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Community Perspectives on Simulation and Data Needs for the Study of

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Natural Hazard Impacts and Recovery

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19 **ABSTRACT**

20 With the aim of fostering the development of robust tools to simulate the impact of natu-
21 ral hazards on structures, lifelines, and communities, the Natural Hazards Engineering Research
22 Infrastructure Computational Modeling and Simulation Center gathered sixty researchers, develop-
23 ers, and practitioners working in Natural Hazards Engineering (NHE) for a workshop to prioritize

24 research questions and identify community needs for data and computational simulation capabilities.
25 Participants used their wide-ranging expertise in earthquake, coastal, and wind hazards from
26 engineering, planning, data sciences, and social sciences perspectives to identify five major thrusts
27 of recommended future work, including detailed suggestions for each : 1) development of hous-
28 ing and household recovery models; 2) integration of existing models into flexible computational
29 workflows; 3) investment in the collection of high-value open data; 4) commitment to sharing and
30 utilizing high-value data; 5) development of versatile, multidisciplinary testbed studies. Participant
31 responses and workshop data were analyzed with the help of an ontology that the authors designed
32 to support data classification in a broad range of NHE applications. The paper also includes
33 observations and suggestions for planning and conducting interactive workshops of this type.

34 INTRODUCTION

35 Regional risk assessment models for various natural hazards have advanced dramatically in
36 recent years, but models for different types of hazards have largely been developed independently
37 of each other. The 1971 San Fernando earthquake catalyzed substantial US investment in earthquake
38 engineering and led to the development of methods and tools for some of the first regional seismic
39 risk assessments (FEMA, 2011a) and performance-based earthquake engineering studies (Council,
40 2018). The development of risk assessment tools for other types of hazards initially lagged but
41 has improved rapidly in recent years. For example, regional risk assessment methods have been
42 released by FEMA for hurricane (FEMA, 2011c), flood (FEMA, 2011b), and tsunami (FEMA,
43 2017) hazards, in addition to the Florida Public Loss Model (Chen et al., 2009) for hurricanes.
44 Performance-based engineering methods for wind (ASCE, 2019; Barbato et al., 2013) and tsunami
45 (Attary et al., 2017) hazards are currently under development. The traditional reliance on empirical
46 models to estimate response and damage to the built environment within FEMA's Hazus Earthquake
47 Methodology and other initiatives has now been complemented by more sophisticated approaches
48 that take advantage of new data sources to support higher-resolution simulations that can incorporate
49 interdependencies between natural, built, and human systems to reveal multi-faceted consequences
50 and a richer description of recovery processes [e.g., SimCenter's rWHALE (Deierlein et al., 2020)]

51 and NIST CoE's IN-CORE (Gardoni et al., 2018) tools]. High-resolution regional and city-level
52 damage and loss simulations, coupled with advanced computational and information technologies
53 to manage and process high-resolution data, are enabling the development of advanced simulation
54 models that consider the disaster recovery process.

55 Emerging research holds the promise of creating digital representations of cities through the
56 compilation of high-resolution building inventories, demographic information, and economic data
57 sourced from a combination of conventional data sources (e.g., U.S. Census Bureau, U.S. Bureau
58 of Economic Analysis, U.S. Bureau of Labor Statistics) and more novel data harvesting techniques
59 (e.g., satellite image recognition, assessor databases) (Wang et al., 2021; Fan et al., 2021; Shahat
60 et al., 2021; Ford and Wolf, 2020). Digital representations of cities provide a baseline for natural
61 hazards engineering (NHE) researchers to perform city-level assessments that aim to estimate not
62 only the physical damage to the built environment, but also the associated socioeconomic conse-
63 quences following the natural hazard event. As an extension, these city-level models could support
64 complex, multi-disciplinary studies of questions related to post-disaster recovery, such as behavioral
65 patterns of people and household decisions (Nejat and Ghosh, 2016), compression of redevelop-
66 ment and decision-making processes (Olshansky et al., 2012), temporary population displacement
67 and permanent relocation (Esnard et al., 2011; Costa et al., 2020), and socioeconomic disparities
68 (Zhang and Peacock, 2009; Peacock et al., 2014; Hamideh et al., 2018; Wyczalkowski et al., 2019).
69 These studies explore disaster impacts for specific neighborhoods, populations, business sectors,
70 and services at a high-resolution and provide outputs that support more sophisticated evaluation of
71 disaster recovery planning alternatives and risk mitigation strategies.

72 While such simulations offer opportunities for NHE research and practice, it is important to
73 keep in mind that the reliability, reproducibility, and replicability (National Academies of Sciences,
74 Engineering, and Medicine, 2019) of these complex regional simulations heavily depends on the
75 modeling methodologies that are used along with the associated input data, which is often of
76 variable quality (Roohi et al., 2021). This barrier can, to some extent, be overcome through
77 closer collaboration across the related disciplines, including engineering, computer/data science,

78 and social sciences, capitalizing on synergies and leveraging the advances by each to elevate the
79 collective capacity for large-scale computational simulation and robust data management. Given
80 the nature of this input data, success will require partnerships between academic researchers,
81 practitioners, and the public sector, as well as greater investments in federal, state, and municipal
82 data management, standardization, and open exchange of data.

83 One nexus for such partnerships is available through the Computational Modeling and Simula-
84 tion Center (SimCenter). The SimCenter is supported by the National Science Foundation under the
85 Natural Hazards Engineering Research Infrastructure (NHERI) to develop computational software
86 tools for the NHE researcher community (Deierlein et al., 2020). The SimCenter's underlying strat-
87 egy is to leverage past research and development by integrating models and data from the physical
88 sciences, engineering, and social sciences to help advance new lines of research and educational
89 opportunities in NHE. As such, the SimCenter has focused on building collective capacity within
90 the research community, while engaging other public and private sector stakeholders who are sim-
91 ilarly committed to the study of hazard impacts on communities. The computational workflows
92 developed by the SimCenter support high-resolution, multi-fidelity simulation of hazard impacts
93 from individual buildings to the regional scale. While there are research gaps remaining in faith-
94 fully simulating the damage to the built environment under natural hazards, modeling post-disaster
95 recovery from this damaged state presents a challenge of a different magnitude. It necessitates a
96 multi-disciplinary approach to both (1) compile and standardize large quantities of diverse data,
97 and (2) develop models that can handle the highly complex, nonlinear, and interdependent natural,
98 physical, and societal systems that shape communities and their recovery processes (Miles et al.,
99 2019; Miles, 2018; Deierlein and Zsarnóczay, 2021). The SimCenter is building the foundational
100 computational infrastructure to characterize natural hazards and their effect on the built environ-
101 ment, along with interfaces to demographic and socio-economic data to enable the integration of
102 recovery models into regional simulation workflows.

103 While the computational infrastructure being developed by the SimCenter and other groups
104 holds great potential, its development requires the engagement of both the NHE researcher com-

105 munity as well as practitioners and policymakers to understand their perspectives and needs. The
106 aspirations of academic researchers need to be weighed against the practical expectations of in-
107 dustry and public-sector practitioners, as evidenced by their reliance on trusted methods and tools,
108 such as the Hazus-MH software (FEMA, 2018), or FEMA's published data products, such as flood
109 insurance rate maps (FEMA, 2021). Thus, it is critical to understand the limits of simulation tools
110 developed for research to address the practical constraints of real-life implementation. Building on
111 past examples of successful research-to-practice collaborations [e.g., Kijewski-Correa et al. (2020);
112 Chen et al. (2009)], there is an opportunity to facilitate further engagement through the develop-
113 ment and adoption of common templates founded on open-source principles with standardized data
114 schema to facilitate more collaborative development, deployment, and maintenance of software and
115 supporting data.

116 To encourage such collaborations and understanding of user needs, several workshops have been
117 organized in the last decade by projects sponsored by NSF, NIST, FEMA, and other organizations
118 to engage diverse experts in natural hazard risk mitigation [e.g., McAllister et al. (2019); Poland
119 (2009); Kwasinski et al. (2016); Slotter et al. (2021)]. These workshops were typically focused
120 on particular research products or mitigation programs, which to some extent limited the scope
121 in terms of hazard, geospatial scale of analysis, and component of disaster risk management. In
122 contrast, for the workshop described herein, the SimCenter aspired to collect qualitative data and
123 actionable information on computational and data needs through a broadly-defined sampling of the
124 NHE community, cross-cutting hazards, expertise, and roles.

125 WORKSHOP OVERVIEW

126 The workshop on simulation and data needs was held at the University of California, Berkeley,
127 in January 2020 and designed to (1) engage the community of disaster risk and recovery experts
128 and stakeholders and (2) identify how computational tools can support fundamental and applied
129 research to promote resilience to natural hazards. The workshop agenda was designed to foster
130 knowledge exchange and collect observations and information from participants across multiple
131 hazards (earthquakes, tsunamis, hurricanes, and storms), between disciplines (engineering, plan-

ning, and social-science), and among various roles in the community (policy makers, researchers, practitioners, and software developers). The specific goals of the workshop were as follows:

- Identify the approaches and tools used to evaluate natural hazard impacts and inform risk management strategies.
- Collect and prioritize questions and concerns about mitigating the devastating effects of earthquakes, storms, and other extreme events that have a potential to be evaluated through scenario studies and advanced simulations.
- Identify and prioritize the needs for improved models and supporting data required for computational workflows for advanced simulation of natural hazard impacts.
- Brainstorm strategies to facilitate the development and adoption of multi-disciplinary testbeds and other simulation technologies in research and practice.

Participants

The workshop organizing committee was assembled from SimCenter affiliates with a diverse set of expertise. The number of participants was limited to 60 to foster active discussion, where about 70% of the participants were invited, 20% were selected from respondents to an open invitation, and 10% were graduate students. Invited participants included researchers, developers of natural hazards risk simulation tools, and end-users of regional risk assessment frameworks (see Table S1 for the complete list of participants).

In preparation for the workshop, participants were asked to self-assess where they would position themselves along a spectrum of hazards (multi-hazard, wind, earthquake, or coastal/flood), roles (policy maker, simulation framework specialist, or software developer), and the scales at which they model or analyze data (local, state, or national). As shown in Fig. 1, the distribution of participant responses indicates a reasonable balance across hazards (Fig. 1a), participant roles (Fig. 1b), and scales of engagement (Fig. 1c). About two-thirds of attendees were affiliated with academic institutions (Fig. 1d), and one-third were from public/non-profit (state, federal, and international agencies/foundations) and private/for-profit sectors. Participants were also asked to characterize

158 themselves as data producers and/or consumers, where about ninety percent indicated that they
159 both produce and consume data, with the remainder equally divided between solely producers or
160 consumers of data.

161 **Methods for data collection**

162 The two days were divided into four sessions, each starting with a short plenary that provided
163 an overview of the session theme, followed by a breakout phase. The four sessions focused on (1)
164 connecting to stakeholders, (2) connecting across hazards, (3) data sources, and (4) interdisciplinary
165 engagement (see Fig. S1 for a detailed agenda). During the breakout sessions, participants were
166 divided into three subgroups, based on the backgrounds of participants and focus area of each
167 breakout. Outcomes of the breakout exercises were documented and collected through individual
168 worksheets and group-based easel pads, with pre-defined labels. Artifacts from the breakout
169 sessions were subsequently collected, digitized, processed, and made available to the participants.
170 The discussions in each breakout session were guided by a facilitator, who was briefed on the plan
171 before the workshop and shared highlights and main takeaways of the breakout discussion with the
172 entire workshop group following each breakout.

173 As an example of how the breakout sessions were organized, the Data Sources session focused on
174 the data needs among disaster researchers and practitioners to improve disaster recovery planning.
175 Following a plenary session discussion on the challenges surrounding open data for disaster research
176 and advances in data science that could overcome these challenges, the breakout session participants
177 examined the gaps in open data practices within the natural hazards community. The first activity in
178 the breakout was a Data Mapping activity to (1) prepare a short list of the data that the participant's
179 organization regularly consumes and produces, (2) identify the source or distribution method used
180 to share that data, (3) quantitatively rate the trustworthiness/reliability and usability/accessibility
181 of that data, and (4) assemble a wish list of data that they would like to have available. Shown
182 in Fig. 2 is an example of the Data Map artifacts collected from the respondents, where they
183 identified and ranked quality and accessibility of the datasets (5 indicating a high/favorable score
184 and 1 indicating a low/unfavorable score). The second activity used a Data Scorecard to (1) identify

185 the five questions participants hope to “ask” of the resilience/risk assessment data they engage, (2)
186 indicate which questions they can answer today with the data available to them, (3) assess which
187 data would be most critical to answering these questions in the future, and (4) specify if this data
188 is accessible today. The Data Sources session concluded with a report out from each group and
189 discussion. The participant artifacts from the Data Sources session were transcribed for subsequent
190 analysis.

191 REVEALED DATA CHARACTERISTICS

192 The transition toward standardized workflows and data that enable multi-disciplinary, multi-
193 hazard regional recovery modeling requires a concerted effort to holistically organize high-resolution
194 data so that it is searchable and easily accessible by users. Existing classification systems in the dis-
195 aster science literature [e.g., [IRDR \(2014\)](#); [McAllister et al. \(2019\)](#); [UNDRR \(2019\)](#)] do not capture
196 details that are important for computational simulations of hazard events or describe information
197 that is relevant to different time scales in the risk management cycle of prevention, protection,
198 mitigation, response, and recovery ([DHS, 2016](#)). Existing classifiers tend to narrowly categorize
199 data by the type of natural hazard ([Coburn et al., 2014](#)), which while an obvious and important
200 characteristic, may miss opportunities to examine aspects that could unify the hazard engineering
201 community.

202 To address the shortcomings in existing classifications, a new ontology is proposed in Table 1
203 that builds upon the concepts in existing classification systems, but aims to better describe features
204 that are important for computational simulation of natural hazard events. The ontology identifies
205 the important features of the data and provides a classification that defines the independent features
206 for characterizing the data. The ontological information provides the basis for creating application-
207 specific taxonomies (with specific hierarchies among the features) or, as in this study, to tag data
208 from several perspectives. For example, the type of natural hazard, the context, and the origin are
209 three independent features in Table 1 that were used to characterize features of the data identified
210 by workshop participants.

211 The ontology was informed by the range of data types that workshop participants identified in

212 the Data Map worksheets during the Data Sources breakout session. Additional categories, such as
213 the geographical scale of the data, were considered, but excluded because either the classification
214 within the category was ambiguous or the information provided by the category was redundant.
215 This ontology was used to tag data that was identified during the Data Sources breakout session,
216 thereby enabling a cross-sectional analysis of the data to identify (1) which data was of most value
217 to the participants and (2) potential synergies between categories. This ontology is proposed for
218 review by the NHE community as a first step towards a formal ontology to collect and organize
219 data for simulating natural hazard effects on communities.

220 When identifying the data that participants produced or consumed, each participant named up
221 to five data sets that were later tagged using the ontology terms. Where the data sets identified
222 by the participants described a wide range of data, multiple tags from each category in Table 1
223 were applied. Tags were assigned based only on the available information, and when the tag in a
224 certain category was ambiguous, an unknown tag was assigned rather than resorting to a default or
225 assumed value. For example, when a participant specified that they use "hazard data" for their work,
226 an unknown tag was assigned for the type of natural hazard category. The Table 1 ontology and
227 tagging process was only applied to artifacts from the Data Sources session. Artifacts from other
228 sessions, e.g., the Regional Simulations session, where participants identified specific software
229 tools to perform simulations of natural hazard effects, were simply reported and collected in lists.
230 The datasets from other sessions were not tagged with the proposed ontology because participants
231 were not instructed to classify responses in a structured way. The artifact data sets are publicly
232 available ([Zsarnóczay et al., 2021](#)) and they served as the basis for figures and recommendations
233 summarized later in this paper and the accompanying Supplemental Materials.

234 **IDENTIFIED OPPORTUNITIES TO ENHANCE DISASTER SIMULATION TOOLS AND DATA**

235 During the workshop, participants prioritized questions related to post-disaster recovery that
236 could potentially be answered using advanced computational simulation tools and data, and they
237 identified potential areas where improved simulation capabilities are needed. Examples of the
238 questions raised include: "How does damage to lifelines impact a community's recovery?", "How

239 can a community quickly and effectively restore livelihoods after a disaster?", and "What is the
240 best way to characterize and estimate damage states in structures following a disaster event?".
241 When asked to identify the five most important questions in their work, participants focused
242 most prominently on themes related to the following: recovery of households (17%), damage in
243 the built environment (15%), evaluation of mitigation policies (11%), evacuation and population
244 displacement (9%), and recovery of utilities and other critical services (9%), where N=150. A list
245 with additional themes identified is included in Table S2, along with a database of the questions
246 participants prioritized. Participants indicated that over two-thirds of these questions cannot be
247 answered today, and approximately three-quarters of the participants indicated that they are currently
248 unable to answer the majority of their own most pressing questions.

249 Based on the workshop discussions, combined with the insights generated through processing
250 of the collected data and artifacts, the following five opportunity areas for computational simulation
251 of natural hazard effects were identified:

- 252 1. development of housing and household recovery models;
- 253 2. integration of existing models into flexible computational workflows;
- 254 3. investment in the collection of high-value open data;
- 255 4. commitment to sharing and utilizing high-value data;
- 256 5. development of versatile, multidisciplinary testbed studies.

257 Focusing on these areas has the potential to strengthen connections between segments of the
258 NHE community across various hazard types and between disciplines to address the most pressing
259 questions that were raised during the workshop. The following subsections elaborate on the five
260 areas and how they emerged as opportunities identified in the workshop.

261 **1. Development of housing and household recovery models**

262 Housing was singled out by participants as a key entry point to engage in recovery modeling,
263 particularly if linked to the broader context of recovery of neighborhoods, communities, and lifeline
264 infrastructure. Table 2 provides a summary of the housing-related applications and related data

265 needs as identified by the workshop participants. Information on households and their recovery
266 was a prominent theme in the top five questions that workshop participants ask of their data
267 (Table S2), and it was frequently mentioned among the aspirational data they identified (Fig. 5).
268 Many workshop participants emphasized that the understanding and modeling of housing recovery
269 needs to go beyond building damage and population counts to consider socioeconomic aspects of
270 households and communities [e.g., [Comerio \(1998\)](#)].

271 The following are some of the key priorities that can help advance housing recovery modeling
272 frameworks, computational simulation tools, and workflows.

- 273 • **Account for neighborhood conditions and community context:** The ability to char-
274 acterize and model community and neighborhood facets, such as businesses and lifeline
275 infrastructure, will help quantify the spatial distribution of demands on local and regional
276 systems and institutions after disaster events. This is particularly important to account for
277 in- and out-migration and population displacement and relocation. The long-term recovery
278 and post-disaster redevelopment processes in Christchurch, New Zealand, and New Orleans,
279 Louisiana, provide good examples of how displacement and migration of people can shape
280 the recovery of communities and residential housing.
- 281 • **Develop comprehensive and linkable building-level housing inventories to facilitate
282 coupling of engineering and social science data and models:** Data integration and simu-
283 lation workflows of residential housing damage, restoration, and recovery are predominantly
284 static, often not to the individual parcel or household level, and lacking in demographic
285 and socio-economic characteristics of residents. As tools and computational platforms are
286 developed to perform higher-resolution simulations, semi-heuristic models can be used to
287 generate high-resolution data from census block-level inputs. Methodologies developed
288 by researchers affiliated with the NIST-funded Center of Excellence for Risk-based Com-
289 munity Resilience Planning provide opportunities to link high-resolution spatial data on
290 households and housing units to single and multi-family residential buildings and to critical
291 infrastructure ([Rosenheim et al., 2019](#)). Increasing the granularity of such data is critical,

292 as noted during the workshop, to reveal the benefit of specific planning and policy actions,
293 though with the important caveat that privacy and ethical concerns of collecting input data
294 and reporting risks and vulnerability of residents must be carefully managed.

295 • **Capture non-engineered residential buildings as part of housing inventory:** Basic
296 building information is available for most areas in the United States at a census block-level
297 resolution. Non-engineered buildings present unique challenges. These typically wooden
298 or unreinforced masonry buildings are designed based on empirical rules in building codes
299 and they often include several undocumented modifications that can have a considerable
300 impact on structural performance (Sparks and Saffir, 1990). Several publications in the
301 literature highlight the disproportionate contribution of these buildings to the damage and
302 losses in recent disasters (Sparks, 1986; Morse-Fortier, 2015; Sandink et al., 2019; Amini
303 and Memari, 2020). Since these buildings are a substantial part of the residential housing
304 inventory and they are key contributors to losses in natural hazard events, it is important to
305 identify and collect additional information on the attributes driving their performance.

306 These opportunities will require sustained interdisciplinary expertise and contributions. As
307 discussed shortly, empirical studies and testbeds will be particularly critical to the design and
308 development of computational workflows that account for multi-faceted aspects of post-disaster
309 household and community recovery.

310 **2. Integration of existing models into flexible computational workflows**

311 Sessions I and II of the workshop were organized to identify: (1) simulation tools that are
312 currently used by NHE researchers and practitioners to evaluate natural hazard effects on buildings,
313 lifeline infrastructure systems, and other community assets, (2) simulation needs that are not being
314 addressed by current simulation technologies, and (3) factors that impede the use of computational
315 simulations by NHE researchers and practitioners. During the breakout sessions, the 60 workshop
316 participants identified 237 unique analysis tools and software applications for NHE simulations.
317 As shown in Fig. 3, simulation tools are distributed across the risk assessment workflow (Fig. 4),

318 from characterization of assets and hazards to estimation of damage and consequences, along with
319 planning tools. Among the six categories shown in Fig. 3, the one with the fewest tools available
320 is simulation of indirect consequences (e.g., the USGS PAGER software, which provides rapid
321 fatality and economic loss estimates following significant earthquakes worldwide). When asked to
322 identify the challenges associated with simulation to support risk assessment and mitigation, the
323 overwhelming response was that there is a lack of standardization and interoperability between the
324 various software applications. Participants noted that many of the software systems are configured
325 in a stand-alone fashion, such that output from one application requires substantial manipulation
326 before it can be used as input to the next.

327 Among the 369 non-unique software names recorded by participants, the Hazus (27 mentions)
328 and IN-CORE (18 mentions) software applications stand out by far as the most commonly identified
329 software. These applications 1) span the entire workflow, and thus are identified by participants
330 active in only a particular phase as well as those with activities spanning all phases, 2) are products
331 of two recognized federal agencies (FEMA and NIST, respectively), and 3) are publicly available
332 free of charge. While IN-CORE is Python-based and open source, which facilitates customization
333 by users to meet their specific needs, Hazus is a closed-source system with a fixed set of modules,
334 which has limited flexibility. Hazus offers comprehensive features to estimate losses to a wide
335 variety of assets (buildings, bridges, highways, and lifeline infrastructure) under multiple hazards,
336 which makes it attractive for use by practitioners in the public and private sectors.

337 Beyond the significant challenges associated with manipulating data and linking software to
338 create integrated multi-phase workflows, workshop participants identified features that would make
339 a substantial improvement to currently available software:

- 340 • **Usability:** Software documentation, training resources, and intuitive user interfaces are
341 important to make software easy to use. Documentation of the underlying methods and
342 models is important for users to understand and have confidence in the simulation results.
- 343 • **Flexibility:** Software that is open-source and designed with a modular architecture is
344 important to allow users to modify software to their specific needs.

- **Reliability:** Ideally, software components and systems should be verified and validated to ensure that they run correctly and provide accurate results. Verification procedures and practices vary greatly, while rigorous validation is less common because of the inherent uncertainties in the problem, the sparsity of comprehensive damage and loss data, and the lack of standard protocols for validation.
- **Multiple scales:** Few software tools exist to support multi-scale simulation, which could take the form of variable levels of spatial and temporal resolution.
- **Cascading events:** Few software tools are capable of simulating cascading events.
- **Quantified uncertainty:** Characterization and propagation of various sources of uncertainty in a disaster simulation would allow quantification of the uncertainty in the simulation results. Currently available tools do not provide comprehensive uncertainty quantification.
- **Consequences and recovery:** Only a small number of software tools are available for the simulation of consequences and recovery after a disaster. Understanding this stage of the natural hazard cycle is critical to assessing the impact of events and shaping mitigation policy. A large amount of data has been collected after recent disasters (Kijewski-Correa et al., 2021; Wartman et al., 2020; van de Lindt et al., 2018; Sutley et al., 2021; Peek et al., 2020), which should help with the development of new models and tools if there is sufficient interest from the community.
- **High-performance computing (HPC):** Few software tools can take advantage of access to cloud computing or open HPC clusters, such as NHERI DesignSafe (Rathje et al., 2020), and local clusters at universities. Several legacy tools have deprecated dependencies that are not compatible with modern HPC environments and recent data formats.

It is notable that the scientific application framework developed at the SimCenter in part responds to a number of these identified challenges by supporting the integration of existing models into natural hazard risk assessment workflows (Deierlein et al., 2020). Such a workflow is an assembly of software modules (Fig. 4) and interfaces that allow the combination of various methods while maintaining a seamless end-to-end data transfer. The workflow begins on the left with modules that

characterize the assets (e.g., buildings and infrastructure) and the hazard (e.g., earthquake ground shaking, wind speed or pressure, etc.). This information provides input to structural analyses to assess the response and damage to the assets. Finally, on the right, the asset performance data is used as input to simulate repairs and the recovery of communities. The application framework provides outputs in a standardized format to facilitate interfacing with tools that support planning and policy-making. The workflow modules are designed to utilize supporting databases and perform simulations with state-of-the-art uncertainty quantification approaches including surrogate models and efficient forward propagation methods. Thus, the outcomes of the workshop and the challenges listed above are guiding the future development of the application framework.

3. Investment in the collection of high-value open data

One of the major barriers to the enhancement and integration of software is the lack of access to critical datasets, particularly those with greater granularity and spatial extent than what is available today. When asked to identify aspirational data sources, the majority of responses (54%, N=183) expressed the need for additional high-value and higher-resolution data that is not available today (see Fig. 5 for details). Among the additional data needed, information on buildings (14%, N=183), households, businesses, and services (13%), recovery processes (12%), and hazards (5%) were frequently mentioned. Examples of high-value data under these sub-themes are reported in Table 3.

Participants also recognized the opportunities generated by improving the accessibility and trustworthiness of existing datasets (23%, N=183, Fig. 5), especially when it comes to information about lifelines; and the need for more data to calibrate and validate numerical models of hazards, damage, consequences, and recovery (17%). These themes are discussed in more detail in the following subsection.

Participants speculated they would produce only about 22% of the listed aspirational datasets, and more than half of the data they rely upon would be from databases that cover the entire nation and often provided by federal agencies (e.g., probabilistic hazard maps, building inventories, demographic data). Some of the identified needs require new workflows to generate the data, but

399 often it would be sufficient to enhance existing data collection approaches so that they capture
400 additional high-value data and maintain it in desirable formats for computational modeling and
401 simulation. The following should guide such future investments in high-value data:

- 402 • **Refine 4D resolution:** The high-fidelity models that guide targeted mitigation decisions
403 must be calibrated and validated against site-specific, parcel-level hazard and exposure
404 data. Achieving the required level of granularity and specificity in building characteristics,
405 behavior, and performance requires navigation of new sets of privacy issues and proprietary
406 restrictions. Furthermore, hazard and exposure characteristics often evolve at a faster rate
407 than the release cycle of the corresponding data, for example, census data is released
408 in decadal cycles. The temporal resolution of datasets needs to be better aligned with the
409 underlying system dynamics to assure availability of more accurate pre-disaster benchmarks.
410 The updating rate may even be adapted when these dynamics change, such as releasing more
411 frequent updates following a disaster to better capture recovery characteristics. In a post-
412 disaster context, longitudinal studies and more granular information about the impact on
413 communities is required to support the development of quantitative models of the recovery
414 process. The NSF, NIST, and other entities are investing in vital disaster recovery research
415 and empirical studies. Such studies, including those that are region- and hazard-specific,
416 can offer a rich source of baseline data for individual sectors (e.g., housing, business,
417 critical infrastructure, civil infrastructure), as well as community systems (e.g., system
418 interdependence, neighborhood decline/stability).
- 419 • **Anticipate diverse use cases:** Data collection for a specific purpose is often performed
420 by persons with limited understanding of the potential uses of the data for other purposes.
421 For example, a tax assessor or National Flood Insurance Program (NFIP) claims adjuster
422 has a specific data schema and conducts subjective assessments and classifications of
423 building components. The labels assigned in this process might not be accurate from a
424 structural engineering perspective. Engineers often find it challenging to use such data
425 to infer structural vulnerabilities in a natural hazard risk assessment. To maximize the

426 likelihood of meeting diverse user needs, the approach to data generation shall be informed
427 by interdisciplinary perspectives when the underlying schema is designed and the data
428 classification within that schema is defined.

429

- 430 • **Promote standards across data providers:** The data needed to explore questions of
431 community resilience is generally fragmented because each producer (e.g., municipal de-
432 partments, insurers, and federal agencies) uses its own schema and methodology. This leads
433 to diverse standards for collecting, tagging, and vetting this data. The quality and comple-
434 tness of the produced data and metadata would greatly benefit from enforcing consistency
435 and ideally centralizing the production efforts. At a minimum, producers should be aligned
436 under consensus standards that are communicated and promoted by designated persons [see
437 concept of ‘Data Evangelists’ [Andrei Lyskov \(2019\)](#)].

438

- 439 • **Value the entire data life cycle:** Producing data that has high value and potential for re-use
440 requires considerable time and effort. Data producers often find this work a heavy burden
441 and they may lack the incentives, expertise, capacity, and resources to follow through. The
442 emphasis is often placed on data collection while the “dirty work” of quality assurance,
443 metadata association, documentation of the methodology, and long-term curation is often
444 not resourced and recognized at the level it deserves.

445 It is worth noting that the data relevant to community resilience is increasingly being generated
446 and managed through digital workflows, and the cost of collecting several important data types
447 is already low and continues to decrease rapidly. These factors enable the generation of robust
448 repositories of images, documents, and other relevant data. New modalities such as crowdsourcing
449 and citizen science further expand the venues for data generation. Thus, taking the suggested steps
450 toward generating high-value data does not necessarily demand a significant increase in investment.
Resourcing seems secondary to the more critical need to redesign policies and practices for data
collection and generation.

451 **4. Commitment to sharing and utilizing high-value data**

452 While participants routinely consume open data in their analyses and simulations, the lack of
453 access to high-value data often forces them to limit the scope of their work to problems that can
454 be solved with the data available. During the breakout session on data sources, participants were
455 asked to list up to five data products they consume and produce in their work. This information was
456 processed using the ontology presented earlier by assigning labels to each participant based on the 5
457 pieces of data they listed. Fig. 6 shows the number of participants assigned to each label—note that
458 each participant could get multiple labels assigned both within a category and across categories.
459 Almost all participants consume data that is publicly available (96%), largely from government
460 providers (96%), and the result of direct observations (98%). Respondents had heavy reliance
461 on data describing the built environment (91%), the natural environment (68%), and households
462 (64%). Table 4 lists examples of consumed data under these themes. Almost every participant
463 needed exposure (98%) data, and a strong majority also used information that characterizes the
464 hazard (70%). The majority (66%) focused on earthquake and geohazards, a direct consequence
465 of the participant demographics (Fig. 1a). Significantly fewer participants mentioned data sources
466 that provide information about direct damages, their consequences, and activities surrounding
467 preparedness and recovery. This lack of utilization is likely due to the scarcity of such data because
468 a large number of participants expressed interest in these themes when listing aspirational data (Fig.
469 5).

470 As visualized in Fig. 7, the data consumed by participants in their analyses and simulations
471 had moderate levels of trustworthiness (mean=3.72/5.00, where 5 is highly trustworthy), with only
472 62.4% scoring 4 or above. Even though these datasets were regularly engaged, participants assessed
473 them as only moderately accessible (mean=3.53/5.00, with 5 indicating highly accessible). In fact,
474 only 56.4% of the data consumed by participants was perceived as easy to access (i.e., receiving a
475 score of 4 or above).

476 Participants tended to produce data similar to what they consumed (Fig. 6), predominantly fo-
477 cused on the built environment (74%, e.g., city-level building inventories, responses from structural

478 analysis models) and the natural environment (35%, e.g., ground motion datasets, hurricane wind
479 speed projections). The number of responses for consumed datasets was in some cases significantly
480 larger than the number for produced datasets due to a larger proportion of “consumers” among par-
481 ticipants (see response totals for consumed and produced datasets in Fig. 6). More respondents
482 produced data through computer simulation than the number of those who consumed such data (19
483 vs. 12 out of 47 responses). While consumed data was primarily from the earlier phases of the
484 natural hazard risk assessment workflow, the produced data is more evenly distributed across the
485 workflow phases.

486 As detailed in Fig. 7, the data participants produced is comparable to the data they consumed
487 in terms of perceived trustworthiness (mean=3.65/5.00). Even though participants have greater
488 control over the trustworthiness of their data products, only 57% (N=112) of them scored 4 or
489 higher. Participants further admitted they were not good “data citizens”, producing data perceived
490 as markedly less accessible than the data they consume from others (mean=2.79/5.00). Only 32%
491 (N=112) of the data they generate is actually accessible to others (i.e., rated 4 or higher), with only
492 40% (N=35, see Fig. 6) of them sharing at least some of their produced data publicly. Fig. 6
493 also visualizes the disproportionate consumption of public data that results in highly private data
494 products—63% (N=35) of participants store some of their produced data privately and 46% (N=35)
495 of participants have none of their produced data published or publicly available.

496 These observations on data management are not uncommon and stem from the challenges sur-
497 rounding the adoption of FAIR (Findable, Accessible, Interoperable, Reproducible) data standards
498 ([Wilkinson et al., 2016](#)). While frameworks stand ready to guide research communities toward
499 adopting FAIR principles ([GoFAIR.org, 2021](#)), it must be acknowledged that FAIR demands more
500 of the data producer than just making the data accessible. Appropriate documentation of the
501 methodology applied to collect and process the data is also an important part of the principles.
502 The benefits of doing so are considerable as other producers within a community also adopt this
503 philosophy when they share their high-value data. More importantly, as noted by [Wilkinson et al.](#)
504 ([2016](#)), "The primary limitation of humans, however, is that we are unable to operate at the scope,

505 scale, and speed necessitated by the scale of contemporary scientific data and the complexity of
506 e-Science." By embracing FAIR data standards and encouraging data producers to provide sufficient
507 context for their data research, communities will be able to leverage the power of automation and
508 machine learning and can work with data at the scale demanded by current problems.

509 From a technological perspective, the formula for exposing open data is clear: ensuring pub-
510 lished data have appropriate schema, are exposed using open data standards, and take advantage of
511 the interfaces that have been developed to bring it seamlessly into workflows. However, the ability
512 to act upon this formula is considerably hindered in the fields studying disasters and community
513 resilience because the required data is generated in a highly distributed fashion across numerous
514 agencies, municipalities, and institutions. Inevitably, these entities have divergent data sharing
515 policies and practices and often lack expertise in, and capacity for, sound data management. In
516 some cases, local government data providers have partnered with the private sector to manage and
517 share their data [e.g., [Socrata \(2021\)](#); [Tyler Technologies \(2021\)](#)], though not all municipalities
518 have the resources or inclination to do so. These challenges are only compounded by additional
519 barriers erected by the unique cultures, policies, and regulations within these entities. For example,
520 restrictions may limit access to private or sensitive data, possibly regulated by an Institutional
521 Review Board (IRB) protocol or privacy laws. Data producers may further be averse to the risk of
522 liability due to data misuse or misinterpretation. In other cases, business interests (e.g., services
523 that would be obsolete if the data were open) or other concerns over competitive advantage (e.g.,
524 desire to maintain exclusive publishing rights) prevail. Thus, while the technical formula is clear,
525 the formula to change human and organizational behavior is yet to be discovered.

526 Nevertheless, the participants identified several priority areas to increase the amount of high-
527 value data exposed in our community:

- 528 • **Enhance discoverability:** While data may be available online, it is not always easy to
529 find. Users struggle to stay abreast of all the new data initiatives, services, and providers.
530 Clearinghouses and centralized data initiatives such as DHS Exchange Core and OpenFEMA
531 are especially valuable in this rapidly evolving landscape. More fundamentally, semantic

532 incompatibilities can inhibit the identification of relevant data through automated queries.
533 Such incompatibilities arise because each data producer uses their own disciplinary views
534 to design a schema for their data. Fortunately, advances in the semantic web can bridge the
535 potentially disparate views of data consumers and producers to make more data discoverable
536 [see Schema.org Publishing Guidelines for the Geosciences v1.1 [Shepherd et al. \(2020\)](#)].

- 537 • **Enhance integration:** Disaster simulations require continuously evolving data from diverse
538 sources. Even open data is often difficult to retrieve and consume. Onerous access restric-
539 tions and cumbersome formats may require users to manually download and pre-process
540 the data. Large-scale, automated disaster assessments will require federated databases
541 that allow producers to maintain and update the data while providing seamless integration
542 with consumers' computational workflows. Data producers should publish Application Pro-
543 gramming Interfaces (APIs) and expose their descriptions in a machine-consumable manner
544 (e.g., OpenAPI). Shakemap from USGS is a good example. Although several producers
545 share geospatial data through ArcGIS Online, this data would have even greater value when
546 exposed through Web Map Service (WMS) or Web Feature Service (WFS) endpoints using
547 non-proprietary Open Geospatial Consortium (OGC) standards (see the emerging OGC
548 Web API Guidelines: [Open Geospatial Consortium \(2019\)](#)). Updated versions of OGC
549 standards are adopting semantic principles to improve discoverability and foster seamless
550 integration within workflows. These are currently being integrated into open-source tools
551 like GeoServer ([GeoServer, 2021](#)) and QGIS ([QGIS, 2021](#)).
- 552 • **Expose more than data:** As reliability and trustworthiness of data is as critical as access
553 itself, the adoption of data standards and establishment of consistent data processing methods
554 is critical. Ideally, these standards and methods are coupled with quality control processes
555 that include quantifiable confidence measures [see StEER QC codes as an example [Roueche
556 et al. \(2019\)](#)]. Standardized data must be exposed with well-structured metadata and
557 appropriate documentation of associated data collection, processing, and quality assurance
558 methodologies. Standard data schema can be shared at schema.org to encourage adoption.

559 To further support robust verification and reproducibility of results, producers should expose
560 not only derived data (e.g., statistics and calibrated models), but also the raw data itself.
561 Data producers should strive to leverage platforms that provide tools for automated testing
562 and versioning such as GitHub ([GitHub Inc., 2021](#)) and GitLab ([GitLab Inc., 2021](#)).

- 563 • **Promote community validation.** As more high-value data—including models—is ex-
564 posed, its wider use will foster the discovery of errors and omissions. Data producers
565 can improve the trustworthiness of their data by supporting cross-validation studies and
566 establishing a mechanism for user feedback, rating, and issue reporting.
- 567 • **Convert legacy data.** There is valuable legacy data that has yet to be brought into reposi-
568 tories, and in some cases, will require digitization from archival files. Data from landmark
569 disaster events is particularly valuable and an initiative to compile, digitize, process and
570 expose these legacy datasets would be highly beneficial for the disaster science community.

571 Ultimately, the true potential of open data is only realized when enough of us—and ideally
572 all of us—commit to the above initiatives. This level of adoption necessitates a substantial shift
573 in the politics and culture surrounding data. Such a shift can be facilitated by the alignment of
574 corresponding incentives (possibly by creating higher consequences for non-compliance through
575 data publishing requirements of sponsors and journals) and by lowering the barriers to publishing
576 data openly considering the limited capacity and experience of most data producers. Given the
577 considerable reliance on external data providers, particularly at all levels of government, the
578 suggested efforts must be coupled with their sustained advocacy on the importance of reliable and
579 accessible data.

580 **5. Development of versatile, multidisciplinary testbed studies**

581 In addition to diverse data needs, diverse disciplinary expertise is required to simulate and study
582 the recovery of communities after a disaster. The opportunities listed above outline initiatives that
583 would facilitate data access, enable the exploration of impactful questions, and promote sharing
584 these results with others. In spite of those improvements, entering this space will remain challenging

585 and will still require a substantial time investment. Participants agreed that testbeds provide helpful
586 and much-needed examples that can encourage interested newcomers, such as graduate students
587 and non-academic professionals, to invest in recovery simulation. Testbeds can be designed around
588 the opportunities revealed in this paper and become vehicles of change while serving their main
589 purpose as illustrative examples. A modular testbed that integrates various tools and corresponding
590 data could serve multiple functions:

- 591 • **Benchmark models:** Testbed exercises can become benchmarks to evaluate and periodically
592 assess the performance of various natural hazard risk assessment workflows. Such
593 evaluations could inform the community about the expected benefits of choosing a particular
594 workflow or, within a workflow, making different choices regarding the level of fidelity, the
595 specific input data, the hazard scenario, or a subclass of models. Reporting results from
596 alternative solutions of the same problem would also facilitate verification and measuring
597 the robustness of various workflows. If the testbed location is chosen to coincide with a
598 historical event site, it can also be used for hindcasting exercises and validation purposes.
- 599 • **Serve as a template:** As long as both the simulation platform and the input data are publicly
600 available, testbeds are large example problems that can be used as a template to develop
601 new workflows or initiate new studies. This promotes technology transfer from academia
602 to the private sector and can encourage large government organizations to update their tools
603 more frequently. Reproducing results is easier if a large part of a community works from
604 the same template and builds credibility and trust in both the models and their outputs.
- 605 • **Demonstrate best practices and serve as a proof-of-concept:** Testbeds can demonstrate
606 best practices in workflow design, present caveats, and illustrate how lack of data or low-
607 fidelity models in one phase can compromise the entire simulation. These illustrations can
608 also promote robust data management—i.e., data standardization and documentation of all
609 models and data used for a simulation, including appropriate citations to their DOIs. When
610 it comes to sensitive demographic data, testbeds can present best practices to work with the
611 typically lower-resolution available information and still provide meaningful insights.

- **Promote tools and datasets:** Although many well-known proprietary tools have free, open-source alternatives, these are less promoted and the majority of the community is often not aware of them (e.g., ArcGIS and QGIS). A comprehensive collection of data and software resources in testbed examples facilitates the discovery of open-source tools and public data. Additionally, testbeds can expose gaps in workflows (i.e., desirable functionality not supported by any open software) and provide a platform to curate and explore new methods and models to fill those gaps.
- **Promote interdisciplinary collaboration and engage stakeholders:** Testbeds designed around a tangible narrative about important problems (e.g., disproportionate impact of disasters on vulnerable populations) can raise awareness and solicit feedback from disaster recovery researchers, affected community members (residents, leaders, and policymakers), and other stakeholders. Observing how data and models from one domain affect the simulations in another can also generate feedback and collaboration across disciplines.

The location or geographic focus of a testbed can have a large impact on its utility in serving the above functions. A good location has substantial data available to characterize the hazard, the built and natural environments, and the socioeconomic attributes of the population. It also helps if the local government is interested, supports these simulations with data, and brings forward local policy-related questions that can be informed by simulation results.

Groups of participants reviewed existing studies during breakout sessions and suggested eight potential testbed locations that we grouped into four geographical areas. Table 5 provides a summary of the opportunities in each area (a detailed description of the desirable features is available in Table S3). The suggested locations reinforce that natural hazard risk is governed by different hazards in the West and East Coasts of the United States. While Christchurch in New Zealand and Kathmandu in Nepal were suggested as good examples that were recently impacted by severe earthquakes and have both valuable data and support from the local government, participants (primarily from a North American context) were generally concerned about data availability and lack of familiarity with the local environment in non-US regions.

639 Within the United States, regional studies on the West Coast often focus on the San Francisco
640 Bay Area (Deierlein et al., 2020; ATC, 2018; Detweiler and Wein, 2018b), but there are recent
641 examples from Los Angeles (Kang et al., 2019; Cook et al., 2021) and Seattle (Marafi et al., 2020)
642 as well. In California, wildfires (Lautenberger, 2017), fires following earthquakes (Detweiler and
643 Wein, 2018a), and flooding due to atmospheric rivers (USGS, 2011) present additional hazards on
644 top of the earthquake risk. In the Northwest, subduction earthquakes and potential tsunamis can
645 represent a markedly different environment. The East Coast has several large metropolitan areas
646 that are affected by various wind and water-borne hazards. The consequences of hurricanes in
647 the coastal regions of Texas (Hamideh and Rongerude, 2018), North Carolina (Wang et al., 2019),
648 and New Jersey (Deierlein et al., 2020; Kijewski-Correa et al., 2020) have been studied recently.
649 The longitudinal study in Lumberton, NC (Sutley et al., 2021) already offers valuable data and the
650 city is expected to become a prime location for hindcasting and recovery model calibration. Three
651 groups of workshop participants independently suggested South Florida for consideration because
652 a large population is frequently exposed to severe storms, in addition to threats from sea level rise
653 and other climate change effects. Miami-Dade County was specifically mentioned because there
654 is a large number of industrial facilities in the region as well as because Miami is a major city and
655 tourist destination with considerable high-rise residential development.

656 Besides large regional studies with millions of households, recently created smaller testbeds
657 [e.g., Seaside, OR in Park et al. (2019)] demonstrate that by focusing on a few thousand buildings,
658 researchers can develop high quality exposure and household data. These smaller testbeds can also
659 be computationally more affordable to run large sensitivity studies that might not be feasible for
660 large regions. Such smaller studies can serve as proofs-of-concept and benchmarks for new models
661 and methodologies.

662 CONCLUDING REMARKS

663 The workshop organized by the NHERI SimCenter in early 2020 to review and discuss sim-
664 ulation and data needs to support disaster recovery planning provided important insights into the
665 prerequisites for the next generation of studies on the regional impact of disasters and post-disaster

recovery of communities. The investigation of households and their homes emerged from discussions as an area with abundant opportunities for collaboration between various disciplines in natural hazards engineering. Participants identified a large number of existing tools and recognized the need to better integrate these into computational workflows to facilitate sharing and re-using models and results. The high-fidelity simulations that can support more nuanced risk mitigation policies and recovery planning will require additional building and demographic information. Investments in robust and trustworthy methods to collect such information and make it publicly accessible in a standardized format is necessary for our community to be able to tackle large-scale problems at high fidelity. In this paper, and in the supporting digital data, the authors share specific examples of high-value data that participants frequently mentioned as critical information for their work. Finally, testbeds were highlighted as multi-purpose tools for sharing, benchmarking, and promoting data, models, and workflows in the NHE community and beyond.

In addition to the opportunity areas that are the main focus of this paper, a few remarks about workshop design are shared below to support future organizers:

- Breakout sessions with structured exercises rather than only discussions allow organizers to collect rich insights and evidence from participants. This increases the likelihood of identifying pathways for meaningful advancements in the NHE field. We hope that the collected data—published at DesignSafe ([Zsarnóczay et al., 2021](#))—provides a helpful reference.
- Designing workshop exercises around the data that we intended to collect worked well for this workshop, although further improvements might have been possible if the post-processing methodology and ontology had been conceived beforehand.
- The choice between labeling artifacts ourselves or asking participants to assign their own labels is not trivial. The former requires more work after the workshop and leaves more to interpretation when confronted with ambiguous answers. The latter requires more time in each breakout during the workshop to ensure participants understand the ontology and are not overwhelmed by the task. We advise against asking participants to choose from pre-

defined labels without first providing specific and detailed descriptions of each label to avoid them inadvertently biasing the labeling process. Even then, participant-assigned labels are subject to greater inconsistencies due to variances in interpretation and participants' perceptions of themselves and their responses. Alternatively, labels can be more consistent when assigned after the event by a limited number of persons with a common frame of reference.

- Successful workshops organized since the one in this paper, with a similar approach to bringing several projects together and focus on overarching issues and synergies [e.g., [Rosinski et al. \(2021\)](#); [NIST Center for Risk-Based Community Resilience Modeling \(2021\)](#)], affirm that the NHE community continues to benefit from this type of interaction. Future workshops could expand to international events. Such a broad audience would provide opportunities to recognize diverse NHE contexts and to promote changes that support greater collaboration and reproducible research at a global scale.

DATA AVAILABILITY

Some or all data, models, or code generated or used during the study are available in a repository online ([Zsarnóczay et al., 2021](#)) in accordance with funder data retention policies.

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722 **SUPPLEMENTAL MATERIALS**

723 Tables S1-S3 and Figure S1 are available online in the ASCE Library (ascelibrary.org).

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TABLE 1. Proposed ontology for natural hazard engineering data.

Category	Description
Natural Hazard	Which type of natural hazard does the data describe?
Earthquake & Geo	Ground motion, Liquefaction, Landslide, Sinkhole
Wind	Hurricane, Tropical storm, Nor'easter, Tornado
Water	Flood, Storm surge, Tsunami, Sea level rise
Climate	Extreme temperature, Drought
Fire	Wildfire, Fire following earthquake
Phase	Which phase of the simulation workflow does the data belong to?
Exposure	Characterize the built and social environment and how it changes over time before or between disasters.
Hazard	Characterize historical hazard events or parametrize models to simulate the frequency and intensity of synthetic scenarios.
Damage	Describe the damage after past events or parametrize models to simulate the damage in synthetic scenarios.
Consequences	Describe the consequences (e.g., losses, injuries, disruption) after past events or parametrize models to simulate consequences in synthetic scenarios.
Recovery	Describe the recovery process after past events or parametrize models to simulate recovery after synthetic scenarios.
Context	Which part of the local environment does the data belong to?
Natural env.	Topography, bathymetry, soil conditions, etc.
Built env.	Structures and infrastructure components in the area
Households	Individual members or households in the population
Businesses	Individual businesses in the economy at-large
Services	Education, insurance industry, medical infrastructure, etc.
Origin	How was the data generated?
Simulation	Computer simulation using numerical models to produce synthetic data
Experiment	Controlled experimental tests (both engineering and social sciences)
Observation	Field data, including satellite, street-view, and reconnaissance images, surveys, polls, data from social media, and data from monitoring systems and sensors.
Provider	Who provides the data?
Public sector	Government agencies
Private sector	For-profit and non-governmental organizations
Academic entity	Universities
Access	Where is the data stored?
Private	Available only to the producer and is difficult or impossible to share; for example, results stored in a non-standard format on a local hard drive.
Shared	Available upon request or subscription to a service run by the producer; data is stored in a format that is readable at least by expert users.
Published	Available upon subscription to a journal or a service independent from the data producer; for example, data archived or published by journals.
Public	Open access

TABLE 2. Examples of housing-related applications and related data needs for planning and policy-making (source: Workshop participants)

Context	Examples
Session I Connecting to Stakeholders	Simulation of cascading effects. Modeling of post-disaster recovery to anticipate potential long-term effects of different disaster scenarios, and to be applicable to a range of temporal and spatial scales.
Session II Connecting Across Experts	Simulation of re-occupancy and functional (physical) recovery of homes. Comparison of various policies and strategies for funding and prioritization of building retrofits. Ability to prioritize among multiple housing restoration or recovery options.
Session III Data Sources	Most household data consumed is sourced from the US Census Bureau, specifically the American Community Survey (ACS); few researchers are producing household-level data. Data relating to structural features of houses, damages to homes, and socio-economic characteristics of households.
Session IV Interdisciplinary Engagement	Longitudinal studies and investigations of multiple facets of community recovery. Testbeds that explore various scenarios and plausible futures to enhance our understanding of myriad impacts, consequences, and patterns of recovery spatially and temporally.

TABLE 3. Examples of additional high-value data listed among aspirational data needs (source: Workshop participants)

Theme	Recurring Examples
Buildings	Information on the structural system in tax assessor databases; Information on structural retrofits and modifications; Inventories with building-specific information for entire cities.
Households, Businesses, and Services	High-resolution insurance penetration data; Information on supply chains for local businesses; High-resolution information about workplaces of each household (both location and industry)
Recovery	Longitudinal data about household decisions after a disaster; Population displacement and its effect on neighborhood recovery; Availability and timeline of various funding sources
Hazard	Real-time, high-resolution inundation hazard data (flood, storm surge, tsunami); High-resolution (parcel-level) hurricane wind data

TABLE 4. Examples of Consumed Data by Dominant Theme (source: Workshop participants)

Dominant Themes	Recurring Examples
Built Environment	Tax assessors; FEMA (Hazus exposure data and performance models); Microsoft (building footprints); Homeland Infrastructure Foundation-Level Data (HIFLD); Zillow
Households	US Census Bureau (specifically the American Community Survey); Bureau of Labor Statistics
Natural Environment	US Geological Survey (USGS); National Oceanic and Atmospheric Administration (NOAA); Pacific Earthquake Engineering Research Center (PEER)
Structural damage	Damage assessments sourced from images; Component-level damage data (e.g., walls, roof, interior contents)

TABLE 5. Recommended testbed locations and corresponding research opportunities (source: Workshop participants).

Location	Opportunities
State of Florida / Southern Florida / Miami-Dade County	<p>Topology, bathymetry, land use and land cover data available.</p> <p>Detailed information available about historical storms.</p> <p>Exposure data available about buildings and transportation infrastructure.</p> <p>First-floor elevation information needed—machine learning opportunity.</p> <p>Several industrial facilities are major contributors to local employment while contributing to the risk of environmental damage.</p> <p>High insurance penetration and information about insurance is available.</p>
Pacific Northwest / San Francisco Bay Area / Los Angeles Metro Area	<p>Local governments have a history of collaboration with experts from academia and industry.</p> <p>Post-disaster damage and consequence data available for recent earthquakes and some of the recent wildfire events.</p> <p>Maps of historical event intensities and probabilistic forecasts of future events are available for earthquakes and tsunamis.</p> <p>Tall building inventory available in San Francisco and water network information available in Los Angeles.</p> <p>First-floor elevation information needed—machine learning opportunity.</p> <p>High-resolution geographical information about known structural vulnerabilities (e.g., cripple walls, soft-stories) is needed.</p> <p>Tech companies are major employers in the LA, SF, and Seattle metro areas. Investigation of the displacement of their workforce presents an opportunity for collaboration.</p> <p>Existing benefit-cost analysis (BCA) models by FEMA could be benchmarked and enhanced.</p> <p>Investigation of the impact of disasters on the wine industry is another opportunity for collaboration.</p>
Christchurch, New Zealand	<p>Rich data available on the impact of the earthquakes in 2011; including data on cordons and their effects on local businesses.</p> <p>Liquefaction-prone area with detailed information available about soil characteristics.</p>
Kathmandu, Nepal	Rich data available on the impact of the earthquake in 2015; including shaking intensities, damage, and aggregate casualty information

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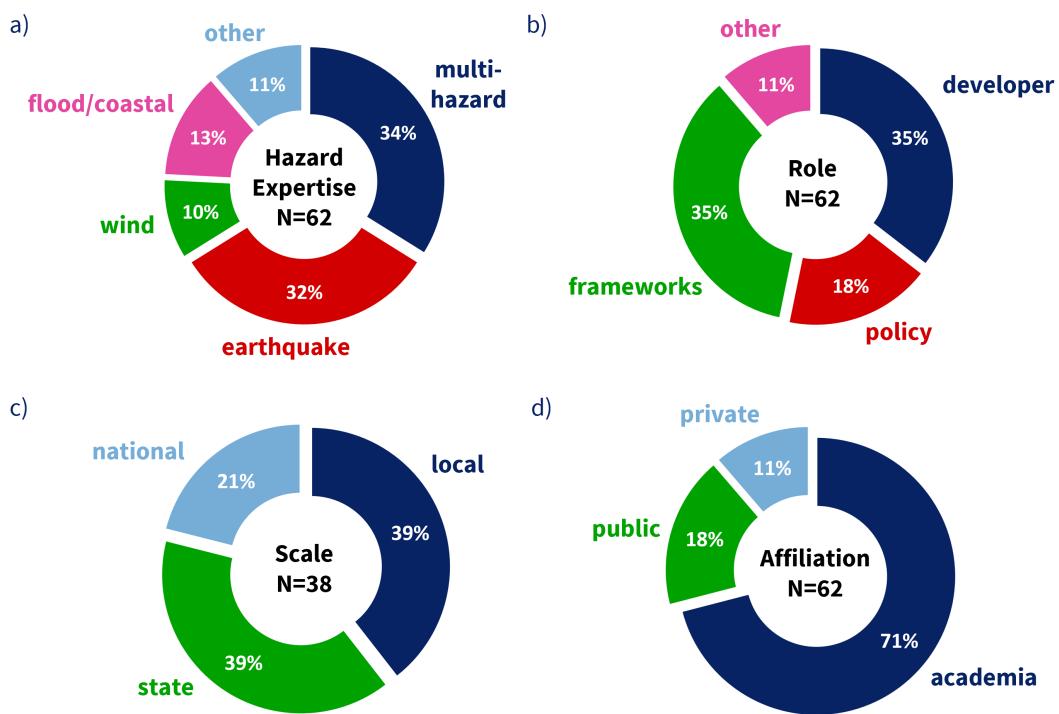


Fig. 1. Distribution of participants' self-reported (a) hazard expertise, (b) role, (c) scale in their work on disaster risk and resilience, and (d) affiliation. N in the middle of the charts shows the number of responses received from participants for each question.

PARTICIPANT 2		Note: on all scales, 1=low and 5=high	
INPUT DATA (CONSUMER)		OUTPUT DATA (PRODUCER)	
Dataset: Ocean Weather Inc, Wind Fields, Press.		Dataset: Coastal Hazards System	
Source: DWI		Storage/Distribution: Web (most parameters), local (spectra)	
Trustworthy/Reliable? 5	Accessible/Useable? 2	Trustworthy/Reliable? 5	Accessible/Useable? 4
Dataset: Wind Fields, Press Fields		Dataset: Wave Information System	
Source: NOAA /NCEP		Storage/Distribution: Web -THREDD Server	
Trustworthy/Reliable? 3	Accessible/Useable? 4	Trustworthy/Reliable? 5	Accessible/Useable? 5
Dataset: DEMS, Bathym Data		Dataset: Field Data -Field Research Facility	
Source: Multiple - Corps Distr, FEMA, GEBLO		Storage/Distribution: Web -THREDD Server	
Trustworthy/Reliable? 3	Accessible/Useable? 2-4	Trustworthy/Reliable? 4	Accessible/Useable? 5
Dataset: Hurricane Best Tracks		Dataset: LIDAR Bathy /Topo	
Source: NHC /NOAA		Storage/Distribution: Web /request	
Trustworthy/Reliable? 5	Accessible/Useable? 4	Trustworthy/Reliable? 4	Accessible/Useable? 4
Dataset: Validation Data - Surge ^{waves/watmals} Water Levels		Dataset:	
Source: USGS, NOAA/NDRC		Storage/Distribution:	
Trustworthy/Reliable? 4	Accessible/Useable? 5	Trustworthy/Reliable?	Accessible/Useable?

2025 WISH LIST						
Reliable DEMs time stamped regionally integrated	Computational grid archive	Infrastructure/asset databases, time Stamped dynamic	Coastal processes field data for waves, water Validation levels, surge	Dep'tn damage relationship databases detailed by structure type in construction		
PRODUCE	CONSUME	PRODUCE	CONSUME	PRODUCE	CONSUME	PRODUCE

Fig. 2. Data map example.

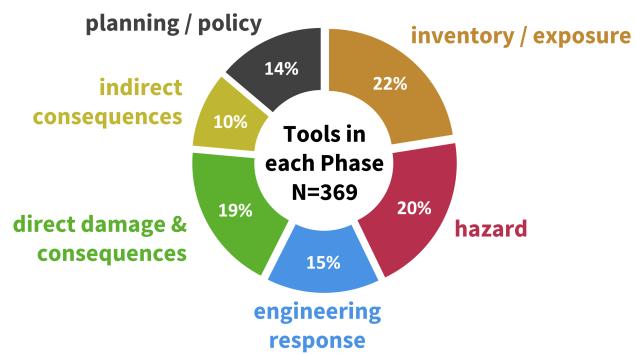


Fig. 3. Relative number of available software tools in each phase of the natural hazard risk assessment workflow. (source: N=369 responses from Workshop participants).

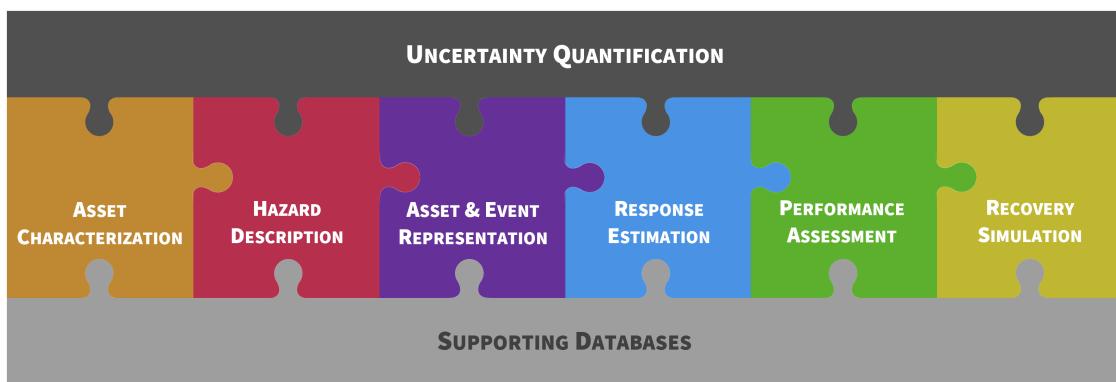


Fig. 4. Conceptualization of the SimCenter's natural hazard risk assessment workflow.

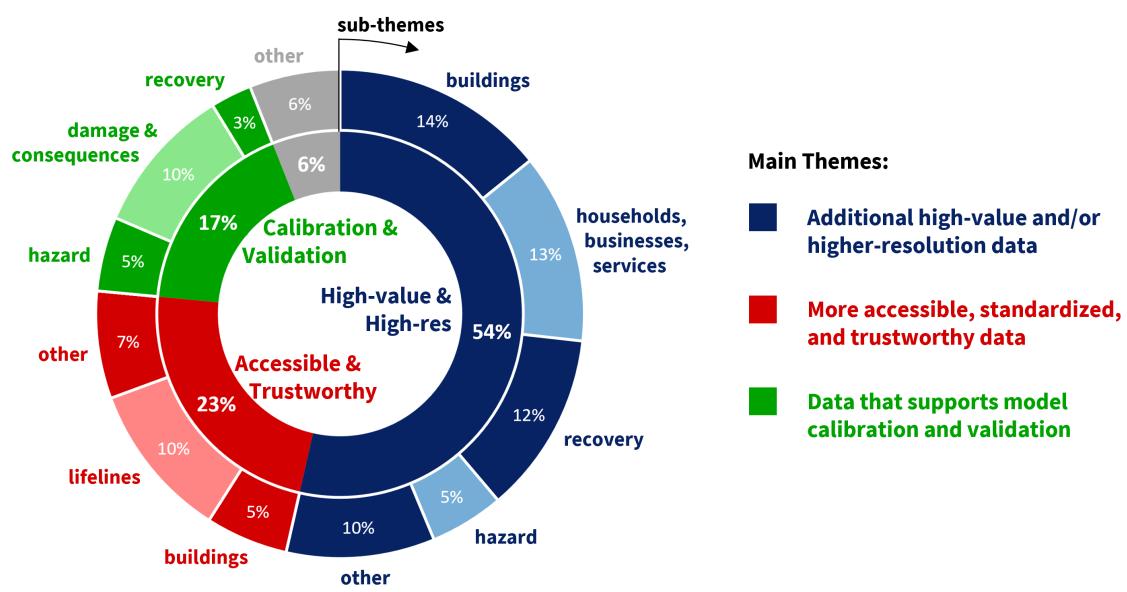


Fig. 5. Popular themes in aspirational data sources (source: Workshop participants, N=183)

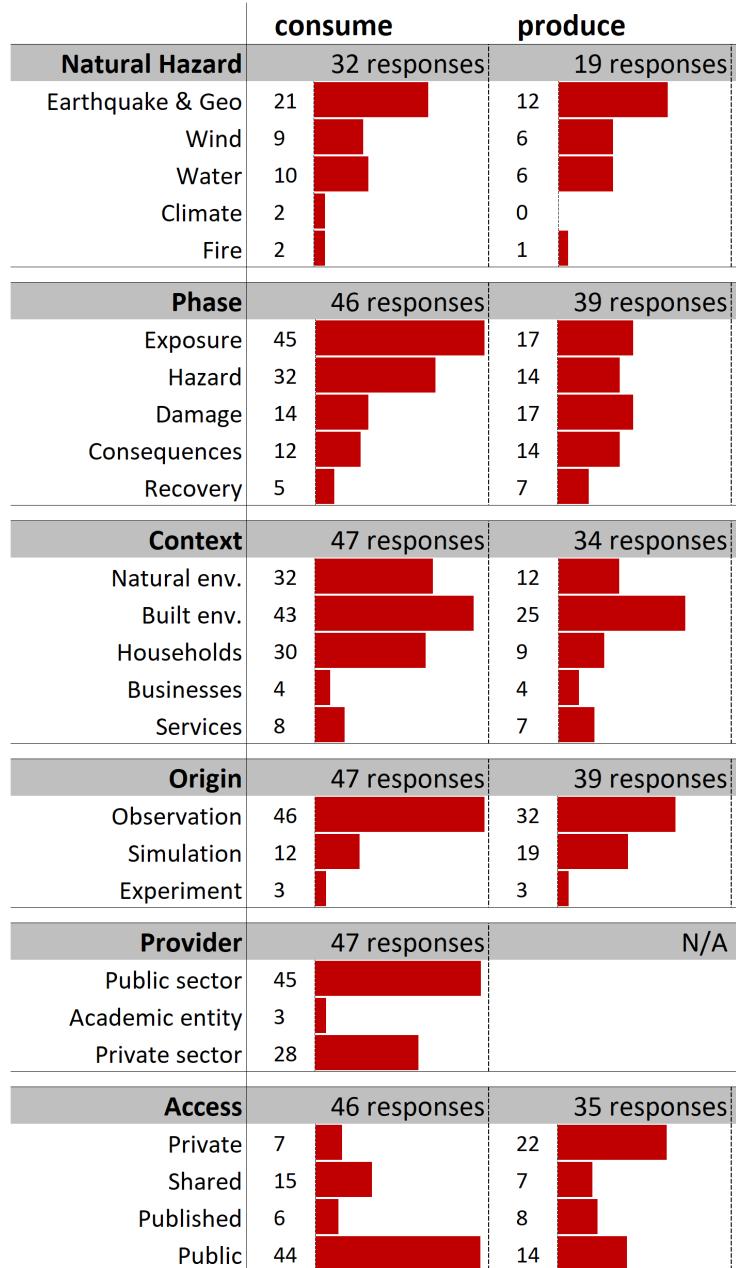


Fig. 6. Distribution of consumed and produced data across key attributes. The provider class for produced data could not be reported to protect respondent anonymity. (source: Workshop participants)

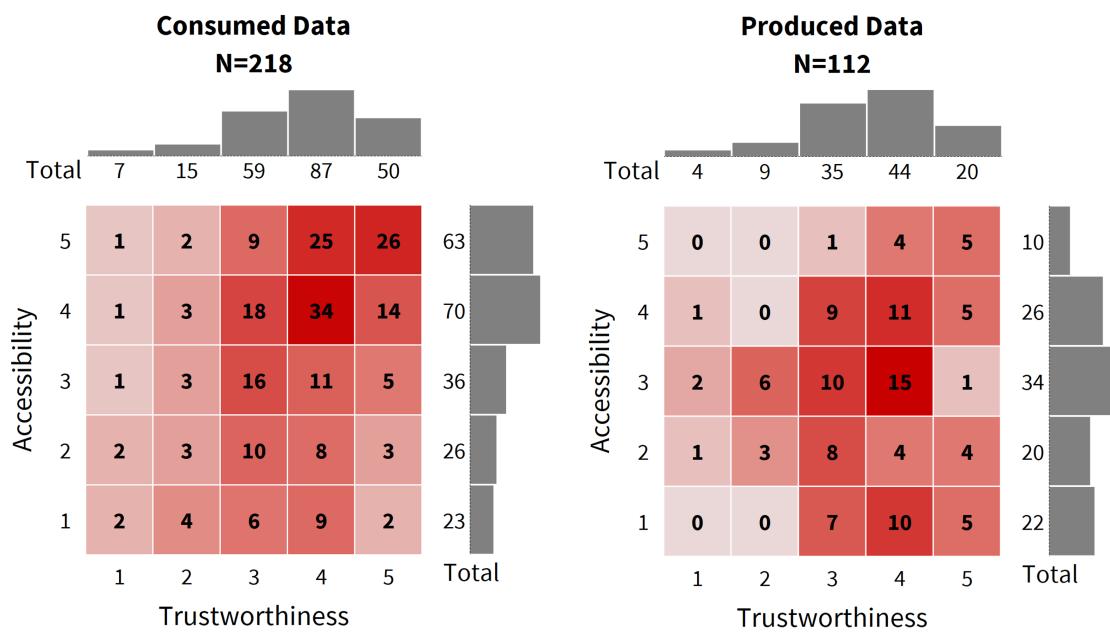


Fig. 7. Distribution characterizing the accessibility and reliability of consumed and produced data (source: Workshop participants).