Natural Hazards Perspectives on Integrated, Coordinated, Open, Networked (ICON) Science

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Key Points:

- Natural hazards pose risks that span across multiple sectors and spatiotemporal scales
- Effective risk management requires integrated approaches, coordinated processes, open science, and networked efforts
- The ICON approach brings the scientific community, stakeholders, and decision-makers together in developing equitable and inclusive risk management strategies

Abstract

This article is composed of one integrated commentary about the state of ICON principles (Goldman et al., 2021) in natural hazards and a discussion on the opportunities and challenges of adopting them. Natural hazards pose risks to society, infrastructure, and the environment. Hazard interactions and their cascading phenomena in space and time can further intensify the impacts. Natural hazards' risks are expected to increase in the future due to environmental, demographic, and socioeconomic changes. It is important to quantify and effectively communicate risks to inform the design and implementation of risk mitigation and adaptation strategies. Multihazard multisector risk management poses several nontrivial challenges, including: i) integrated risk assessment, ii) Earth system data-model fusion, iii) uncertainty quantification and communication, and iv) crossing traditional disciplinary boundaries. Here, we review these challenges, highlight current research and operational endeavors, and underscore diverse research opportunities. We emphasize the need for integrated approaches, coordinated processes, open science, and networked efforts (ICON) for multihazard multisector risk management.

Plain Language Summary

Natural hazards pose huge risk to life and property. These risks are dynamic and deeply uncertain. A comprehensive understanding of natural hazards and proper tools to account for dynamic risk are crucial to informing risk management. Integrated approaches, coordinated processes, open science, and networked efforts help address multihazard multisector risk management challenges in a comprehensive framework.

1 Introduction

Natural hazards drive major damages to communities, infrastructure, and ecosystems across the globe. Recent European floods (Cornwall, 2021), droughts in South Africa (Pascale et al., 2020), and wildfires (for example in the United States (Swain, 2021) and Euro-Mediterranean region (Giannatos et al., 2021)) highlight how human and natural systems are exposed and vulnerable to natural hazards. Between 2000 to 2019, natural hazard-related disasters caused over 1 million deaths worldwide and over 2 trillion U.S. dollars in global economic losses (United Nations Office for Disaster Risk Reduction, 2020). These impacts are expected to rise in the future with coevolving natural and human systems subject to the impacts of multiple hazards, including extreme weather events, sea-level rise, anthropogenic disturbances, and climate change. There is growing recognition of the critical need to improve the understanding and prediction of natural hazards, characterize multihazard multisector risk, and enhance the communication of risk and its associated uncertainties to inform the design of effective risk management strategies (IPCC, 2021).

Multihazard multisector risk management requires a comprehensive understanding of different interacting systems and processes, including the feedback between human and natural systems (Byers et al., 2018; Mora et al., 2018; Piontek et al., 2014). A growing number of scientific studies (e.g., Bates et al., 2021; Cook et al., 2018; Hirabayashi et al., 2013; Strömberg, 2007) provide valuable new insights on the potential impacts of a single hazard on a specific sector and in a specific region. However, there is a lack of integrated frameworks, coordinated processes, open science, and networked efforts that can account for the complex interactions across natural and human systems in the context of multiple interacting stresses and over a wide range of spatiotemporal scales (Figure 1).

This commentary highlights the challenges and opportunities for multihazard multisector risk management, acknowledging the pressing need for integrated (I) approaches, coordinated (C) processes, open (O) science, and networked (N) efforts. We discuss the challenges and research opportunities related to i) integrated risk assessment, ii) Earth system data-model fusion, iii) crossing traditional disciplinary boundaries, and iv) uncertainty quantification and communication, and further emphasize the immediate need for ICON science (Goldman et al., 2021).

2 Challenges and Research Opportunities

2.1 Integrated Risk Assessment

A sound understanding of risk drivers and their dynamic interactions is critical to inform the design of risk management strategies. Quantifying multihazard multisector risk is challenging as it requires the integrated assessment of complex interactions between hazard probabilities, exposure, and the vulnerability of the affected human or ecological system to the hazards (IPCC, 2021). In addition, multihazard risks are dynamic and are modulated by several factors, including environmental degradations, demographic changes, and socioeconomic conditions. Understanding the interactions among the risk drivers is crucial to achieving a comprehensive view of the integrated system. Developing an integrated system requires a priori planning to integrate different components while ensuring open access and interoperability across data types and models.

Earth system modeling efforts are generally focused on understanding the impacts of a single hazard in isolation, emphasizing risk assessment in limited sectors. However, these individual hazards often demonstrate compounding and cascading behaviors, where the resulting multihazard multisector risk becomes increasingly difficult to assess using conventional techniques. Furthermore, the conventional risk assessment techniques are mostly concentrated on predicting hazards instead of the actual risk or impacts. Risk predictability is often limited to decision-making across a range of spatiotemporal scales due to the lack of coordinated databases (Fuchs et al., 2012; Rakhal et al., 2021).

Improving the risk prediction capabilities of Earth system models demands networked efforts among the scientific community, stakeholders, and agencies for database development and management with implications to inform mutually beneficial risk mitigation and adaptation strategies. For instance, tropical cyclones, flooding, and landslide risk prediction ahead of sufficient lead time allow risk managers enough time to take necessary steps for preparedness and damage mitigation (Burston et al., 2015; Dale et al., 2014), whereas the lack of predictability in earthquakes complicates the disaster mitigation and preparedness activities (Sobolev, 2011). Understanding the natural hazard phenomena and driving processes is critical to improving hazard and risk predictability.

The availability of high-resolution datasets and modeling resources have opened opportunities for integrated multihazard multisector risk assessment across a wide range of spatial and temporal scales. There is also an increasing acknowledgment of the need to systematically integrate risk management efforts into policy, plans, and programs for sustainable development. Strategic and integrated efforts to promote community resilience to disasters have been initiated through the Hyogo Framework for Action 2005-2015 (HFA, 2021) and the Millennium Development Goals (United Nations, 2021). The Sendai Framework for Disaster Risk Reduction (Trogrlić et al., 2017) and the 2030 United Nations Sustainable Development Goals (Desa et al., 2016) underscore the pressing need for inclusive and integrated multihazard risk management approaches. These networked efforts are designed to be mutually beneficial across multiple stakeholders.

Community risks to natural hazards are often quantified using an index such as the US National Risk Index (FEMA, 2021), and Global Climate Risk Index (Eckstein et al., 2021). Scientific communities have made substantial progress in understanding the potential impacts of multihazard on multiple sectors and from local to global scales (Chester et al., 2019, 2020; Koks et al., 2019; Wright et al., 2019). Furthermore, World Meteorological Organization's guidelines have emphasized the need for multi-hazard impact-based forecast and warning services to disseminate accurate and understandable weather and climate information (Zhongming et al., 2015). Satellite remote sensing, citizen science, and low-tech sensing could be instrumental in supporting local-level risk management, particularly in the data-scare region (Talchabhadel et al., 2021; Paul et al., 2018). Additional networked initiatives such as community-based modeling and data collection that integrate traditional wisdom, indigenous knowledge, and experts' opinion have been effective for multihazard risk management (Miles, 2018; Rakhal et al., 2021; Sanders et al., 2020). An integrated framework promotes synthesis, cross-disciplinary integration, and open science across the Earth science communities that can facilitate the development of new modeling tools to systematically analyze hazard processes, stressors, and responses in a problem-driven solution-oriented framework.

2.2 Earth System Data-Model Fusion

Recent advances in big data, high-performance computing systems, cloud computing, and community-based modeling, among others, have opened the doors for more integrated and coordinated efforts on modeling, prediction, and risk assessment of natural hazards (Emerton et al., 2016; Farahmand & AghaKouchak, 2013; Yousefi et al., 2020). There are, however, salient challenges that the modeling communities across disciplines of natural hazards have recognized. Natural hazards often have a diverse impact at various spatial and temporal scales, and hence require a scalable modeling effort. The spatial and temporal scales associated with hazards vary with their types, which are often incompatible and inconsistent with hazard models, available datasets, and decision-making scales. Data collection for localized hazards (e.g., flash-flooding and landslides) is often challenging than for hurricanes/cyclones and droughts that generally affect a wider area. The integration of such datasets in multihazard models poses a particular challenge in resolving local-scale processes. Also, developing

FAIR (Findable, Accessible, Interoperable, and Reusable) (Wilkinson et al., 2016) datasets with coordinated and networked approaches through interagency and intergovernmental efforts is still a challenge. FAIR data and model-based practices in publication and policy reports, for instance, provide pathways for advancing discoveries in multihazard research and decision-making through open science. Whether datasets are in-situ or remotely sensed, they are not without uncertainties, which adds further challenge to integrate with hazard models. The integration of human systems is often challenging in such hazard models (Howley, 2021; Sima, 2021), hence the lack of a comprehensive assessment of exposure and vulnerability of people and properties to hazards. Also, note that the development and maintenance of databases and integrated hazard models demand continuous computational and financial resources and networked efforts from researchers in the community and monitoring agencies for open access to data.

The availability of novel observational datasets presents ample opportunities for improving our understanding, modeling, and predictions of natural hazards. Data collection has started to become coordinated through large research community networks, including the Long-Term Ecological Research (https://lternet.edu/), the Great Lake Ecological Observatory Network (https://gleon.org/), the United States Geological Survey(https://www.usgs.gov/), the National Ecological Observatory Network(https://www.neonscience.org/), and the French network of Critical Zone Observatories(https://www.ozcar-ri.org/), among others. However, there is a need for greater coordination within each data system to ensure internal consistency and develop crosswalk tools to enable the interoperability of data products among these efforts. Recent advances in data assimilation and machine learning techniques provide opportunities to integrate high-resolution in-situ and remote-sensing observations into hazard models. Free and open-source data and code sharing platforms like GitHub (https://github.com/) and Google Colaboratory (Carneiro et al., 2018) have been effective tools for open science. Open data initiatives, including OpenDRI (https://www.opendri.org/) and DesInventar (https://www.desinventar.net/) provide systematic, homogeneous, and compatible databases of natural hazards. Recent advances in high-performance computing systems such as the National Center for Atmospheric Research Cheyenne (https://www2.cisl.ucar.edu/resources/computational-systems/cheyenne) allow the wider research community to run computationally intensive numerical models. In addition, cloud-based tools such as Google Earth Engine (Amani et al., 2020), Amazon Web Services (Neela et al., 2021) and EOfactory (https://eofactory.ai/) have been crucial to forging collaborations among diverse research communities worldwide.

Coordinated modeling efforts across disciplines can promote the Earth system modeling by developing, supporting, and disseminating open-source codes, documentation, and integrated software modules. Some examples include National Center for Atmospheric Research (NCAR) community models (Neale et al., 2010), International Institute for Applied System Analysis' community water model (Burek et al., 2020), Community Surface Dynamics Modeling System (CSDMS) (Tucket et al., 2021), European Flood Awareness System (EFAS) (Smith et al., 2016), and Global Landslide Hazard Assessment Model (LHASA) with Global Landslide Catalog (GLC) (Kirschbaum & Stanley, 2018). These modeling resources can help improve the understanding of complex connections that drive the Earth system and predict high-impact hazard events to potentially inform decisions about policy and resource allocation for hazard mitigation and adaptation strategies.

2.3 Uncertainty Quantification and Communication

Risk communication requires a sound understanding of future risks with quantification of associated uncertainties, and a coordinated approach among disciplines (Scolobig, 2015). Natural hazard risks are dynamic and deeply uncertain. Deep uncertainty refers to a situation "where the system model and its input parameters are not known or widely agreed on by the stakeholders to the decision" (Lempert, 2002). For instance, deep uncertainty in flood risk projections arises from different system components, and propagates along the modeling chain that consists of emission scenarios, general circulation models, downscaling techniques, hydrological models, hydraulic models, and exposure and vulnerability components (Sharma et al., 2021). All components of the ICON science permeate through this modeling chain of uncertainty quantification. In addition, these uncertainties often propagate through multisector systems. For example, agricultural planning and management efficacy are subject to uncertainties stemming from an integrated agricultural, atmospheric, and hydrologic modeling systems. However, current approaches to estimate hazards sample only a relatively small subset of the known unknowns such as model structures and parameters while neglecting the cross-sectoral feedback mechanisms. Such assumptions ignore the impacts of key uncertainties on hazards and dynamics. This can drastically underestimate the tails of the hazard probability distribution (Wong et al., 2018). In addition, natural hazards' warnings/alerts are communicated generally through the discrete single-valued warning products. Most often, such products do not openly provide associated uncertainty measures and make them publicly available. It could be partly because different studies have highlighted "uncertainty" as a major challenge in risk communication, including the challenges associated with establishing reliable sources of warning, consistency in the communication strategies, the credibility of the source, and accuracy of the information (Carr et al., 2016). Failing to effectively communicate risk and uncertainty could lead to overconfidence in risk perception and result in poor decisions and outcomes (Zarekarizi et al., 2020). Uncertainty characterization is, therefore, critical to improving the credibility of natural hazards and risk information.

2.4 Crossing Traditional Disciplinary Boundaries

Multihazard multisector risk management requires integrating multiple areas of expertise that bring together different disciplines in multi-, inter-, and/or trans-disciplinary research (Wehrden et al., 2019). Such integration can span across Earth science, engineering, social science, data science, and decision science, among others. For instance, the development of flood prediction and information dissemination systems require reliable weather predictions (atmospheric science), land surface modeling (Earth science), big data analysis (data science), high-performance computing system (computer engineering), a user-friendly web-based information portal (information science), risk communication (social science), and a continuous automated monitoring network (electrical/electronic engineering). It further demands coordinated approaches and networked efforts that are designed for mutual benefit among governmental/non-governmental institutions, industries, policymakers, decision-makers, and practitioners. However, designing, implementing, and evaluating cross-disciplinary, mutually beneficial research remains challenging. Researchers, research institutions, and funding organizations still lack a concrete framework for promoting and implementing mechanisms to foster ICON-based research collaborations. In addition, differing research methods, languages, and knowledge barriers among disciplines compound the complexity of ICON science implementation (Barringer et al., 2020; Pischke et al., 2017).

The key question is: How can we promote and strengthen ICON-based cross-disciplinary research? Scientific communities have recognized the need for cross-disciplinary research. Nonetheless, the full use of ICON principles remains nascent. The National Research Council Committee on Facilitating Interdisciplinary Research (NRC, 2005) identified key driving forces to promote interdisciplinary research: i) the inherent complexity of nature and society, ii) the desire to explore problems and questions that are not confined to a single discipline, iii) the need to solve societal problems, and iv) the power of new technologies. In addition, collaborative research proposals have been gaining increasing emphasis from funding organizations. For example, the United States National Science Foundation (NSF) adopts convergence as one of the Ten Big Ideas for future NSF investments (NSF, 2021). NSF identifies convergence research as having two primary characteristics: i) research driven by a specific and compelling problem, and ii) deep integration across disciplines.

3 Call to Action

Scientific efforts, policies, and decision-making on multihazard multisector risk management require mechanistic understanding of hazards as well as their interactions and propagations. This includes understanding how hazard and risk may change across a wide range of spatiotemporal scales and how that risk may be reduced through disaster risk reduction efforts. Such efforts may be through both structural (large scale infrastructures) and nonstructural (e.g., early warning system, hazard zoning and land use planning) measures (Kundzewicz et al., 2018). As we highlight in this commentary, ICON provides a unique opportunity to bring scientific communities, policymakers, decision-makers, and the public together, facilitating the development of equitable and inclusive risk management strategies. The need for ICON-efforts permeates through multihazard risk assessment and management in terms of integrated risk assessment, data-model fusion, uncertainty quantification and communication, crossing traditional disciplinary boundaries, and gears toward developing mutually beneficial efforts, and beyond.

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References

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., et al. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 5326–5350.

Barringer, S. N., Leahey, E., & Salazar, K. (2020). What catalyzes research universities to commit to interdisciplinary research? *Research in Higher Education*, *61*(6), 679–705.

Bates, P. D., Quinn, N., Sampson, C., Smith, A., Wing, O., Sosa, J., et al. (2021). Combined modeling of US fluvial, pluvial, and coastal flood hazard under current and future climates. *Water Resources Research*, *57*(2). https://doi.org/10.1029/2020wr028673

Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., et al. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters: ERL [Web Site]*, *13*(5), 055012.

Burston, J., Ware, D., & Tomlinson, R. (2015). The real-time needs of emergency managers for tropical cyclone storm tide forecasting: results of a participatory stakeholder engagement process. Natural Hazards, 78(3), 1653–1668.

Burek, P., Satoh, Y., Kahil, T., Tang, T., Greve, P., Smilovic, M., et al. (2020). Development of the Community Water Model (CWatM v1.04) – a high-resolution hydrological model for global and regional assessment of integrated water resources management. Geoscientific Model

Development. https://doi.org/10.5194/gmd-13-3267-2020
Carr, R. H., Montz, B., Maxfield, K., Hoekstra, S., Semmens, K., & Goldman, E. (2016). Effectively Communicating Risk and Uncertainty to the Public: Assessing the National Weather Service's Flood Forecast and Warning Tools. *Bulletin of the American Meteorological Society*. https://doi.org/10.1175/bams-d-14-00248.1
Carneiro, T., Medeiros Da NóBrega, R. V., Nepomuceno, T., Bian, G.-B., De Albuquerque, V. H. C., & Filho, P. P. R. (2018). Performance Analysis of Google Colaboratory as a Tool for Accelerating Deep Learning Applications. IEEE Access, 6, 61677–61685.
Chester, M. V., Markolf, S., & Allenby, B. (2019). Infrastructure and the environment in the anthropocene. *Journal of Industrial Ecology*, *23*(5), 1006–1015.
Chester, M. V., Shane Underwood, B., & Samaras, C. (2020). Keeping infrastructure reliable under climate uncertainty. *Nature Climate Change*. https://doi.org/10.1038/s41558-020-0741-0
Cook, K. L., Andermann, C., Gimbert, F., Adhikari, B. R., & Hovius, N. (2018). Glacial lake outburst floods as drivers of fluvial erosion in the Himalaya. *Science*, *362*(6410), 53–57.
Cornwall, W. (2021). Europe's deadly floods leave scientists stunned. *Science*, *373*(6553), 372–373.
Dale, M., Wicks, J., Mylne, K., Pappenberger, F., Laeger, S., & Taylor, S. (2014). Probabilistic flood forecasting and decision-making: an innovative risk-based approach. Natural Hazards, 70(1), 159–172.
Desa, U. N., & Others. (2016). Transforming our world: The 2030 agenda for sustainable development. Retrieved from https://stg-wedocs.unep.org/bitstream/handle/20.500.11822/11125/unepswiosm1inf7sdg.pdf?sequence=1
Eckstein, D., Künzel, V., & Schäfer, L. (2021). Global Climate Risk Index 2021. *Who Suffers Most from Extreme Weather Events?*, 2000–2019.
Emerton, R. E., Stephens, E. M., Pappenberger, F., Pagano, T. C., Weerts, A. H., Wood, A. W., et al. (2016). Continental and global scale flood forecasting systems. *WIREs. Water*, *3*(3), 391–418.
Farahmand, A., & AghaKouchak, A. (2013). A satellite-based global landslide model. *Natural Hazards and Earth System Sciences*, *13*(5), 1259–1267.
Fuchs, S., Birkmann, J., & Glade, T. (2012). Vulnerability assessment in natural hazard and risk analysis: current approaches and future challenges. *Natural Hazards*, *64*(3), 1969–1975.
Giannaros, T. M., Kotroni, V., & Lagouvardos, K. (2021). Climatology and trend analysis (1987–2016) of fire weather in the Euro-Mediterranean. International Journal of Climatology, 41(S1). https://doi.org/10.1002/joc.6701
Goldman, A. E., S. R. Emani, L. C. Pérez-Angel, J. A. Rodríguez-Ramos, J. C. Stegen, and P. Fox (2021), Special collection on open collaboration across geosciences , Eos, 102, https://doi.org/10.1029/2021EO153180. Published on 06 January 2021.
Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., et al. (2013). Global flood risk under climate change. *Nature Climate Change*, *3*(9), 816–821.
Howley, K. (2021). Natural Hazards Have Unnatural Impacts—What More Can Science Do? *Eos*. https://doi.org/10.1029/2021eo154552
HFA. (2021). Hyogo Framework for Action 2005–2015: Building the resilience of nations and communities to disasters. 2005. http://www.unisdr.org/2005/wcdr/intergover/official-doc/L-docs/Hyogo-framework-for-action-english.pdf. Accessed 21 November 2021.
NRC. (2005). National Research Council. Institute of Medicine, National Academy of Engineering, National Academy of Sciences, Committee on Science, Engineering, and Public Policy, & Committee on Facilitating Interdisciplinary Research. *Facilitating Interdisciplinary Research*. National Academies Press.
IPCC. (2021): Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and

B. Zhou (eds.)]. Cambridge University Press.
Koks, E. E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S. A., et al. (2019). A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, *10*(1), 2677.
Kirschbaum, D., & Stanley, T. (2018). Satellite-Based Assessment of Rainfall-Triggered Landslide Hazard for Situational Awareness. Earth's Future. https://doi.org/10.1002/2017ef000715
Kundzewicz, Z. W., Hegger, D. L. T., Matczak, P., & Driessen, P. P. J. (2018). Opinion: Flood-risk reduction: Structural measures and diverse strategies. Proceedings of the National Academy of Sciences of the United States of America, 115(49), 12321–12325.
Lempert, R. J. (2002). A new decision sciences for complex systems. *Proceedings of the National Academy of Sciences of the United States of America*, *99 Suppl 3*, 7309–7313.
Miles, S. B. (2018). Participatory Disaster Recovery Simulation Modeling for Community Resilience Planning. *International Journal of Disaster Risk Science*, *9*(4), 519–529.
Mora, C., Spirandelli, D., Franklin, E. C., Lynham, J., Kantar, M. B., Miles, W., et al. (2018). Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. *Nature Climate Change*, *8*(12), 1062–1071.
Neale, R. B., Chen, C.-C., Gettelman, A., Lauritzen, P. H., Park, S., Williamson, D. L., et al. (2010). Description of the NCAR community atmosphere model (CAM 5.0). NCAR Tech. Note NCAR/TN-486+ STR, 1(1), 1–12.
Neela, S., Neyyala, Y., Pendem, V., Peryala, K., & Kumar, V. V. (2021). Cloud Computing Based Learning Web Application Through Amazon Web Services. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 472–475).
NSF. (2021). National Science Foundation. NSF's 10 big ideas - special report. Retrieved June 30, 2021, from https://www.nsf.gov/news/special_reports/big_ideas/index.jsp
Pascale, S., Kapnick, S. B., Delworth, T. L., & Cooke, W. F. (2020). Increasing risk of another Cape Town "Day Zero" drought in the 21st century. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(47), 29495–29503.
Paul, J. D., Buytaert, W., Allen, S., Ballesteros-Cánovas, J. A., Bhusal, J., Cieslik, K., et al. (2018). Citizen science for hydrological risk reduction and resilience building. WIREs. Water, 5(1), e1262.
Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. B., Deryng, D., Elliott, J., et al. (2014). Multisectoral climate impact hotspots in a warming world. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3233–3238.
Pischke, E. C., Knowlton, J. L., Phifer, C. C., Gutierrez Lopez, J., Propato, T. S., Eastmond, A., et al. (2017). Barriers and Solutions to Conducting Large International, Interdisciplinary Research Projects. *Environmental Management*, *60*(6), 1011–1021.
Rakhal, B., Sharma, S., Ghimire, G., Adhikari, T., & Shrestha, R. (2021). Nepal's Communities Brace for Multihazard Risks. *Eos*. https://doi.org/10.1029/2021eo159039
Talchabhadel, R., Nakagawa, H., Kawaike, K., Yamanoi, K., Musumari, H., Adhikari, T. R., & Prajapati, R. (2021). Appraising the potential of using satellite-based rainfall estimates for evaluating extreme precipitation: A case study of august 2014 event across the west rapti river basin, Nepal. Earth and Space Science (Hoboken, N.J.), 8(8). https://doi.org/10.1029/2020ea001518
Tucker, G. E., Hutton, E. W. H., Piper, M. D., Campforts, B., Gan, T., Barnhart, K. R., et al. (2021, July 13). CSDMS: A community platform for numerical modeling of Earth-surface processes. Geosci. Model Dev. https://doi.org/10.5194/gmd-2021-223
Sanders, B. F., Schubert, J. E., Goodrich, K. A., Houston, D., Feldman, D. L., Basolo, V., et al. (2020). Collaborative modeling with fine-resolution data enhances flood awareness, minimizes differences in flood perception, and produces actionable flood maps. *Earth's Future*, *8*(1).

https://doi.org/10.1029/2019ef001391
Scolobig, A. (2015). Brief Communication: The dark side of risk and crisis communication: legal conflicts and responsibility allocation. *Natural Hazards and Earth System Sciences*, *15*(6), 1449–1456.
Sharma, S., Gomez, M., Keller,K., Nicholas, R., & Mejia, A. (2021). Regional Flood Risk Projections under Climate Change. *Journal of Hydrometeorology* 22, no. 9: 2259-2274.
Sima, R. (2021). Where Do People Fit into a Global Hazard Model? *Eos*. https://doi.org/10.1029/2021eo154550
Smith, P. J., Pappenberger, F., Wetterhall, F., Thielen del Pozo, J., Krzeminski, B., Salamon, P., et al. (2016). Chapter 11 - On the Operational Implementation of the European Flood Awareness System (EFAS). In T. E. Adams & T. C. Pagano (Eds.), Flood Forecasting (pp. 313–348). Boston: Academic Press.
Sobolev, G. A. (2011). Seismicity dynamics and earthquake predictability. Natural Hazards and Earth System Sciences, 11(2), 445–458.
Strömberg, D. (2007). Natural Disasters, Economic Development, and Humanitarian Aid. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *21*(3), 199–222.
Swain, D. L. (2021). A shorter, sharper rainy season amplifies California wildfire risk. *Geophysical Research Letters*, *48*(5). https://doi.org/10.1029/2021gl092843
Trogrlić, R. Š., Cumiskey, L., Triyanti, A., Duncan, M. J., Eltinay, N., Hogeboom, R. J., et al. (2017). Science and Technology Networks: A Helping Hand to Boost Implementation of the Sendai Framework for Disaster Risk Reduction 2015–2030? *International Journal of Disaster Risk Science*, *8*(1), 100–105.
UNDRR. (2020). United Nations Office for Disaster Risk Reduction. United Nations Office for Disaster Risk Reduction. *Human Cost of Disasters: An Overview of the Last 20 Years 2000-2019*. United Nations.
United Nations. (2013).Nations, U., & United Nations. (2013). The Millennium Development Goals Report 2013. Millennium Development Goals Report. https://doi.org/10.18356/2e9902b5-en. Assessed on 22 November 2021.
Wehrden, H. von, von Wehrden, H., Guimarães, M. H., Bina, O., Varanda, M., Lang, D. J., et al. (2019). Interdisciplinary and transdisciplinary research: finding the common ground of multi-faceted concepts. *Sustainability Science*. https://doi.org/10.1007/s11625-018-0594-x
Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J. J., Appleton, G., Axton, M., Baak, A., et al. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data, 3,* 160018.
Wong, T. E., Klufas, A., Srikrishnan, V., & Keller, K. (2018). Neglecting model structural uncertainty underestimates upper tails of flood hazard. *Environmental Research Letters*. https://doi.org/10.1088/1748-9326/aacb3d
Wright, D. B., Bosma, C. D., & Lopez-Cantu, T. (2019). U.S. hydrologic design standards insufficient due to large increases in frequency of rainfall extremes. *Geophysical Research Letters*, *46*(14), 8144–8153.
Yousefi, S., Pourghasemi, H. R., Emami, S. N., Pouyan, S., Eskandari, S., & Tiefenbacher, J. P. (2020). A machine learning framework for multi-hazards modeling and mapping in a mountainous area. *Scientific Reports*. https://doi.org/10.1038/s41598-020-69233-2
Zarekarizi, M., Srikrishnan, V., & Keller, K. (2020). Neglecting uncertainties biases house-elevation decisions to manage riverine flood risks. *Nature Communications*, *11*(1), 5361.
Zhongming, Z., Linong, L., Wangqiang, Z., Wei, L., & Others. (2015). WMO guidelines on multi-hazard impact-based forecast and warning services. Retrieved from http://resp.llas.ac.cn/C666/handle/2XK7JSWQ/11530

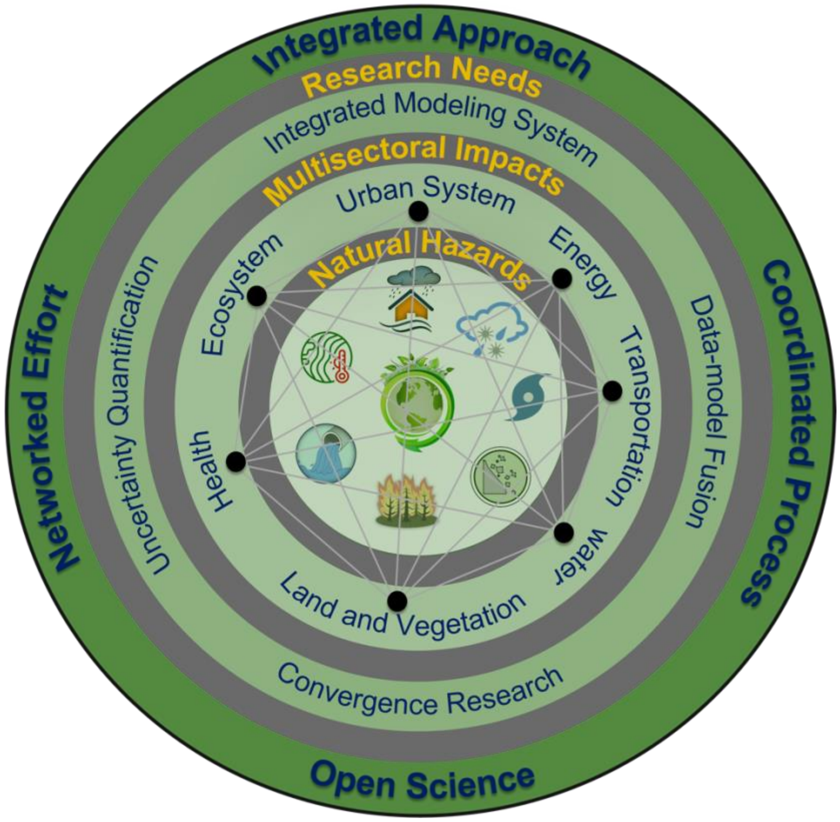

Figure 1: Multihazard multisector risk management under the Integrated, Coordinated, Open, and Networked (ICON) science framework. Natural hazards can be geophysical (e.g., earthquakes, landslides, and volcano), hydrometeorological (e.g., flood and avalanches), biological (disease epidemics and animal/insect plagues) and climatological (e.g., droughts and wildfires), among others. Natural hazards pose multisectoral impacts, including urban system, energy, transportation, water, land and vegetation, health, and ecosystem, among others.