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Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework

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A R T I C L E I N F O

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A B S T R A C T

INFORM Risk Index is a global indicator-based disaster risk assessment tool that combines hazards, exposure, vulnerability and lack of coping capacity indicators with the purpose to support humanitarian crisis management decisions considering the current climate and population. In this exploratory study, we extend the Index to include future climate change and population projections using RCP 8.5 climate projections of coastal flood, river flood and drought, and SSP3 and SSP5 population projections for the period 2036 to 2065. For the three hazards considered, annually 1.3 billion people (150% increase), 1.8 billion people (249% increase) and 1.5 billion people (197% increase) in the mid-21st century are projected to be exposed under the 2015, SSP3 and SSP5 population estimates, respectively. Drought shows the highest exposure levels followed by river flood and then coastal flood, with some regional differences. The largest exposed population is projected in Asia, while the largest percent changes are projected in Africa and Oceania. Countries with largest current and projected risk including non-climatic factors are generally located in Africa, West and South Asia and Central America. An uncertainty analysis of the extended index shows that it is generally robust and not influenced by the methodological choices. The projected changes in risk and coping capacity (vulnerability) due to climate change are generally greater than those associated with population changes. Countries in Europe, Western and Northern Asia and Africa tend to show higher reduction levels in vulnerability (lack of coping capacity) required to nullify the adverse impacts of the projected amplified hazards and exposure. The required increase in coping capacity (decreased vulnerability) can inform decision-making processes on disaster risk reduction and adaptation options to maintain manageable risk levels at global and national scale. Overall, the extended INFORM Risk Index is a means to integrate Disaster Risk Reduction and Climate Change Adaptation policy agendas to create conditions for greater policy impact, more efficient use of resources and more effective action in protecting life, livelihoods and valuable assets.

1. Introduction

In recent years, climate-related risks have been amplified as a result of a changing climate, unplanned urbanization, demographic pressures, land-use and land-cover change, biodiversity loss and ecosystem degradation (European Commission, 2014, 2013; Poljansek et al., 2017). Average annual deaths caused by such events increased from an average of 26,000 per year between 1995 and 2004 to 34,000 between 2005 and 2014. Estimated annual economic losses from disasters amount to around 300 billion US$ globally (UNISDR, 2015a). These human and economic losses are likely to continue to increase as climate change progresses and population increases (IPCC, 2018).

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According to the Intergovernmental Panel on Climate Change (IPCC), 1.5 °C of global warming above pre-industrial levels (Paris Agreement lower cap) will likely be surpassed in the late 2030s or early 2040s without mitigation and reach the range of 2.9 to 3.4 °C by the end of the century (IPCC, 2018; UNDRR, 2019). Global temperature increases lead to non-linear changes in intensity and frequency of natural hazards such as river flood (Alfieri et al., 2016, 2015), coastal flood (storm surge) (Vousdoukas et al., 2018a), drought and heatwave (IPCC, 2014a; Mysiak et al., 2018; Naumann et al., 2018; Sylla et al., 2018). This increases the necessity of inclusive development and effective humanitarian relief to mitigate climate change risk to mortality, food and water security, livelihood and consequent impacts including inequality, instability, violence and displacement (IFRC, 2019; UN, 2020).

To tackle the risk of increasingly severe and frequent natural and anthropogenic weather and climate related disasters, greater science-policy based on improved knowledge, stronger evidence and a greater focus on transformative processes at all stages of the Disaster Risk Management (DRM) cycle (prevention, reduction, preparedness, response and recovery) are essential (FAO, 2008; Poljansek et al., 2017; UNDP, 2015). The UN Sendai Framework for Disaster Risk Reduction (UNISDR, 2015b) calls on science and policy to construct rigorous knowledge of disaster risk and consequent impacts and to develop adequate preventive policies to mitigate the risk of disasters. Qualitative and quantitative approaches are useful for assessing the effectiveness of such preventive policies. Indicator-based risk assessment frameworks combine hazard, exposure and vulnerability and are used both for analysing risks and assessing the progress made (Bakkensen et al., 2017; EEA, 2015).

The World Risk Index (BEH, 2020; Welle and Birkmann, 2015), ND-GAIN Country Index (University of Notre Dame, 2018), Global Climate Risk Index (Eckstein et al., 2021) and INFORM Risk Index (De Groeve et al., 2015) are examples of global indicator-based assessments. Among these, INFORM Risk Index, developed by the Joint Research Centre (JRC) of the European Commission, has gained increasing popularity due to its comprehensive framework, use of open data and transparent methodology (Bornhofen et al., 2019; Casajus Valles et al., 2021; FAO, 2018a, 2018b; GFDRR, 2015; IFRC, 2020; IOM, 2019; Messina et al., 2019; Pigott et al., 2017; Poljansek et al., 2017, 2021; Thow et al., 2021, 2020; WHO, 2017). It is designed as a common evidence base for global humanitarian risk analysis in response to recommendations by several international organizations including the World bank (World Bank, 2013) and the Office for Coordination of Humanitarian Affairs (OCHA, 2014). The index identifies "countries at risk from humanitarian emergencies that could overwhelm current national response capacity, and therefore lead to a need for international assistance" (OCHA, 2020a). Although the index measures the risk of humanitarian emergencies, it is equally relevant for development and disaster risk reduction (DRR) actors, and for high income countries. It provides a snapshot of multi-hazard disaster risk encompassing each country's exposure, vulnerability and coping capacity to current natural and human-induced hazards (Marin-Ferrer et al., 2017; Thow et al., 2020).

The INFORM Risk Index has been used or adapted by many national and international organizations and agencies such as the European Civil Protection and Humanitarian Aid Operations (ECHO), OCHA, Foreign, Commonwealth and Development Office (FCDO), the World Food Programme (WFP), the United Nations International Children's Emergency Fund (UNICEF), World Health Organization (WHO), the US Department of State, and the US Agency for International Development (USAID) (Messina et al., 2019; Thow et al., 2021, 2020, 2017). Examples of INFORM Risk Index use include the development of standard operating procedures for El Niño events, led by OCHA and Food and Agriculture Organization (FAO); the support for humanitarian and development planning and UN Integrated Strategy for the Sahel by OCHA; and providing an evidence base for investments in priorities for Ebola outbreak mitigation and prevention by WHO (Thow et al., 2021, 2017). The index framework and database has been used in the United Nations Central Emergency Response Fund (CERF) Index of Risk and Vulnerability (CIRV) (CERF, 2018, 2016), global disaster displacement risk model by International Displacement Monitoring Centre (IDMC, 2017), and JRC Global Disaster Alert and Coordination System (GDACS) (JRC, 2021). Several impact assessment studies have also adapted the index in various contexts, such as for pandemics (Pigott et al., 2017), agricultural development (Bornhofen et al., 2019), mortality to natural hazards (Shi et al., 2016) and floods and landslides (Gaire et al., 2015) (See Table SM1).

Climate change is one of the major drivers of disaster and development losses, affecting the security and well-being of communities (UNDRR, 2019). Developing tools for climate risk-informed decision-making and monitoring, reporting and evaluation (MRE) purposes such as risk indices can facilitate the global response to limiting warming to 1.5 °C (IPCC, 2018; UNISDR, 2015b; Wijenayake, 2019). Direct human climate change risks are associated with subsequent hazards, population exposure and population vulnerability and capacity to prepare for and manage amplified risks (Byers et al., 2018). Country level risk indices at a global scale currently exist, but are primarily based on analyses using observational data and do not account for projected climate change impacts nor socioeconomic development (e.g., Global Climate Risk Index by GermanWatch and World Risk Index from Bündnis Entwicklung Hilft). The need for an improved understanding of the dynamics of climate related risk components (hazard, exposure and vulnerability) has been highlighted in numerous documents (e.g., Birkmann et al., 2015; Debortoli et al., 2019; Dilling et al., 2015; Ford et al., 2018; IPCC, 2014a; Jurgilevich et al., 2017; Rohat, 2018; Rohat et al., 2019).

Some indices include the dynamic aspects of climate change risk in their exposure assessments. The Notre Dame Global Adaptation Initiative (ND-GAIN), for example, measures a country's vulnerability to climate disruptions for six life-supporting sectors, namely food, water, health, ecosystem services, human habitat and infrastructure, considering projected impacts of climate-related hazards such as extreme sea level, flood and heatwave (University of Notre Dame, 2018). Similar approaches have been employed in several local, national and regional risk and vulnerability studies (Debortoli et al., 2019; ESPON, 2011; Jurgilevich et al., 2017; KC et al., 2015; Mysiak et al., 2018; RESIN, 2018). By making the implicit assumption that vulnerability and capacity will remain constant, these indices do not consider the evolution of these elements over time nor the requirements to offset changes in climatic drivers (Debortoli et al., 2019; Fawcett et al., 2017; Ford et al., 2018; Magnan et al., 2016).

Recent studies have applied Shared Socioeconomic Pathways (SSPs) to project vulnerability and coping capacity drivers (Andrijevic et al., 2020; Birkmann et al., 2020; Rohat, 2018; Yang and Cui, 2019). SSPs include a comprehensive framework for joint consideration of socio-economic development and climate change mitigation and adaptation challenges (O'Neill et al., 2017; Riahi et al., 2017; van Vuuren et al., 2017). Socioeconomic projections with consistent 21st century narratives are available for the SSPs for population (KC and Lutz, 2017), urbanization (Jiang and O'Neill, 2017), gross domestic product (Dellink et al., 2017), educational attainment and age structure dynamics (Crespo Cuaresma, 2017), global income inequality (national Gini coefficients) (Rao et al., 2019) and governance (Andrijevic et al., 2020).

There are still substantial challenges to integrating SSP projections into risk assessments (IIASA, 2018; O'Neill et al., 2020). Their application to domains beyond climate change, such as the Sustainable Development Goals (SDGs) which shape INFORM vulnerability and coping capacity dimensions, are constrained (O'Neill et al., 2020). For instance, The World in 2050 (TWI2050) (IIASA, 2018) found no matching SSPs able to simultaneously cover the full range SDGs. Furthermore, complexities exist in addressing global shocks such as pandemics, technological breakthroughs, economic crises and other natural or human-caused disruptions (O'Neill et al., 2020). Currently such disruptions are considered implicit possibilities within scenarios without information on causal events (O'Neill et al., 2020). Disruptions caused by the

COVID-19 crisis, for example, may result in discontinuities in development and societal pathways (Dunz et al., 2021), and subsequently the transformational changes may surpass the range of mitigation and adaptation challenges encompassed by the SSPs. O'Neill et al. (2020) suggest a broader research programme to explore the SSP space beyond the current narratives.

Integrating climate change projections and future adaptation measures in the INFORM Risk Index would be an important contribution for its partners in terms of horizon scanning and global humanitarian risk monitoring (Messina et al., 2019). In this study, we extend the INFORM Risk Index to include projected future climate-change hazards and risks. By incorporating the dynamics of climate change on the intensity and frequency of climate related hazards into INFORM, we are the first to address humanitarian risk including climate change at a global level. The climate-related hazards are extended using a Representative Concentration Pathway (RCP) projection and the exposure dimension using corresponding SSPs. In assessing projected changes in hazard and exposure, we estimate the change in coping capacity (vulnerability) required to compensate for the changes. The analysis includes an uncertainty analysis of the natural hazard and exposure component of the extended index using a quasi-Monte Carlo approach.

2. Methodology and data

2.1. INFORM Risk Index

INFORM Risk Index is a composite country-level indicator designed as a tool for managing humanitarian crises (JRC, 2019; Marin-Ferrer et al., 2017). INFORM is a collaboration of the Inter-Agency Standing Committee and the European Commission, led by JRC (Thow et al., 2020). The INFORM framework includes: i) Hazards and Exposure – events that could occur and exposure to them; ii) Vulnerability – susceptibility of communities to those hazards; and iii) Lack of Coping Capacity – lack of resources available to alleviate their impact (Fig. 1) (Cardona and Carreño, 2011; Marin-Ferrer et al., 2017; Oppenheimer et al., 2014; Wisner et al., 2005). A total of 75 indicators are used for INFORM Risk Index, and annual updates have been provided since 2015. The components are normalized to score of 1 to 10 and aggregated using either an arithmetic or geometric mean depending on the metric. Details on the index calculation methodology can be found in Marin-Ferrer et al. (2017) and Thow et al. (2020).

INFORM Risk Index hazard and exposure data are based on probabilistic hazards combined with the latest population estimates. Six natural hazards are included: earthquakes, tsunamis, floods, tropical cyclones, droughts and epidemics. These hazards are currently (prior to this study) considered natural in the INFORM framework even though humans are impacting some of them. Human hazards include conflict intensity or a probability of future conflict (HIIK, 2019) and the projected conflict risk within the next four years (JRC, 2017). Exposed population is considered in terms of both total exposed population and exposed population relative to the total.

The vulnerability dimension encompasses socioeconomic vulnerability and vulnerable groups. Socioeconomic vulnerability is comprised of development and deprivation, inequality and aid dependency. The vulnerable groups category refers to "the population that has specific characteristics which make it at a higher risk of needing humanitarian assistance than others or being excluded from financial and social services", which is sometimes defined as social vulnerability (Cutter et al., 2003; Fekete, 2009). It encompasses uprooted people (refugees and displaced population) and other vulnerable groups identified based on health condition, age dependency and food security. The lack of coping capacity dimension is composed of institutional and infrastructure components. The institutional component evaluates government efficacy in perusing DRR activities and contains DRR and governance factors. The infrastructure component is a combination of communication, physical infrastructure and access to healthcare (Marin-Ferrer et al., 2017). The vulnerability and the lack of coping capacity indicators are both based on the latest year's data.

In terms of robustness of the index methodology and validation, some research and review articles have compared the INFORM conceptual framework and database with other indicator-based assessments (Beccari, 2016; Fetzek and Mazo, 2014; Visser et al., 2020). Visser et al., 2020 analyze and compare the INFORM Risk Index with other operational national-scale performance indices. They address five metadata-related reliability topics which are important in the context of risk indicators and indices thereof: 1) vagueness in definitions; 2) presence of uncertainty information; 3) missing data; 4) temporal positioning; and 5) role of aggregation and normalization procedures. Accordingly,

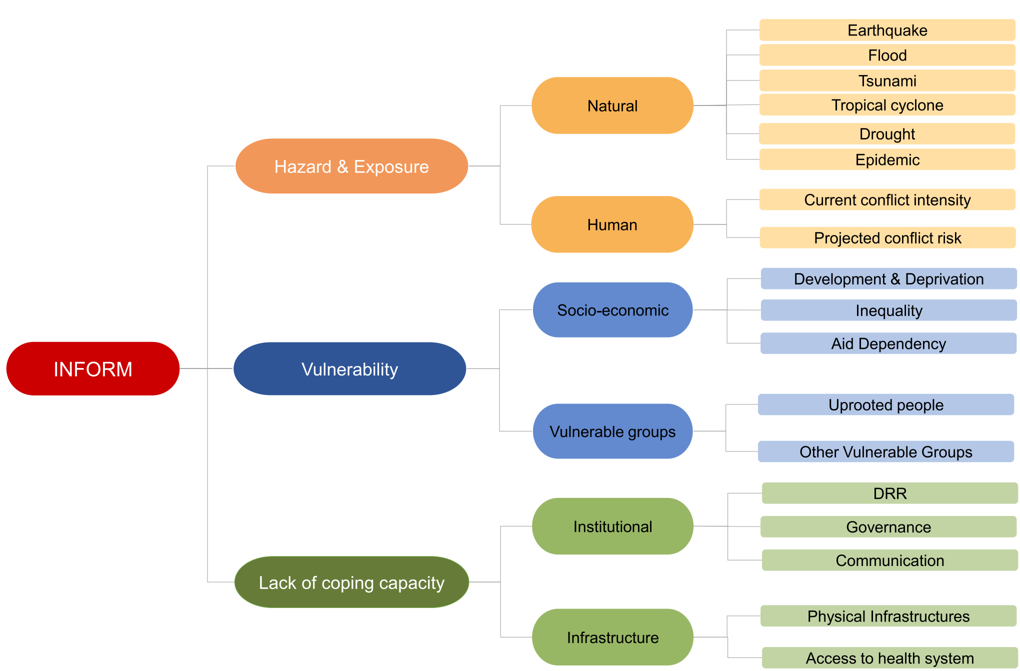

Fig. 1. *INFORM framework 2021*. Adapted from Thow et al. (2020).

INFORM Risk Index shows acceptable performance among the criteria in comparison to the others.

2.2. Climate change and population projections in INFORM Risk Index

The climate-related hazards in the current index are based on United Nations International Strategy for Disaster Reduction (UNISDR) Global Risk Assessment (GAR, 2015), FAO Agricultural Stress Index (ASI) (Rojas, 2018) and Emergency Events Database (EM-DAT) (CRED, 2019) data for different hazard intensities (Table 1). In this study, three INFORM Risk Index hazards are adapted and used within the extended framework: River flood, coastal flood and drought (Table 1).

The INFORM Risk Index hazard and exposure dimensions are extended using climate change and population projections based on the IPCC RCPs and corresponding SSPs for the mid-21st century (2036–2065). RCPs describe the evolution of future atmospheric greenhouse gas concentrations (GHGs) and associated climate impacts without any assumptions on mitigation actions (IPCC, 2014c; Pedde et al., 2019; van Vuuren et al., 2011). We apply RCP 8.5 which is the IPCC pathway with the largest atmospheric GHGs (8.5 W m^{-2} radiative forcing by 2100) and typically considered a business as usual scenario. Kebede et al. (2018) suggest that by considering RCP 8.5 we maximize the sampling of uncertainty in future climate changes and provide a challenging yet plausible scenario context to test the robustness of human and natural systems and climate change adaptation measures.

The SSPs consider different socio-economic futures, and the challenges they present for climate mitigation and adaptation as socio-economic factors impact the actions needed to meet climate and sustainability targets (O'Neill et al., 2017, 2014). Van Vuuren et al. (2014) developed a scenario matrix to address the effectiveness of various RCP-SSP combinations in year 2100 using different integrated assessment models (IAMs). They determine that SSP2, SSP3 and SSP5 can be combined with RCP 8.5 and show the lowest uncertainty for SSP5. In addition, Kebede et al. (2018) argue that after 2050 only SSP3 and SSP5 can produce the high emissions required for RCP 8.5.

SSP3 envisages relatively low income growth; low human capital investments; high fertility and population growth rates in the currently high fertility countries and low fertility rates and low or negative population growth in the currently low fertility countries; low migration; and slow urbanization. World population is projected to increase from 7.3 billion in 2015 to 9.8 billion in 2050 (34%) (Fig. 2; Table SM2). At the continental scale, the largest population increases are projected in Africa (96% or 1.1 billion), Asia (28% or 1.3 billion), and South America (28% or 0.12 billion) and the smallest in Europe (−8.1% or −0.06 billion).

SSP5 foresees a development narrative with relatively high-income growth; increased education and health investment; rapid demographic transition; low population growth in currently high fertility countries; high level fertility in currently low fertility countries; substantial migration; and rapid and not well managed urbanization. Global population is projected to increase from 7.3 billion in 2015 to 8.4 billion (15%) under SSP5 (Fig. 2; Table SM2). All continents are projected to increase in population, but the distribution of the increase is considerably more uniform in SSP5 compared to SSP3. The largest increases are projected in Oceania (60% or 0.23 billion), Africa (46% or 0.5 billion) and North America (29% or 0.16 billion) and the smallest in South America (2% or 0.01 billion) and Asia (7% or 0.3 billion).

To encompass a wide range of impacts and to generate highly divergent and challenging scenario contexts across multiple scales, we extend the INFORM Risk Index considering mid-21st century (2036–2065) climate projections from RCP 8.5 coupled with population projections from both SSP3 and SSP5. The extended index accounting for climate and population change projections is performed in three main steps (Fig. 3). In the first step, we compute the climate risk for the historical period and the projected mid-21st century period according to RCP 8.5 with the exposed population fixed at the 2015 values from the Global Human Settlement Layer (GHSL, Pesaresi et al., 2016) (Fig. 3a). This isolates the climate change risk without accounting for projected changes in population. In the second step, we apply the SSP3 and SSP5 population projections to the RCP 8.5 hazard projections to determine the projected exposure (Fig. 3b). This provides a combined measure of the risks associated with both projected climate and population change. In the last step, we investigate the change in vulnerability/coping capacity required to counteract the change in mid-21st century hazard and exposure from step 2 (Fig. 3c). To do so, we fix the current risk (i.e., hazard and exposure analysis based on historical climate and 2015 population), alter the hazard and exposure using the RCP 8.5 projections, and compute the combined vulnerability/coping capacity component using geometric averaging. For comparison, we compute the percent change in the combined vulnerability/coping capacity between the historical and RCP 8.5 projections. The mathematical details of each step can be found in the Supplementary Material.

2.2.1. River flood

Flood hazard in the current INFORM Risk Index framework is assessed using GAR 2015 flood inundation levels for 25-, 50-, 100-, 200-, 500- and 1,000-year return periods (RPs) developed at a 1-km grid spacing. The potential exposed population (PEP) is estimated for each of the RPs assuming exposure for any positive flood depth. The expected annual exposed population (EAEP) is estimated as the integral sum of the PEP for all flood frequencies (Marin-Ferrer et al., 2017). A range of Global flood models (GFMs) capable of providing river flood maps have been developed rapidly over the last decade and are typically based on a cascade of meteorological-hydrological-hydraulic models (e.g., CaMa-UT from the University of Tokyo (Yamazaki et al., 2011), the CIMA-UNEP model developed for the UNISDR Global Assessment Report 2015 (GAR) (Rudari et al., 2015), the European Centre for Medium-Range Weather Forecasts (ECMWF) model (Pappenberger et al., 2012), the GLObal Flood Risk with IMAGE Scenarios (GLOFRIS) model by Deltares (Winsemius et al., 2013), and the model developed by JRC (Dottori et al., 2016). These models are particularly suited to estimate potential inundation levels for different flood probabilities and hence simulate the impacts of climate change on the future flood hazard.

In this study, we extend the original INFORM Risk Index river flood component using results from the JRC model (Alfieri et al., 2017; Dottori et al., 2018, 2016), which benefits from continuous research efforts and operational improvements of the Copernicus Emergency Management Service (EMS) – Global Flood Awareness System (GloFAS) (Alfieri et al., 2013, 2020b; Bernhofen et al., 2018). The frequency and magnitude of present and future flood events are taken from seven hydrological simulations run with the LISFLOOD model (van der Knijff et al., 2010) which span from 1971 to 2120 at a daily 1-km resolution. The atmospheric forcing of the hydrological simulations is taken from seven CMIP5 RCP8.5 projections downscaled with EC-EARTH3-HR at the common resolution of 0.35° (~40 km at the equator) (Alfieri et al.,

Table 1
Overview of the current and proposed coverage of hazards and risk.

Hazards	Current	Climate Change Extension
Riverine Floods	Expected annual exposed population by GAR2015 global flood hazard.	Expected annual exposed population based on CMIP5 JRC GLOFAS hazard maps (Dottori et al., 2016, 2018).
Storm Surges	Expected annual exposed population by GAR2015 storm surge.	Probabilistic CMIP5 coastal flood projections of extreme sea level (combined mean sea level, tides, wind-waves and storm surges) (Vousdoukas et al. 2018a).
Droughts	Observed probability of agricultural of droughts (based on ASI) (Rojas, 2018) and population affected (EMDAT).	SPEI (Beguería et al., 2014; Vicente-Serrano et al., 2010) based on statistically downscaled CMIP5 precipitation and surface temperature projections.

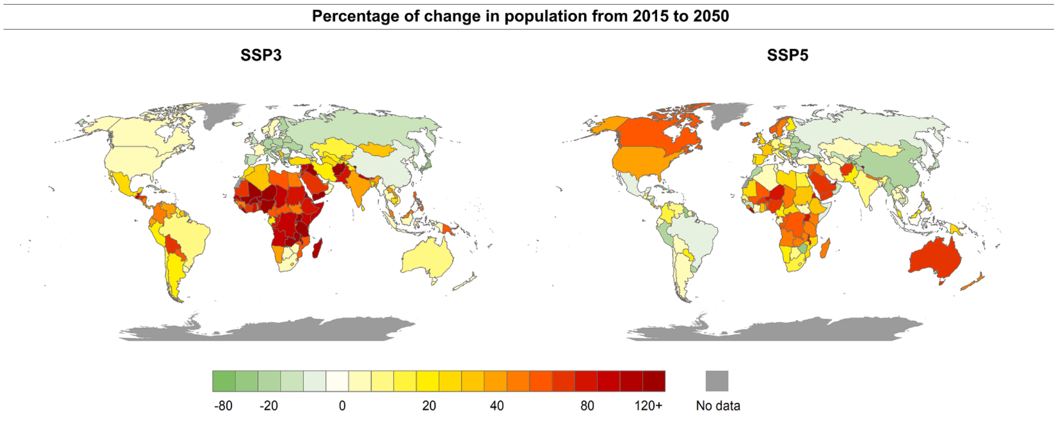

Fig. 2. Percentage of change in population in 2050 under SSP3 and SSP5 relative to 2015.

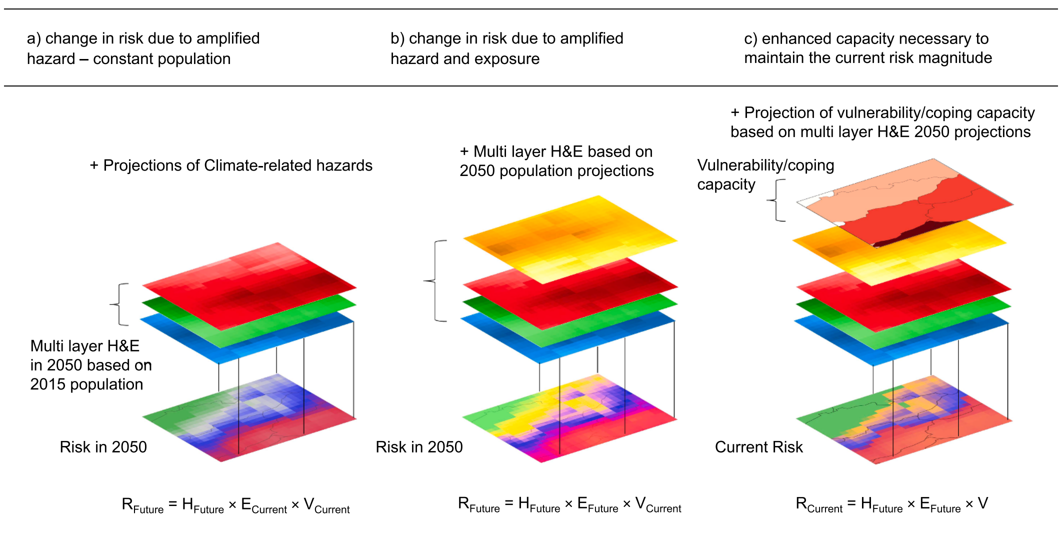

Fig. 3. INFORM Risk analysis stages including the components of hazard (H), exposure (E) and vulnerability/lack of coping capacity (V).

2017). Estimates of population affected by each RP (10-, 20-, 50-, 100-, 200- and 500-year) for each ensemble member are computed using population density for the year 2015 from the Global Human Settlement Layer (GHSL, Pesaresi et al., 2016), averaged over the 30-year time slices and aggregated at country level for the historical period (1976–2005) and future period (2036–2065). PEP and EAEP are computed in the same manner as is done with the original INFORM Risk Index for river flood (Alfieri et al., 2020a). Exposure under SSPs is here considered as country-based multipliers (the ratio between SSPs projected population and GHSL 2015).

2.2.2. *Coastal flood*

In the original INFORM Risk Index, the coastal flooding component is represented by storm surge levels obtained from GAR 2015 at a 1-km spacing for the 10-, 25-, 50-, 100- and 250-year RPs; instead, we consider extreme sea levels (ESL). ESLs result from a combination of factors including mean sea level, tides, wind-waves, storm surges, and vertical land movement. A non-exhaustive list of global models and datasets used in the context of coastal flooding includes GLOFRIS (Ward et al., 2013) and Aqueduct Global Flood Analyser (Ward et al., 2020), Dynamic Interactive Vulnerability Assessment (DIVA) (Brown et al., 2016; Vafeidis et al., 2008), Global Tide and Surge Reanalysis (GTSR) (Muis et al., 2016), and LISFLOOD-FP (Dottori et al., 2016; Vousdoukas et al., 2020). In a study from Vousdoukas et al. (2016), different inundation modelling approaches were compared in terms of their applicability to coastal flood mapping. The authors conclude that LISFLOOD-FP showed better predictive skill for large-scale studies, particularly for global analysis.

To extend the INFORM Risk Index, we use the probabilistic coastal flood simulations of ESL for different return periods (5-, 10-, 20-, 50-, 200-, 500-, and 1000-year events) for RCP 8.5 for the mid-century from LISFLOOD-FP (Vousdoukas et al., 2018a,b). The effects of sea level rise (SLR) are assessed through a set of simulations using the global Delft3D-Flow Flexible Mesh (D-FLOW FM) setup; rising ESLs are primarily driven by thermal expansion (Jevrejeva et al., 2016), followed by contributions from ice mass-loss from glaciers and ice sheets in Greenland and Antarctica. Atmospheric forcing from a six-member Coupled Model Intercomparison Project Phase 5 (CMIP5) ensemble is used to calculate projections of waves and storm surges as well as their changes in relation to the historical period (1980–2014) (Vousdoukas et al., 2018a,b). We use the coastal flood projections resulting from the ensemble median of all ensemble members for the historical period (1980–2014) and future projection (2036–2065).

We overlay the obtained inundation maps for each RP (Vousdoukas et al., 2018b) with the population density maps (GHSL 2015, SSP3 and SSP5) to compute the PEP. Afterwards, the EAEP is estimated as the integral sum of PEP for all flood frequencies (Alfieri et al., 2020a). It should be noted that the year range of historical period and the RPs considered for the coastal flood simulations are somewhat inconsistent with those for river flood (and drought for historical period) due to data availability reasons.

2.2.3. Drought

Drought hazard in the original INFORM Risk Index is considered as a combination of agriculture and population affected by drought. Agricultural drought, measured using the ASI, is defined as a dry period in a region over the cropping season in which at least 30% of the crop area is under stress for a duration exceeding 10 days. The average annual population affected by drought is based on historical events in the EM-DAT database for the last 25 years (CRED, 2019). Measuring the intensity and impact of drought events is often more complex than for other natural hazards such as floods that cause immediate and structural damages (UNDRR, 2019). Numerous indices have been developed to characterize drought event intensity, frequency and duration (EC, 2019, 2017; Svoboda and Fuchs, 2016).

To extend the INFORM Risk Index for climate change, we use the standardized precipitation evapotranspiration index (SPEI), which has gained recent popularity to assess meteorological droughts and can be computed using precipitation and surface temperature data (Beguería et al., 2014; Spinoni et al., 2019; Vicente-Serrano et al., 2010). SPEI is a multi-scalar drought index based on climatic data, namely precipitation and potential evapotranspiration (PET). It measures drought severity according to its intensity and duration and can be used to identify the onset and end of drought episodes. Here we use surface temperature and precipitation from 21 AOGCMs from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset to compute SPEI. NEX-GDDP is comprised of daily precipitation and minimum and maximum temperature from statistically downscaled CMIP5 AOGCM simulations for RCP 8.5 to a 0.25° grid (NCCS, 2020). PET is estimated from the NEX-GDDP surface temperatures according to the Hargreaves (1994) formulation modified by Droogers and Allen (2002). For the scope of our analysis, we consider 12-month SPEI which captures medium-term water deficits and hydrological droughts likely to affect agriculture, but also river discharge and groundwater recharge (Farinosi et al., 2020; Liu and Chen, 2021; Naumann et al., 2018). SPEI is computed at each grid point for the historical reference period (1976–2005), and projected RCP 8.5 (2036–2065). Drought is then computed using parameters from the reference period. We consider a location to be in drought when SPEI less than -1.5, which is defined as the threshold for severe and extreme drought (Smirnov et al., 2016; Törnros and Menzel, 2014; UK Centre for Ecology and Hydrology, 2020). Exposure is therefore binary for each land grid cell, i.e., either the total population is exposed, or no population is exposed. As a limitation, for very small countries (e.g., small Pacific Islands) drought is not computed due to their lack of representation in the driving CMIP5 models. The same challenge has been noted in several other studies using global climate models (e.g., Keener et al., 2012; Smirnov et al., 2016; The World Bank, 2016).

2.3. Sensitivity and uncertainty analysis

Uncertainty analyses can help determine whether the main results change substantially when the methodological choices vary over a reasonable range of possibilities (Nardo et al., 2005; OECD, 2008; Tate, 2012). Uncertainty in the weighting and aggregation process is introduced by varying the weights based on the extent to which the indicators compensate each other. The degree of "compensation" denotes the potential tradeoffs between indicators during the aggregation process. It expresses to what extent lower performance in some indicators (such as worsening in exposure levels to climate-related hazards) can be compensated by higher performance in others (such as an increase in socioeconomic, institutional and governance performance). Using additive aggregators with high degree of compensation (e.g., arithmetic mean) implies that the importance of one or more of the indicators with low performance may not be adequately represented in the aggregated index. In contrast, using aggregators with low degree of compensation (e.g., geometric mean) can better account for indicators with lower performance in the aggregated index. Aggregators with a low degree of compensation would provide better insight for policymakers on each country's deficiencies and where to allocate resources to improve the imbalances (Marzi et al., 2019, 2018; OECD, 2008; Ruiz and Cabello, 2021). As an example, combining INFORM's natural and human hazard components using additive approach (high degree of compensation) implies that to have a high hazard and exposure score for a country both components should be high simultaneously. Instead, the use of a geometric average (low degree of compensation) indicates that it is sufficient for a country to have a high score either in the natural hazard or the human hazard category to have an overall high hazard and exposure score.

In this study, sensitivity to the input data is determined by comparing the correlation ratio for each climate-related hazard both in original and extended INFORM Risk indices. To control the aggregation tradeoffs, we apply the ordered weighted average (OWA) operator introduced by Yager (1988) using quasi-Monte Carlo approach, which in our case requires 3,000 simulations of different combinations. The OWA operator controls the level of compensation by using a different order of weights (Jin et al., 2017; Mysiak et al., 2018). A detailed explanation of OWA simulation and correlation ratio can be found in the Supplementary Material.

3. Results and discussion

3.1. Climate-related impacts on exposed population

3.1.1. River flood

The impacts of climate-related amplified hazards under RCP8.5 on population from the current, SSP3 and SSP5 scenarios are analysed for the historical and mid-21st century periods. Globally, annual exposure to river floods in the mid-21st century is projected to increase to 126 million people (141%) considering fixed 2015 population, 175 million people (235%) under SSP3 and 139 million people (166%) under SSP5 (Fig. 4 and Table SM4). Regionally, Asia experiences the largest projected absolute exposed population to river floods, with 103 million people exposed in 2050s (+193%) with 2015 population, 134 million people (+280%) under SSP3 and 108 million people (+206%) under SSP5. South America, however, faces the largest percent change with a 295% increase with 2015 population, 428% under SSP3 and 302% under SSP5. Considering the total and regional population exposure, changes in amplified hazard show a considerably stronger effect than the differences in population between constant and SSPs. The largest projected changes primarily occur in SSP3 which has the largest total population growth.

EM-DAT observations suggest similar regional flood exposure patterns for historical data (UNISDR, 2015a). Flood exposure is more frequent in Asia and Africa than other continents, but poses an increasing danger also in South America where annual average affected people by floods between the period 2005 to 2014 increased nearly fourfold to 2.2 million people compared to the period 1995 to 2004 (UNISDR, 2015a). The projected results are comparable to other global impact studies (Farinosi et al., 2020; Arnell et al., 2019). Farinosi et al. (2020) and Arnell et al. (2019) find that the greatest increase in river flood frequency occurs in Asia (especially south and south east Asia) and Africa, with the largest increase in exposure in Asia under SSP3.

3.1.2. Coastal flood

Coastal floods are globally projected to annually affect 64 million people (+15%) in the mid-21st century considering fixed 2015 population, 72 million (+29%) under SSP3 and 70 million (+26%) under SSP5 (Fig. 4 and Table SM4). The largest population exposed is projected in Asia with 41 million people exposed (+16%) under the 2015

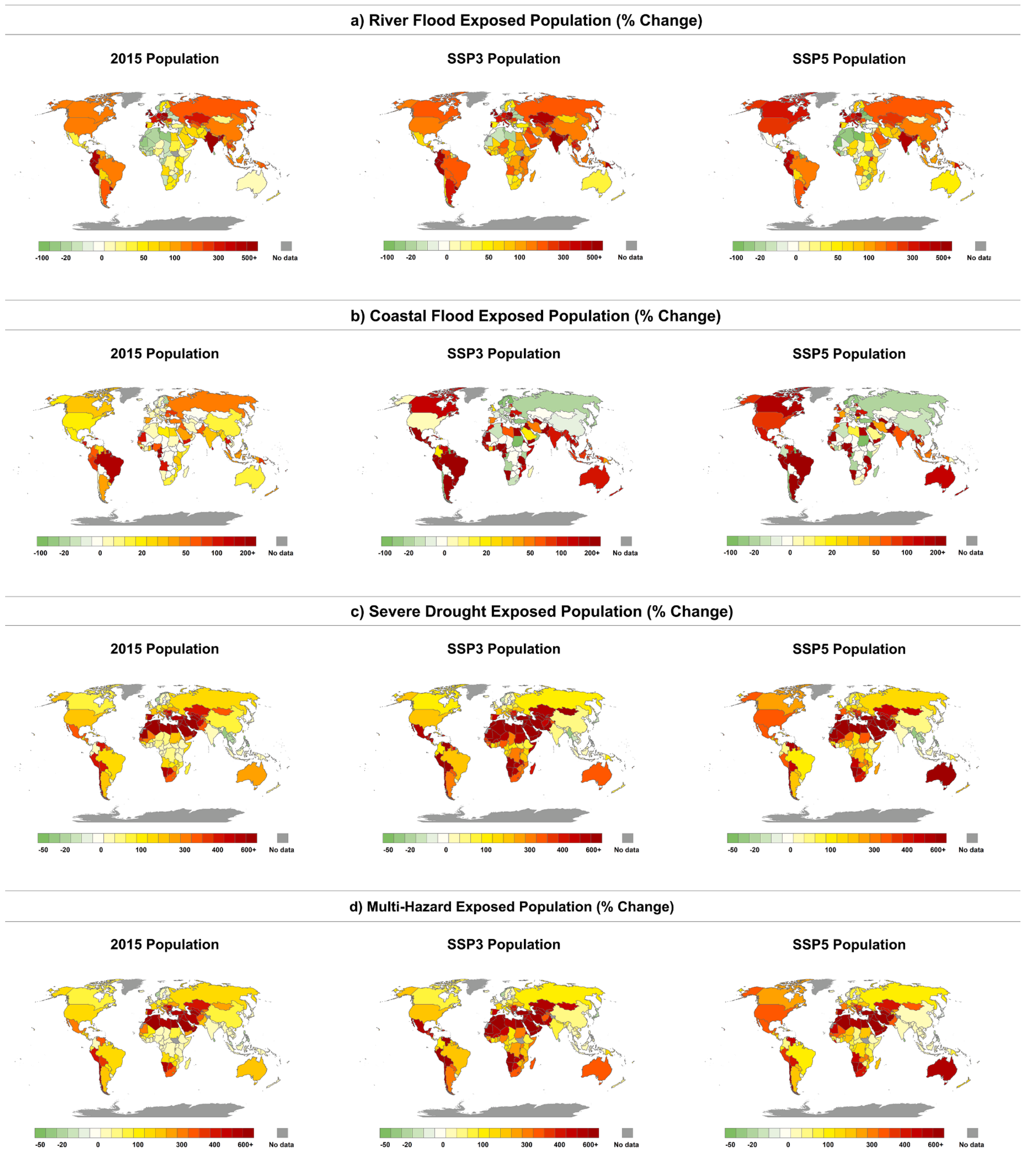

Fig. 4. Mid-21st century projected percent change in population exposed to a) river flood; b) coastal flood; c) drought; and d) multi-hazard. The left, centre and right columns show the population estimates for 2015, SSP3, and SSP5, respectively.

population, 43 million people (+21%) under SSP3 and 40 million people (+13%) under SSP5. The largest percent increase in population exposed is projected in Africa (27% with 2015 population, 245% under SSP3 and 154% under SSP5) and South America (53% with 2015 population, 158% under SSP3 and 108% under SSP5). Comparing the total and regional projected exposure between the 2015, SSP3 and SSP5 populations illustrates that the general patterns tend to remain similar due to the strong climate change signal, but the population differences between the scenarios tend to alter the intensity of the exposure.

EM-DAT observations reveal that historically, lower-middle-income countries have been hit harder by storms between 1995 and 2015 in terms of lives lost compared to the previous decade. Asia is particularly affected by frequent storms, especially in the southern and southeastern regions which account for 21% of the total number of storms and more than 80% of storm mortality (UNISDR, 2015a). Recent global impact studies confirm that Asia, especially South Asia, is projected to experience the largest change and population exposed to coastal flooding (Arnell et al., 2019; Kirezci et al., 2020). The estimates of the population exposed to events exceeding a 100-year RP in the mid-21st century with 2015 population are comparable to those of a recent study by Kirezci et al., 2020 (~170 million people, 17% increase). In the case of coastal floods, the projected changes are consistent with the population changes in Fig. 2 illustrating that Africa, South America and Asia experience higher exposure under SSP3, while Europe, North America and Oceania experience relatively higher exposure under SSP5. In Canada and Australia, large changes under SSP3 are caused by large population density changes along the coasts (Lemmen et al., 2016; Manson, 2005; NASA, 2010). The low migration assumption under SSP3 implies that the largest population growth occurs in the areas with currently high population densities. Therefore, the population changes in the coastal zones tend to be greater than the total population changes in the country.

3.1.3. Drought

Severe and extreme drought (defined as 12-month SPEI less than −1.5) in the mid-21st century is globally projected to annually affect 1.1 billion people (+169%) with the 2015 population, 1.5 billion (+280%) under SSP3 and 1.3 billion (+224%) under SSP5 (Fig. 4 and Table SM4). The largest absolute exposed population is projected in Asia, with 545 million people exposed (+125%) under the 2015 population, 782 million people (+222%) under SSP3 and 633 million people (+161%) under SSP5. The largest percent increases in population exposed are projected in Oceania (223% with 2015 population, 317% under SSP3 and 501% under SSP5) and in Africa (229% with 2015 population, 501% under SSP3 and 354% under SSP5). Consistent with coastal flood, the projected drought changes correspond with population changes between the SSP scenarios. Under SSP3 the largest increases are projected in Asia, Africa and South America aligning with the greatest population increases; and under SSP5 the largest increases are projected in Europe, North America and Oceania also aligning with the largest population increases. These spatial patterns are comparable to those from Farinosi et al. (2020) and Arnell et al. (2019) who find the largest absolute population exposed in Africa and Asia under SSP3.

Increase in severe and extreme drought occurs in nearly every country with the greatest increase primarily in the northern subtropic latitudes affecting Western Asia, Southern Europe and North Africa. Spinoni et al. (2020) find that drought characteristics are projected to increase over the Mediterranean region, the Horn of Africa and Asia under RCP 8.5. In addition, Naumann et al. (2018) show that drought length is projected to increase primarily in northern, western and southern Africa, the Caribbean, Central America, southern Europe, and West Asia under 1.5 °C and higher warming scenarios. According to Farinosi et al. (2020), magnitude and frequency of droughts in mid-century will significantly increase in Central America, Africa, the Mediterranean and Central Asia.

3.1.4. Combined hazard

Considering the combined hazards (river flood, coastal flood and drought) at a global scale, annually 1.3 billion people (+150%), 1.8 billion people (+249%) and 1.5 billion people (+197%) in the mid-21st century are projected to be exposed considering the 2015, SSP3 and SSP5, respectively (Fig. 4 and Table SM4). The largest absolute population exposed to multi-hazard exposure is found in Asia with 689 million people exposed (+120%) with 2015 population, 958 million people (+206%) under SSP3 and 781 million people (+150%) under SSP5. The largest relative increases in exposure occur in Africa (185% with 2015 population, 430% under SSP3 and 300% under SSP5) and Oceania (197% with 2015 population, 285% under SSP3 and 448% under SSP5). Very few countries show a reduction in future exposure to the combined climate change hazard (e.g. Norway with 2015 and SSP3 population, Philippines with 2015 and SSP5 population and Japan under SSP3 population scenario).

Amplified drought tends to have the highest humanitarian impacts while coastal flood tends to have the lowest, which is reflected in the correspondence of the multi-hazard and drought exposure spatial patterns (Fig. 4c compared to Fig. 4d). Farinosi et al. (2020) find that in most of the regions, drought exposure is larger than floods except central east Africa. EM-DAT historical observations show that more than one billion people were affected by droughts in the period 1995–2015 which was more than a quarter of all people affected by all types of weather-related disasters worldwide.

3.2. Extended INFORM Risk Index

Here we calculate the extended INFORM Risk Index by accounting for the exposed populations to each hazard presented above coupled with the vulnerability/lack of coping capacity reduction required to keep the current risk level. As a first step, we compare the climate-related components (river flood, coastal flood and drought; Figure SM5) of the extended index for the historical climate to those from the original index using the Pearson correlation coefficient (De Groeve et al., 2015; OECD, 2008). The correlations range from 0.85 for droughts and to 0.66 for river floods, and are all statistically significant ($p < 0.001$). These correspond to correlation strengths in the range “moderate” to “strong” according to the classes defined by (Akoglu, 2018; Bendanillo et al., 2016) suggesting that the new and original variables are statistically compatible.

The modified climate-related components of INFORM Risk Index coupled with the Natural Hazard-Exposure and Risk indices (including earthquakes, tsunamis and epidemics) and absolute changes under various development scenarios (2015, SSP3 and SSP5 populations) are considered (Fig. 5). Countries with largest natural hazard and exposure are mainly located in Asia and the Americas while those with the largest risk are generally located in Africa, Western and Southern Asia and Central America. Myanmar, Vietnam, Japan, Philippines and Pakistan are projected to have the highest risk of floods, while Iran, Turkey, Afghanistan, Chile and Mexico are projected to be highly prone to droughts regardless of the population scenario considered. Afghanistan is the most vulnerable country due to underperformances in both natural hazard/exposure and disaster risk indices. A list of top 25 countries projected with the highest exposure to future natural hazards under SSP3 and SSP5 scenarios is provided in Tables SM7 and SM8, respectively.

We use risk classifications with five thresholds from very low to very high identified using hierarchal clustering model introduced by Marin-Ferrer et al. (2017) (Table SM9). Risk classification in the form of a hierarchical scale provides a systematic and consistent way to identify risk. Risk classes provide a greater ability to monitor, control and even manage risk because root causes of risk can be better identified. The scope of the fixed threshold obtained from the clustering analysis is to provide solid perception of risk classes among users (Marin-Ferrer et al., 2017). According to the results, shifts in risk classes are very infrequent among various development scenarios. This result is somewhat unexpected considering the large variations in hazard and exposure levels for various development scenarios (Table SM9). Only for a relatively small number of countries, the variations in hazard and exposure levels are projected to result in shifts in risk classes between the historical climate and the combined RCP 8.5 SSP scenarios (Table SM10). For these countries, the current adaptive capacity level is not able to counter the amplified hazards coupled with population growth causing a shift into a higher risk class. Hence, these countries would need to enhance their coping capacities in the future to maintain their current risk class (discussed in detail below). This can facilitate the assessment of the likelihood and impact on the humanitarian situation and capacity building which is partially based on perception of risk classes among donors (e.g., OCHA, 2021; OCHA, 2020b).

3.3. Vulnerability and coping capacity changes

As a final step of the extended INFORM Risk Index analysis, we determine the change in vulnerability/lack of coping capacity required to return to the original level of risk associated with the historical climate and 2015 population (Fig. 6). In computing the requirements to overcome the adverse effects of climate and population change, vulnerabilities not associated with climate and population change, such as uprooted people, food security and access to health systems, are

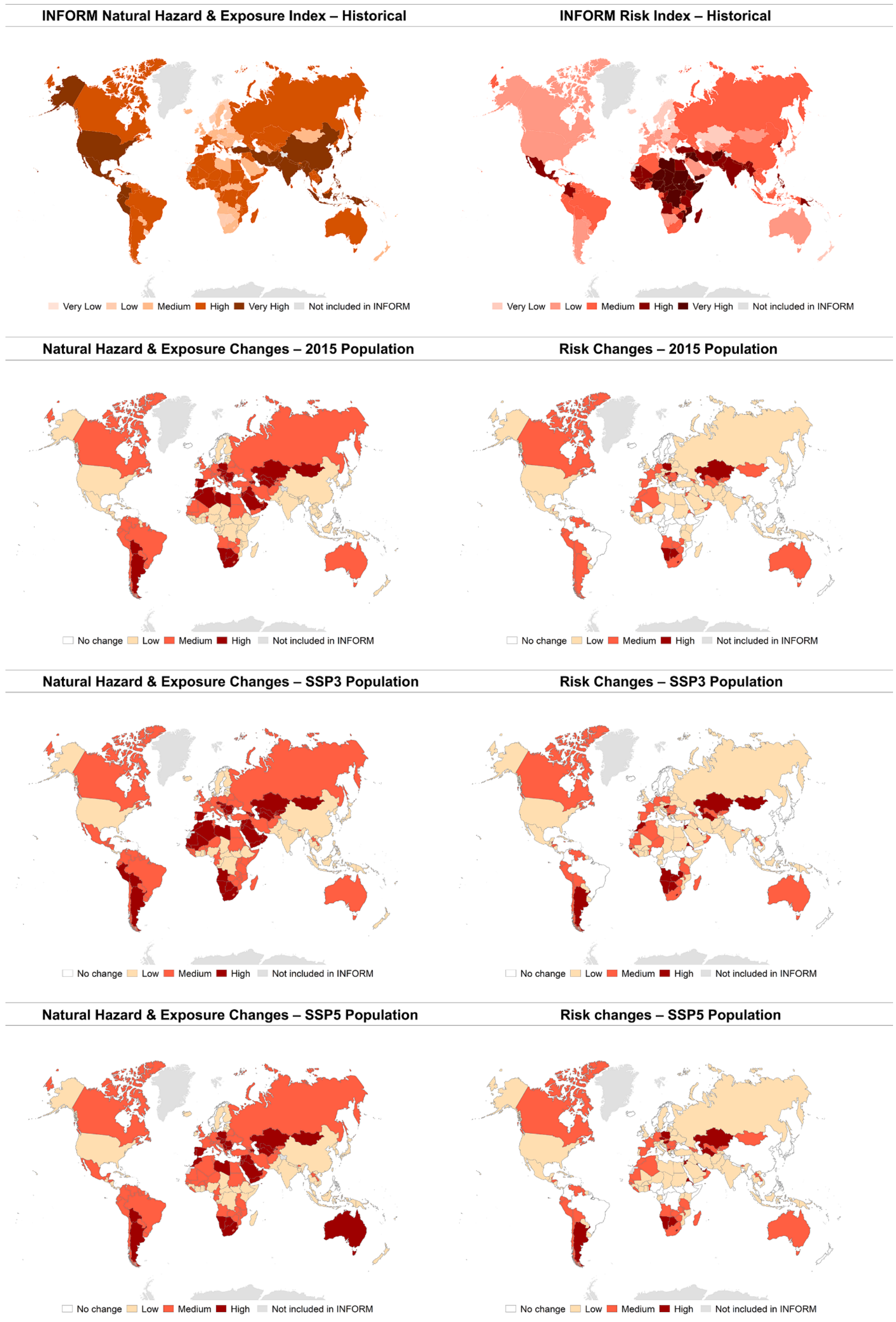

Fig. 5. Historical INFORM Natural Hazard and Exposure (top row) and Risk indices and absolute changes projected for the mid-21st century under various development scenarios indicated in the panel title.

considered fixed between the scenarios. To classify the countries, four classes (no, low, medium and high reduction) have been identified using agglomerative hierarchical clustering procedure based on Ward's minimum variance criterion (Marin-Ferrer et al., 2017).

Most countries must enhance their future coping capacities to nullify the adverse impacts of the projected mid-21st century amplified hazards and exposure. The countries that require the highest reduction are currently ranked as very low and low risk countries since they have the highest potential to shift to a higher risk category as a result of climate change and/or population change (Table SM11). For example, Namibia shifts from low to medium in both SSPs resulting in a large change. In contrast, in countries with very high current risk levels (mainly non-industrialized countries), an increase in climate change hazard does not result in a risk class change and subsequent vulnerability (lack of coping capacity) reduction since their current risk is already at or near the highest level. For example, South Sudan is currently in the very high risk class and therefore cannot increase its risk even with increased exposure to climate change hazards.

This highlights the importance of the international disaster risk community to enhance integration of and coherence between DRR and climate change adaptation (CCA) to maintain manageable risk levels. Aligning both DRR and CCA policy agendas create conditions for greater policy impact, more efficient use of resources and more effective action in protecting life, livelihoods and valuable assets. Lack of integration leads to insufficient protection and wasteful use of resources. Sound understanding of vulnerabilities, risk determinants and people's

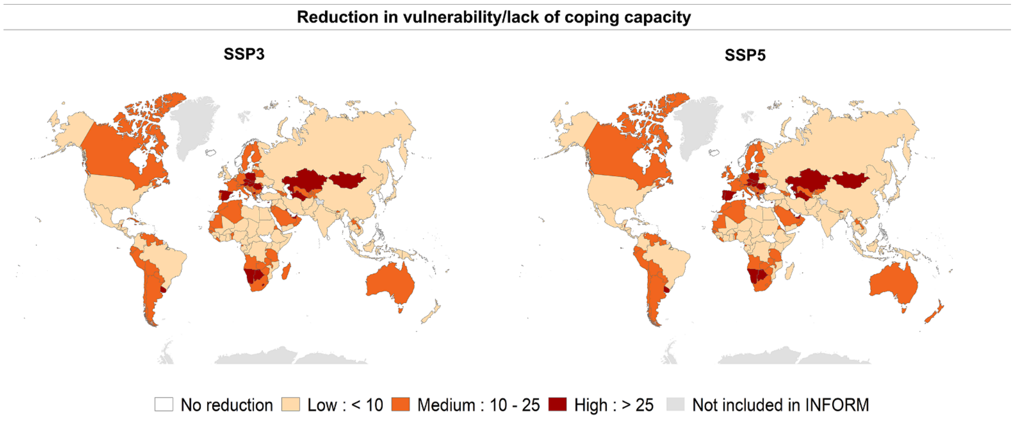

Fig. 6. Percentage of reduction in vulnerability/lack of coping capacity for SSP3 (left) and SSP5 (right) required to maintain the current risk considering exposure to amplified hazards.

mindsets are equally important for both. Although DRR and CCA are different in many respects, both of these transformative processes emphasize the deeply rooted determinates of vulnerability and the role of citizens and organisations as agents of individual and social change.

The required reduction in vulnerability/lack of coping capacity is mainly driven by increases in hazard rather than population (Fig. 6). Only for a relatively small number of countries, the variations in population levels are projected to result in shifts in vulnerability/lack of coping capacity classes between the combined RCP 8.5 SSP3 and SSP5 scenarios (Table SM12). The primary reason for the shifts is due to population growth patterns under different the SSPs. High-income countries (e.g., Denmark and South Korea) show greater population growth under SSP5 while low-medium income countries (e.g., Cuba and Tajikistan) show greater growth under SSP3. Accordingly, it can be inferred that climate change amplified hazards play the primary role in future vulnerability/lack of coping capacity variability rather than population scenarios.

To quantify the impact of amplified hazards and population growth on vulnerability/lack of coping capacity reductions, we compare the SSP and 2015 population vulnerability/lack of coping capacity reduction percentages. To do so, we compute percent change in the vulnerability/lack of coping capacity between each population scenario with fixed standardized climatic and non-climatic risk factors (baseline INFORM Risk). We then calculate the percent change of the sum of the standardized scores (scale of 1 to 10) between the baseline and the projections. Globally, the sum of the vulnerability/lack of coping capacity standardized scores increases by 10% with 2015 population, 13% under SSP3 and 12% under SSP5. This suggests that on average at a global scale the interaction between climate change and population growth explains 3% in SSP3 and 2% in SSP5 of the total change, reflecting the fact that the climate change has larger effect on the increase of INFORM vulnerability/lack of coping capacity dimension in our analysis. This disparity would be reduced slightly under a mitigation scenario, however, RCP 8.5 best matches the current GHG trajectory (Fuss et al., 2014), and the difference between the RCPs in the mid-21st century is relatively small (IPCC, 2013). Furthermore, SSP3 population growth (34% globally) only plays a slightly more important role than that of SSP5 (15% globally) despite the large difference.

Recent studies confirm similar tradeoffs between climate forcing and population changes (e.g., Byers et al., 2018; Farinosi et al., 2020; Harrington and Otto, 2018; Smirnov et al., 2016). For instance, Byers et al. (2018) show that global mean temperature rise has a considerably stronger effect than the differences in population between the SSPs. Arnell et al. (2019) find that highest impact on droughts and floods occurs under the SSP3 scenario where population increases are greatest. According to IPCC 2018 special report on global warming of 1.5° C, at higher risk thresholds (RCP 8.5), the world's poorest populations are expected to be disproportionately impacted, particularly in cases of great inequality in Africa and southern Asia such as SSP3 (Hoegh-Guldberg et al., 2018).

The Paris Agreement established a global adaptation goal for enhancing adaptive capacity and reducing vulnerability to climate change. It seeks to contribute to sustainable development and ensure an adequate adaptation response in the context of the 1.5° temperature goal (UNISDR, 2015b). The United Nations Framework Convention on Climate Change (UNFCCC) Least Developed Countries Expert Group developed technical guidelines to reduce climate change vulnerability by adaptive capacity building and to facilitate CCA integration into new and existing policies, programmes and activities, in particular development planning processes and strategies (UNFCCC, 2012). In our study, we designed an MRE framework by which the policymakers can quantitatively measure the level of enhanced adaptive capacity and vulnerability reduction required to tackle the adverse climate change impacts. Our results and methodology provide a solid base for planning relevant policies in efforts to ensure adequate adaptation responses. The proposed framework also facilitates the policy integrations between DRR and CCA as suggested by UNDRR (2019).

In summary, we find that under RCP8.5, many countries will experience a significant change in the climate-related hazard and exposure by mid-century regardless of the SSP scenario. Such changes increase the disaster risk and may lead to severe future humanitarian crises across the globe. To alleviate the impacts of amplified risk, countries should significantly increase their coping capacity (reduce their vulnerability) to disaster risk. We caution that the modelling projections presented here potentially contain large uncertainties. Nevertheless, DRR and CCA should be the main policy response to mitigate the adverse effects of climate-related amplified hazard and risk. Moreover, climate change has a considerably larger effect on the future increase of INFORM risk and vulnerability reduction than changes in population growth within the socio-economic development scenarios.

3.4. Sensitivity and uncertainty analysis

The correlation ratios for each climate-related hazard both in the original INFORM Risk Index and the climate change extended index for the historical climate and 2015 population are analysed (Table 2). The results show that the correlation ratios of the original and new variables in the composite index are all in the range of 0.5 to 0.6. Their similarity suggests that the final aggregated INFORM in both cases may maintain similar importance levels among the variables.

Scores for the uncertainty analysis range from 1 to 10 where low (high) scores implies low (high) risk levels (Fig. 7). The 5th and 95th

Table 2
Correlation ratio for each climate-related hazard in original INFORM Risk Index 2021 (EC, 2021) and the new index (including the historical climate and 2015 population data for river flood, coastal flood and drought).

	River Flood	Coastal Flood	Drought
Original INFORM	0.50	0.60	0.49
Extended INFORM (historical)	0.58	0.53	0.56

percentiles of the simulations are considered to eliminate the extreme cases of compensation (full and non– compensatory tradeoffs) (Lafortune et al., 2018; Saisana and Saltelli, 2008). The higher the uncertainty, the greater caution that should be taken on any conclusions. Moving toward a higher degree of compensation tends to result in a lower INFORM risk score, while moving toward a lower degree of compensation results in larger risk score. For high-risk countries (e.g., Philippines), underperformance among the indicators leads to higher risk scores with a low degree of compensation. Contrarily, the underperformance is relaxed when shifting toward the higher level of compensation and yields lower risk scores.

In order to understand better the level of confidence of the INFORM natural hazard and exposure dimension scores, we follow the methodology proposed by Poljansek et al. (2020) and Saisana and Saltelli (2008). To do so, we calculate the percentage of the OWA simulations that fall in the five INFORM natural hazard and exposure classes. We then calculate the percentage of the match with the extended INFORM natural hazard and exposure final scores for SSP3 and SSP5 (Table SM15 and SM16). The numbers represent the frequency a country remains in the same natural hazard and exposure risk classes. For more than 70% of the countries, the SSP3 and SSP5 risk classes are matched with the classes with highest probabilities suggesting that the index in these countries is robust and not strongly influenced by the final aggregation and weighting choice. Saisana and Saltelli (2008) suggest that a greater than 50% match is acceptable when using a Monte Carlo approach for assessing composite index uncertainties as is done here. The index in the remaining 30% of the countries fluctuates between risk classes (e.g., Austria and Bahamas) and any conclusion on the performance of these countries should be drawn with some caution. The results depend also on the theoretical framework and data used but are for the majority of simulations independent of the methodological choices (weighting and aggregation). The dominant source of the deviations arises from the degree of compensation among the indicators. Hence, the tradeoffs should be made explicit for choosing aggregators that reflect the intended degree of compensation.

4. Conclusions

Extreme weather and climate related events are increasingly causing fatalities and economic losses throughout the globe. This has prompted an increased effort in many countries to adopt DRR and CCA policies and mitigation measures, often supported by evidence-based decision-making tools such as indicator-based assessments. The INFORM Risk Index is a multi-hazard humanitarian disaster risk index depicting the exposure and vulnerability of countries to current natural and anthropogenic hazards and risks. In this exploratory study, we extend the INFORM Risk Index to also encompass projected future climate change risks (hazard) and population changes (exposure). We consider population from 2015 and two socio-economic scenarios (SSP3 and SSP5) and climate from a scenario that encompasses a wide range of impacts (RCP8.5) for the mid-21st century. The climate-related hazards considered are river flood, coastal flood and drought.

For the three hazards considered, the exposure results show that globally by the mid-21st century 1.3 billion people will be exposed to the amplified climate-related hazards with 2015 population, 1.8 billion people under SSP3 and 1.5 billion people under SSP5. Amplified drought has the highest humanitarian impact, river flood the second highest and coastal flood the lowest. Regionally, the largest population exposed to amplified hazards is projected in Asia and Africa, and the smallest exposure is projected in Oceania and South America. The exposure under SSP5 tends to be more uniform across the continents compared to SSP3 due largely to lower population growth rates in non-industrialized nations and higher growth rates in industrialized nations. Among the top 20 countries with current largest population, Vietnam and Egypt have the largest per capita exposed population to flood and drought.

Despite the considerable variations in hazard and exposure levels for various development scenarios, the risk magnitude changes generally within defined risk classes that range from very low risk to very high risk. An assessment of future vulnerability/lack of coping capacity suggests that several countries especially in Europe, western and northern Asia and Africa will need higher reduction levels to maintain the current disaster risk. Most of these countries are currently ranked as very low and low risk countries since they have the highest potential to shift to a higher risk category as a result of climate change and/or population change.

Investigating the interactions between climate change hazard and population scenarios, we find that the sum of the vulnerability/lack of coping capacity standardized scores increases by 10% with 2015 population, 13% under SSP3 and 12% under SSP5. This suggests that climate change has a considerably larger effect on the increase of INFORM vulnerability/lack of coping capacity dimension than changes in population. It is important to note that only three climate change hazards are considered in this initial study; adding additional hazards would likely increase the climate change impacts on the INFORM Risk Index.

An uncertainty analysis using a quasi Monte-Carlo approach validates the stability of natural hazard and exposure classes of the extended index. For more than 70% of the countries, the SSP3 and SSP5 risk classes are matched with the classes with highest probabilities over all of the simulations. The dominant source of the deviations arises from the degree of compensation among the indicators. Hence, the tradeoffs should be made explicit when choosing methodologies that reflect the intended degree of compensation.

Our analysis provides a means to quantify the magnitude of how changes are to be made on vulnerability/lack of coping capacity to disaster risk. Moreover, when considered within an operational framework, it allows for objective measurement and comparison of performance/impact of policy actions on the aforementioned changes at a global level. INFORM Risk provides new insights into policymaking especially in the context of policy coherence for sustainable development (PCSD). In line with the Sustainable Development Agenda (United Nations, 2021), it helps to move the focus from the symptoms only to addressing the underlying causes of economic, social, environmental and governance challenges.

The methods and analysis presented here could be further extended in several ways. As literature suggests, different global climate models (GCMs) yield different results under same climate scenarios; the pattern of change on the hazard component of the extended INFORM Risk can be included by considering an ensemble study of different GCM projections. In this context, the uncertainty of not only the hazard component, but also of the exposure and the vulnerability components of risk under future scenarios should be assessed. Moreover, high divergence of forcing from the different RCPs occur mainly beyond mid-century. Extending to the end of the century should include a larger suite of climate change scenarios ranging from the 1.5 °C Paris scenario to RCP 8.5. With the larger suite climate change scenarios, other SSP scenarios should also be considered. Furthermore, other climate-related hazards with large humanitarian impacts such as heatwaves, urban flood and extreme winds should also be considered.

CRediT authorship contribution statement

Sepehr Marzi: Conceptualization, Data curation, Formal analysis,

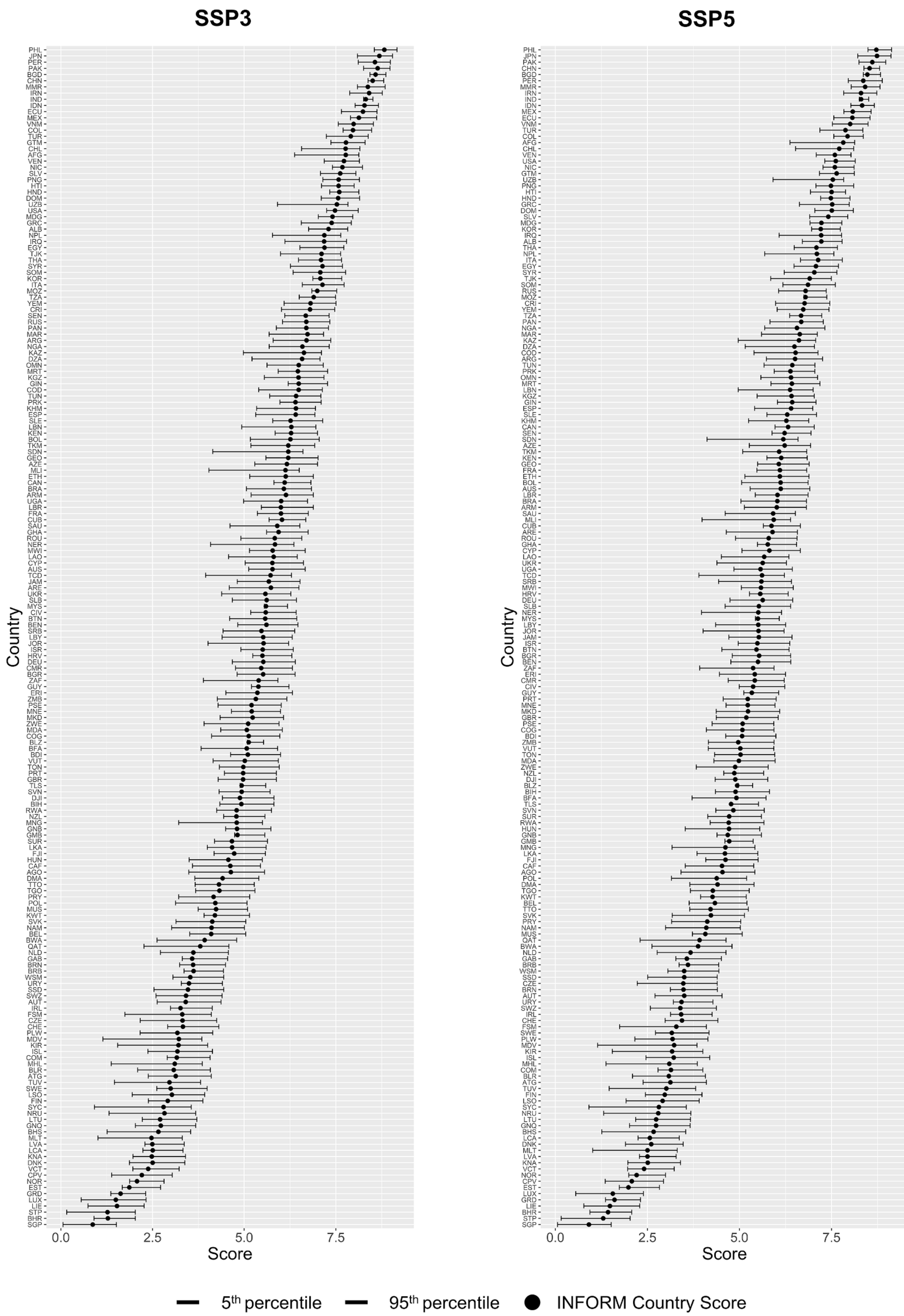

Fig. 7. Impact on natural hazard and exposure index scores of various combinations of OWA weights ordered by ANDNESS levels. Countries are ordered by extended INFORM natural hazard and exposure scores for SSP3 and SSP5. The dots represent the INFORM score for the country and the error bar bounds indicate the uncertainty levels at the 5th and 95th percentiles of the OWA simulations. The three letter country code defiutions are shown in Table SM14.

Methodology, Visualization, Writing – original draft, Writing – review & editing. **Jaroslav Mysiak:** Supervision, Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Arthur H. Essenfelder:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Jeremy S. Pal:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Luca Vernaccini:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – review & editing. **Malcolm N. Mistry:** Data curation, Formal analysis, Writing – review & editing. **Lorenzo Alfieri:** Data curation, Methodology, Writing – review & editing. **Karmen Poljansek:** Supervision, Conceptualization, Writing – review & editing. **Montserrat Marin-Ferrer:** Supervision, Conceptualization, Writing – review & editing. **Michalis Vousdoukas:** Data curation, Writing – review &

editing.

Data availability

The exposure, vulnerability, and risk datasets at the country level are available on request from the corresponding author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2021.102393.

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