

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

3
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18
19 **Key Points:**

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

25
26 **Abstract**

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

39 **1 Introduction**

40 Natural hazards drive major damages to communities, infrastructure, and ecosystems across the
41 globe. Recent European floods (Cornwall, 2021), wildfires in the United States (Swain, 2021), and
42 drought in South Africa (Pascale et al., 2020) highlight how human and natural systems are exposed
43 and vulnerable to natural hazards. Between 2000 to 2019, natural hazard-related disasters caused over
44 2 trillion United States (U.S.) dollars in global economic losses and over 1 million deaths worldwide
45 (United Nations Office for Disaster Risk Reduction, 2020). These impacts are expected to rise in the
46 future with coevolving natural and human systems subject to the impacts of multiple hazards, including
47 extreme weather events, sea-level rise, anthropogenic disturbances, and climate change. There is
48 growing recognition of the critical need to improve the understanding and prediction of natural hazards,
49 characterize multihazard multisector risk, and enhance the communication of risk and its associated
50 uncertainties to inform the design of effective risk management strategies (IPCC, 2021).

51 Multihazard multisector risk management requires a comprehensive understanding of different
52 interacting systems and processes, including the feedback between ecosystems, human systems, and
53 climate systems (Byers et al., 2018; Mora et al., 2018; Piontek et al., 2014). A growing number of
54 scientific studies (Bates et al., 2021; Cook et al., 2018; Hirabayashi et al., 2013; Strömberg, 2007)
55 provide valuable new insights on the potential impacts of a single hazard on a specific sector and in a
56 specific region. However, there is a lack of integrated frameworks, coordinated processes, open science,
57 and networked efforts that can account for the complex interactions across natural and human systems
58 in the context of multiple interacting stresses and over a wide range of spatiotemporal scales (Figure
59 1).

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

66

67 **2 Challenges and Research Opportunities**

68 **2.1 Integrated risk assessment**

69 A sound understanding of risk drivers and their dynamic interactions is critical to inform the design
70 of risk management strategies. Quantifying multihazard multisector risk is challenging as it requires
71 the integrated assessment of hazard probabilities, the exposure of people and assets, and the
72 vulnerability or susceptibility to consequent damage. In addition, multihazard risks are dynamic and
73 are modulated by several factors, including climatic conditions, demographic changes, and
74 socioeconomic conditions. Understanding the interactions among the risk drivers is crucial to achieving
75 a comprehensive view of the integrated system. Developing an integrated system requires a priori
76 planning to integrate different components while ensuring open access and interoperability across data
77 types and models.

78 Earth system modeling efforts are generally focused on understanding the impacts of a single
79 hazard in isolation, emphasizing risk assessment in limited sectors. However, these individual hazards
80 often demonstrate compounding and cascading behaviors, where the resulting multihazard multisector
81 risk becomes increasingly more difficult to be assessed using conventional techniques. Furthermore,
82 the conventional risk assessment techniques are mostly concentrated on predicting hazards instead of
83 the actual risk or impacts. Risk predictability is often limited to decision-making across a range of
84 spatiotemporal scales due to the lack of coordinated databases (Fuchs et al., 2012; Rakhal et al., 2021).
85 Improving the risk prediction capabilities of Earth system models demands networked efforts among
86 the scientific community, stakeholders, and agencies for database development and management with
87 implications to inform mutually beneficial risk mitigation and adaptation strategies. For instance,
88 tropical cyclones, flooding, and landslide risk prediction ahead of sufficient lead time allow risk
89 managers enough time to take necessary steps for preparedness and damage mitigation; whereas the
90 lack of predictability in earthquakes complicates the disaster mitigation and preparedness activities.
91 Understanding the natural hazard phenomena and generation processes is critical to improve hazard
92 and risk predictability.

93 The challenges outlined above raise several questions for researchers and policymakers. How can
94 we develop an open-source integrated modeling framework that can account for complex interactions
95 and dependencies among human and natural systems? How do the cascading hazards and associated
96 risks change with evolving climatic conditions, socioeconomic developments, and settlement patterns?
97 How do mitigation and adaptation strategies change risk perception? How can we upscale knowledge
98 from basin-scale process understanding to regional-scale hazards and risks modeling, and vice versa?

99 The availability of high-resolution datasets and modeling resources have opened opportunities for
100 integrated multihazard multisector risk assessment across a wide range of spatial and temporal scales.
101 There is also an increasing acknowledgment of the need to systematically integrate risk management
102 efforts into policy, plans, and programs for sustainable development. Strategic and integrated efforts to
103 promote community resilience to disasters have been initiated through Hyogo Framework for Action
104 2005-2015 and Millennium Development Goals. The Sendai Framework for Disaster Risk Reduction
105 (Trogrlić et al., 2017) and the 2030 United Nations Sustainable Development Goals (Desa et al., 2016)
106 underscore the pressing need for inclusive and integrated multihazard risk management approaches.
107 These networked efforts are designed to be mutually beneficial across multiple stakeholders.

108 Community risks to natural hazards are often quantified using an index such as the US National
109 Risk Index (FEMA, 2021), and Global Climate Risk Index (Eckstein et al., 2021). Scientific
110 communities have made substantial progress in understanding the potential impacts of multihazards on
111 multisectors and from local to global scales (Chester et al., 2019, 2020; Koks et al., 2019; Wright et al.,
112 2019). Furthermore, World Meteorological Organization's guidelines have emphasized the need for
113 multi-hazard impact-based forecast and warning services to disseminate accurate and understandable
114 weather and climate information. Satellite remote sensing, citizen science, and low-tech sensing could
115 be instrumental in supporting local-level risk management, particularly in the data-scarce region.
116 Additional networked initiatives such as community-based modeling and data collection that integrate

117 traditional wisdom, indigenous knowledge, and experts' opinion have been effective for multihazard
118 risk management (Miles, 2018; Rakhal et al., 2021; Sanders et al., 2020).

119

120 **2.2 Earth System Data-Model Fusion**

121 Recent advances in big data, high-performance computing systems, cloud computing, and
122 community-based modeling, among others, have opened the doors for more integrated and coordinated
123 efforts on modeling, prediction, and risk assessment of natural hazards (Emerton et al., 2016;
124 Farahmand & AghaKouchak, 2013; Yousefi et al., 2020). There are, however, salient challenges that
125 the modeling communities across disciplines of natural hazards have recognized. Natural hazards
126 impact at various spatial and temporal scales, and hence a need for scalable modeling efforts. The
127 spatial and temporal scales associated with hazards vary with their types, which are often incompatible
128 and inconsistent with hazard models, available datasets, and decision-making scales. Data collection
129 for large-scale (regional) hazards such as hurricanes/cyclones and droughts are easier than that of small-
130 scale (local) hazards like riverine flooding and landslides. The integration of such datasets in
131 multihazard models poses a particular challenge in resolving local-scale processes. Also, developing
132 FAIR (Findable, Accessible, Interoperable, and Reusable) (Wilkinson et al., 2016) datasets with
133 coordinated and networked approaches through interagency and intergovernmental efforts is still a
134 challenge. FAIR data and model-based practices in publication and policy reports, for instance, provide
135 pathways for advancing discoveries in multihazard research and decision-making through open science.
136 Whether datasets are in-situ or remotely sensed, they are not without uncertainties, which adds further
137 challenge to integrate with hazard models. The integration of human systems is often challenging in
138 such hazard models (Howley, 2021; Sima, 2021), hence the lack of a comprehensive assessment of
139 exposure and vulnerability to people and properties. Also, note that the development and maintenance
140 of databases and integrated hazard models demand continuous computational and financial resources,
141 and networked efforts from researchers in the community and monitoring agencies for open access to
142 data.

143 The challenges outlined above suggest several questions for researchers. How can we make
144 optimal use of sparse station networks, remotely sensed radar and satellite retrievals, numerical weather
145 prediction products, and global climate model outputs to provide high resolution forcing to modeling
146 integrated human and natural systems? How can the Earth system models capture both local as well as
147 large-scale dynamics? What are the efficient ways to couple models to understand compounding and
148 cascading hazards? What is the best choice of spatiotemporal model resolution for specific hazard and
149 risk assessment? Can we develop a modular framework for risk assessment across spatiotemporal
150 scales? How do we integrate human system feedback into a multihazard modeling framework?

151 The availability of novel observational datasets presents significant opportunities for improving
152 our understanding, modeling, and predictions of natural hazards. Data collection has started to become
153 coordinated through large research community networks, including the Long-Term Ecological
154 Research, the Great Lake Ecological Observatory Network, the United States Geological Survey, the
155 National Ecological Observatory Network, and the French network of Critical Zone Observatories,
156 among others. However, there is a need for greater coordination within each data system to ensure

157 internal consistency and develop crosswalk tools to enable the interoperability of data products among
158 these efforts. Recent advances in data assimilation and machine learning techniques provide
159 opportunities to integrate high-resolution in-situ and remote-sensing observations into hazard models.
160 Free and open-source data and code sharing platforms like GitHub and Google Collaboratory have been
161 effective tools for open science. Open data initiatives, including OpenDRI and DesInventar provide
162 systematic, homogeneous, and compatible databases of natural hazards. Recent advances in high-
163 performance computing systems such as the National Center for Atmospheric Research Cheyenne
164 allow the wider research community to run computationally intensive computer models. In addition,
165 cloud-based tools such as Google Earth Engine, Amazon Web Services, and EOfactory have been
166 crucial to forging collaborations among diverse research communities worldwide.

167 Coordinated modeling efforts across disciplines can promote the Earth system modeling by
168 developing, supporting, and disseminating open-source codes, documentation, and integrated software
169 modules. Some examples include- National Center for Atmospheric Research (NCAR) community
170 models, International Institute for Applied System Analysis' community water model, Community
171 Surface Dynamics Modeling System (CSDMS), European Center for Medium-Range Weather
172 Forecasts (ECMWF), European Flood Awareness System (EFAS), and Global Landslide Hazard
173 Assessment Model (LHASA) with Global Landslide Catalog (GLC). These modeling resources can
174 help improve the understanding of complex connections that drive the Earth system and predict high-
175 impact hazard events to potentially inform decisions about policy and resource allocation for hazard
176 mitigation and adaptation strategies.

177

178 **2.3 Uncertainty quantification and communication**

179 Risk communication requires a sound understanding of future risks with quantification of
180 associated uncertainties, and a coordinated approach among disciplines (Scolobig, 2015). Natural
181 hazard risks are dynamic and deeply uncertain. Deep uncertainty refers to a situation “where the system
182 model and its input parameters are not known or widely agreed on by the stakeholders to the decision”
183 (Lempert, 2002). For instance, deep uncertainty in flood risk projections arises from different system
184 components, and propagates along the modeling chain that consists of emission scenarios, general
185 circulation models, downscaling techniques, hydrological models, hydraulic models, and exposure and
186 vulnerability components (Sharma et al., 2021). All components of the ICON science permeate through
187 this modeling chain of uncertainty quantification. In addition, these uncertainties often propagate
188 through multisector systems. For example, agricultural planning and management efficacy are subject
189 to uncertainty propagation stemming from an integrated agricultural, atmospheric, and hydrologic
190 modeling system. However, current approaches to estimate hazards sample only a relatively small
191 subset of the known unknowns such as model structures and parameters while neglecting the cross-
192 sectoral feedback mechanisms. Such assumptions ignore the impacts of key uncertainties on hazards
193 and dynamics. This can drastically underestimate the tails of the hazard probability distribution (Wong
194 et al., 2018). In addition, natural hazards' warnings/alerts are communicated generally through the
195 discrete single-valued warning products. Most often, such products do not openly provide associated
196 uncertainty measures and make them publicly available. It could be partly because different studies

197 have highlighted “uncertainty” as a major challenge in risk communication, including the challenges
198 associated with establishing reliable sources of warning, consistency in the communication strategies,
199 the credibility of the source, and accuracy of the information (Carr et al., 2016). Failing to effectively
200 communicate risk and uncertainty could lead to overconfidence in risk perception, and result in poor
201 decisions and outcomes (Zarekarizi et al., 2020).

202 Key questions associated with uncertainty quantification include the following: What are the
203 decision-relevant uncertainties driving natural hazards and risks estimates? How does uncertainty
204 propagate along with the integrated socioeconomic, environmental, and infrastructure systems? What
205 are the coordinated approaches for uncertainty characterization, quantification, and reduction in hazard
206 predictions and risk assessment? Key questions associated with uncertainty communication include the
207 following. What are the effective tools and approaches to communicate uncertain hazards and risk
208 information? How do policymakers, decision-makers, and communities perceive uncertainty? What
209 changes are needed to make uncertainty an integral part of risk assessment? How do risk perceptions
210 impact mitigation, preparedness, and response behavior, and how do these change when the estimated
211 risk accounts for uncertainty?

212

213 **2.4 Crossing traditional disciplinary boundaries**

214 Multihazard multisector risk management requires integrating multiple areas of expertise that
215 bring together different disciplines in multi-, inter-, and/or trans-disciplinary research (Wehrden et al.,
216 2019). Such integration can span across Earth science, engineering, social science, data science, and
217 decision science, among others. For instance, the development of flood prediction and information
218 dissemination systems require reliable weather predictions (atmospheric science), land surface
219 modeling (Earth science), big data analysis (data science), high-performance computing system
220 (computer engineering), a user-friendly web-based information portal (information science), risk
221 communication (social science), and a continuous automated monitoring network (electrical/electronic
222 engineering). It further demands coordinated approaches and networked efforts that are designed for
223 mutual benefit among governmental/non-governmental institutions, industries, policymakers, decision-
224 makers, and practitioners. However, designing, implementing, and evaluating cross-disciplinary,
225 mutually beneficial research remains challenging. Researchers, research institutions, and funding
226 organizations still lack a concrete framework for promoting and implementing mechanisms to foster
227 ICON-based research collaborations. In addition, differing research methods, languages, and
228 knowledge barriers among disciplines compound the complexity of ICON science implementation
229 (Barringer et al., 2020; Pischke et al., 2017).

230 The key question is: How can we promote and strengthen ICON-based cross-disciplinary research?
231 Scientific communities have recognized the need for cross-disciplinary research. Nonetheless, the full
232 use of ICON principles remains nascent. The National Research Council Committee on Facilitating
233 Interdisciplinary Research (NRC, 2005) identified key driving forces to promote interdisciplinary
234 research: i) the inherent complexity of nature and society, ii) the desire to explore problems and
235 questions that are not confined to a single discipline, iii) the need to solve societal problems, and iv)
236 the power of new technologies. In addition, collaborative research proposals have been gaining

237 increasing emphasis from funding organizations. For example, the United States National Science
238 Foundation (NSF) adopts convergence as one of the ten Big Ideas for future NSF investments (NSF,
239 2021). NSF identifies convergence research as having two primary characteristics: i) research driven
240 by a specific and compelling problem, and ii) deep integration across disciplines.

241

242 **3 Call to Action**

243 Scientific efforts, policies, and decision-making on multihazard multisector risk require a sound
244 understanding of risk and its drivers, from local to global scales. This includes understanding how risk
245 may change across a wide range of spatiotemporal scales and how that risk may be reduced through
246 disaster risk reduction efforts. Such efforts may be through both structural (such as mitigation
247 measures) and nonstructural (such as adaptation that promotes resilience) means. As we highlight in
248 this commentary, ICON provides a unique opportunity to bring scientific communities, policymakers,
249 decision-makers, and the public together, facilitating the development of equitable and inclusive risk
250 management strategies. The need for ICON science permeates through multihazard risk assessment and
251 management in terms of integrated risk assessment, data-model fusion, uncertainty quantification and
252 communication, crossing traditional disciplinary boundaries, and gears toward developing efforts to be
253 mutually beneficial, and beyond.

254

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262

263 **References**

- 264 Barringer, S. N., Leahey, E., & Salazar, K. (2020). What catalyzes research universities to commit to
265 interdisciplinary research? *Research in Higher Education*, 61(6), 679–705.
- 266 Bates, P. D., Quinn, N., Sampson, C., Smith, A., Wing, O., Sosa, J., et al. (2021). Combined modeling of US
267 fluvial, pluvial, and coastal flood hazard under current and future climates. *Water Resources Research*,
268 57(2). <https://doi.org/10.1029/2020wr028673>
- 269 Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., et al. (2018). Global exposure and
270 vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters:*
271 *ERL [Web Site]*, 13(5), 055012.
- 272 Carr, R. H., Montz, B., Maxfield, K., Hoekstra, S., Semmens, K., & Goldman, E. (2016). Effectively
273 Communicating Risk and Uncertainty to the Public: Assessing the National Weather Service’s Flood
274 Forecast and Warning Tools. *Bulletin of the American Meteorological Society*.
275 <https://doi.org/10.1175/bams-d-14-00248.1>
- 276 Chester, M. V., Markolf, S., & Allenby, B. (2019). Infrastructure and the environment in the anthropocene.
277 *Journal of Industrial Ecology*, 23(5), 1006–1015.
- 278 Chester, M. V., Shane Underwood, B., & Samaras, C. (2020). Keeping infrastructure reliable under climate
279 uncertainty. *Nature Climate Change*. <https://doi.org/10.1038/s41558-020-0741-0>
- 280 Cook, K. L., Andermann, C., Gimbert, F., Adhikari, B. R., & Hovius, N. (2018). Glacial lake outburst floods

281 as drivers of fluvial erosion in the Himalaya. *Science*, 362(6410), 53–57.
 282 Cornwall, W. (2021). Europe’s deadly floods leave scientists stunned. *Science*, 373(6553), 372–373.
 283 Desa, U. N., & Others. (2016). Transforming our world: The 2030 agenda for sustainable development.
 284 Retrieved from [https://stg-](https://stg-wedocs.unep.org/bitstream/handle/20.500.11822/11125/unepswiosm1inf7sdg.pdf?sequence=1)
 285 [wedocs.unep.org/bitstream/handle/20.500.11822/11125/unepswiosm1inf7sdg.pdf?sequence=1](https://stg-wedocs.unep.org/bitstream/handle/20.500.11822/11125/unepswiosm1inf7sdg.pdf?sequence=1)
 286 Eckstein, D., Künzel, V., & Schäfer, L. (2021). Global Climate Risk Index 2021. *Who Suffers Most from*
 287 *Extreme Weather Events, 2000–2019*.
 288 Emerton, R. E., Stephens, E. M., Pappenberger, F., Pagano, T. C., Weerts, A. H., Wood, A. W., et al. (2016).
 289 Continental and global scale flood forecasting systems. *WIREs. Water*, 3(3), 391–418.
 290 Farahmand, A., & AghaKouchak, A. (2013). A satellite-based global landslide model. *Natural Hazards and*
 291 *Earth System Sciences*, 13(5), 1259–1267.
 292 Fuchs, S., Birkmann, J., & Glade, T. (2012). Vulnerability assessment in natural hazard and risk analysis:
 293 current approaches and future challenges. *Natural Hazards*, 64(3), 1969–1975.
 294 Goldman, A. E., S. R. Emani, L. C. Pérez-Angel, J. A. Rodríguez-Ramos, J. C. Stegen, and P. Fox (2021),
 295 Special collection on open collaboration across geosciences, *Eos*,
 296 102, <https://doi.org/10.1029/2021EO153180>. Published on 06 January 2021.
 297 Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., et al. (2013). Global
 298 flood risk under climate change. *Nature Climate Change*, 3(9), 816–821.
 299 Howley, K. (2021). Natural Hazards Have Unnatural Impacts—What More Can Science Do? *Eos*.
 300 <https://doi.org/10.1029/2021eo154552>
 301 NRC. (2005). National Research Council. Institute of Medicine, National Academy of Engineering, National
 302 Academy of Sciences, Committee on Science, Engineering, and Public Policy, & Committee on
 303 Facilitating Interdisciplinary Research. *Facilitating Interdisciplinary Research*. National Academies
 304 Press.
 305 IPCC. (2021): Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the
 306 Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P.
 307 Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M.
 308 Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and
 309 B. Zhou (eds.)]. Cambridge University Press.
 310 Koks, E. E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S. A., et al. (2019). A global
 311 multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, 10(1), 2677.
 312 Lempert, R. J. (2002). A new decision sciences for complex systems. *Proceedings of the National Academy of*
 313 *Sciences of the United States of America*, 99 Suppl 3, 7309–7313.
 314 Miles, S. B. (2018). Participatory Disaster Recovery Simulation Modeling for Community Resilience
 315 Planning. *International Journal of Disaster Risk Science*, 9(4), 519–529.
 316 Mora, C., Spirandelli, D., Franklin, E. C., Lynham, J., Kantar, M. B., Miles, W., et al. (2018). Broad threat to
 317 humanity from cumulative climate hazards intensified by greenhouse gas emissions. *Nature Climate*
 318 *Change*, 8(12), 1062–1071.
 319 NSF. (2021). National Science Foundation. NSF’s 10 big ideas - special report. Retrieved June 30, 2021, from
 320 https://www.nsf.gov/news/special_reports/big_ideas/index.jsp
 321 Pascale, S., Kapnick, S. B., Delworth, T. L., & Cooke, W. F. (2020). Increasing risk of another Cape Town
 322 “Day Zero” drought in the 21st century. *Proceedings of the National Academy of Sciences of the United*
 323 *States of America*, 117(47), 29495–29503.
 324 Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. B., Deryng, D., Elliott, J., et al. (2014). Multisectoral climate
 325 impact hotspots in a warming world. *Proceedings of the National Academy of Sciences of the United*
 326 *States of America*, 111(9), 3233–3238.
 327 Pischke, E. C., Knowlton, J. L., Phifer, C. C., Gutierrez Lopez, J., Propato, T. S., Eastmond, A., et al. (2017).
 328 Barriers and Solutions to Conducting Large International, Interdisciplinary Research Projects.
 329 *Environmental Management*, 60(6), 1011–1021.
 330 Rakhal, B., Sharma, S., Ghimire, G., Adhikari, T., & Shrestha, R. (2021). Nepal’s Communities Brace for
 331 Multihazard Risks. *Eos*. <https://doi.org/10.1029/2021eo159039>

332 Sanders, B. F., Schubert, J. E., Goodrich, K. A., Houston, D., Feldman, D. L., Basolo, V., et al. (2020).
333 Collaborative modeling with fine-resolution data enhances flood awareness, minimizes differences in
334 flood perception, and produces actionable flood maps. *Earth's Future*, 8(1).
335 <https://doi.org/10.1029/2019ef001391>

336 Scolobig, A. (2015). Brief Communication: The dark side of risk and crisis communication: legal conflicts and
337 responsibility allocation. *Natural Hazards and Earth System Sciences*, 15(6), 1449–1456.

338 Sharma, S., Gomez, M., Keller, K., Nicholas, R., & Mejia, A. (2021). Regional Flood Risk Projections under
339 Climate Change. *Journal of Hydrometeorology* 22, no. 9: 2259–2274.

340 Sima, R. (2021). Where Do People Fit into a Global Hazard Model? *Eos*.
341 <https://doi.org/10.1029/2021eo154550>

342 Strömberg, D. (2007). Natural Disasters, Economic Development, and Humanitarian Aid. *The Journal of*
343 *Economic Perspectives: A Journal of the American Economic Association*, 21(3), 199–222.

344 Swain, D. L. (2021). A shorter, sharper rainy season amplifies California wildfire risk. *Geophysical*
345 *Research Letters*, 48(5). <https://doi.org/10.1029/2021gl092843>

346 Trogrlić, R. Š., Cumiskey, L., Triyanti, A., Duncan, M. J., Eltinay, N., Hogeboom, R. J., et al. (2017). Science
347 and Technology Networks: A Helping Hand to Boost Implementation of the Sendai Framework for
348 Disaster Risk Reduction 2015–2030? *International Journal of Disaster Risk Science*, 8(1), 100–105.

349 UNDRR. (2020). United Nations Office for Disaster Risk Reduction. United Nations Office for Disaster Risk
350 Reduction. *Human Cost of Disasters: An Overview of the Last 20 Years 2000-2019*. United Nations.

351 Wehrden, H. von, von Wehrden, H., Guimarães, M. H., Bina, O., Varanda, M., Lang, D. J., et al. (2019).
352 Interdisciplinary and transdisciplinary research: finding the common ground of multi-faceted concepts.
353 *Sustainability Science*. <https://doi.org/10.1007/s11625-018-0594-x>

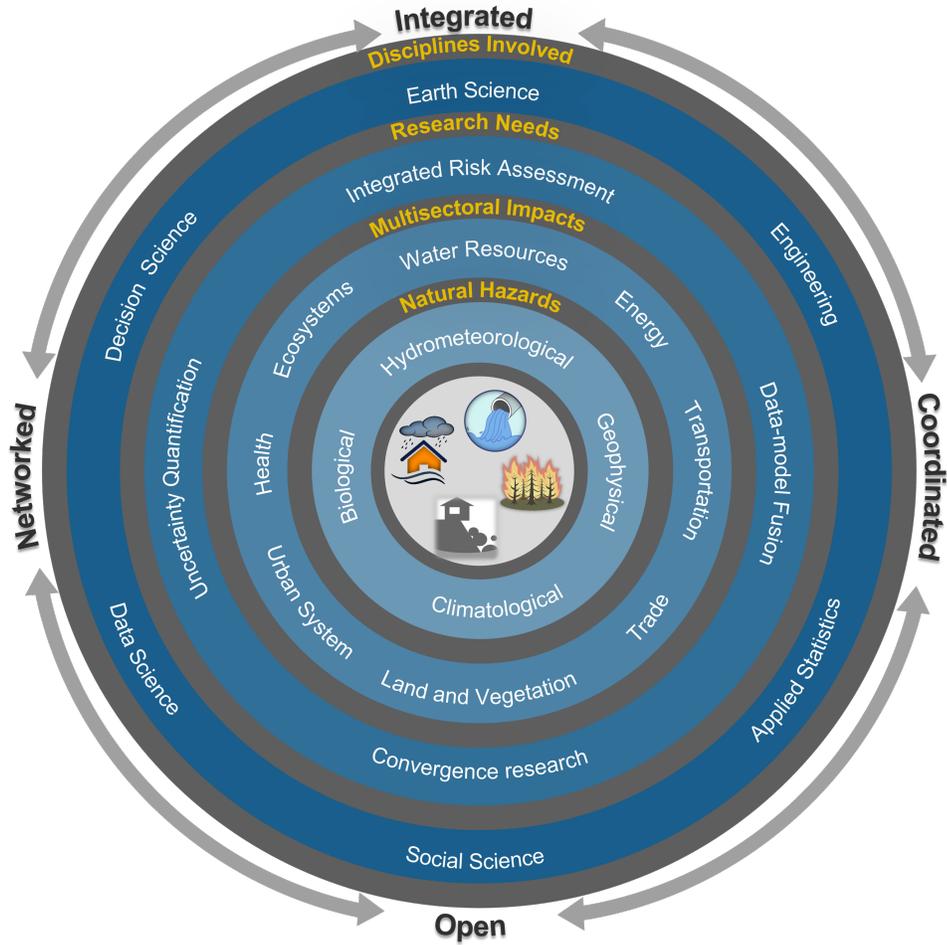
354 Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J. J., Appleton, G., Axton, M., Baak, A., et al. (2016). The
355 FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*, 3, 160018.

356 Wong, T. E., Klufas, A., Srikrishnan, V., & Keller, K. (2018). Neglecting model structural uncertainty
357 underestimates upper tails of flood hazard. *Environmental Research Letters*. [https://doi.org/10.1088/1748-](https://doi.org/10.1088/1748-9326/aacb3d)
358 [9326/aacb3d](https://doi.org/10.1088/1748-9326/aacb3d)

359 Wright, D. B., Bosma, C. D., & Lopez-Cantu, T. (2019). U.S. hydrologic design standards insufficient due to
360 large increases in frequency of rainfall extremes. *Geophysical Research Letters*, 46(14), 8144–8153.

361 Yousefi, S., Pourghasemi, H. R., Emami, S. N., Pouyan, S., Eskandari, S., & Tiefenbacher, J. P. (2020). A
362 machine learning framework for multi-hazards modeling and mapping in a mountainous area. *Scientific*
363 *Reports*. <https://doi.org/10.1038/s41598-020-69233-2>

364 Zarekarizi, M., Srikrishnan, V., & Keller, K. (2020). Neglecting uncertainties biases house-elevation decisions
365 to manage riverine flood risks. *Nature Communications*, 11(1), 5361.



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367 **Figure 1:** Multihazard multisector risk management under the Integrated, Coordinated, Open and Networked
 368 (ICON) science framework. Natural hazards can be geophysical (earthquakes, landslides, and volcano),
 369 hydrometeorological (flood and avalanches), biological (disease epidemics and animal/insect plagues) and
 370 climatological (droughts and wildfires), among others.