Earth's Future

COMMENTARY
10.1029/2022EF003093

Special Section:
Advancing flood characterization, modeling, and communication

Key Points:
- Designing flood-risk information for decisions about property-scale flood adaptation poses nontrivial conceptual and operational challenges
- Many national-scale flood-risk estimates fail to account for regional flood-risk dynamics, especially information that integrates projected future changes
- Promising avenues toward more actionable flood-risk information include improving uncertainty characterization, design transparency, and risk communication

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Citation:
Cooper, C. M., Sharma, S., Nicholas, R. E., & Keller, K. (2022). Toward more actionable flood-risk information. *Earth's Future*, *10*, e2022EF003093. https://doi.org/10.1029/2022EF003093

Received 4 AUG 2022
Accepted 28 OCT 2022
Corrected 12 JUL 2023

This article was corrected on 12 JUL 2023. See the end of the full text for details.

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Toward More Actionable Flood-Risk Information

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Abstract The increasingly urgent need to develop knowledge and practices to manage flood risks drives innovative information design. However, experts often disagree about design practices. As a result, flood-risk estimates can diverge, leading to different conclusions for decision-making. Using examples of household-scale fluvial (riverine) flood-risk information in the United States, we assess design features and risk communication approaches that may lead to more actionable information for decision-making. We argue that increased attention to uncertainty characterization and model diagnostics is a critical intermediate step for developing simpler approaches for designing flood-risk information. Simpler frameworks are desirable because flood risks change over time, and simpler frameworks are less costly to update. Developing frameworks for large spatial domains require collaboration grounded in principles of open science. Finally, systematically evaluating how decision-makers access and use information can provide new insights to guide risk communication and information design.

Plain Language Summary Climate change can cause temperatures to rise and precipitation to become more extreme. The impacts of these changes on flooding vary in space and time and are uncertain. For example, changes in future flooding differ between urban and rural areas. We discuss the diversity of available approaches for creating flood-risk information. We suggest avenues for improvement, including (a) refining model diagnostics and uncertainty characterization to identify simpler model frameworks; (b) increasing information transparency and accessibility; and (c) improving understanding of links between decision-making and risk communication.

1. Actionable Flood-Risk Information

Disasters linked to climate change and development have received increasing attention worldwide (Coronese et al., 2019; Eckstein et al., 2021). Floods are an especially damaging example of these disasters (Jonkman & Vrijling, 2008; Whitfield, 2012). Many organizations expend considerable resources on improving the ability to predict and forecast flood events. Predicting floods is challenging as climate and other changes impact flooding in complex ways across space and time (Beevers et al., 2020; Sharma et al., 2018; Vorogushyn et al., 2018). Decisions by individuals and households can play a critical role in the dynamics and magnitude of risks (Haer et al., 2019). Actionable risk information can help decision-makers to better manage risks (e.g., through implementing protective measures) (Hoch & Trigg, 2019; Judi et al., 2018). At the same time, improved information can also negatively affect some. For example, designating an area as a high flood-risk zone can reduce property values (Daniel et al., 2009). Developing comprehensive information to inform decision-making requires holistic information design and usage considerations.

Defining the essential features of actionable information requires consideration of fundamental flood risk characteristics. Flood-risk estimates are often deeply uncertain, meaning "the system model and input parameters to the system model are not known or widely agreed on by the stakeholders to the decision" (Lempert, 2002). Flood hazards stem from diverse and interacting mechanisms (pluvial, fluvial, or coastal) and vary in magnitude and extent across spatial and temporal scales and settings (e.g., urban vs. rural) (Hirabayashi et al., 2013; Savage et al., 2016). Existing information sources represent the drivers of risk (hazard, exposure, and vulnerability) in different ways (de Moel et al., 2015). Hazard refers to flood extent and depth (Beevers et al., 2020; Savage et al., 2016). Exposure characterizes the people and properties at risk for a given hazard, and vulnerability describes the sensitivity of risk for exposed people and property (Armal et al., 2020).

Supervision: R. E. Nicholas, K. Keller
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Writing – original draft: C. M. Cooper, S. Sharma
Writing – review & editing: C. M. Cooper, S. Sharma, R. E. Nicholas, K. Keller

Approaches to estimating flood hazards vary in how and whether they integrate landscape changes, weather patterns, and climate change projections (Ward et al., 2013; Wing et al., 2017). Further, although flood-risk dynamics are spatially heterogeneous, standardized and equitable approaches for risk estimates are needed to guide flood-risk policy (Emrich et al., 2020; Kind et al., 2017). Finally, forecasting floods in the days or weeks immediately before flood events require different approaches than generating longer-term risk estimates (Vorogushyn et al., 2018).

Many socioeconomic factors influence how and whether flood-risk information influences decision-making. Regulatory timeframes for updating design standards often lag behind the scientific and technological state-of-the-art (Luke et al., 2018). Many states do not legally require flood risk disclosures upon the sale of a property. The lack of flood disclosure requirements puts potential homebuyers at risk of unknowingly buying a flood-prone home (Lightbody & Chapman, 2019). Information providers and users have diverse needs, priorities, and values (Hewitt et al., 2021). For example, the prevailing norms of science may lead providers to focus on technical and scientific metrics rather than the objective of improving decisions (Findlater et al., 2021). In addition, a growing body of evidence suggests that information co-production is crucial to producing credible and relevant information (Dilling & Lemos, 2011; Findlater et al., 2021; Soden et al., 2017). Maximizing the usability of information in decision-making requires, at a minimum, that the information is designed with high levels of transparency and can be accessed easily at no cost.

Existing literature can guide the design of actionable flood-risk information. In this commentary, we summarize key features from this literature, compare examples of household-level fluvial flood-risk information sources in the United States (US), and discuss research avenues for improvements. We focus on fluvial flood-risk information for longer-term projections of flood likelihood and severity for simplicity but recognize that integrating all flooding sources and information types is necessary and even more complex.

2. Primary Components of More Comprehensive Fluvial Flood-Risk Information

The flood-risk assessment literature provides detailed insights into the components needed for more comprehensive information. However, regional differences in flood dynamics create variability in the magnitude of impact these different components have in influencing flood risk. In Figure 1, we illustrate differences in the primary components of a selection of flood-risk information sources. In this section, we describe the components in Figure 1 and argue that regional differences in flood-risk dynamics create a need for regional flood-risk assessment frameworks.

Several studies highlight the dominant role of climate in flood peak estimates (Alfieri et al., 2018; Wong et al., 2018). Climate models do not resolve fine-scale hydrometeorological processes (i.e., local weather), particularly precipitation extremes (Collet et al., 2018; Nissan et al., 2019). Modelers often use dynamical or statistical downscaling methods to generate climate projections for local-scale analyses (Merz et al., 2014). The choice of downscaling method (e.g., adopting a statistical or a dynamical approach) has implications for the kinds of uncertainty that propagate from climate model outputs to hydrologic and hydraulic models. Combined, differences in downscaling techniques and model resolutions can contribute to variations in climate forcing (e.g., extreme rainfall) in river flow (hydrologic models). Weather generators provide a potential avenue for producing probabilistic inferences about future flooding scenarios and, as a result, offer an alternative to static estimates of future flooding (Steinschneider et al., 2019). Downscaling methods and weather generators have limited capabilities to generate high-resolution, precise estimates of global change, but they are necessary for producing locally-relevant flood hazard estimates (Qin & Lu, 2014; Steinschneider et al., 2019). As discussed further in Section 4, the choice of climate scenario, downscaling techniques, and weather generators propagate uncertainty in flood-risk estimates.

Hydrological models help to estimate river flow within a catchment by representing complex dynamics with parameters and mathematical equations. River flow estimates provide boundary conditions needed for hydraulic models and to generate flood inundation depth and extent estimates. River flow projections establish the boundary condition for the hydraulic models necessary to estimate flood inundation extent and depth (Judi et al., 2018; Rajib et al., 2020). Limitations in observational records create challenges when developing models for any catchment (Clark et al., 2017). Because extreme floods occur infrequently, they have minimal data records and require modeling with sparsely distributed monitoring infrastructure (Bayazit, 2015). Additional challenges arise when

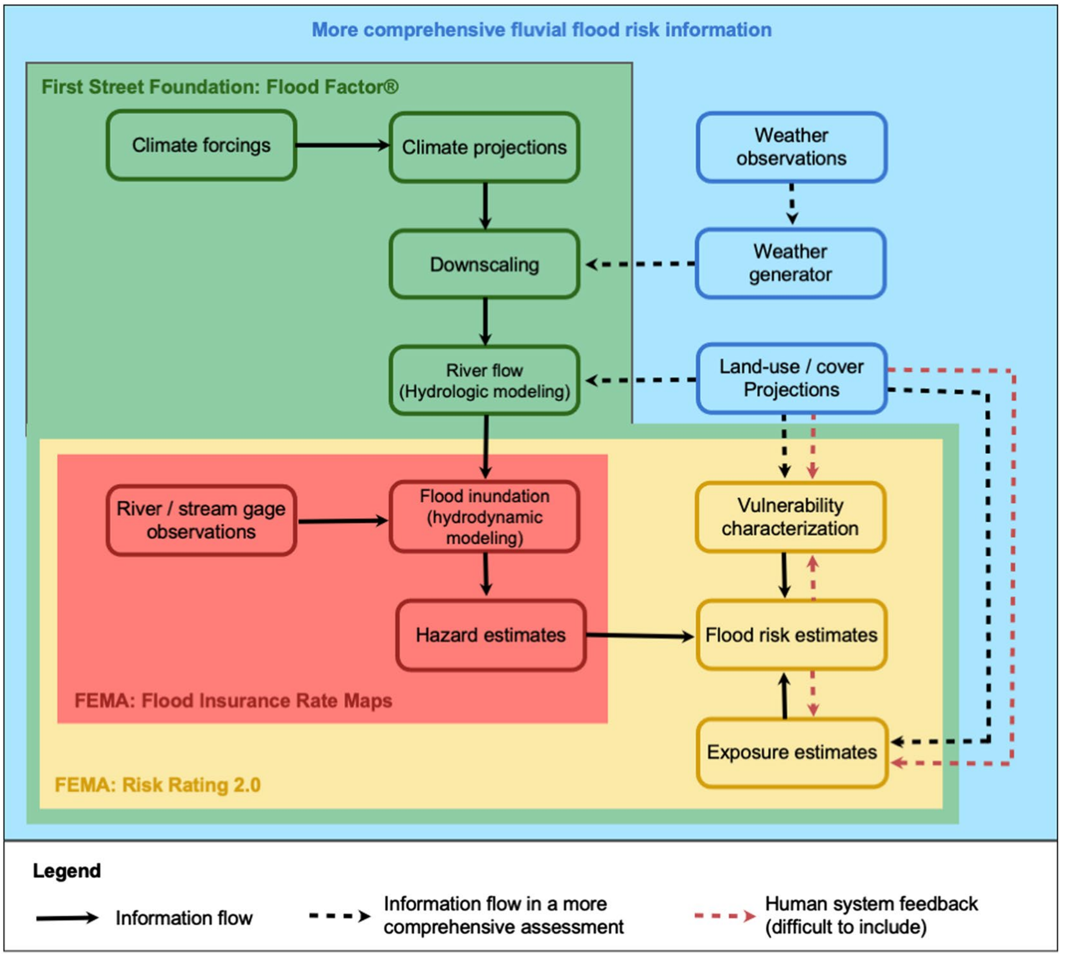

Figure 1. Flow diagram illustrating an evolution in the level of sophistication of the available information characterizing fluvial flood risk in the United States. The outer square (light blue) includes the components that existing literature indicates can impact flood risk estimates.

using empirical relationships to characterize conditions in ungauged catchments (Wong et al., 2018). Modeling approaches have evolved to include methods for capturing antecedent moisture conditions and model regional processes such as snowmelt (Chang & Franczyk, 2008; Judi et al., 2018).

Flood inundation estimates require reliable surface topographic data and geometric representation of the river channel (Bures et al., 2019; Dey et al., 2019; Z. Liu & Merwade, 2018). Digital elevation models (DEMs) provide detailed topographic data. The quality and resolution of DEMs affect the accuracy of the extracted topographic features (Dey et al., 2019). High-resolution DEMs that fully represent the topographic features at local relevant scales are often unavailable. Scientists produce high-resolution DEMs by applying remote sensing technology such as Light Detection and Ranging (LiDAR) (Hilldale & Raff, 2008). However, LiDAR cannot penetrate the water surface to yield bathymetric results and, therefore, cannot capture submerged river channel features (Bures et al., 2019). LiDAR and DEM information are often integrated with field-surveyed bathymetry data to improve the representation of riverbed topography. The quality of bathymetric data decreases with water depth and river turbulence (Z. Liu & Merwade, 2018).

National-scale data about land use/cover are available through the National Land Cover Database (NLCD) (Jin et al., 2019). Still, they must be integrated with hydrologic and hydraulic models (Sohl et al., 2016). The NLCD is updated every 5 years and provides nationwide data based on 30-m resolution Landsat data. Land cover projection datasets are available but at coarser spatial resolutions (Sohl et al., 2014). Recent studies have used historical land cover datasets to create land-use change scenarios to project historical development trends into the future (Alexander et al., 2017). Advancing these efforts may help to identify primary drivers of flood risk.

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Vulnerability and exposure are highly dynamic features of flood risk influenced by local policies, governmental decisions, and individual actions (Dubbelboer et al., 2017; Hemmati et al., 2021). Changes in vulnerability and exposure also alter the frequency and magnitude of flooding (Michaelis et al., 2020). Channelization projects and levees can increase community vulnerability by increasing urbanization and floodplain development (Chang & Franczyk, 2008). Of course, if flood mitigation structures fail, increased growth (exposure) may amplify losses (Di Baldassarre et al., 2015; Haer et al., 2020). The reliability of flood-mitigation infrastructure under future climatic conditions is unclear. Although necessary for understanding risk, estimates of exposure and vulnerability are subject to false assumptions or bias, threatening the external validity of any source of flood-risk information (Michaelis et al., 2020).

Interactions between human decisions and flood hazards are complex and confounded by uncertainty propagation in subsequent components of flood-risk. The red dashed arrows in Figure 1 indicate interactions between the system components and human decision-making. Available methods for assessing vulnerability and exposure often rely on data such as historical insurance claims (Knighton et al., 2020; Mobley et al., 2020; Wing et al., 2020) or national scale survey data such as the US Census (Koks et al., 2015; Maldonado et al., 2016; Zhou et al., 2017). Modelers often need to translate this data across spatial scales, potentially limiting the applicability for local decision problems. Further, limited approaches provide insights into future changes due to decision-making. Because human decisions impact the climate system, climate information that does not integrate the impacts of human decision-making may lead to overconfident estimates of flood risk (Ward et al., 2013).

In this section, we described the primary components of fluvial flood-risk information. Aggregating the many system components necessary for estimating flood risk often leads to challenges such as aggregation bias (Pollack et al., 2022). Flood-risk estimates vary depending on factors such as the choice of models and data availability. The components included here only include those needed for fluvial flood-risks estimates, including coastal and pluvial (urban) flooding adds even more uncertainty. A more comprehensive source of flood-risk information would integrate each component in Figure 1. As discussed in Section 4, model diagnostics and uncertainty characterization are central to understanding flood-risk estimates.

3. Fluvial Flood-Risk Information in the US

There is a wide range of approaches for estimating fluvial flood risk in the US. In Table 1, we compare a selection of desirable features for actionable flood-risk information. We include sources that provide or contribute to fluvial household flood-risk information at the continental US scale. The considered academic research examples, while not explicitly developed to aid decision-making, demonstrate variations in design choices. As illustrated in Table 1, many opportunities for improvement remain.

Several organizations contribute to developing flood-risk information in the US. Federal standards set by the Federal Emergency Management Authority (FEMA) guide the design of Flood Insurance Rate Maps (FIRMs), which draw from local flood studies as opposed to flood models (FEMA, 2020). FIRMs, among other purposes, are used in FEMA's Risk Rating structure to determine flood insurance rates. FIRMs have many notable shortcomings, including limited spatial coverage and neglecting to account for changing environmental conditions (Pralle, 2019; Soden et al., 2017). FEMA recently transitioned to a new risk rating structure, Risk Rating 2.0, which aims to represent actuarial risk through a more comprehensive characterization of vulnerability and exposure, which includes the integration of proprietary catastrophe models (Congressional Research Service, 2021). Risk Rating 2.0 makes some progress in modernizing FEMA's approach to flood-risk mapping; however, many alternative approaches exist.

The First Street Foundation's Flood Factor®, a continental-scale flood-risk model, incorporates climate change and pluvial, fluvial, and coastal flood-risk estimates for individual properties (First Street Foundation, 2020). Flood Factor® fills some information gaps in FIRMs and provides limited opportunities to compare flood-risk estimates from different sources. The approach demonstrates an increase in the number of properties at risk from flooding relative to FEMA estimates (Bates et al., 2021). The new information reveals the advantages of applying large-scale computational models to provide actionable decision-making information. At the same time, it highlights challenges in producing information for applications in local decision-making.

The models used to produce Flood Factor® integrate a subset of the available models and methods. Academic research provides different approaches and strategies for characterizing additional components of flood risk

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Table 1
Comparison of Available Household Fluvial Flood-Risk Information Sources

	Flood-Risk Information Sources						
Desired Features and Components	Risk Rating 2.0	Flood Factor®	Wobus et al. 2019	Judi et al. 2018	Rajib et al. 2020	Zarekarizi et al. 2021	Liu et al. 2015
Climate Change Integrates climate change projections	does not integrate	integrates climate change projections	integrates climate change projections	integrates climate change projections	does not integrate	does not integrate	integrates climate change projections
Vulnerability and Exposure Considers vulnerability and exposure	considers either vulnerability or exposure	considers either vulnerability or exposure	considers vulnerability and exposure	considers vulnerability and exposure	considers either vulnerability or exposure	does not consider	considers vulnerability and exposure
Landscape Change Integrates land-cover/use changes	no land-cover/use	land-cover/use but no change	land-cover/use but no change	land-cover/use but no change	land-cover/use but no change	no land-cover/use	no land-cover/use
Uncertainty Characterization Characterizes two or more sources	no uncertainty characterization	characterizes one source of uncertainty	characterizes one source of uncertainty	characterizes one source of uncertainty	no uncertainty characterization	no uncertainty characterization	characterizes one source of uncertainty
Simplicity Simple framework to implement	complexity in some aspects	relatively simple to implement	complexity in some aspects	relatively simple to implement	complexity in some aspects	complexity in some aspects	complexity in some aspects
Transparency Open source data and code	no data or code	no data or code	no data or code	no data or code	no data or code	data and code accessibility statement	data and code accessibility statement
Access Accessible at no cost	available online at no cost	available online at no cost	open access	open access	published in closed access journal	open access	open access
Legally Accepted Product is legally binding	legally binding	not legally binding	not legally binding	not legally binding	not legally binding	not legally binding	not legally binding

Note. A comprehensive source of actionable flood-risk information would include the darkest blue shade for every feature or component. However, improvements may still be possible for the darkest blue shades. We show various information sources to exemplify the range of design approaches and the continued opportunities for improvement.

(examples include: Judi et al., 2018; J. Liu et al., 2015; Rajib et al., 2020; Wobus et al., 2019; Zarekarizi et al., 2021). The methods used in these examples demonstrate the diversity of possible approaches for estimating flood risk. However, they are not produced through accessible approaches that would enable comparisons of risk information between different sources.

4. Uncertainty Characterization and Model Diagnostics Can Simplify Flood-Risk Information Frameworks

Uncertainty stems from the choices information producers make about modeling frameworks, distribution parameters, and datasets (Bosshard et al., 2013; Collet et al., 2018) and natural variability (e.g., the random nature of thunderstorms that drive extreme precipitation) (Kiureghian & Ditlevsen, 2009). Key uncertainty sources include model structure, model parameters, channel geometry, surface topography, and human decisions (Beevers et al., 2020; Savage et al., 2016). As illustrated in Table 1, information sources often consider a subset of potentially relevant uncertainties, for example, by focusing on uncertainty in flood peaks (Judi et al., 2018). Failing to consider uncertainty can lead to sizable downward biases in risk estimates (Sriver et al., 2018; Wong et al., 2018) and potentially neglect interactions between uncertainty sources and their propagation into flood risk estimates (Bosshard et al., 2013; Z. Liu & Merwade, 2018). In traditional approaches to estimating river flow and flood inundation, information producers manually adjust a subset of model parameters to calibrate models (Judi et al., 2018; Pianosi et al., 2016). This approximation may fail to identify the decision-relevant parameters and can under-sample parametric uncertainty (Keller et al., 2020).

Uncertainty characterization can also help to inform simpler analytical frameworks. Simple analytical frameworks can be desirable because simpler designs are easier and less costly to reproduce and modify (Helgeson et al., 2020). More complex models often demand, among others, considerable computational resources, specialized expertise, additional time and quality control, and larger input datasets (Hewitt et al., 2021; Vorogushyn et al., 2018). Even with limited uncertainty characterization, the examples in Table 1 already include rather complex frameworks. Future information design may benefit from an increased focus on developing simpler approaches that can be updated easily as new information and data emerge.

There are many ways to characterize uncertainty that may lead to simpler analytical frameworks. Surrogate methods, such as Gaussian process-based emulators, can address parametric uncertainty (Pianosi et al., 2016) to identify dominant flood-risk drivers. Although initially challenging to develop, process-based emulators for high-dimensional models may help to inform simpler modeling frameworks (Helgeson et al., 2020). Recent efforts to advance Bayesian Statistical Inference implemented by stochastic algorithms such as a fast sequential Markov Chain Monte Carlo (MCMC) provide a probabilistic framework for characterizing parametric uncertainties (Kavetski et al., 2018). Several studies outline the potential of representing uncertainty through multi-model systems (Alfieri et al., 2018; Wong et al., 2018). Finally, Bayesian model averaging offers a framework to integrate information based on the credibility of each model output (Keller et al., 2020; Z. Liu & Merwade, 2018). Uncertainty characterization and model diagnostics can help to demonstrate pathways for simplifying analytical frameworks by identifying decision-relevant uncertainties and quantifying the contribution of individual uncertainty sources (see discussions, e.g., in Beevers et al., 2020; Hall & Solomatine, 2008; Keller et al., 2020; Reed et al., 2022; Savage et al., 2016). Because flood dynamics vary regionally, uncertainty characterization may reveal the need for different regional modeling choices.

5. Improving Information Transparency and Accessibility

Challenges for producing actionable information extend beyond design choices. Information transparency is a primary factor in the success of democratic governance systems and, therefore, an essential priority in developing information to inform decision-making (Elliott, 2020). In addition to ethical considerations, a greater emphasis on transparency could advance the capacity for comparing information sources and characterizing uncertainty (Hoch & Trigg, 2019). Open science to promote transparency is a complex and multilayered concept (for more information, see (Dai et al., 2018; Fecher & Friesike, 2014; Munafò et al., 2017). It broadly ensures "the free availability and usability of scholarly publications, the data that result from scholarly research, and the methodologies, including code or algorithms, that were used to generate those data" (NASEM, 2018). Data, methods, computer codes, analysis plans, conflicts of interest, and value judgments determine information transparency (Elliott, 2020).

As illustrated in Table 1, information producers often do not use fully transparent information design processes. Academic studies usually must provide open-source code and data by funding agencies or publication outlets, although the standards can vary considerably (Dai et al., 2018). Flood Factor® offers accessible decision-making information but with limited code and data access. The data is publicly available at aggregated scales (e.g., county level); however, the First Street Foundation provides more detailed information through commercial services (First Street Foundation, 2020). Although FIRMs are freely accessible, FEMA uses some proprietary information in Risk Rating 2.0, and FIRMs rely on local engineering studies (Congressional Research Service, 2021). Reluctance to share code and data can hinder efforts to improve transparency and advance open science.

Across climate science domains, enlisting and maintaining critical and informed providers and users is essential for promoting transparency through open science (NASEM, 2018). Funders can help produce and distribute open-source information by providing web services for sharing information. For example, SWATShare allows users to upload and share models, run simulations, and visualize results (Rajib et al., 2020). Platforms like these could facilitate more systematic approaches to uncertainty characterization and model diagnostics. Improved online platforms can enable collaboration and decrease barriers to sharing code and data.

Information accessibility is critical in determining how information influences decision-making. Ideally, decision-makers can access information easily and for free. Accessible information relies on attributes such as well-designed and up-to-date websites (Hewitt et al., 2021; Yarnal et al., 2006). Flooding information provided by FEMA is accessible through many interactive online tools (for more information see US Global Change Research Program, 2022). These resources require users to visit specific webpages and the information is often not provided in a format that directly provides risk information for individual properties.

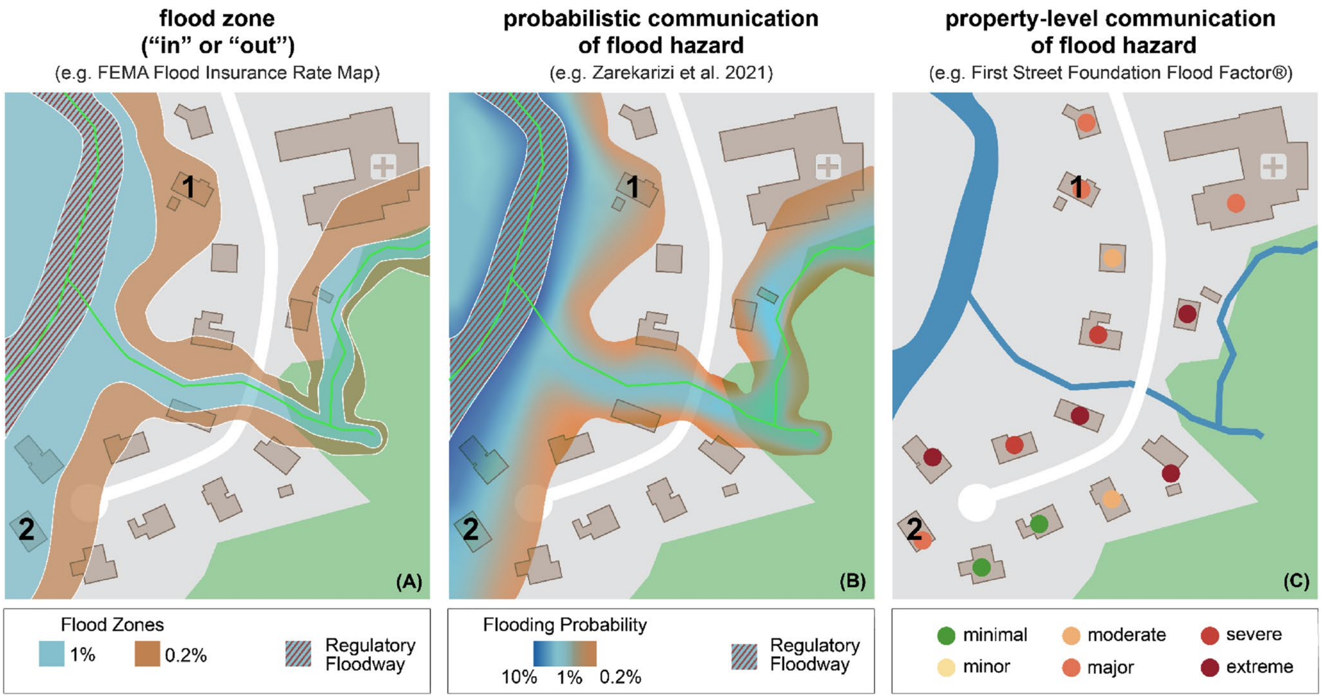

Figure 2. Illustration of the different visual styles used to communicate flood risk. Panel A is similar in style to Federal Emergency Management Authority (FEMA) Flood Insurance Rate Maps (FIRMs); Panel B is based on an academic study that visualizes FEMA flood zones as continuous rather than binary; Panel C uses descriptive risk labels similar to Flood Factor®.

The First Street Foundation (through Flood Factor®) uses an alternative approach for providing information. In addition to a stand-alone website, it is widely available on real estate websites and enables users to compare property-level risk estimates with details provided in FIRMs so users can seamlessly access risk information alongside real estate information. Flood Factor® includes information that may protect potential homebuyers from purchasing flood-prone properties, particularly in states without flood disclosure laws. On the other hand, inaccurate information, such as information that classifies low-risk homes as high-risk, can make low-risk properties more difficult to sell. As new information emerges and becomes more accessible, questions related to their economic ramifications are increasingly important to consider. Few mechanisms are available to evaluate the credibility of information disseminated online (Dai et al., 2018; Twomlow et al., 2022).

Visual choices can impact the accessibility of flood-risk information in several ways. Previous research suggests slight differences in visual styles can lead to different decisions (Dobson et al., 2018; Faulkner et al., 2007; Galloway et al., 2006). Despite evidence that different visual styles influence decision-making, there is limited research evaluating linkages between visual styles and decision-making. In a systematic review of natural disasters and visualization, Twomlow et al. (2022) reported that less than 1% of over 4,500 screened studies addressed the social, political, or cultural context to communicate disaster risk. This review suggests that as new visual styles emerge, little is known about how they impact decision-making.

The different visual styles used to communicate flood risk could influence how users perceive risk. In Figure 2, we illustrate how different visuals may lead decision-makers to varying conclusions about property risk. Decision-makers may understand their risk differently across these three panels, even if the underlying hazard estimate are identical. FIRMs traditionally present flood zones in "x-year terms" (Figure 2a), meaning a home has "at least" the specified level of hazard (e.g., at least a 0.2% chance of flooding in any given year). Culturally, this visual style may be most familiar to users because of its prevalence in public policy. In Figure 2b, the FEMA flood zones are continuous. Continuous flood hazard probabilities provide a more precise estimate of the flooding likelihood relative to binary flood zones (Figure 2a). Finally, Flood Factor®, in addition to being based on different information, uses descriptive risk categories (Figure 2c).

The currently divergent approaches to communicating flood risks can confuse decision-makers. The house labeled "1" in this figure falls within the 500-year flood zone in Figure 2a. However, in Figure 2b (continuous flood probability), House 1 has a higher likelihood of flooding, and in Figure 2c, House 1 has an "extreme risk." A more comprehensive approach to evaluating the links between visual styles and decision-making may help ensure that decision-makers understand the full extent of their risk. The increasing availability of online information provides opportunities to visualize risk in dynamic environments. Emerging approaches such as agent-based models (Haer et al., 2016, 2017) and user-center design (Twomlow et al., 2022) may help to understand the linkages between visual styles and decision-making. Communicating information through visual styles that express risk drivers and their associated uncertainties can ensure that decision-makers realize the full extent of their risk. In the future, systematic approaches to evaluating linkages between information and decision-making could provide new insights for risk communication.

6. Legal Acceptability

Legal acceptability is an important feature of actionable risk information. Standards for insurance rates and building codes require flood hazard estimates (Congressional Research Service, 2021). Property owners with federally-backed mortgages in high-risk flood zones are required to have flood insurance in the US (FEMA, 2020). These policies and standards require standardized approaches for producing information over large spatial domains. Information such as that provided by Flood Factor®, although not legally binding, provides a risk estimate for properties outside FEMA flood zones and can influence the approaches FEMA uses to produce information. Flood-risk design and risk communication choices have important legal ramifications. As such, the features outlined in Table 1 are especially critical to include in the design of legally accepted flood-risk information.

7. Conclusions

We focused this discussion on how household scale fluvial flood-risk information can be designed to guide adaptation decisions. Even in this simplified example of flood-risk information usability, we noted many ways deep uncertainty influences information design. Information producers must choose between many different models, datasets, and frameworks and often lack the tools to determine the best choices for a specific decision problem. Existing literature indicates that comprehensive flood-risk information would include the components in Figure 1. However, no single information source integrates all these components.

Providing transparent and accessible information may require improved collaboration across many organizations and scales. Although challenges remain, there are many opportunities for improvement. Collaborative online web platforms could help information producers share code and data, improving reproducibility. Systematic uncertainty characterization and model diagnostics can lead to simpler designs that enhance the characterization of the most influential drivers of flood risks. These drivers may vary regionally, requiring regionalized efforts to distinguish the primary risk drivers. Information accessibility may improve when information is communicated through visual styles that express risk drivers and their associated uncertainties. More research is needed to understand the linkages between visual styles and decision-making. Continued improvements are especially important for information sources with legal implications.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data sharing does not apply to this article as no datasets were generated or analyzed during this study.

Acknowledgments
We thank Lisa Domenica Iulo, Lara Fowler, and Casey Helgeson for their input. Katerina Kostadinova helped with figure design. Any errors and opinions are, of course, those of the authors. This work was co-supported by the Penn State Initiative for Resilient Communities (PSIRC) through a Strategic Plan seed grant from the Penn State Office of the Provost, the Center for Climate Risk Management (CLIMA), the Rock Ethics Institute, Penn State Law, and the Hamer Center for Community Design; the National Oceanic and Atmospheric Administration, Climate Program Office under NA16OAR4310179; and the Multi-sector Dynamics program area of the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research as part of the multi-program, collaborative Integrated Coastal Modeling (ICoM) project. Any conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding entities.

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Erratum

In the originally published article, there was an error in the statement for ICoM project in the Acknowledgments section, which read "This work was co-supported by the Penn State Initiative for Resilient Communities (PSIRC) through a Strategic Plan seed grant from the Penn State Office of the Provost, the Center for Climate Risk Management (CLIMA), the Rock Ethics Institute, Penn State Law, and the Hamer Center for Community Design; the National Oceanic and Atmospheric Administration, Climate Program Office under NA16OAR4310179; and the Earth System Model Development and Regional program areas of the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research as part of the multi-program, collaborative Integrated Coastal Modeling (ICoM) project." The statement has been corrected to read "This work was co-supported by the Penn State Initiative for Resilient Communities (PSIRC) through a Strategic Plan seed grant from the Penn State Office of the Provost, the Center for Climate Risk Management (CLIMA), the Rock Ethics Institute, Penn State Law, and the Hamer Center for Community Design; the National Oceanic and Atmospheric Administration, Climate Program Office under NA16OAR4310179; and the Multisector Dynamics program area of the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research as part of the multi-program, collaborative Integrated Coastal Modeling (ICoM) project." This may be considered the authoritative version of record.