMANDU, NEPAL

We showcase module #3 using Kathmandu, Nepal, as the selected testbed. The Kathmandu Valley is prone to various natural hazards (e.g., earthquakes, floods, droughts). It also features evolving urban development, a growing population, and high social and physical vulnerabilities (Mesta et al., 2022).

3.1 Stakeholder mapping

We target relevant stakeholders based on the six stakeholder groups determined in Section 2.1 (see Figure 2). Specific stakeholders are identified from the internal database of the National Society of Earthquake Technology - Nepal (NSET), which was developed during previous NSET-led participatory processes related to DRM. We recruit 90 stakeholders in total. For the purposes of the questionnaire (details to follow) and given the relatively small sample size, stakeholders are classified as either “residents”, if they belong to the first stakeholder group (50 in total), or “other stakeholders’, if they belong to one of the remaining five stakeholder groups (40 in total). We establish this division based on the distinct, typically passive (non-decision-making, Pelling, 1998) roles that residents traditionally play in disaster planning (e.g., receiving education on disaster risks, benefitting from DRR policies; Mitchell et al., 2008; Yamori, 2008) compared to all other stakeholders that assume various active roles, including overseeing and managing emergency response and DRR efforts.

The spatial distribution of the recruited residents is roughly even across the Kathmandu Valley. They collectively span all demographic and socioeconomic categories included in the questionnaires, i.e., household income, age of the stakeholder and the household head, household size, number of people with special needs, number of elderly people, number of people under 18, housing tenure status, housing type, occupation, education level. The other stakeholders represent various sectors/fields/industries, such as consulting firms, construction and contractor companies, architectural and structural design companies (classed professional or experts), non-governmental organisations working on DRM, universities, and community services (classed additional stakeholders that serve the public interest), electricity companies (classed utility companies), government departments (e.g., Department of Roads; i.e., regulatory bodies; and Ministry of Water Resources; classed as regulatory bodies and utility companies), local (ward) government (classed as regulatory bodies), manufacturing companies and insurance companies (classed as industry). The “other stakeholder” participants are primarily high-level personnel (i.e., managers or chief officers of companies or organisations) to ensure they can accurately represent the perspectives of their companies or organisations. Figure 6 provides the number of participants in each stakeholder group within the broad category of other stakeholders.

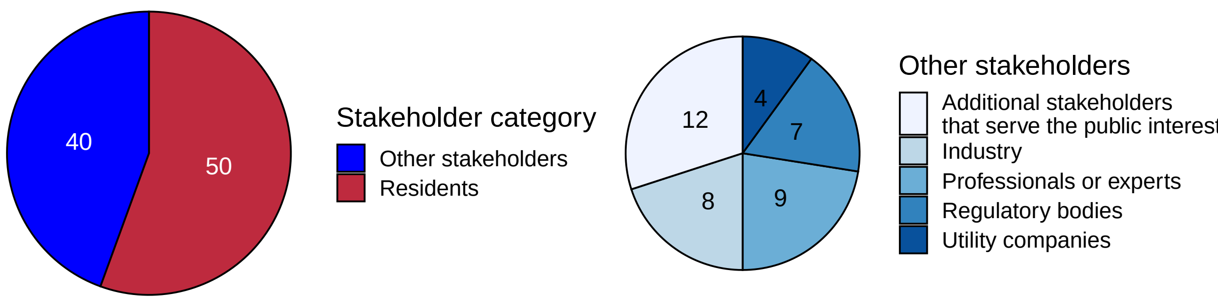

Figure 6. The number of recruited stakeholders in each stakeholder group.

3.2 Structured questionnaire

We develop separate versions of the questionnaire for each stakeholder category (see Figure 7). The 'Residents' questionnaire (see Figure 7) considers the interests of residents. The 'Other stakeholders' questionnaire considers the interests of people they serve. The questionnaires are tailored to the specific context of Kathmandu, Nepal. For example, localised income brackets and educational attainment categories are included in Section A of the questionnaires. The questionnaires were originally developed in English and translated into Nepali.

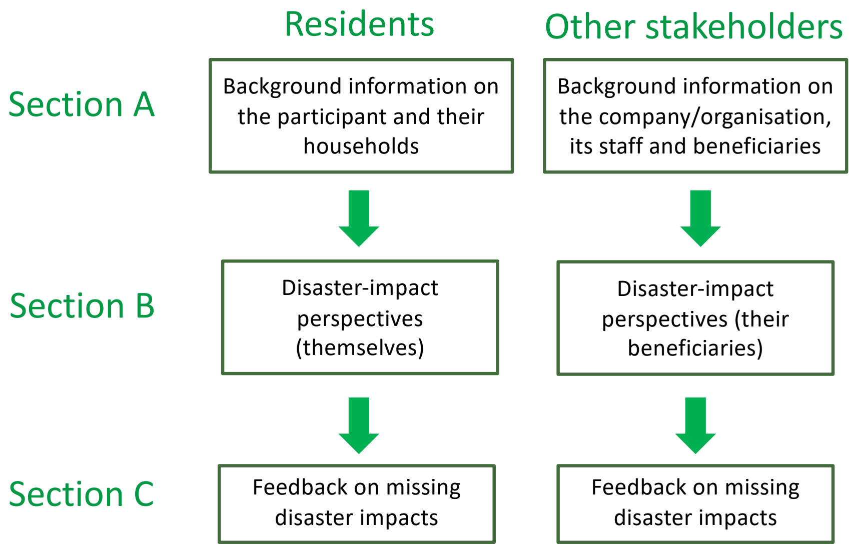

Figure 7. The structure of the two questionnaires developed to capture disaster-impact perspectives of various stakeholders.

3.3 Data processing

We transcribe the questionnaire response data into tibbles (Müller and Wickham, 2023), a common data structure in *R*, and perform statistical analyses using ***RankDIMs*** and ***CompareDIMs***. The ranking of DIMs and calculation of I_{pos} and I_{tot} presented in this section are performed only considering DIMs that capture the same spatial scale and temporal instance. DIMs that only include a description of a specific temporal instance (i.e., immediately after a hazard event) are ranked along with DIMs that capture disaster impacts two weeks following a hazard event. We do not divide the two categories into subgroups in these calculations, i.e., $n_j = 1$ for both stakeholder categories.

Figure 8 provides the top $n_{cus} = 25$ highest ranked disaster impacts at the household level two weeks following a hazard event and the associated S_{DIM_i} values, given that $w_1 = w_2 = 0.5$ for residents and other stakeholders. The top five highest-ranked household-level disaster impacts are, in descending order, fatalities, loss of access to drinking water, loss of access to food, acute severe injuries, and permanent loss of connection with family members. Economic loss due to building damage, typically representing the primary focus of conventional disaster impact assessments, is ranked 21^{st}, preceded by loss of access to water (6^{th}), electricity (7^{th}), and required healthcare (8^{th}), food contamination (9^{th}), loss of access to cellular services (10^{th}), homelessness (11^{th}), communicable diseases (12^{th}), and uninhabitable living conditions (13^{th}), for instance. Other highly ranked disaster impacts include loss of access to sewage treatment services (14^{th}), clean air (15^{th}), community assets (17^{th}), and WiFi services (18^{th}), voluntary relocation (16^{th}), impact on mental well-being (19^{th}) and temporary loss of connection with family members and friends (20^{th}). These results reinforce the need to go beyond simply considering direct physical damage and economic losses in disaster impact assessments.

When higher priority is placed on the perspectives of residents (i.e., $w_1 = 0.7$ for residents and $w_2 = 0.3$ for other stakeholders; see Figure 9), the top 25 most important DIMs remain almost the same, but change in ranking. For example, loss of access to clean air drops from 15^{th} to 18^{th} most important. This is because other stakeholders collectively rank this disaster impact as the 9^{th} most important, whereas residents rank it as the 29^{th} most important.

Figure 10 provides the top n_{cus} = 25 highest ranked disaster impacts at the household level six months following a hazard event as well as their associated S_{DIM_i} values, given that $w_1 = w_2 = 0.5$ for both residents and other stakeholders. It can be seen that the ranking of disaster impacts at a specific spatial scale can change over time. For example, the ranking of loss of access to clean air and community assets at the household level increases at six months (6^{th} and 9^{th}, respectively) relative to two weeks (15^{th} and 17^{th}, respectively). A similar trend is observed for the loss of access to utility services and telecommunication services, including water (6^{th} to 2^{nd}), electricity (7^{th} to 3^{rd}), sewage treatment (14^{th} to 1^{st}), cellular (10^{th} to 5^{th}), and forced temporary rehousing (22^{th} to 19^{th}). The ranking of loss of access to drinking water at the household level drops at six months (7^{th}) compared to two weeks (2^{nd}). These changes in importance rankings reflect the time-dependent nature of stakeholders' priorities that should be accounted for in disaster impact assessments.

Figures 11 and 12 provide the top n_{cus} = 25 highest-ranked disaster impacts at the neighbourhood and region level, respectively, two weeks after a hazard event, given that $w_1 = w_2 = 0.5$ for residents and other stakeholders. The results indicate that the ranking of a disaster impact at a specific temporal instance can change over different spatial scales. For example, fatalities are the most important disaster impact at the household level two weeks after a hazard event, but its ranking drops to 5^{th} at the neighbourhood level and 9^{th} at the regional level. A similar trend is observed for severe acute injuries, which are ranked 4^{th}, 4^{th}, and 11^{th} at the household, neighbourhood, and region level, respectively.

Figures 8, 9, 10, 11, and 12 indicate that disaster impacts related to the natural environment (e.g., reduced air quality, damage to green infrastructure, and loss of natural habitats) are also considered important by stakeholders, in addition to those related to ecosystem services (e.g., access to clean air). These results reflect the intrinsic value of the natural environment to stakeholders (independent of its functionalities to human society; Chan et al., 2016), which is generally not considered in conventional disaster impact assessments.

Figure 13 shows I_{pos} (left panel) and I_{tot} (right panel) for household, neighbourhood, and region spatial scales, plotted as a function of n_{cus} (= n_{sub} in Eqs. 2 and 3), at two weeks (solid lines) and six months (dashed lines) after a hazard event (assuming $w_1 = w_2 = 0.5$ for both categories). The top n_{cus} = 25 highest-ranked disaster impacts at the household, neighbourhood, and region level two weeks after a hazard event lead to an I_{pos} of 0.92, 0.77, and 0.71, respectively, and an I_{tot} of 0.65, 0.54, and 0.53, respectively. Similarly, the top n_{cus} = 30 (= n_{sub}) highest-ranked disaster impacts two weeks after a hazard event lead to an I_{pos} of 0.98, 0.85, and 0.80, and an I_{tot} of 0.76, 0.63, and 0.62, respectively. Both I_{pos} and I_{tot} decrease as the spatial scale increases from household to neighbourhood and region. This is because stakeholders perceive fewer household-level disaster impacts as important than those on larger spatial scales (i.e., neighbourhood and region). For example, for a desired I_{pos} of 0.80 two weeks after a hazard event, end users only need to focus on the top 20 highest-ranked disaster impacts at the household level, but the top 27 or 30 highest-ranked disaster impacts at the neighbourhood or region level, respectively.

The results of ***CompareDIMs*** are first computed for disaster impacts at the three considered spatial scales and a prescribed temporal instance, considering both stakeholder groups collectively. S_{DIM_i} values for fatalities (immediately following a hazard event) at the household, neighbourhood, and region level are 3.71, 3.34, 3.30, and their differences are found to be statistically significant (p-value = 0.03). The S_{DIM_i} value for fatalities at the household level is statistically different from that at the neighbourhood (p-value = 0.04), and region level (p-value = 0.02), but the neighbourhood-level S_{DIM_i} value is not statistically different from that at the region level (p-value = 0.84). These findings imply that both stakeholder categories value fatalities at the household level more than those at the neighbourhood and region level and, therefore, that the household level is the right spatial scale of analyses. However, the power analyses provide a value of 0.54 for the comparison between household- and neighbourhood-level S_{DIM_i} values and 0.64 for the comparison between household-and regional-level S_{DIM_i} values, which are below 0.80. Therefore, the previous conclusion on appropriate modelling resolution should be disregarded until more stakeholder responses are collected to improve the statistical power. To have a power of at least 0.80 under a 5% significance level, the number of responses included in household- and neighbourhood-level S_{DIM_i} values need to be respectively greater than or equal to 165 and 158 for their comparison, and the number of responses included in household- and regional-level S_{DIM_i} values must be at least 130 and 116 for their comparison. Among the 59 disaster impacts considered in this application, none are associated with statistically different S_{DIM_i} values across the three considered spatial resolutions (i.e., a p-value < 0.05 and, possibly, a statistical power > 0.80) for both Welch's two-sample t-test and Welch's ANOVA. This pilot study can be a basis for deciding the number of participants to recruit for future studies.

We also leverage ***CompareDIMs*** to test whether the S_{DIM_i} values of a disaster impact with a specific spatial resolution are different with statistical significance at two temporal instances (i.e., two weeks and six months after a hazard event). In this case, we compute separate S_{DIM_i} values for both stakeholder categories and compare the results obtained. S_{DIM_i} values for loss of access to clean air at the household level two weeks after a hazard event are statistically different (S_{DIM_i} = 2.45, ranked 29^{th}; see Figure 14) compared to those at six months (S_{DIM_i} = 3.50, ranked 10^{th}), in the case of the resident stakeholder category. The associated p-value is less than 0.01, and statistical power is 0.98. However, the same outcome is not produced for the other stakeholders (S_{DIM_i} = 3.39 for two weeks and S_{DIM_i} = 3.74 for six months, with p-value < 0.05 but statistical power equal to 0.51). Conversely, S_{DIM_i} values for forced temporary rehousing at the household level two weeks after a hazard event (S_{DIM_i} = 2.77, ranked 21^{st}; see Figure 14) are statistically different to those at six months (S_{DIM_i} = 3.61, ranked 10^{th}), for the other stakeholders (with p-value < 0.01 and statistical power equal to 0.80). This statement does not hold for the same S_{DIM_i} values computed only for the resident stakeholder category. Some other disaster impacts do produce statistically significant S_{DIM_i} values for both stakeholder categories at two weeks and six months, e.g., loss of access to community assets (see Figure 14). In addition, we leverage ***CompareDIMs*** to test whether the S_{DIM_i} values of a disaster impact with a specific spatial resolution and a prescribed temporal instance for two stakeholder categories are different with statistical significance. For example, S_{DIM_i} values for loss of access to clean air at the household level two weeks after a hazard event for the resident stakeholder category are statistically different to those associated with the other stakeholders (S_{DIM_i} = 2.45 and S_{DIM_i} = 3.39, respectively, p-value < 0.01, and statistical power is 0.96). These findings further emphasise the need to explicitly account for time and identity in the characterisation of DIMs where possible, as different stakeholder groups can have distinct and unique (e.g., time-dependent) requirements regarding the disaster impacts to be assessed.

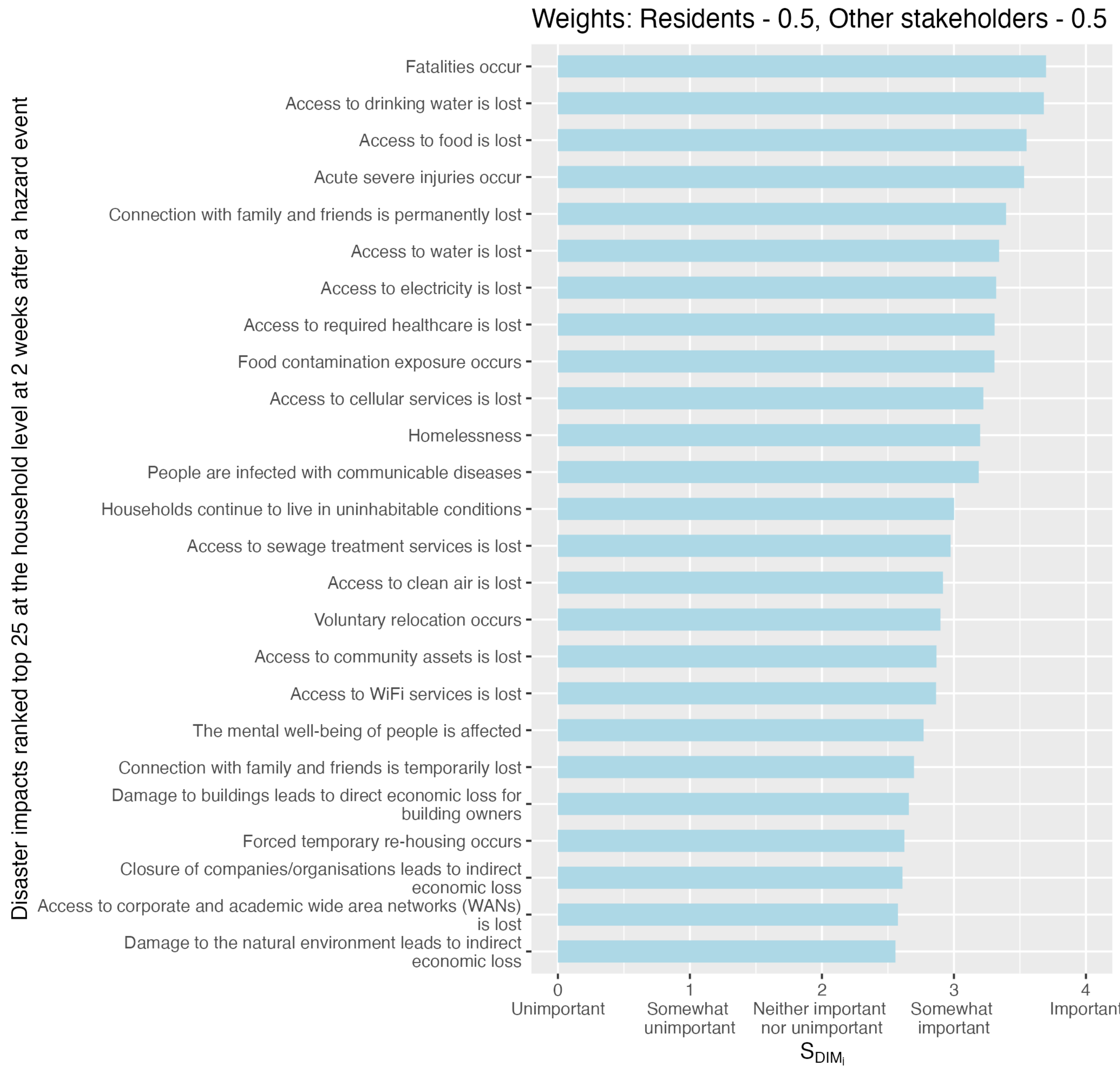

Figure 8. The top 25 highest-ranked disaster impacts at the household level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

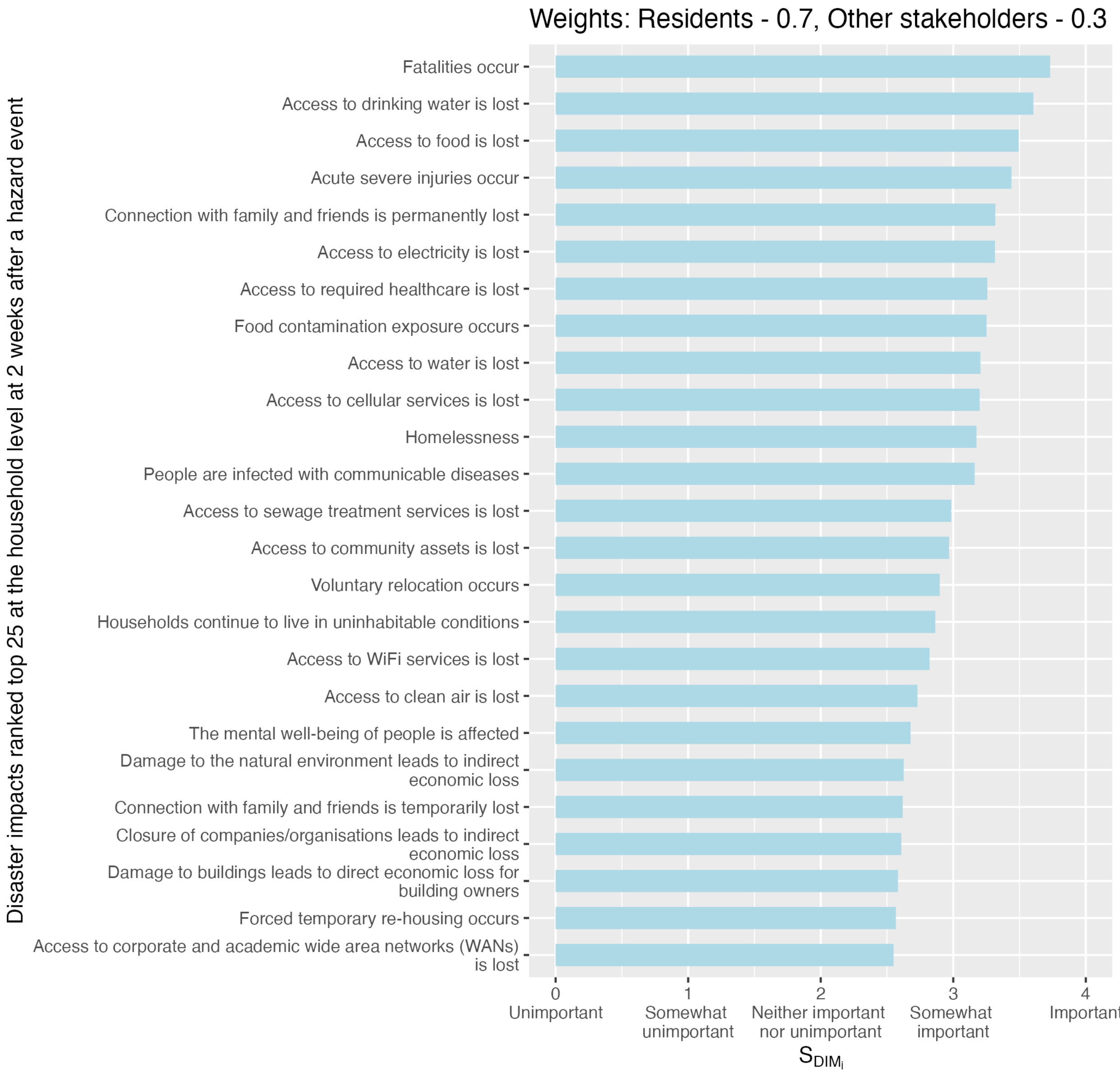

Figure 9. The top 25 highest-ranked disaster impacts at the household level two weeks following a hazard event, assuming $w_1 = 0.7$ for residents and $w_2 = 0.3$ for other stakeholders.

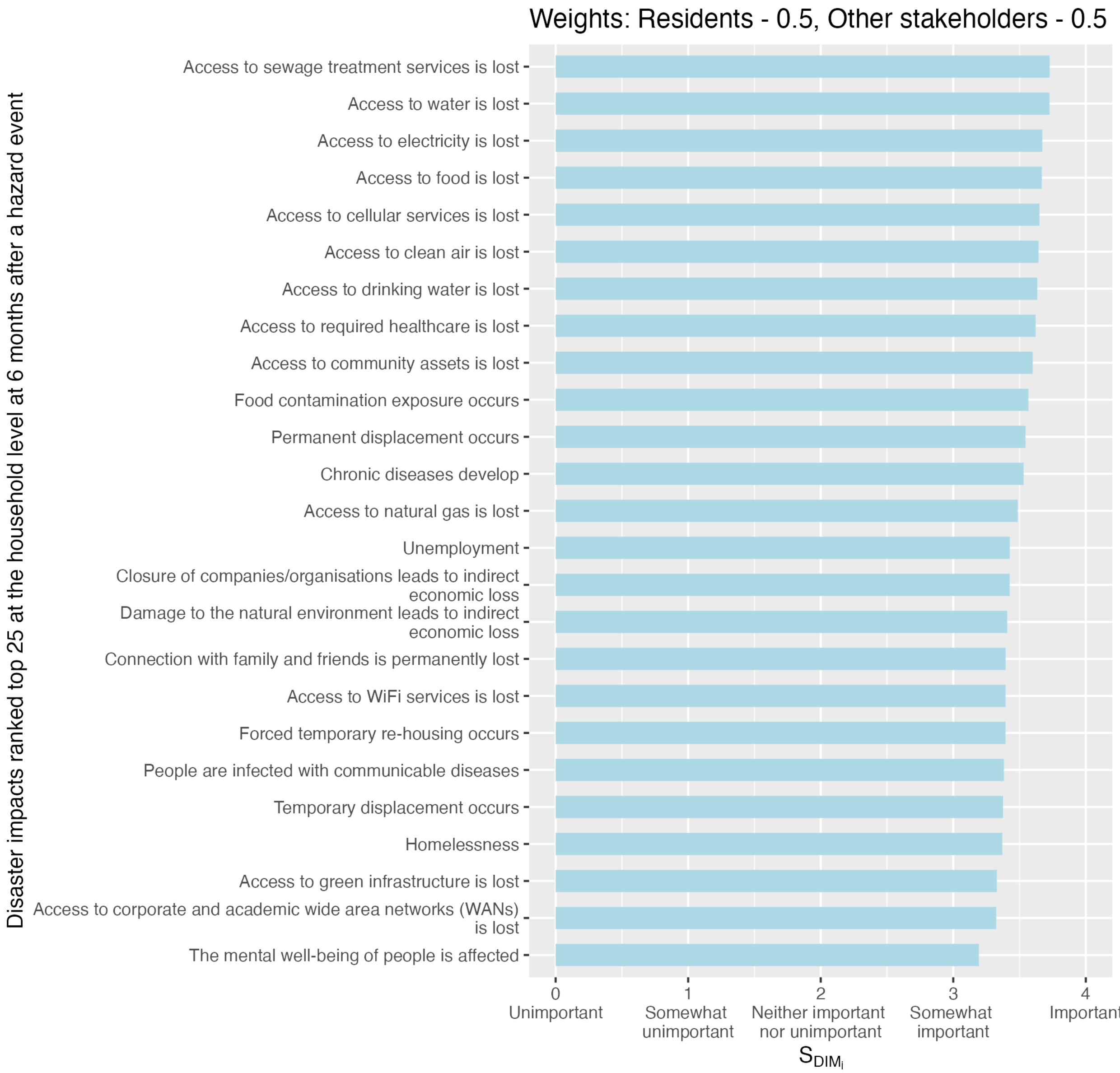

Figure 10. The top 25 highest-ranked disaster impacts at the household level six months following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

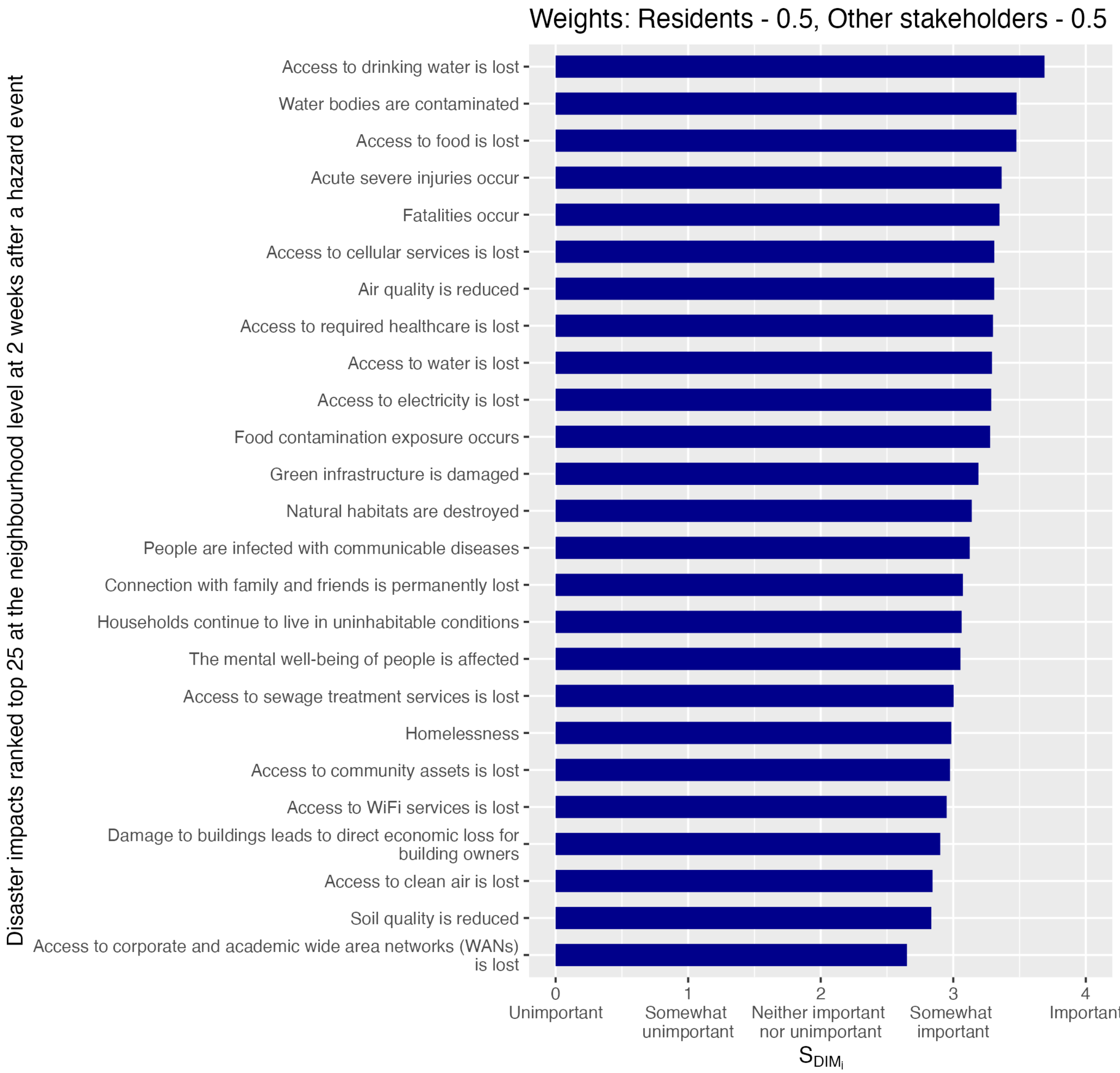

Figure 11. The top 25 highest-ranked disaster impacts at the neighbourhood level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

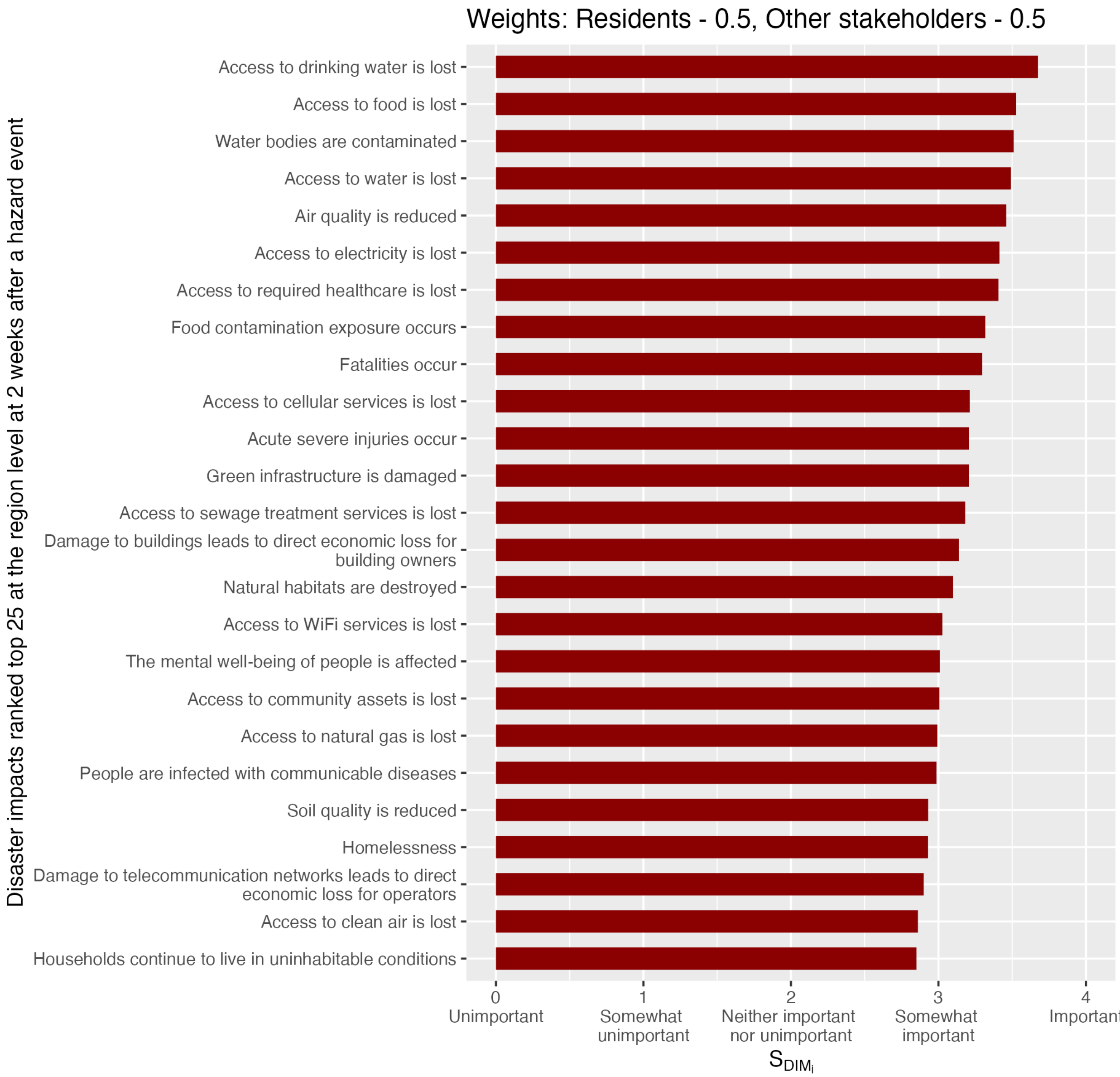

Figure 12. The top 25 highest-ranked disaster impacts at the region level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

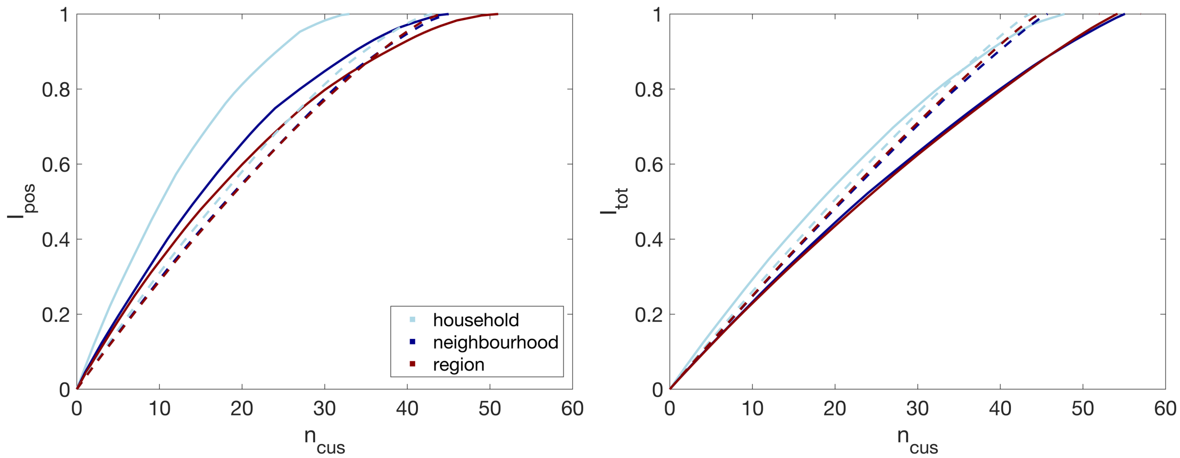

Figure 13. I_{pos} (left panel) and I_{tot} (right panel) plotted as a function of n_{cus} for at the household, neighbourhood, and region level two weeks (solid lines) and six months (dashed lines) after a hazard event

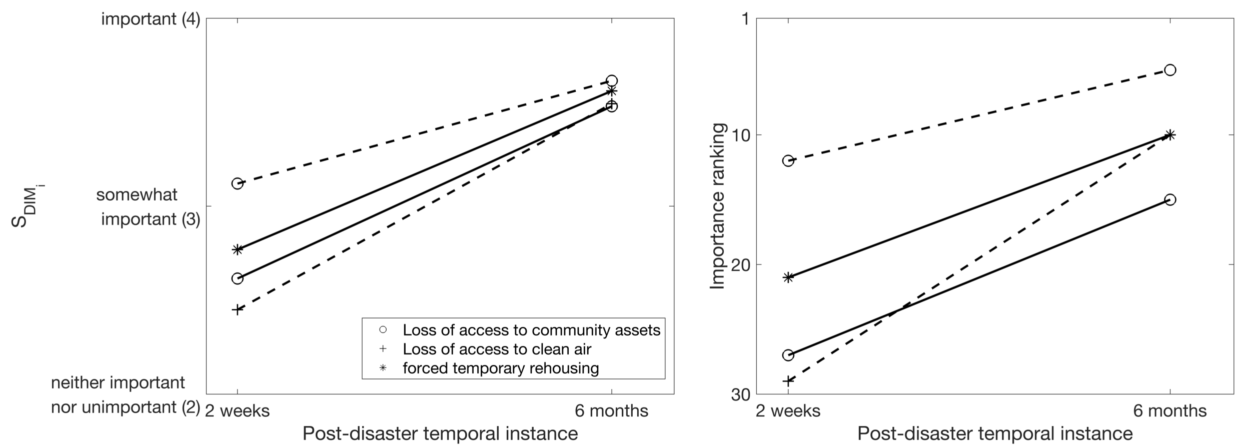

Figure 14. S_{DIM_i} values (left panel) and their ranking (right panel) for three examples DIMs that capture disaster impacts at the household level two weeks and six months after a hazard event. The S_{DIM_i} values are calculated separately for residents (dashed lines) and other stakeholders (solid lines), respectively.

4 CONCLUSIONS

This paper proposes a toolbox for characterising space- and time-dependent disaster impact metrics (DIMs) that account for the bespoke priorities of stakeholders related to disaster impact assessment. The toolbox ultimately helps end users, such as policymakers and disaster impact modellers, to decide which context-specific DIMs to consider in disaster impact assessments. By explicitly accounting for the spatial and temporal dimensions of disaster impacts, it provides an understanding of the required spatial scales and temporal instances to be integrated into disaster impact analyses, in line with recent recommendations of the literature (e.g., Logan et al., 2021; Nocera and Gardoni, 2022; Shen and Hwang, 2019; Rebally et al., 2021)

The DIMs toolbox contains three modules. The first module, which centres on the pool of available DIMs, includes a hierarchical pyramid that provides a conceptual representation of how society functions, facilitating the characterisation and computation of DIMs. The DIMs pyramid also serves as a basis for the structured questionnaires (in module #2) that are developed for a definitive list of stakeholder groups with a vested interest in disaster impact assessment. The questionnaires are used to collect the perspectives of stakeholders and currently consider 59 representative disaster impacts, accounting for three spatial scales of analysis (i.e., household, neighbourhood, and region) and two temporal instances (i.e., two weeks and six months after a hazard event). The second module also contains a data processing package to perform statistical analyses (e.g., hypothesis tests and power analyses) on questionnaire responses, which is integrated in interactive web applications. These statistical analyses provide crucial information for supporting policy-related decision making, such as the most important disaster impacts (in terms of understanding and assessment) for various stakeholder groups at different spatial scales and post-disaster temporal instances.

The third module involves an application of the first two modules to an urban testbed, which in this paper was Kathmandu, Nepal. We recruited 90 stakeholders from two broad stakeholder categories: residents (50 participants) and other stakeholders (including consulting firms, NGOs, construction companies, scholars, government officials, utility companies, and insurers; 40 participants). The results of this application indicate that disaster impacts related to direct physical damage and economic losses are neither the sole concerns of stakeholders nor the most important ones. Instead, loss of access to drinking water and food, utility services (e.g., water, electricity, sewage services), community assets, and clean air, as well as consequences related to social networks (e.g., permanent and temporary loss of connection with friends and family) and the natural environment (e.g., reduced air quality, damage to green infrastructure, and loss of natural habitats), are more important (at least for the stakeholder categories examined). These findings emphasise the need to consider more than just direct physical damage and economic losses in disaster impact assessments. The importance rankings of DIMs change as the emphases placed on the perspectives of different stakeholders and/or temporal instances considered are altered. For example, when the relative emphasis placed on residents' perspectives increases from 0.5 to 0.7, loss of access to clean air drops from the 15^{th} most important disaster impact at the household level two weeks after a hazard event to the 18^{th} most important. Hypothesis tests and power analyses further confirm that the two stakeholder categories considered perceive this DIM differently (p-value < 0.01 with a statistical power of 0.96). Moreover, the importance rankings of some impacts are higher at six months compared to two weeks after a hazard event when the relative emphases placed on residents' and other stakeholders' perspectives are equal ($w_1 = w_2 = 0.5$): loss of access to clean air (15^{th} to 6^{th}), community assets (17^{th} to 9^{th}), utility services and telecommunication services, including water (6^{th} to 2^{nd}), electricity (7^{th} to 3^{rd}), sewage treatment (14^{th} to 1^{st}), cellular services (10^{th} to 5^{th}) at the household level. An opposite trend is observed for loss of access to drinking water at the household level, which decreases in ranking from 2^{nd} at two weeks to 7^{th} at six months. These changes in ranking reflect the dynamic nature of stakeholders' priorities in the post-disaster phase. The findings of the application underline the importance of explicitly accounting for time and stakeholder identities in characterising DIMs. In cases where confident conclusions could not be drawn from the statistical tests, the data processing package was used to determine the number of additional participants required to overcome these issues.

In summary, the DIMs toolbox inherently embraces a participatory approach encouraged in prospective disaster risk management. This work contributes to advancing the utility of disaster impact assessments in critical associated decision-making efforts, such as policy design.

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DATA AVAILABILITY STATEMENT

All study data are made available on GitHub at `https://github.com/wangcb98/DIMs`, except raw questionnaire data, given their sensitivity and as per UCL ethics restrictions.

COMPETING INTERESTS

The authors have no competing interests to declare.

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A Bespoke Approach to Quantifying the Impacts of Disasters, Using Stakeholder-relevant Metrics

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Abstract

Disaster impact metrics (DIMs) are key outputs of natural-hazard risk models/assessments that provide a tangible way of communicating risk. However, typical DIMs are limited in that they tend to capture only direct damage/economic losses, be specifically designed for developed countries, account for just one snapshot in time, and be characterised for individual assets rather than systems. These shortcomings somewhat stem from a lack of understanding around the bespoke requirements of different stakeholders concerning disaster impact/risk assessments. Addressing these limitations, we propose a toolbox for characterising context-specific DIMs that capture relevant stakeholder priorities/requirements. The toolbox includes: (1) a comprehensive, holistic pool of DIMs developed from a literature review and a conceptual representation of societal dependencies; and (2) a stakeholder-centred framework for facilitating the appropriate selection of DIMs from this pool. We demonstrate the framework for Kathmandu, Nepal, revealing that the relative importance of a given disaster impact can change for different stakeholder groups and spatio-temporal dimensions. Impacts related to direct damage/economic losses are not the most crucial concern of the considered stakeholders. Higher priority is placed on characterising accessibility impacts around utilities and social networks, for instance. This work contributes to advancing the usefulness of natural-hazard risk assessments for important decision-making.

Keywords: disaster impact metrics; natural-hazard risk; stakeholder-relevant; questionnaire; Kathmandu

1 INTRODUCTION

Disaster impact metrics (DIMs) are key outputs of disaster risk models that summarise various estimated consequences of modelled hazard events, e.g., earthquakes, floods, hurricanes, and wildfires. They can include the number of damaged or collapsed buildings and/or infrastructure components (e.g., bridges), casualties, the resulting direct economic losses, and business downtime (e.g., Kibboua et al., 2014; Ceferino et al., 2018; Hulsey et al., 2022; Cremen et al., 2020). DIMs could be represented as a summary statistic or in a fully probabilistic manner. Furthermore, they could be computed for one hazard event scenario or a series of stochastically modelled events. DIMs provide a tangible way of communicating potential hazard event consequences that could occur to an urban system in a specific period of time to various stakeholders (e.g., residents, insurers, government officials, and disaster planning authorities; UNDRR, 2015). For example, potential casualties from hypothetical or ongoing disasters represent a direct and prompt means of conveying their severity to the general public, especially residents (Hiroi et al., 1985).

DIMs also inform important policy-related decision-making. For instance, they can be used to guide the emergency response phase efforts of humanitarian organisations or government authorities to appropriately allocate food, rescue crews, and rescue equipment (e.g., Caunhye et al., 2012; Goldschmidt and Kumar, 2019; Cook et al., 2018; Yulianto et al., 2021). In the longer term, they can be leveraged by relevant government agencies to inform the appropriation of disaster relief funds and devise reconstruction programs (e.g., Costa and Baker, 2023; Lallemant et al., 2017; Opabola and Galasso, 2024; Opabola et al., 2023). They can also be used for comparing the sensitivity of urban plans to future disaster risk (Cremen et al., 2023).

However, the existing array of commonly used DIMs is limited in many ways. First, DIMs typically capture only direct physical damage and economic losses (e.g., Silva et al., 2014, 2020; Ellingwood, 2006), neglecting the well-being implications of hazard events on affected communities and the unique challenges that different social groups may face due to such events (Markhvida et al., 2020; Walsh and Hallegatte, 2020; Cremen et al., 2023). This limitation impedes the consideration of equity in disaster impact assessment, obscuring disparities in the distribution of disaster risk for diverse groups and leading to equity-unaware disaster risk reduction (DRR) policies and disaster risk management (DRM) practises (Soden et al., 2023). For example, the Nepal Housing Reconstruction Project (NHRP) provided a fixed-amount reconstruction funding ($3,000; which covered only 30 to 50% of the typical rebuilding cost, Rawal et al., 2021; Galasso and Opabola, 2024) for damaged residences exclusively based on direct physical damage, which impeded the recovery of socially vulnerable communities (Starr, 2018; Platt et al., 2020; Amnesty International, 2017) that could not secure (low-interest) loans or use their savings to fund shortfalls in the repair financing.

DIMs have been predominantly characterised for individual assets (mainly buildings) rather than broader physical and social infrastructure systems and networks (e.g., Erdik, 2017; Erdik et al., 2003; Pitilakis et al., 2006; Khatakho et al., 2021), neglecting the dynamic interdependencies and interactions among people and various infrastructure systems within the built environment (Zimmerman, 2001). In addition, conventional DIMs tend to capture circumstances at just one specific point in time, for instance, the immediate aftermath of a hazard event (e.g., National Planning Commission, 2015; Subedi and Chhetri, 2019; Potter et al., 2015; Yuan, 2008), overlooking the evolving recovery phase across (potentially many) years that is important to consider for long-term planning. Nuances in how various disaster impacts can be tolerated across different time periods (Murphy and Gardoni, 2008; Esmalian et al., 2019; Wiboonratr and Kosavisutte, 2009) as well as spatial scales (Esmalian et al., 2021; Hong et al., 2021; Cetinkaya et al., 2013) are also lost.

Furthermore, existing DIMs are primarily tailored for application to developed countries, for instance for (re-) insurance purposes (e.g., Mitchell-Wallace et al., 2017). This means that they potentially lack relevance for stakeholders in the Global South, where there can be distinct challenges related to disaster impact assessment.

For example, Global South regions can experience disaster-related disruptions to types of infrastructure not typically observed in the Global North, e.g., floating markets (Wattanacharoensil and Sakdiyakorn, 2016). Unique land policies may also lead to very context-specific disaster impacts in the Global South. For instance, the feudal and informal land tenure system of Nepal (Chhatkuli et al., 2019) meant that many people without a land ownership certificate were ineligible for the government reconstruction grant after the 2015 Gorkha earthquakes, and forced to live with the consequences of having to self-fund housing repairs (Amnesty International, 2017).

In general, the shortcomings of DIMs can at least partially be attributed to a lack of research effort on - and therefore, understanding of - the bespoke requirements of different stakeholders concerning disaster impact assessment. Although some studies address multi-stakeholder engagement in disaster risk management (e.g., Chang et al., 2008; Bostick et al., 2017; Gregory et al., 2012; Yang and Zou, 2014; Ellingwood and Kinali, 2009), there is no definitive list of stakeholders that use or rely on the outputs of disaster risk models (i.e., DIMs). Furthermore, there is a lack of quantitative research on stakeholder priorities or perceptions related to these outputs, which are clearly not homogeneous. Pathak et al. (2020) conducted semi-structured interviews with 51 stakeholders in Florida, USA and found that while public sector agencies and non-governmental organisations (NGOs) typically prioritise disaster-related components relevant to their responsibilities (e.g., infrastructure restoration and environmental preservation), private stakeholders (e.g., construction firms, tourism businesses, and financial institutions) and residents tend to value those directly related to their immediate needs or concerns, such as safety and business activities. Differences in priorities exist even within the same category of stakeholders and may result from their diverse capacities to cope with disaster impacts (Dong et al., 2021; Levac et al., 2012). For example, high-income households are likely to be equipped with resources like standby generators, drinking water, food, and an emergency fund for procuring essential services (Costa et al., 2022b; Dong et al., 2021), which - compared to households with less coping capacity - make them more tolerant of (or less interested in understanding) some types of disaster impacts (e.g., drinking water supply and electricity supply; Esmalian et al., 2021).

To address these limitations, we propose a toolbox for characterising context-specific DIMs that meet relevant stakeholder needs. The DIMs toolbox (see Figure 1) includes 1) a pool of representative DIMs developed from a comprehensive literature review of disaster impacts across various contexts and a conceptual representation of how society functions, capturing holistic disaster consequences that extend far beyond direct physical damage or financial losses (e.g., loss of access to food over a period of time, impacts on well being, forced relocation, etc.); 2) a framework to facilitate the appropriate selection of DIMs from this pool (or the development of novel DIMs) for 3) application to a prescribed testbed of interest, by quantitatively assessing stakeholders' disaster-impact perspectives obtained through targeted questionnaires. The results from these targeted questionnaires are analysed through a set of statistical tests integrated within user-friendly web applications. We demonstrate the toolbox using the testbed of Kathmandu, Nepal, considering various stakeholders such as residents (especially those from vulnerable communities at risk and traditionally excluded from decision making), utility companies, consulting firms, non-governmental organisations, construction companies, researchers, government officials, insurers, etc.

We structure this paper as follows. We present the DIMs toolbox in Section 2. We then describe the details and results of the case-study application to Kathmandu, Nepal, in Section 3. We offer some concluding remarks in Section 4.

2 DIMS TOOLBOX

The DIMs toolbox is initially shaped by a stakeholder mapping process, to ensure it comprehensively reflects the breadth of different stakeholders' requirements and priorities concerning disaster impact assessment (e.g., Gregory et al., 2012; Pathak et al., 2020). The toolbox comprises three interconnected modules (see Figure 1). The pool of representative DIMs in module #1 is first developed from a comprehensive literature review of disaster impacts across various contexts and a conceptual representation of how society functions (as summarised in the DIMs pyramid, to be described later). This pool is used to develop the questionnaires of module #2, which are structured in line with the DIMs pyramid. These questionnaires are then deployed in module #3 to capture the context-specific DIMs-related perspectives of various stakeholder groups defined in the mapping process. The stakeholders' responses are analysed using a data processing package (integrated in user-friendly web applications; see supplementary materials) contained in module #2. The outputs of the data processing package include the most relevant DIMs for each targeted stakeholder group. They may also identify the importance of additional context-specific DIMs that were not covered by the original questionnaire, which would be subsequently added to the DIMs pool of module #1, for input to module #2 and further applications in module #3.

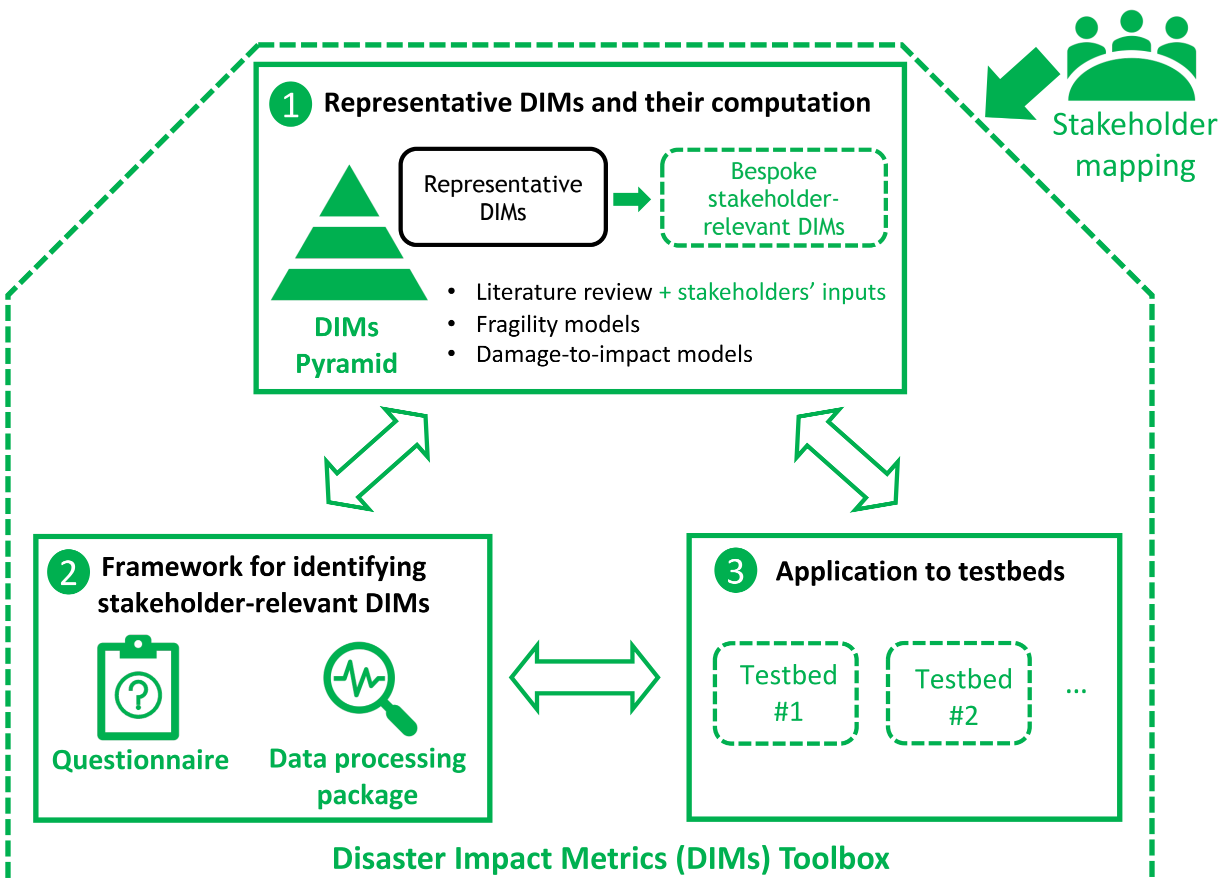

Figure 1. An illustration of the proposed disaster impact metrics (DIMs) toolbox.

2.1 Stakeholder mapping

Stakeholder mapping exercises involve identifying parties interested in the subject under investigation and understanding their specific needs (Walker et al., 2008). We use the stakeholders identified by Chang et al. (2008), Pelling et al. (2023), and Arlikatti et al. (2007) as a basis for the initial mapping process of this work. Chang et al. (2008) identified a wide range of stakeholders that represent public voices on the topic of community disaster resilience, including researchers, local and national government officials (including policymakers and emergency response staff), residents, property/business owners, and industry representatives. Pelling et al. (2023) identified a wide array of stakeholders for normative future visioning exercises (that surface aspirations for future urban environments) in Istanbul, Kathmandu, Nairobi and Quito, including civil society groups representing the urban poor, government officials at the municipal and ward (local) levels, private sector representatives (such as Chambers of Commerce), experts, academics, and journalists. Arlikatti et al. (2007) defined various stakeholder groups related to seismic risk management within the context of the USA, including federal, state and local government authorities, experts (i.e., scientists, professionals, educational institutions), watchdogs (e.g., news media, citizens' and environmental groups), industry/employers of the private sector, and households. We expand the lists of Chang et al. (2008), Pelling et al. (2023), and Arlikatti et al. (2007) through an additional investigation of further literature sources (details to follow). Our mapping process ultimately results in six representative stakeholder groups with a vested interest in disaster impact assessment (see Figure 2; note that the examples provided for each stakeholder group are non-exhaustive): residents, professionals or experts, regulatory bodies (including related agencies), utility companies, industry, and additional stakeholders that serve the public interest.

Residents are directly affected by the disaster and DRR policies informed by disaster impact assessment (e.g., Taeby and Zhang, 2019; Scolobig et al., 2015; Ikeda and Nagasaka, 2011; Egbelakin et al., 2011). Involving residents in the assessment of DIMs constitutes a people-centred approach (Cremen et al., 2023; Scolobig et al., 2015; Marchezini, 2020) that allows the voices of communities potentially at risk to be heard (e.g., Chang et al., 2008; Scolobig et al., 2015; Han et al., 2021; Cremen et al., 2023; Galasso et al., 2021). Residents may be further disaggregated into subgroups (see Figure 2) to better capture potentially diverse perspectives within this heterogeneous set of people, and to facilitate the design of policies that target a specific group (e.g., the urban poor, Wang et al., 2023b).

The other identified stakeholder groups assume various roles in DRM. For example, professionals or experts use relevant information in their practice to evaluate disaster risk and/or make policy recommendations (e.g., Ellingwood and Kinali, 2009; Sechi et al., 2022; Arlikatti et al., 2007; Yang and Zou, 2014). Regulatory bodies (and/or other related agencies) are usually in charge of policy-related decision-making on disaster risk management (e.g., Pathak et al., 2020; Peng et al., 2014; Djalante, 2012; Ellingwood and Kinali, 2009; Yang and Zou, 2014; Langenbruch et al., 2020; Dastous et al., 2008; Bostick et al., 2017; Solarino et al., 2021; Scheer et al., 2014; Markmann et al., 2013). Utility companies provide essential services (e.g., water and wastewater, electricity, telecommunication) crucial for the normal operation and post-disaster recovery of society (e.g., Esmalian et al., 2019; Guidry et al., 2015; Román et al., 2019; Guikema and Quiring, 2012; Kwasinski et al., 2009), which makes them an important stakeholder group in disaster impact assessment (e.g., Chang et al., 2008; Sapapthai et al., 2020; Baroudi and Rapp, 2014). The industry stakeholder group is liable for economic losses from disasters, which may be their own (e.g., in the case of business owners) or those transferred to them from others (in the case of insurers and reinsurers)(e.g., Pathak et al., 2020; Dastous et al., 2008; Scheer et al., 2014; Chang et al., 2008; Peng et al., 2014; Ellingwood and Kinali, 2009; Markmann et al., 2013). Additional stakeholders that serve the public interest include watchdogs for disaster risk management and those that disseminate relevant knowledge to communities (e.g., media and educational institutions; Hiroi et al., 1985; Yang and Zou, 2014; Arlikatti et al., 2007; Yamori, 2008; Solarino et al., 2021; Chang et al., 2008; Markmann et al., 2013) as well as organisations that invest in disaster risk reduction and/or participate in post-disaster rehabilitation (e.g., non-governmental organisations, international organisations, and development banks; Yang and Zou, 2014; RISK, 2003; Clarke and Dercon, 2019; Aniens and Benson, 1999; Pathak et al., 2020).

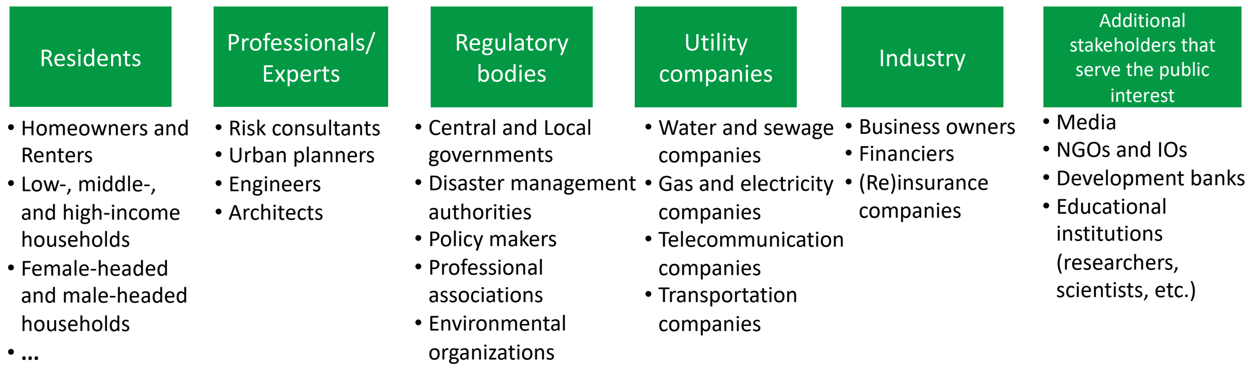

Figure 2. The results of the stakeholder mapping process. NGOs refer to non-governmental organisations and IOs refer to intergovernmental organisations. The term "regulatory bodies" also encompasses other related agencies. Note that the examples provided for each stakeholder group are non-exhaustive.

2.2 Characterising and computing representative DIMs

In line with the requirements of DRM, we define a disaster impact metric as a quantitative measurement of a specific disaster (or more general hazard-related) consequence associated with a specific spatial scale at a prescribed time instance. An example is loss of access to drinking water at the household level two weeks after a hazard event. In this case, the disaster impact of interest is loss of access to drinking water, and the specific spatial scale and temporal instance considered are, respectively, the household level and two weeks after the event. Explicitly accounting for the spatial scale helps to capture variations in disaster impacts and stakeholder requirements across the disaster-affected region (Chang and Tanner, 2022; Frazier et al., 2013) and facilitates the communication of disaster impacts to various levels of stakeholders (e.g., local businesses or national and international businesses, local government or central government; Mardian, 2022). Recognising the temporal dimension of disaster impacts acknowledges the dynamic nature of stakeholders' priorities, e.g., the longer a disaster impact persists, the less tolerable it may become (Murphy and Gardoni, 2008; Esmalian et al., 2019; Wiboonratr and Kosavisutte, 2009; Cremen, 2023). Note that some DIMs may only include a description of a specific spatial scale or a temporal instance, and the extent of space or time considered could be restricted. For example, economic losses caused by building damage at the household level are implicitly associated with the immediate aftermath of a disaster, and reduced air quality two weeks after a hazard event is only relevant at regional or broader-level spatial scales.

The list of representative DIMs is based on a conceptual representation of how society functions, which is depicted using a pyramid (herein referred to as the "DIMs pyramid"; see Figure 3). Components on the lowest level of the DIMs pyramid represent physical infrastructure (including transportation, utilities, buildings, telecommunications) and the natural environment that collectively underpin societal functions. Components on the middle level of the DIMs pyramid encompass the essential services and activities of society that are supported by the infrastructure and environment of the bottom layer. The DIMs pyramid is hierarchical by nature, i.e., each level relies on the presence of the previous one, analogous to Maslow's hierarchy of needs (Maslow and Lewis, 1987).

The structure of the DIMs pyramid is based on an extensive literature review. It exhaustively captures the nine so-called critical functions associated with coastal disaster resilience planning that were identified in Bostick et al. (2017): telecommunication, electricity, housing, transportation, port/shipping industry, clean water, tourism industry, ecosystem health, community and culture. It also reflects the four categories of "Minimum Standards for Disaster Response" proposed by Bayram et al. (2012) (i.e., health, shelter, food and nutrition, and water and sanitation) as well as the basic worldwide needs defined by Sachs (2012) (i.e., access to safe and sustainable water and sanitation, adequate nutrition, primary health services, and basic infrastructure, including electricity, roads, and connectivity to the global information network). Moreover, the DIMs pyramid shares a similar structure to the Built Environment Model proposed by Infrastructure and Projects Authority (2021), in which interconnected infrastructure systems provide the foundation for the services on which society depends, all of which are ultimately built upon the natural environment.

The DIMs pyramid conceptualises the pathway for realising disaster impacts on society, serving as a theoretical basis for the characterisation (and computation) of DIMs. In essence, DIMs are characterised by disruptions to the middle-level social and economic infrastructure, which result from damage to physical infrastructure and the natural environment on the lowest level. This damage is estimated using broadly defined 'fragility' models (e.g., Scawthorn et al., 2006; Kircher et al., 2006; Vickery et al., 2006, among many others). Note that the fragility of the natural environment could relate to disaster-induced changes in species abundance and composition (Nilsson and Grelsson, 1995; Meisner et al., 1987; Nilsson et al., 1991; Franz and Bazzaz, 1977). The damage information produced by fragility models is translated into disruption to (middle-level) social and economic infrastructure using models generally termed as 'damage-to-impact' (or 'consequence') (Gentile et al., 2022). For example, the damage-to-impact model in Wang et al. (2023a) estimates the number of households who relocate after an earthquake, considering damage to workplace and residential buildings as well as socio-economic factors such as household-level place satisfaction and household demographics. The damage-to-impact model proposed by Logan et al. (2023) estimates the number of people with lack of access to essential services due to physical infrastructural damage resulting from inundation caused by sea-level rise. The damage-to-impact model in Reed et al. (1984) estimates environmental disturbances resulting from oil spills on fisheries. Table 1 summarises definitions related to the lowest level of the DIMs pyramid and provides examples of associated fragility models. Table 2 provides definitions related to the middle level of the DIMs pyramid and examples of associated damage-to-impact models. For DIMs that depend on multiple middle-level components, a judgment-driven or empirical function is required to translate the outputs of damage-to-impact models into the final outcome (details to follow). This function could be, for example, the minimum or multiplication of damage-to-impact model outputs. Both the spatial scale and temporal instance of interest can influence the components of each layer considered in the conceptualisation of a DIM, as well as the types of models deployed at each calculation stage. Note that vulnerability ("hazard-to-impact") models (e.g., Gentile et al., 2022; Yepes-Estrada et al., 2016) could be used to provide a direct path from the lowest level of the pyramid to the top, with only implicit reference to the middle level. We do not discuss these types of models further however, because this paper aims to characterise DIMs in a more fundamental sense.

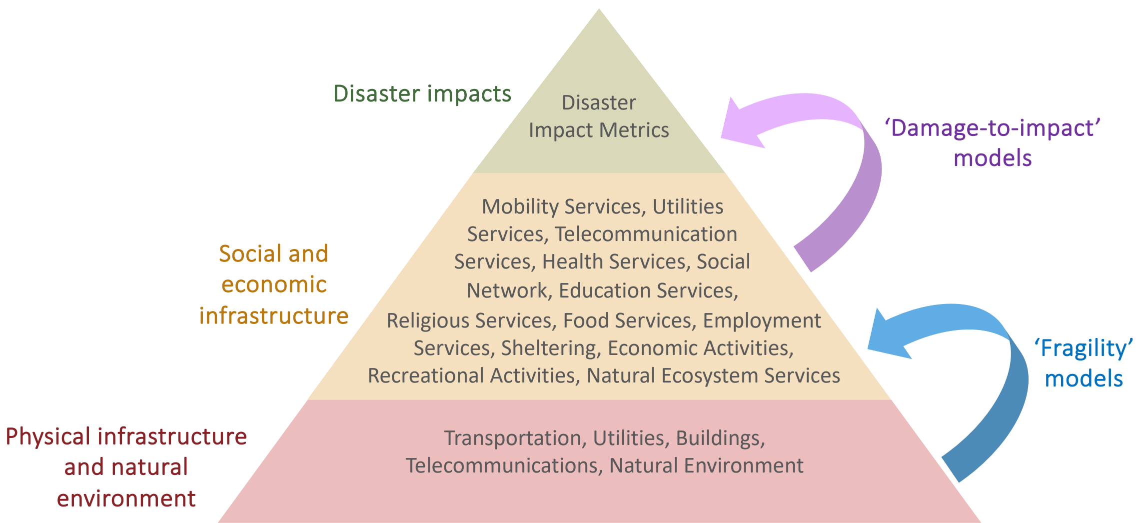

Figure 3. The proposed hierarchical DIMs pyramid for characterising and computing disaster impact metrics.

Table 1. Definition of components in the lowest level of the DIMs pyramid that represent physical infrastructure and the natural environment. Also provided are examples of fragility models for estimating associated damage. The definition of components is derived from Britannica Dictionary (2024) and Vocabulary (2024) unless otherwise specified.

Component	Definition	Example fragility models
Transportation	Various systems and/or associated infrastructure components (e.g., roads, tunnels, bridges, airports, railways, etc.) by which the movement of persons and goods from place to place is accomplished.	Nocera et al. (2018); Cantillo et al. (2019); Freckleton et al. (2012); Chen et al. (2015); Guo et al. (2017); Matini et al. (2022)
Utilities	Infrastructure systems supporting public services related to electricity, water, gas, sewage, etc.	Iannacone et al. (2022); Zhang et al. (2020, 2022); Costa et al. (2019); Mohagheghi and Javanbakht (2015); Hou et al. (2019); Kwasinski et al. (2009); Hossain et al. (2021); Mazumder et al. (2022)
Buildings	All types of structural assets (e.g., a house, hospital, school, etc.) with a roof and walls that are used as a place for people to live, work, do activities, store things, etc.	Kircher et al. (2006); Vickery et al. (2006); Scawthorn et al. (2006)
Telecommunication	Infrastructure systems supporting communication over a distance by cable, telegraph, telephone, or satellite.	Kwasinski et al. (2009); Patricelli et al. (2009); Parajuli and Haynes (2016); Cardoni et al. (2022); De Iuliis et al. (2021)

Natural environment	Natural resources, natural habitats, natural ecosystems that exist within nature as well as green infrastructure. It provides food, water, fuel, clean air and other services crucial for sustaining life and well-being (The Chartered Institution of Water and Environmental Management, 2024).	Nilsson and Grelsson (1995); Meisner et al. (1987); Nilsson et al. (1991); Dosi (2001); King et al. (2005); Sun et al. (2015)

Table 2. Definition of components in the middle-level of the DIMs pyramid that represent social and economic infrastructure. Also provided are examples of damage-to-impact models for estimating the disruption to each component. The definition of components is derived from Britannica Dictionary (2024) and Vocabulary (2024) unless otherwise specified.

Component	Definition	Associated physical infrastructure and/or natural environment	Example damage-to-impact models
Mobility services	Services that are supported by transportation systems, and transport passengers from place to place via one or more transport modes, e.g., private car, car sharing and rental, underground, rail, bus, bike, motorbikes, taxi, etc.	Transportation	Aschenbruck et al. (2007); Chang and Tanner (2022); Bhattacharjee and Baker (2023); Boakye et al. (2022); Silva-Lopez et al. (2022); Horner and Widener (2011); Wei and Mukherjee (2022); Zamanifar and Hartmann (2021); Horner and Widener (2011)
Utility services	Services supported by utility systems. For example, the provision of water and wastewater services, electricity, natural gas, etc.	Utilities	Costa et al. (2022b); Balaei et al. (2021); Brozović et al. (2007); Opabola and Galasso (2023); Purwar et al. (2020); Chambers et al. (2021); Mitra et al. (2021); Romero et al. (2010); Tabucchi et al. (2010)
Telecommunication services	Services supported by telecommunication systems. For example, the provision of a landline service, cellular services, broadcast services, and internet services.	Telecommunication	Jrad et al. (2004); Van Wyk and Starbird (2020); O'Reilly et al. (2006); Marshall et al. (2023); Mohamadi et al. (2019)
Health services	The provision of medical care by doctors, dentists, and psychologists via hospitals, clinics, remote consultation, etc.	Transportation, Utilities, Buildings, Telecommunication	Alisjahbana et al. (2022a); Ceferino et al. (2020); Jacques et al. (2014); Hu et al. (2015); Friedman et al. (2022); Suk et al. (2020)

Social network	The inherent social fabric of communities bonded via community assets and social ties, e.g., family, neighbours, friends, co-workers (Wellman and Wortley, 1990).	Transportation, Utilities, Buildings, Telecommunication	Costa et al. (2022c); Wang et al. (2023a); Costa et al. (2022a); Nejat et al. (2020); Miles and Chang (2011)
Education services	The provision of systematic instruction, especially at a school, college, or university (in-person and online).	Transportation, Utilities, Buildings, Telecommunication	Alisjahbana et al. (2022b); Nouri et al. (2011); Esnard et al. (2018); Shiwaku and Shaw (2016); Shiwaku et al. (2016); Anelli et al. (2019)
Religious services	Services supporting the act of public worship following prescribed rules.	Utilities, Buildings, Telecommunication	Ngwacho (2020); Aten and Topping (2010); Strader et al. (2019)
Food services	The provision of nutritious substances that people eat or drink to maintain life and growth (including drinking water).	All	Horner and Widener (2011); Rathore et al. (2021); Altay and Ramirez (2010); Nozhati et al. (2019); Zeuli et al. (2018)
Employment services	The provision of jobs and stable sources of livelihood.	All	Hulsey et al. (2022); Sarnosky et al. (2022); Nocera and Gardoni (2019); Cremen et al. (2020); Liu et al. (2020); Qiu et al. (2018)
Sheltering	The provision of housing (place to live) on different timescales, including permanent homes, temporary housing, and public shelters.	Utilities, Buildings	Wang et al. (2022); Costa et al. (2022a); Nappi et al. (2019); Zhao et al. (2017); Vecere et al. (2017); Chen et al. (2013)
Economic activities	Processes that lead to the manufacture of goods or the provision of services (Eurostat, 2024). Disaster impacts on economic activities can lead to direct economic loss to business owners (as well as relevant employees) and wider indirect economic loss. The economic loss due to direct property or infrastructure damage (e.g., replacement cost of a house) is also included.	All	Cremen et al. (2020); Costa and Baker (2021); Markhvida and Baker (2023); Markhvida et al. (2020); Nocera and Gardoni (2019); Wu et al. (2012); Mao et al. (2020); Hallegatte (2008); Chiou et al. (2013); Martins et al. (2016)

Recreational activities	Discretionary activities that people do to refresh their bodies and minds and make their leisure time enjoyable. Examples of recreational activities are hiking, swimming, camping, meditation, reading, playing games and dancing (National Center for Biotechnology Information, 2024).	All	Sandifer et al. (2017); Gertler et al. (2015); Whitworth and May (2006); Faaui et al. (2017); Zhu et al. (2019); Kauppila and Karjalainen (2012); Thomas et al. (2013)
Natural ecosystem services	Conditions and processes through which the natural environment (ecosystems, and the species that comprise them) sustain and fulfil life. Natural ecosystem services regulate and support the functioning of built environments. These services include, e.g., provision of clean air, flood management, water purification, provision of natural habitats for wildlife (Scotland's Nature Agency, 2023).	Natural environment	Ascott et al. (2016); Rui et al. (2018); Sandifer et al. (2017); Dang et al. (2018); Yang et al. (2015); Chiang et al. (2014); Nelson et al. (2013); Reed et al. (1984)

Figure 4 provides an example of how the DIMs pyramid facilitates the characterisation and computation of a DIM, which is loss of access to food at the household level two weeks after an event of interest. A household's access to food at this time instance primarily relates to food services, but is simultaneously dependent on mobility services (which enable the household to reach a grocery store; Nozhati et al., 2019; Smith and Frankenberger, 2018), utility services (that facilitate food preservation; Nozhati et al., 2019), employment services (that enable food to be affordable; Naqvi and Monasterolo, 2021), telecommunication services (that allow households to receive information on the availability of food retailers and disaster relief goods; Zhong et al., 2022; Swanson and Guikema, 2023), and sheltering (that facilitate food preparation; Kim et al., 2021). These services ultimately depend on different physical infrastructure and/or the natural environment. For example, food services are supported by buildings (e.g., food retailers, factories), the natural environment (that creates the conditions necessary for avoiding food-related contamination and for crop and livestock farming; Zeuli et al., 2018), transportation, utilities, and telecommunication (e.g., for the smooth running of, and coordination with, the food supply chain; Reddy et al., 2016; Okumura, 2012). Once the pathway for characterising the DIM of interest has been identified, its calculation can be performed using a bottom-up approach. Physical damage is first calculated using appropriate fragility models for buildings (e.g., those related to food retailers, residential buildings, workplaces; Baker et al., 2021), transportation infrastructure (e.g., Nocera et al., 2018; Cantillo et al., 2019), utility infrastructure (e.g., Iannacone et al., 2022; Zhang et al., 2020; Costa et al., 2019; Hossain et al., 2021), telecommunication infrastructure (e.g., Kwasinski et al., 2009; Cardoni et al., 2022), and the natural environment (e.g., Meisner et al., 1987; Sun et al., 2015). These damages are then translated, using damage-to-impact models, into two-week disruptive effects on food services (e.g., Horner and Widener, 2011; Rathore et al., 2021), mobility services (e.g., Horner and Widener, 2011; Silva-Lopez et al., 2022), utility services (e.g., Costa et al., 2022b; Opabola and Galasso, 2023; Brozović et al., 2007), telecommunication services (e.g., O'Reilly et al., 2006; Van Wyk and Starbird, 2020), employment services (e.g., Nocera and Gardoni, 2019; Hulsey et al., 2022; Sarnosky et al., 2022), and sheltering (e.g., Wang et al., 2022; Zhao et al., 2017; Vecere et al., 2017). These disruptions are finally synthesised into the DIM using some judgment-driven or empirical function. For example, Nozhati et al. (2019) considered food security (i.e., the opposite of loss of access to food) as the intersection (∩) of food availability (relying on the functionality of a household's home and a food retailer), accessibility (relying on the functionality of mobility services between households and food retailers), and affordability (relying on the functionality of employment services).

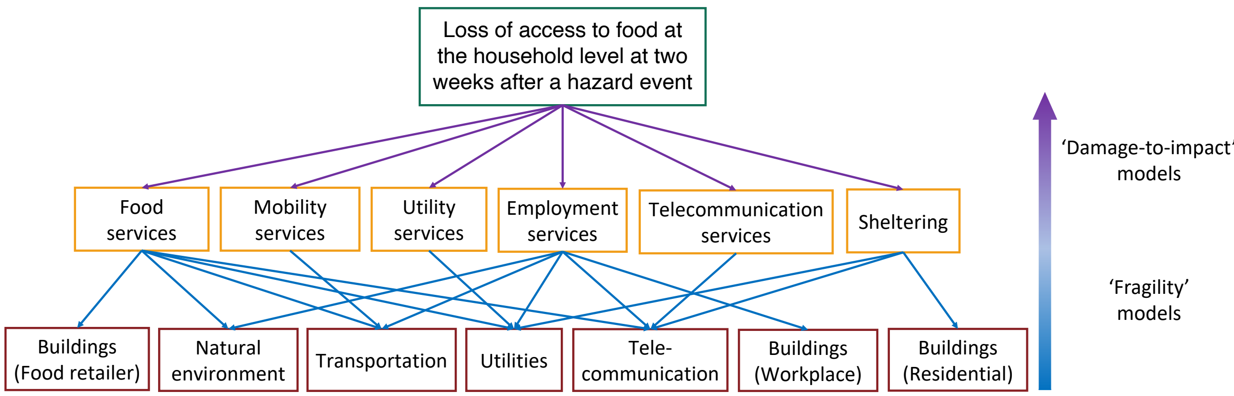

Figure 4. Using the DIMs pyramid to facilitate the characterisation and computation of a specific DIM, which is loss of access to food at the household level, two weeks after a hazard event.

2.3 Framework for identifying stakeholder-relevant disaster impact metrics

The second module of the DIMs toolbox contains questionnaires that are developed and structured based on the contents of module #1. These questionnaires are used to collect quantitative disaster-impact perspectives of different stakeholder groups identified in the stakeholder mapping process. Module #2 also contains a data processing package (integrated within web applications in *R Shiny* - see supplementary material; Chang et al., 2023) to perform various statistical analyses on the questionnaire responses. These statistical analyses are used to understand the perceived importance of characterising and computing different DIMs over varying spatial scales and temporal instances across stakeholder groups.

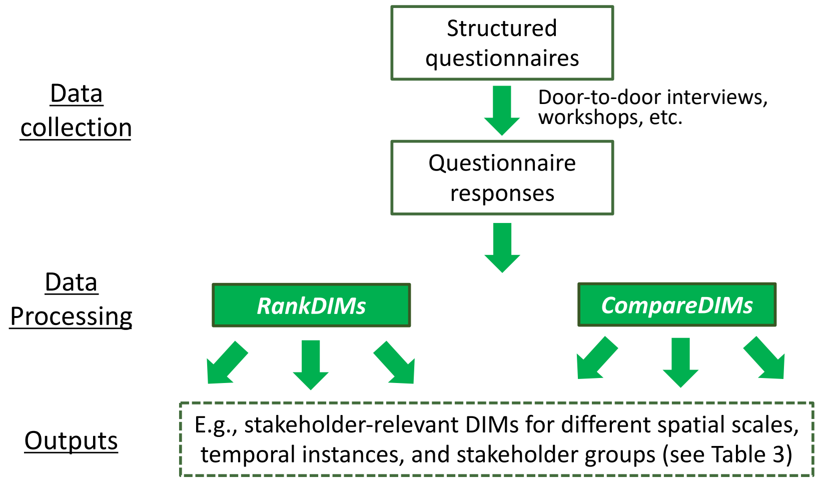

Figure 5. A framework for identifying stakeholder-relevant DIMs. The framework leverages structured questionnaires and *R*-based web applications developed for statistical analyses: ***'RankDIMs'*** and ***'CompareDIMs'***.

2.3.1 Structured questionnaire

The questionnaire consists of three sections (see supplementary materials). Section A records socioeconomic and demographic information on respondents as well as their households (for residential stakeholders) or background information on the associated organisation or company, its staff, or its beneficiaries (for all other stakeholders). This information includes, for example, the area in which the respondent resides in or serves (rural or urban areas; Mitsova et al., 2018), household income bracket (Cutter et al., 2003), the age group of household members or staff (Paul and Routray, 2011), the gender of the household head (Cutter et al., 2003; Flatø et al., 2017), the size of the household or the organisation/company (Cutter et al., 2003; Ivancevich et al., 1998), and the number of persons with special needs within the household or the organisation/company (Cutter et al., 2003). Section A is included because it provides information that can lead to the definition of more precise subgroups within the broad groups of stakeholders defined as part of the mapping process (see Figure 2).

Section B asks respondents to provide their perspectives on (i.e., importance scores for) each DIM, using a scale from -1 to 4 (see Table 3), with higher values indicating higher importance and -1 indicating irrelevance. This scale has proven useful for attitude and perspective measurement (Oppenheim, 2000; Boynton and Greenhalgh, 2004). Section B is divided into two parts, in line with the DIMs pyramid (see Figure 3). Part I contains questions about disaster impacts on the natural environment (whereas damage to physical infrastructure is implicitly captured via questions related to the resultant economic loss in Part II), corresponding to the lowest level of the DIMs pyramid. Part II includes questions about disaster impacts on social and economic infrastructure, corresponding to the middle level of the DIMs pyramid. Section B questions are based on the list of representative DIMs formulated in module #1. They currently capture 59 disaster impacts, three spatial scales of analyses (household, neighbourhood, i.e., a geographically localised community within a larger city, town, suburb or rural area, and region, i.e., a city-size area) and two temporal instances (two weeks and six months, corresponding to short-term emergency response and intermediate recovery phases, respectively; Department of Homeland Security, 2016). The questionnaire also allows respondents to specify the maximum duration for which different disaster impacts can be tolerated, if the respondents do not consider the disaster impacts to be relevant at the specified temporal instances. Section C invites respondents to define and provide an importance score for additional DIMs not considered in

Section B. The questionnaire is adaptable to the specific context of interest; ideally, a unique version of the questionnaire should be developed for each stakeholder group and the specific lens of interest (e.g., whether an organisation is providing perspectives in relation to its employees or those that it serves).

Table 3. Different opinions on disaster impact metrics and the associated importance score.

Not relevant	Unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Important
-1	0	1	2	3	4

2.3.2 Data processing package

Module #2 integrates two interactive web applications (using the *Shiny* package in *R*) that can be leveraged to perform statistical analyses on questionnaire responses. ***RankDIMs*** produces relative measurements of importance and can be used to understand stakeholders' priorities at different spatial scales and temporal instances. ***CompareDIMs*** then determines whether absolute changes in importance across different spatial scales, temporal instances, and stakeholder groups are statistically significant. Table 4 summarises examples of outputs produced by the data processing package.

Table 4. Examples of outputs produced by the data processing package. Note that n_{cus} and n_{sub} are end-user defined integers.

Examples of output	Description
Q1	At a specific temporal instance after a hazard event, what are the top n_{cus} most important disaster impacts for a specific spatial scale of analysis, and how do these results change when varying emphasis is placed on the perspectives of different stakeholder groups.
Q2	How does the importance of a specific disaster impact change across different considered spatial scales and temporal instances.
Q3	How much collective importance is captured by a subset of DIMs (containing n_{sub} entries).
Q4	For a specific disaster impact and temporal instance, is there a statistically significant difference in the importance at different spatial scales.
Q5	For a specific disaster impact and spatial scale, is there a statistically significant difference in the importance at different temporal instances.
Q6	What is the sample size (i.e., number of responses) necessary to draw conclusive results from the previous outputs with a specified confidence level for a given statistical hypothesis test.

RankDIMs determines the rankings of all DIMs included in the questionnaire according to the average weighted importance score, S_{DIM_i}, given by:

$$S_{DIM_i} = \sum_{j=1}^{N_g}[w_j \cdot \sum_{l=1}^{n_j}(w_{j,l} \cdot \frac{\sum_{p=1}^{n_{j,l}} S_{DIM_{i,j,l,p}}}{n_{j,l}})] \tag{1}$$

where DIM$_i$ is the ith DIM considered, w_j is the weight placed on the jth stakeholder group ($\sum_{j=1}^{N_g} w_j = 1$), N_g is the number of stakeholder groups ($1 \leq N_g \leq 6$; this number should be determined for the specific context of interest), n_j is the number of subgroups in the jth stakeholder group (see Figure 2 for examples of subgroups within each stakeholder group), $w_{j,l}$ is the weight placed on the lth subgroup within the jth stakeholder group ($\sum_{l=1}^{n_j} w_{j,l} = 1$), $n_{j,l}$ is the number of participants in the lth subgroup within the jth stakeholder group, $S_{DIM_{i,j,l,p}}$ is the importance score for the ith DIM given by the pth participant in the lth subgroup within the jth stakeholder group. w_j and $w_{j,l}$ reflect how much the end user values the perspectives of each stakeholder group (and corresponding subgroups) in a relative sense. The weights could be determined using, for example, the Analytic Hierarchy Process (Saaty, 1988). This procedure requires the end users to perform a series of pairwise comparisons for each stakeholder group (as well as any subgroups within it), based on qualitative descriptions of relative importance that are measured on a numeric scale. S_{DIM_i} is therefore determined from all stakeholder groups (and subgroups) in line with how many stakes they hold. ***RankDIMs*** creates separate ranking lists for each combination of spatial scale and temporal resolution, to ensure meaningful and fair comparisons between DIMs.

RankDIMs produces two other metrics: the positive importance ratio, I_{pos}, and the total importance ratio, I_{tot}, which quantify how much importance is captured by a specific subset of DIMs (analogous to the percentage of variance or information represented by each principle component in principle component analysis, Ringnér, 2008). I_{pos} captures only positive perceptions of importance, whereas I_{tot} accounts for all perceptions of importance. Both metrics exclude irrelevant DIMs (i.e., with $S_{DIM_i} < 0$). They can be written as

$$I_{pos} = \begin{cases} \frac{\sum_{k=1}^{n_{sub,pos}} (S_{DIM_k} - 2)}{\sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2)} & if \sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2) > 0 \\ 0 & if \sum_{i=1}^{n_{tot,pos}} (S_{DIM_i} - 2) = 0 \end{cases} \tag{2}$$

$$I_{tot} = \begin{cases} \frac{\sum_{k=1}^{n_{sub,rel}} S_{DIM_k}}{\sum_{i=1}^{n_{tot,rel}} S_{DIM_i}} & if \sum_{i=1}^{n_{tot,rel}} S_{DIM_i} > 0 \\ 0 & if \sum_{i=1}^{n_{tot,rel}} S_{DIM_i} = 0 \end{cases} \tag{3}$$

where $n_{sub,pos}$ is the number of DIMs in the customised subset with $S_{DIM_i} > 2$ (since 2 indicates "neither important nor unimportant"; see Table 3), $n_{sub,rel}$ is the number of DIMs in the customised subset with $S_{DIM_i} \geq 0$ (and n_{sub} is the total number of DIMs in this subset), $n_{tot,pos}$ is the total number of DIMs considered with $S_{DIM_i} > 2$, $n_{tot,rel}$ is the total number of DIMs considered with $S_{DIM_i} \geq 0$ (and n_{tot} is the total number of DIMs considered), and S_{DIM_k} is as previously defined. The outputs of ***RankDIMs*** can shed light on the disaster impacts that should be prioritised in future DRR policy making, for instance. They ultimately help to inform the level of computational resources required for modelling DIMs (Nocera and Gardoni, 2022; Ujjwal et al., 2019).

CompareDIMs performs two statistical hypothesis tests - Welch's Analysis of Variance (ANOVA; Liu, 2015) and Welch's two-sample t-test (Derrick et al., 2016) - on varying numbers of S_{DIM_i} values. These values can correspond to two separate DIMs or the same DIM for two different stakeholder groups; in the former case, w_j in equation 1 is quantified to reflect the number of participants per stakeholder group and in the latter case, it is set to 1. Welch's ANOVA is used to test whether three or more S_{DIM_i} values are different with statistical significance. A common threshold for statistical significance is 0.05 (Greenland et al., 2016). Welch's two-sample t-test is used to test whether two S_{DIM_i} are different with statistical significance. This test assumes that the sample S_{DIM_i} values being compared are normally distributed but does not require equal variances. The implementation of this test within the ***CompareDIMs*** application also includes power analyses that determine the extent to which the sample sizes are large enough to produce the correct test outcome (Cohen, 1992). The common threshold for power analyses is 0.80 when a 0.05 significance level is used (Greenland et al., 2016).

The hypothesis test outputs of ***CompareDIMs*** help end users to better understand the spatial resolution and temporal instances for which disaster impacts and associated policies should be modelled/designed and whether opinions on these differ across stakeholder groups. The power analyses can be used to estimate how many samples (questionnaire responses) are required to reach a certain confidence level in the test results.

3 APPLICATION TO A TESTBED: KATHMANDU, NEPAL

We showcase module #3 using Kathmandu, Nepal, as the selected testbed. The Kathmandu Valley is prone to various natural hazards (e.g., earthquakes, floods, droughts). It also features evolving urban development, a growing population, and high social and physical vulnerabilities (Mesta et al., 2022).

3.1 Stakeholder mapping

We target relevant stakeholders based on the six stakeholder groups determined in Section 2.1 (see Figure 2). Specific stakeholders are identified from the internal database of the National Society of Earthquake Technology - Nepal (NSET), which was developed during previous NSET-led participatory processes related to DRM. We recruit 90 stakeholders in total. For the purposes of the questionnaire (details to follow) and given the relatively small sample size, stakeholders are classified as either "residents", if they belong to the first stakeholder group (50 in total), or "other stakeholders', if they belong to one of the remaining five stakeholder groups (40 in total). We establish this division based on the distinct, typically passive (non-decision-making, Pelling, 1998) roles that residents traditionally play in disaster planning (e.g., receiving education on disaster risks, benefitting from DRR policies; Mitchell et al., 2008; Yamori, 2008) compared to all other stakeholders that assume various active roles, including overseeing and managing emergency response and DRR efforts.

The spatial distribution of the recruited residents is roughly even across the Kathmandu Valley. They collectively span all demographic and socioeconomic categories included in the questionnaires, i.e., household income, age of the stakeholder and the household head, household size, number of people with special needs, number of elderly people, number of people under 18, housing tenure status, housing type, occupation, education level. The other stakeholders represent various sectors/fields/industries, such as consulting firms, construction and contractor companies, architectural and structural design companies (classed professional or experts), non-governmental organisations working on DRM, universities, and community services (classed additional stakeholders that serve the public interest), electricity companies (classed utility companies), government departments (e.g., Department of Roads; i.e., regulatory bodies; and Ministry of Water Resources; classed as regulatory bodies and utility companies), local (ward) government (classed as regulatory bodies), manufacturing companies and insurance companies (classed as industry). The "other stakeholder" participants are primarily high-level personnel (i.e., managers or chief officers of companies or organisations) to ensure they can accurately represent the perspectives of their companies or organisations. Figure 6 provides the number of participants in each stakeholder group within the broad category of other stakeholders.

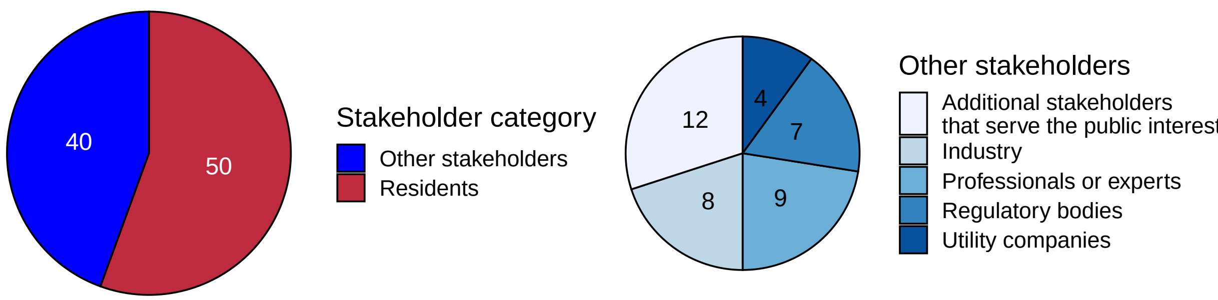

Figure 6. The number of recruited stakeholders in each stakeholder group.

3.2 Structured questionnaire

We develop separate versions of the questionnaire for each stakeholder category (see Figure 7). The 'Residents' questionnaire (see Figure 7) considers the interests of residents. The 'Other stakeholders' questionnaire considers the interests of people they serve. The questionnaires are tailored to the specific context of Kathmandu, Nepal. For example, localised income brackets and educational attainment categories are included in Section A of the questionnaires. The questionnaires were originally developed in English and translated into Nepali.

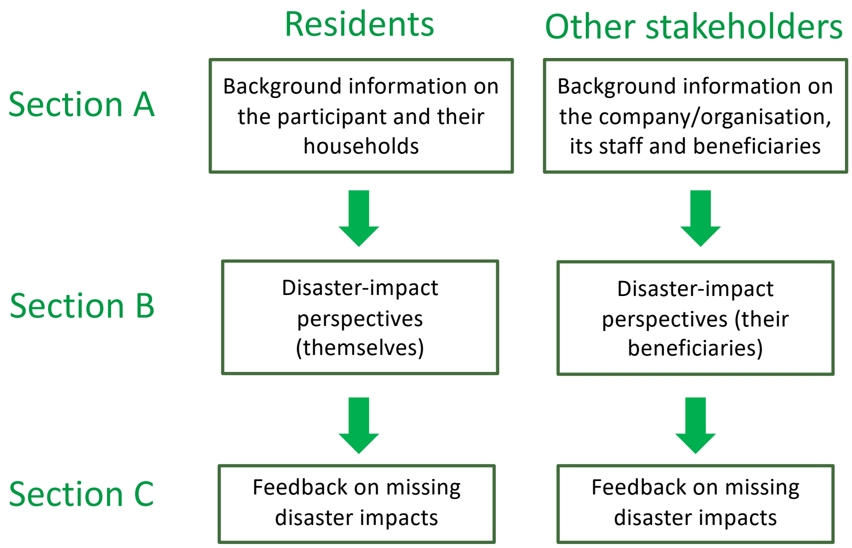

Figure 7. The structure of the two questionnaires developed to capture disaster-impact perspectives of various stakeholders.

3.3 Data processing

We transcribe the questionnaire response data into tibbles (Müller and Wickham, 2023), a common data structure in *R*, and perform statistical analyses using ***RankDIMs*** and ***CompareDIMs***. The ranking of DIMs and calculation of I_{pos} and I_{tot} presented in this section are performed only considering DIMs that capture the same spatial scale and temporal instance. DIMs that only include a description of a specific temporal instance (i.e., immediately after a hazard event) are ranked along with DIMs that capture disaster impacts two weeks following a hazard event. We do not divide the two categories into subgroups in these calculations, i.e., $n_j = 1$ for both stakeholder categories.

Figure 8 provides the top $n_{cus} = 25$ highest ranked disaster impacts at the household level two weeks following a hazard event and the associated S_{DIM_i} values, given that $w_1 = w_2 = 0.5$ for residents and other stakeholders. The top five highest-ranked household-level disaster impacts are, in descending order, fatalities, loss of access to drinking water, loss of access to food, acute severe injuries, and permanent loss of connection with family members. Economic loss due to building damage, typically representing the primary focus of conventional disaster impact assessments, is ranked 21^{st}, preceded by loss of access to water (6^{th}), electricity (7^{th}), and required healthcare (8^{th}), food contamination (9^{th}), loss of access to cellular services (10^{th}), homelessness (11^{th}), communicable diseases (12^{th}), and uninhabitable living conditions (13^{th}), for instance. Other highly ranked disaster impacts include loss of access to sewage treatment services (14^{th}), clean air (15^{th}), community assets (17^{th}), and WiFi services (18^{th}), voluntary relocation (16^{th}), impact on mental well-being (19^{th}) and temporary loss of connection with family members and friends (20^{th}). These results reinforce the need to go beyond simply considering direct physical damage and economic losses in disaster impact assessments.

When higher priority is placed on the perspectives of residents (i.e., $w_1 = 0.7$ for residents and $w_2 = 0.3$ for other stakeholders; see Figure 9), the top 25 most important DIMs remain almost the same, but change in ranking. For example, loss of access to clean air drops from 15^{th} to 18^{th} most important. This is because other stakeholders collectively rank this disaster impact as the 9^{th} most important, whereas residents rank it as the 29^{th} most important.

Figure 10 provides the top n_{cus} = 25 highest ranked disaster impacts at the household level six months following a hazard event as well as their associated S_{DIM_i} values, given that $w_1 = w_2 = 0.5$ for both residents and other stakeholders. It can be seen that the ranking of disaster impacts at a specific spatial scale can change over time. For example, the ranking of loss of access to clean air and community assets at the household level increases at six months (6^{th} and 9^{th}, respectively) relative to two weeks (15^{th} and 17^{th}, respectively). A similar trend is observed for the loss of access to utility services and telecommunication services, including water (6^{th} to 2^{nd}), electricity (7^{th} to 3^{rd}), sewage treatment (14^{th} to 1^{st}), cellular (10^{th} to 5^{th}), and forced temporary rehousing (22^{th} to 19^{th}). The ranking of loss of access to drinking water at the household level drops at six months (7^{th}) compared to two weeks (2^{nd}). These changes in importance rankings reflect the time-dependent nature of stakeholders' priorities that should be accounted for in disaster impact assessments.

Figures 11 and 12 provide the top n_{cus} = 25 highest-ranked disaster impacts at the neighbourhood and region level, respectively, two weeks after a hazard event, given that $w_1 = w_2 = 0.5$ for residents and other stakeholders. The results indicate that the ranking of a disaster impact at a specific temporal instance can change over different spatial scales. For example, fatalities are the most important disaster impact at the household level two weeks after a hazard event, but its ranking drops to 5^{th} at the neighbourhood level and 9^{th} at the regional level. A similar trend is observed for severe acute injuries, which are ranked 4^{th}, 4^{th}, and 11^{th} at the household, neighbourhood, and region level, respectively.

Figures 8, 9, 10, 11, and 12 indicate that disaster impacts related to the natural environment (e.g., reduced air quality, damage to green infrastructure, and loss of natural habitats) are also considered important by stakeholders, in addition to those related to ecosystem services (e.g., access to clean air). These results reflect the intrinsic value of the natural environment to stakeholders (independent of its functionalities to human society; Chan et al., 2016), which is generally not considered in conventional disaster impact assessments.

Figure 13 shows I_{pos} (left panel) and I_{tot} (right panel) for household, neighbourhood, and region spatial scales, plotted as a function of n_{cus} (= n_{sub} in Eqs. 2 and 3), at two weeks (solid lines) and six months (dashed lines) after a hazard event (assuming $w_1 = w_2 = 0.5$ for both categories). The top n_{cus} = 25 highest-ranked disaster impacts at the household, neighbourhood, and region level two weeks after a hazard event lead to an I_{pos} of 0.92, 0.77, and 0.71, respectively, and an I_{tot} of 0.65, 0.54, and 0.53, respectively. Similarly, the top n_{cus} = 30 (= n_{sub}) highest-ranked disaster impacts two weeks after a hazard event lead to an I_{pos} of 0.98, 0.85, and 0.80, and an I_{tot} of 0.76, 0.63, and 0.62, respectively. Both I_{pos} and I_{tot} decrease as the spatial scale increases from household to neighbourhood and region. This is because stakeholders perceive fewer household-level disaster impacts as important than those on larger spatial scales (i.e., neighbourhood and region). For example, for a desired I_{pos} of 0.80 two weeks after a hazard event, end users only need to focus on the top 20 highest-ranked disaster impacts at the household level, but the top 27 or 30 highest-ranked disaster impacts at the neighbourhood or region level, respectively.

The results of ***CompareDIMs*** are first computed for disaster impacts at the three considered spatial scales and a prescribed temporal instance, considering both stakeholder groups collectively. S_{DIM_i} values for fatalities (immediately following a hazard event) at the household, neighbourhood, and region level are 3.71, 3.34, 3.30, and their differences are found to be statistically significant (p-value = 0.03). The S_{DIM_i} value for fatalities at the household level is statistically different from that at the neighbourhood (p-value = 0.04), and region level (p-value = 0.02), but the neighbourhood-level S_{DIM_i} value is not statistically different from that at the region level (p-value = 0.84). These findings imply that both stakeholder categories value fatalities at the household level more than those at the neighbourhood and region level and, therefore, that the household level is the right spatial scale of analyses. However, the power analyses provide a value of 0.54 for the comparison between household- and neighbourhood-level S_{DIM_i} values and 0.64 for the comparison between household-and regional-level S_{DIM_i} values, which are below 0.80. Therefore, the previous conclusion on appropriate modelling resolution should be disregarded until more stakeholder responses are collected to improve the statistical power. To have a power of at least 0.80 under a 5% significance level, the number of responses included in household- and neighbourhood-level S_{DIM_i} values need to be respectively greater than or equal to 165 and 158 for their comparison, and the number of responses included in household- and regional-level S_{DIM_i} values must be at least 130 and 116 for their comparison. Among the 59 disaster impacts considered in this application, none are associated with statistically different S_{DIM_i} values across the three considered spatial resolutions (i.e., a p-value < 0.05 and, possibly, a statistical power > 0.80) for both Welch's two-sample t-test and Welch's ANOVA. This pilot study can be a basis for deciding the number of participants to recruit for future studies.

We also leverage ***CompareDIMs*** to test whether the S_{DIM_i} values of a disaster impact with a specific spatial resolution are different with statistical significance at two temporal instances (i.e., two weeks and six months after a hazard event). In this case, we compute separate S_{DIM_i} values for both stakeholder categories and compare the results obtained. S_{DIM_i} values for loss of access to clean air at the household level two weeks after a hazard event are statistically different (S_{DIM_i} = 2.45, ranked 29^{th}; see Figure 14) compared to those at six months (S_{DIM_i} = 3.50, ranked 10^{th}), in the case of the resident stakeholder category. The associated p-value is less than 0.01, and statistical power is 0.98. However, the same outcome is not produced for the other stakeholders (S_{DIM_i} = 3.39 for two weeks and S_{DIM_i} = 3.74 for six months, with p-value < 0.05 but statistical power equal to 0.51). Conversely, S_{DIM_i} values for forced temporary rehousing at the household level two weeks after a hazard event (S_{DIM_i} = 2.77, ranked 21^{st}; see Figure 14) are statistically different to those at six months (S_{DIM_i} = 3.61, ranked 10^{th}), for the other stakeholders (with p-value < 0.01 and statistical power equal to 0.80). This statement does not hold for the same S_{DIM_i} values computed only for the resident stakeholder category. Some other disaster impacts do produce statistically significant S_{DIM_i} values for both stakeholder categories at two weeks and six months, e.g., loss of access to community assets (see Figure 14). In addition, we leverage ***CompareDIMs*** to test whether the S_{DIM_i} values of a disaster impact with a specific spatial resolution and a prescribed temporal instance for two stakeholder categories are different with statistical significance. For example, S_{DIM_i} values for loss of access to clean air at the household level two weeks after a hazard event for the resident stakeholder category are statistically different to those associated with the other stakeholders (S_{DIM_i} = 2.45 and S_{DIM_i} = 3.39, respectively, p-value < 0.01, and statistical power is 0.96). These findings further emphasise the need to explicitly account for time and identity in the characterisation of DIMs where possible, as different stakeholder groups can have distinct and unique (e.g., time-dependent) requirements regarding the disaster impacts to be assessed.

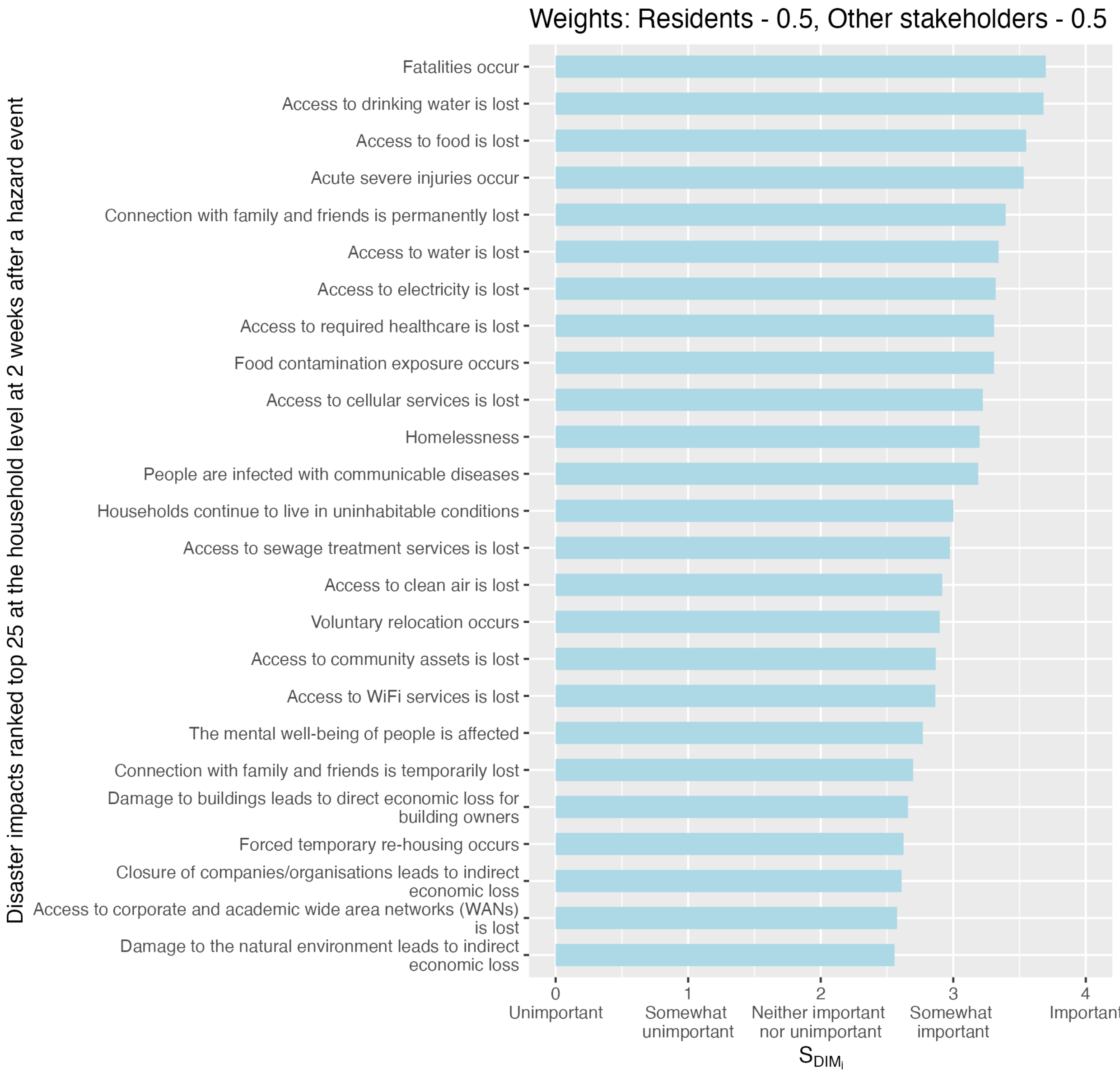

Figure 8. The top 25 highest-ranked disaster impacts at the household level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

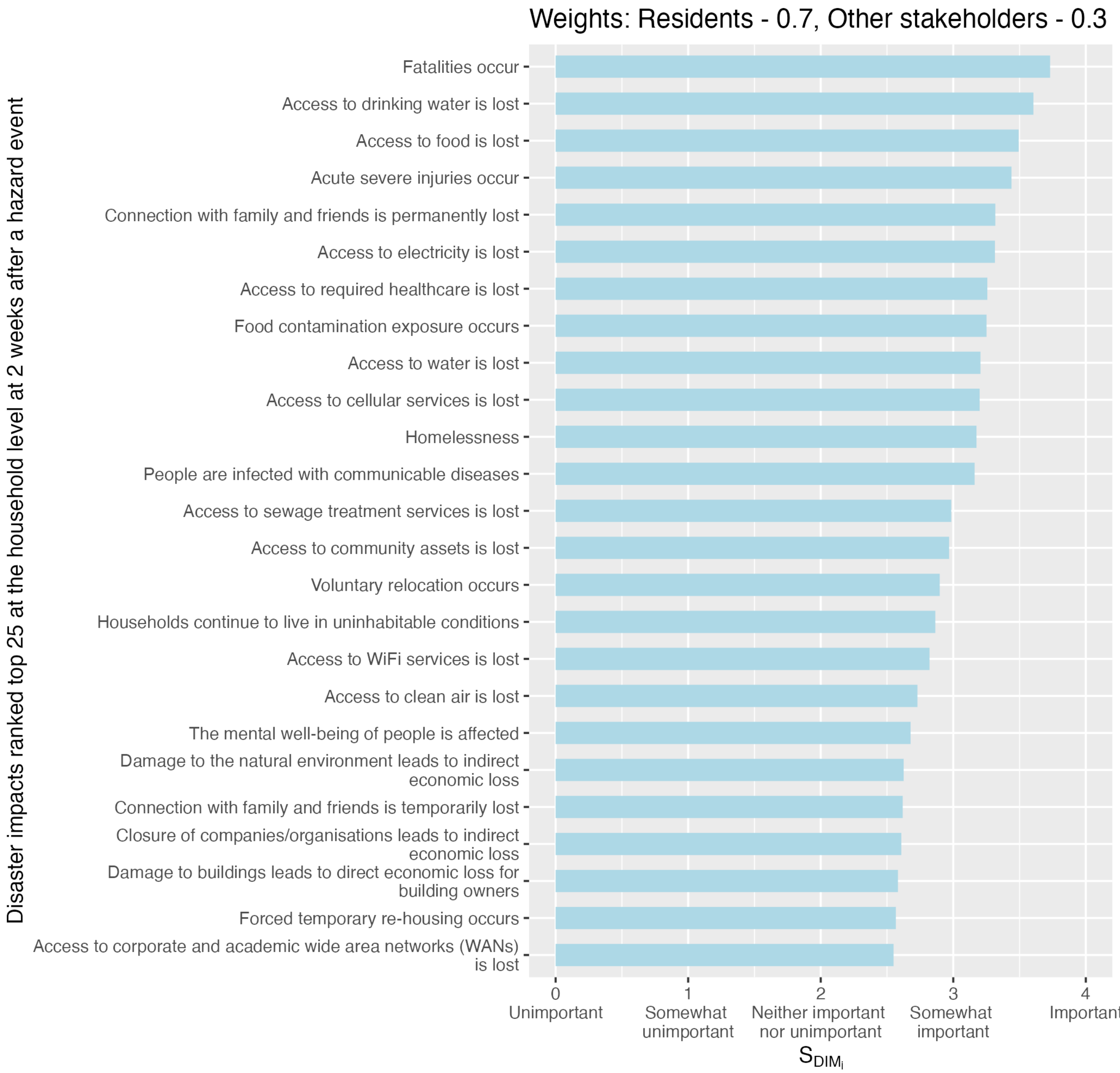

Figure 9. The top 25 highest-ranked disaster impacts at the household level two weeks following a hazard event, assuming $w_1 = 0.7$ for residents and $w_2 = 0.3$ for other stakeholders.

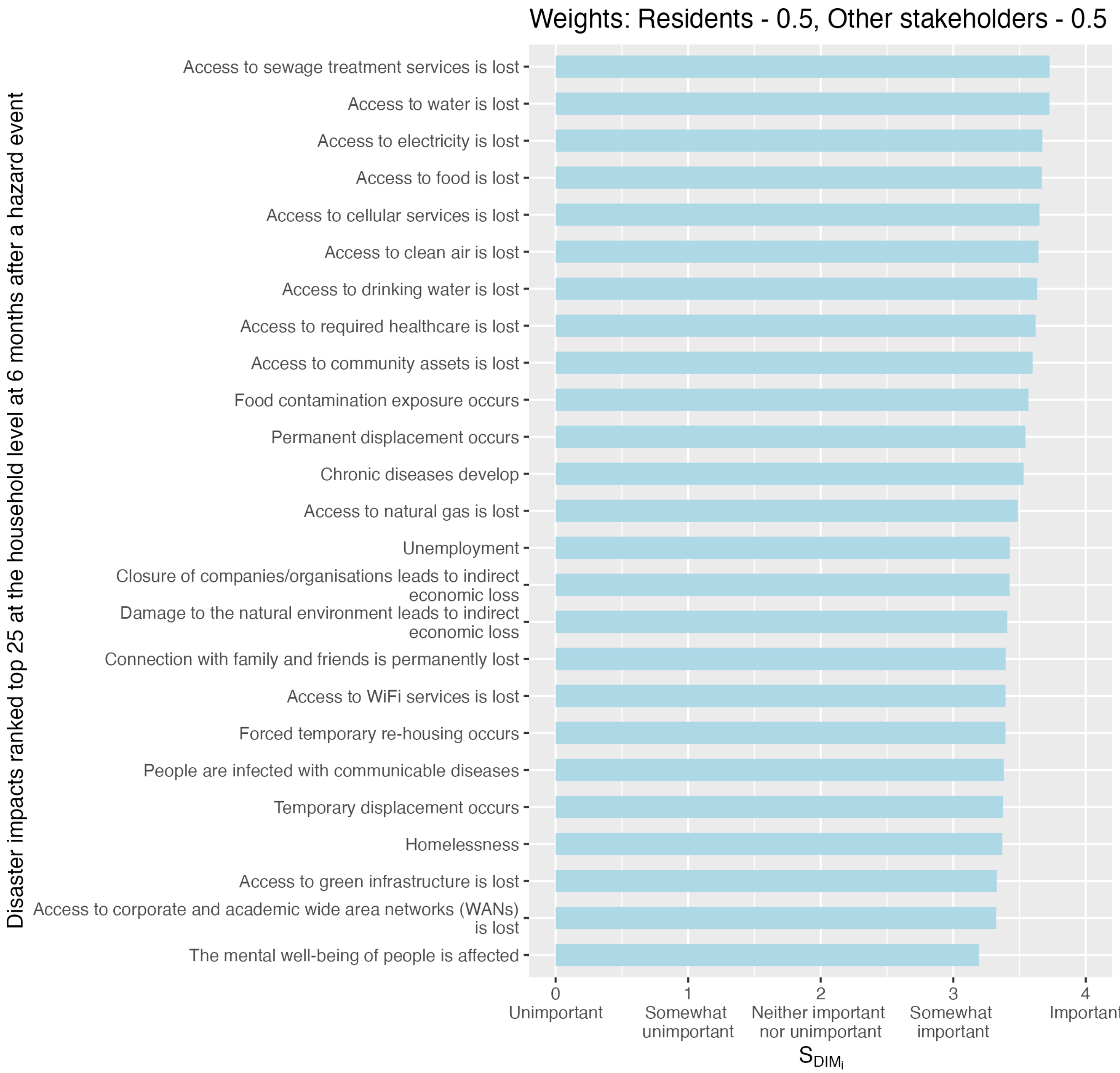

Figure 10. The top 25 highest-ranked disaster impacts at the household level six months following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

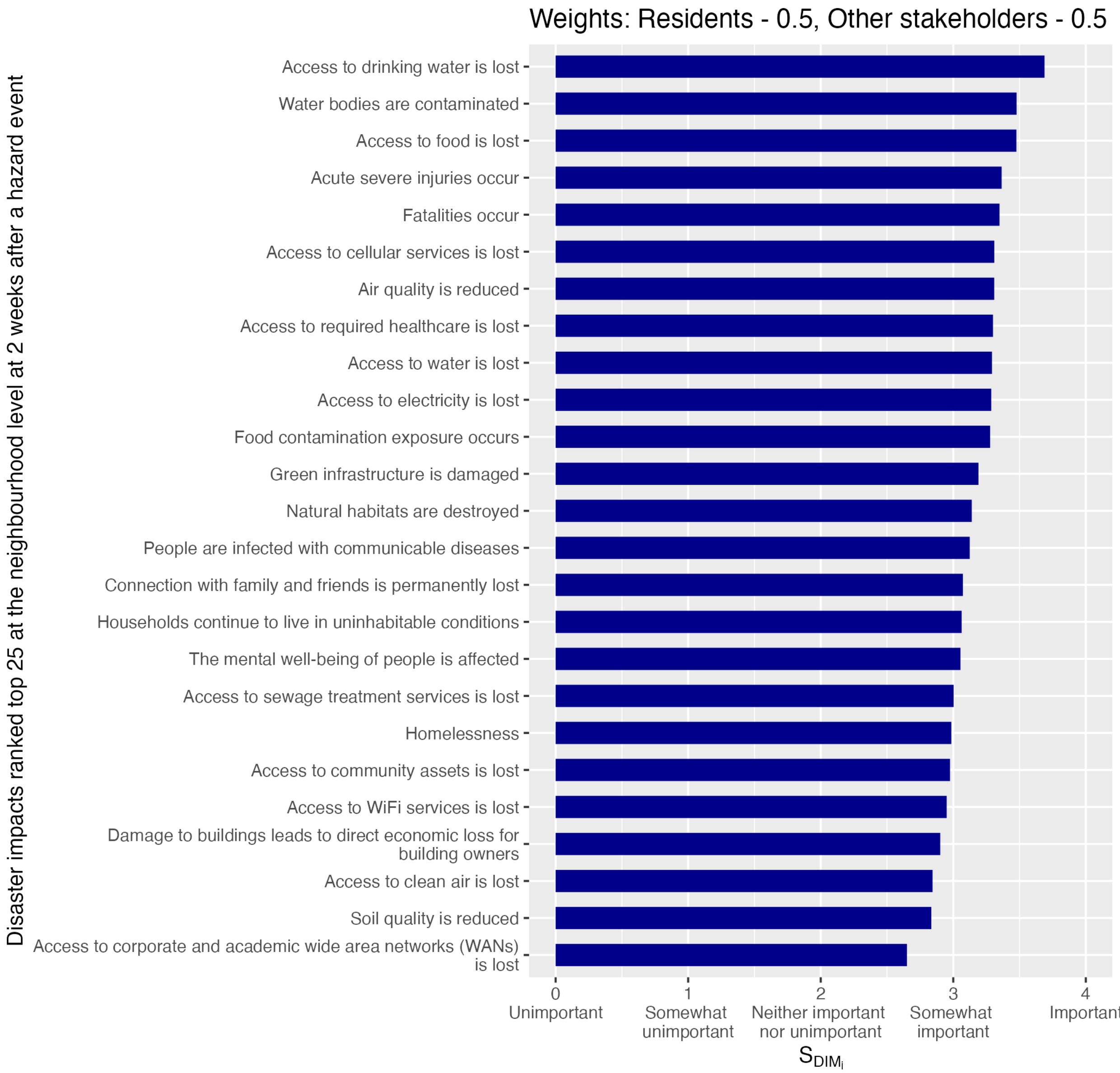

Figure 11. The top 25 highest-ranked disaster impacts at the neighbourhood level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

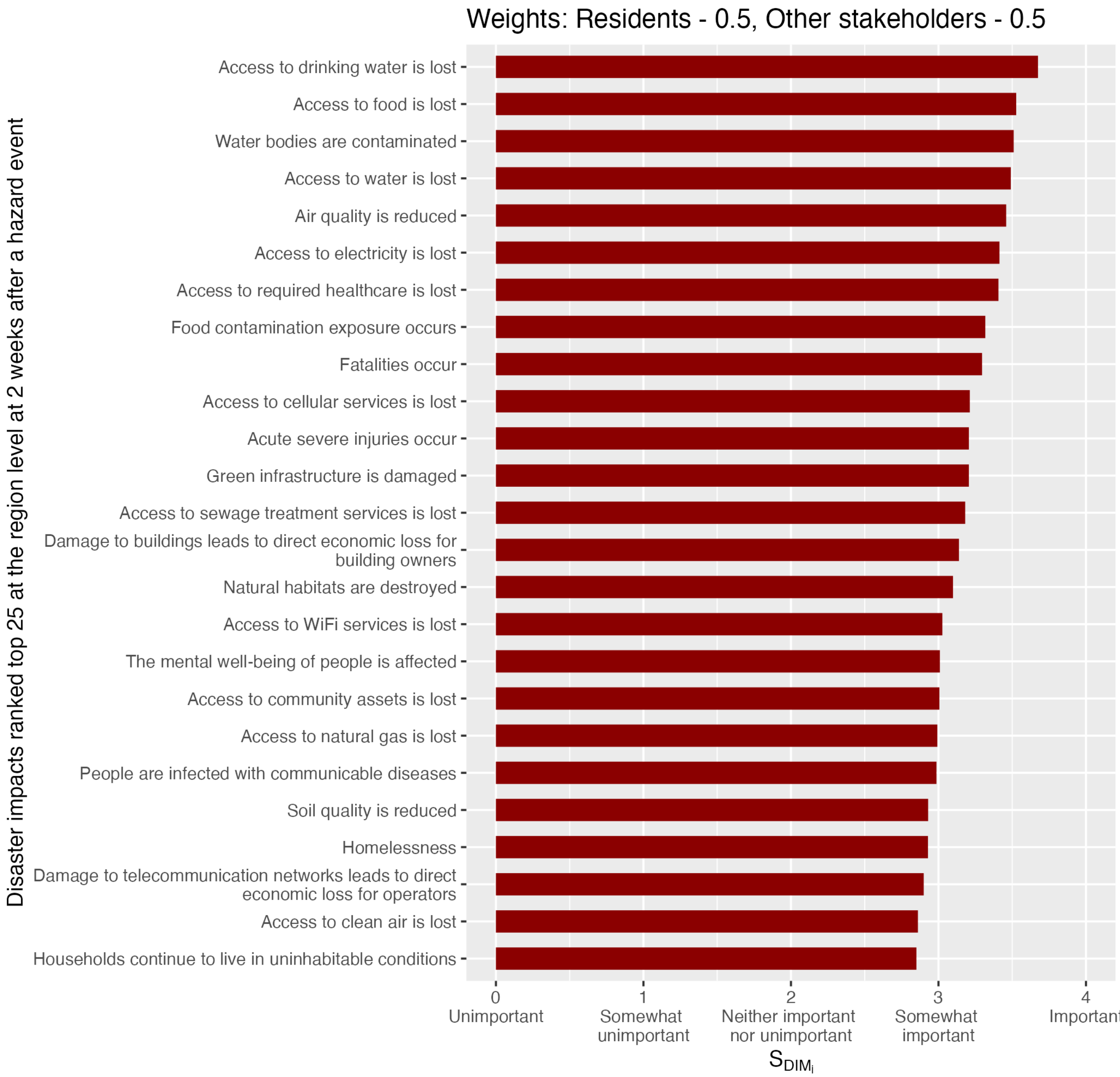

Figure 12. The top 25 highest-ranked disaster impacts at the region level two weeks following a hazard event, assuming $w_1 = w_2 = 0.5$ for residents and other stakeholders.

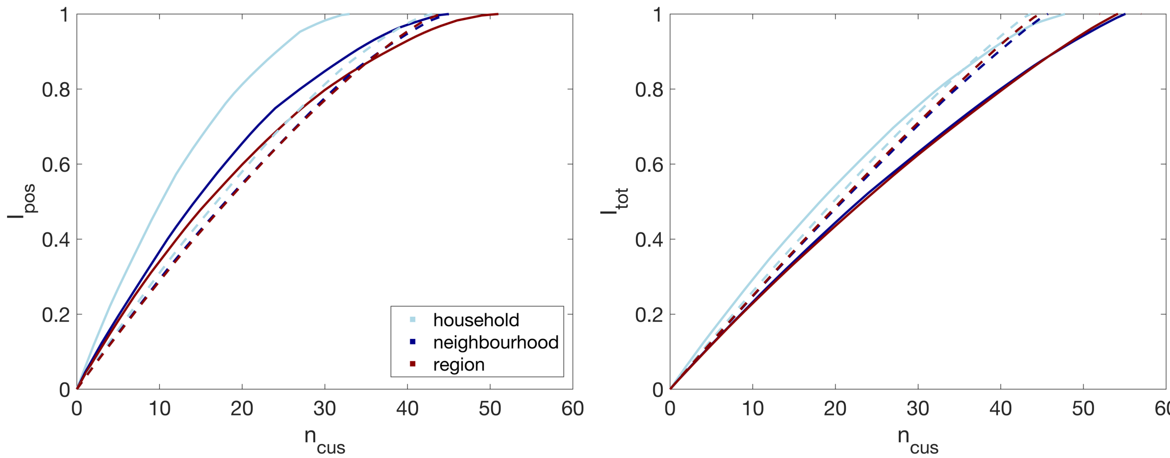

Figure 13. I_{pos} (left panel) and I_{tot} (right panel) plotted as a function of n_{cus} for at the household, neighbourhood, and region level two weeks (solid lines) and six months (dashed lines) after a hazard event

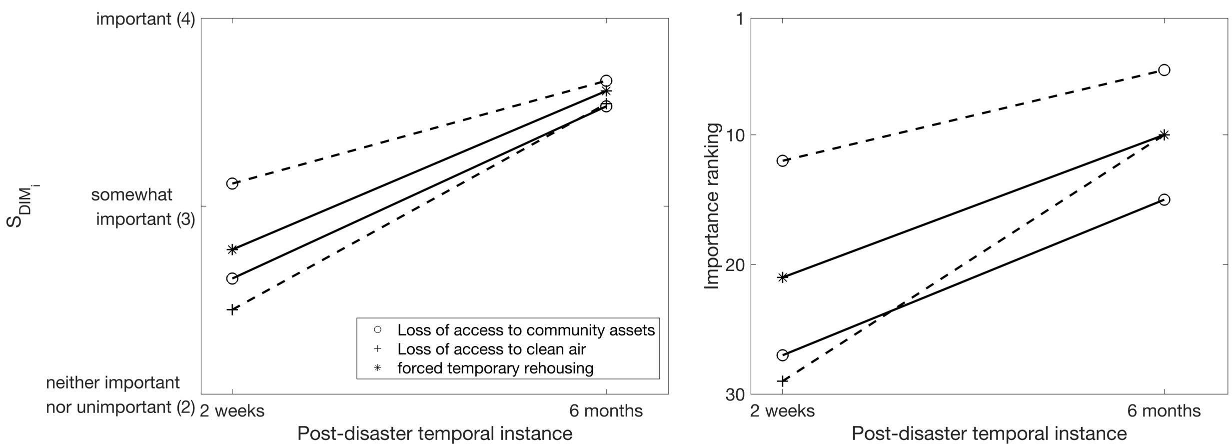

Figure 14. S_{DIM_i} values (left panel) and their ranking (right panel) for three examples DIMs that capture disaster impacts at the household level two weeks and six months after a hazard event. The S_{DIM_i} values are calculated separately for residents (dashed lines) and other stakeholders (solid lines), respectively.

4 CONCLUSIONS

This paper proposes a toolbox for characterising space- and time-dependent disaster impact metrics (DIMs) that account for the bespoke priorities of stakeholders related to disaster impact assessment. The toolbox ultimately helps end users, such as policymakers and disaster impact modellers, to decide which context-specific DIMs to consider in disaster impact assessments. By explicitly accounting for the spatial and temporal dimensions of disaster impacts, it provides an understanding of the required spatial scales and temporal instances to be integrated into disaster impact analyses, in line with recent recommendations of the literature (e.g., Logan et al., 2021; Nocera and Gardoni, 2022; Shen and Hwang, 2019; Rebally et al., 2021)

The DIMs toolbox contains three modules. The first module, which centres on the pool of available DIMs, includes a hierarchical pyramid that provides a conceptual representation of how society functions, facilitating the characterisation and computation of DIMs. The DIMs pyramid also serves as a basis for the structured questionnaires (in module #2) that are developed for a definitive list of stakeholder groups with a vested interest in disaster impact assessment. The questionnaires are used to collect the perspectives of stakeholders and currently consider 59 representative disaster impacts, accounting for three spatial scales of analysis (i.e., household, neighbourhood, and region) and two temporal instances (i.e., two weeks and six months after a hazard event). The second module also contains a data processing package to perform statistical analyses (e.g., hypothesis tests and power analyses) on questionnaire responses, which is integrated in interactive web applications. These statistical analyses provide crucial information for supporting policy-related decision making, such as the most important disaster impacts (in terms of understanding and assessment) for various stakeholder groups at different spatial scales and post-disaster temporal instances.

The third module involves an application of the first two modules to an urban testbed, which in this paper was Kathmandu, Nepal. We recruited 90 stakeholders from two broad stakeholder categories: residents (50 participants) and other stakeholders (including consulting firms, NGOs, construction companies, scholars, government officials, utility companies, and insurers; 40 participants). The results of this application indicate that disaster impacts related to direct physical damage and economic losses are neither the sole concerns of stakeholders nor the most important ones. Instead, loss of access to drinking water and food, utility services (e.g., water, electricity, sewage services), community assets, and clean air, as well as consequences related to social networks (e.g., permanent and temporary loss of connection with friends and family) and the natural environment (e.g., reduced air quality, damage to green infrastructure, and loss of natural habitats), are more important (at least for the stakeholder categories examined). These findings emphasise the need to consider more than just direct physical damage and economic losses in disaster impact assessments. The importance rankings of DIMs change as the emphases placed on the perspectives of different stakeholders and/or temporal instances considered are altered. For example, when the relative emphasis placed on residents' perspectives increases from 0.5 to 0.7, loss of access to clean air drops from the 15^{th} most important disaster impact at the household level two weeks after a hazard event to the 18^{th} most important. Hypothesis tests and power analyses further confirm that the two stakeholder categories considered perceive this DIM differently (p-value < 0.01 with a statistical power of 0.96). Moreover, the importance rankings of some impacts are higher at six months compared to two weeks after a hazard event when the relative emphases placed on residents' and other stakeholders' perspectives are equal ($w_1 = w_2 = 0.5$): loss of access to clean air (15^{th} to 6^{th}), community assets (17^{th} to 9^{th}), utility services and telecommunication services, including water (6^{th} to 2^{nd}), electricity (7^{th} to 3^{rd}), sewage treatment (14^{th} to 1^{st}), cellular services (10^{th} to 5^{th}) at the household level. An opposite trend is observed for loss of access to drinking water at the household level, which decreases in ranking from 2^{nd} at two weeks to 7^{th} at six months. These changes in ranking reflect the dynamic nature of stakeholders' priorities in the post-disaster phase. The findings of the application underline the importance of explicitly accounting for time and stakeholder identities in characterising DIMs. In cases where confident conclusions could not be drawn from the statistical tests, the data processing package was used to determine the number of additional participants required to overcome these issues.

In summary, the DIMs toolbox inherently embraces a participatory approach encouraged in prospective disaster risk management. This work contributes to advancing the utility of disaster impact assessments in critical associated decision-making efforts, such as policy design.

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DATA AVAILABILITY STATEMENT

All study data are made available on GitHub at `https://github.com/wangcb98/DIMs`, except raw questionnaire data, given their sensitivity and as per UCL ethics restrictions.

COMPETING INTERESTS

The authors have no competing interests to declare.

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Supplementary Information for "A Bespoke Approach to Quantifying the Impacts of Disasters, Using Stakeholder-relevant Metrics"

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1 Completing the testbed questionnaires

The testbed questionnaires were completed in three in-person workshops held by National Society of Earthquake Technology - Nepal (NSET) on 22 July 2023, 27 July 2023, and 28 August 2023, (26, 23, and 1 residents and 6, 0, and 34 other stakeholders per round respectively; see Figure S1). Each workshop began with an introduction to the background of the study. Transportation reimbursement and lunch boxes were provided to the stakeholders as compensation, in line with the ethics guidelines of University College London and NSET.

Figure S1. Workshops held by NSET in Kathmandu, Nepal (July - August 2023), in which recruited stakeholders completed the structured questionnaires.

2 *RankDIMs* and *CompareDIMs* web applications

2.1 Data

The required input data for both web applications are:

1. One or more *tibbles*. Each tibble contains questionnaire responses to all questions provided by all participants in a specific stakeholder group (or category). Each row contains responses for individual participants and each column contains all responses to a given question. Each cell contains either text (e.g., for question A2 (in part A of the 'other stakeholders' questionnaire) that request details on stakeholder roles within the company or organisation they represent), one number (for single-answer quantitative questions; see Figure S2), or a list of both numbers and/or text (for multiple-answer questions; see Figure S3). The responses for multiple-answer questions must be organised in the same order as shown in Figures S3 and S4;

2. Four string vectors that contain information on codes (question numbering) for each questionnaire question. Three of these vectors contain the codes of questions related to DIMs of each spatial scale

(e.g., "B6.1", "B7.1", "B8.1", "B10.1", "B12.1", etc., for household-level DIMs). The fourth vector contains codes of questions on disaster impacts across all spatial scales (e.g., "B31", see Figure S4). Each vector must be accompanied by another one that contains the descriptions of the corresponding disaster impacts (e.g., "access to green infrastructure is lost").

B5-2. Green infrastructure in your region is damaged.

Your answer:____________________________

Figure S2. An example of a single-answer question. Red text indicates the order in which the data should be provided within the corresponding cells of the tibble.

B8-2. Access to green infrastructure is lost across your neighbourhood.

For two weeks	For six months	Third entry
First entry	Second entry	Fourth entry

Figure S3. An example of a multiple-answer question. Red text indicates the order in which the data should be provided within the corresponding cells of the tibble.

B38. Permanent displacement occurs.

You	Your neighbourhood	Your region
First entry	Second entry	Third entry

Figure S4. An example of a question that involves all spatial scales.

2.2 Graphical user interfaces

Figures S5 and S6 provide the graphical user interfaces (GUIs) of the ***RankDIMs*** and ***CompareDIMs*** web applications. The various temporal instances and spatial scales considered in the applications are as described in Section 2. The applications currently account for the two stakeholder categories considered in the case study (i.e., residents and other stakeholders); future versions will capture all six representative stakeholder groups outlined in Section 2.

The input panel of the ***RankDIMs*** GUI asks users to select the temporal instance of interest, the weights assigned to each stakeholder category (w_j), the number of DIMs to consider ($n_{cus} = n_{sub}$), and a specified disaster impact to provide the ranking and S_{DIM_i} value for, across all spatial scales.

The ***CompareDIMs*** GUI contains three panels. The left panel requests information for comparing S_{DIM_i} values related to a specific disaster impact across different spatial scales, for a prescribed temporal instance, and set of stakeholder categories ("resident", "other stakeholders" or "both"). The middle panel is used to input information for comparing S_{DIM_i} values related to a specific disaster impact across different temporal instances, for a prescribed spatial resolution, and set of stakeholder categories ("resident", "other stakeholders” or “both”). The right panel requests information to compare the S_{DIM_i} values obtained by each stakeholder category for a given DIM. The current version of the application requires inputs to be provided for all three panels before the calculations can be run. This issue is intended to be rectified in future versions of the application, which will also allow for more general comparisons across different disaster impacts.

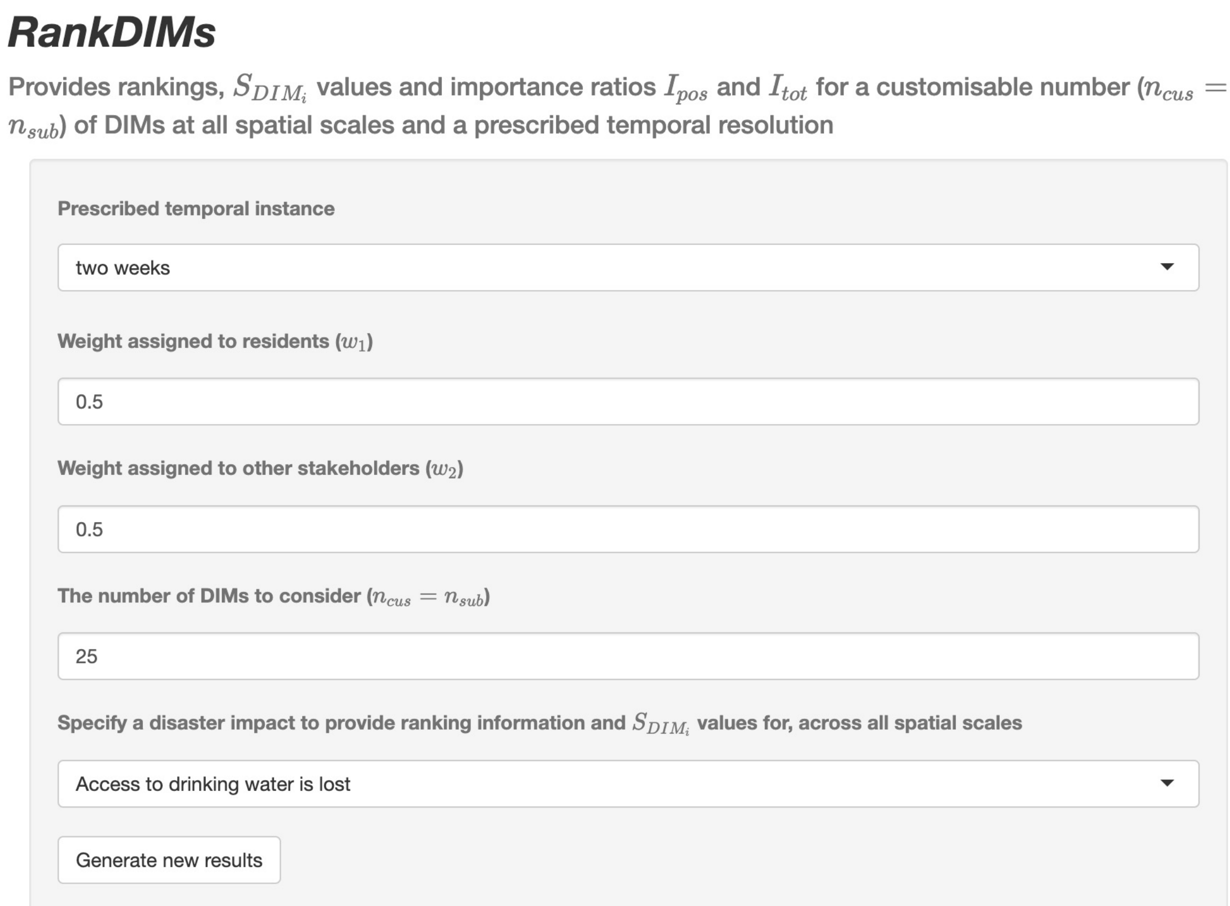

Figure S5. The GUI of ***RankDIMs***.

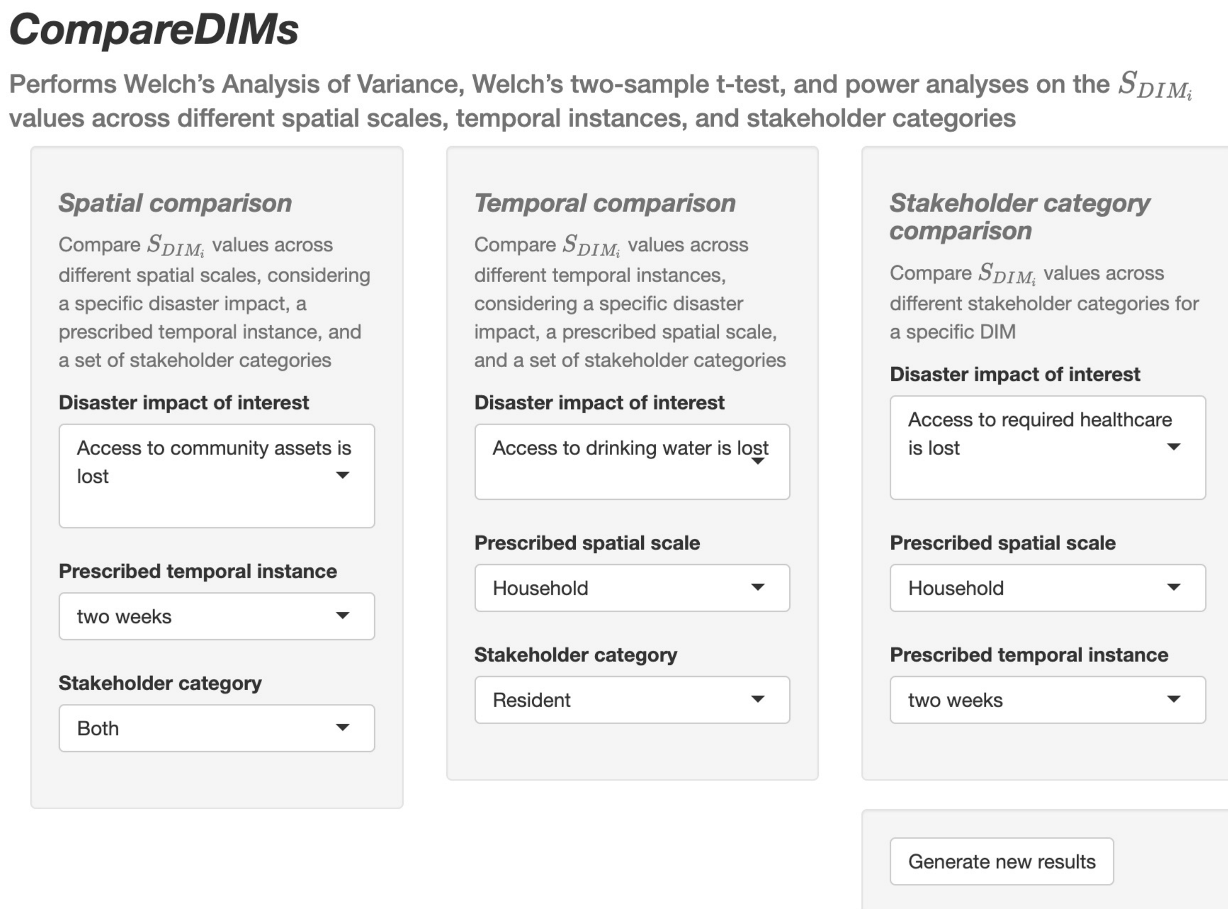

Figure S6. The GUI of ***CompareDIMs***.

RankDIMs outputs visualisations of rankings (similar to Figures 8 to 12 in Section 3.3 of the main text), importance ratios (I_{pos} and I_{tot}; see Figure S7), as well as separate ranking and S_{DIM_i} information for the disaster impact specified as part of the input (see Figure S8). The outputs of ***CompareDIMs*** are text descriptions of the results of its statistical tests described in Section 2.3.2 of the main text (e.g., Figures S9, S10, and S11).

The positive importance ratio (I_{pos}) and total importance ratio (I_{tot}) captured by the list of top $n_{cus} = n_{sub}$ DIMs at different spatial scales:

space	positive.importance.ratio	total.importance.ratio
household	0.92	0.65
neighbourhood	0.77	0.54
region	0.71	0.53

Figure S7. Example outputs of ***RankDIMs***. The positive importance ratio (I_{pos}) and total importance ratio (I_{tot}) captured by the list of top $n_{cus} = n_{sub}$ DIMs at household, neighbourhood, and region level.

The selected disaster impact is ranked #2 at the household level, with an average weighted importance score of 3.681, #1 at the neighbourhood level, with an average weighted importance score of 3.698, and #1 at the region level, with an average weighted importance score of 3.698.

Figure S8. Example outputs of ***RankDIMs***. Rankings and S_{DIM_i} values for the disaster impact associated with a prescribed temporal instance specified as part of the input, at household, neighbourhood, and region level.

Spatial comparison (Welch's Analysis of Variance and two-sample t-test and power analyses)

Result_ANOVA

The differences in importance scores for access to community assets is lost at the household, neighbourhood, and region level two weeks after the event are found to be NOT statistically significant with p-value= 0.5594, and importance scores being 3.12, 3.24, and 3.32, respectively.

Result_t_test

The differences in importance scores for access to community assets is lost at the household and neighbourhood levels two weeks after the event are found to be NOT statistically significant with p-value = 0.5093, statistical power = 0.1006, and importance scores being 3.12 and 3.24, respectively. To have a power of 0.80, the required sample sizes for household- and neighbourhood-level responses are 896 and 896, respectively.

The differences in importance scores for access to community assets is lost at the household and region levels two weeks after the event are found to be NOT statistically significant with p-value = 0.2832, statistical power = 0.1876, and importance scores being 3.12 and 3.32, respectively. To have a power of 0.80, the required sample sizes for household- and region-level responses are 338 and 338, respectively.

The differences in importance scores for access to community assets is lost at the region and neighbourhood levels two weeks after the event are found to be NOT statistically significant with p-value = 0.6549, statistical power = 0.07287, and importance scores being 3.32 and 3.24, respectively. To have a power of 0.80, the required sample sizes for region- and neighbourhood-level responses are 1954 and 1954, respectively.

Figure S9. Example outputs of ***CompareDIMs***. Results for the comparison of S_{DIM_i} values obtained across different spatial scales, considering a specific disaster impact, a prescribed temporal instance, and a set of stakeholder categories, specified by inputs in the ‘Spatial comparison’ panel.

Temporal comparison (Welch's two-sample t-test and power analyses)

Result

The differences in importance scores for access to drinking water is lost at the household level at two weeks and six months after the event are found to be NOT statistically significant with p-value = 0.4366, statistical power = 0.1207, and importance scores being 3.49 and 3.656, respectively. To have a power of 0.80, the required sample sizes for responses associated with two weeks and six months after the event are 631 and 412, respectively.

Figure S10. Example outputs of ***CompareDIMs***. Results for the comparison of S_{DIM_i} values obtained across different temporal instances, considering a specific disaster impact, a prescribed spatial scale, and a set of stakeholder categories, specified by inputs in the 'Temporal comparison' panel.

Stakeholder category comparison (Welch's two-sample t-test and power analyses)

Result

The differences in importance scores associated with residents and other stakeholders, respectively, for access to required healthcare is lost at the household level two weeks after the event are found to be NOT statistically significant with p-value = 0.2459, statistical power = 0.2115, and importance scores being 3.18 and 3.436, respectively. To have a power of 0.80, the required sample sizes for responses of residents and other stakeholders are 289 and 226, respectively.

Figure S11. Example outputs of ***CompareDIMs***. Results for the comparison of S_{DIM_i} values obtained by each stakeholder category for a given DIM, as specified by inputs in the 'Stakeholder category comparison' panel

To access the source codes for the web applications, please go to `https://github.com/wangcb98/DIMs/tree/main/web_applications`.

3 Questionnaires

To access the questionnaires developed for the Kathmandu testbed application, please go to `https://github.com/wangcb98/DIMs/tree/main/questionnaires_KTM`.