HAZARDOUS WEATHER PREDICTION AND COMMUNICATION IN THE MODERN INFORMATION ENVIRONMENT

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Understanding the dynamic, interconnected processes that characterize the modern hazard information system can transform the creation, communication, and use of weather and climate information.

When a hurricane approached Galveston, Texas, in 1900, meteorological forecasting and information dissemination capabilities were limited. Although warnings were communicated to people in Galveston prior to landfall, the hurricane inundated the town with an unanticipated 15-ft storm surge. Entire neighborhoods were swept away, even sturdy buildings on high ground that meteorologists and residents had thought were safe.[1] Thousands of people—an estimated 20% of Galveston's population—died.

Much has changed since then. Today, a potential hurricane is tracked and forecast from the time it is a small atmospheric disturbance over the ocean. As the disturbance evolves, meteorologists use satellite and aircraft observations, computer models, and other information to create updated forecasts of its path and evolution. If a storm threatens U.S. landfall, forecasters issue increasingly detailed forecasts and warnings, and public officials recommend protective actions in areas at risk. This information is updated and disseminated multiple times per day, and it is rapidly communicated, interpreted, and recommunicated through broadcast media, the Internet, interpersonal interactions, and other channels. Assisted by digital technologies, members of the public can rapidly—often continuously—obtain new information about the threat and discuss it with people around the world. Together, these processes produce a vast, rapidly evolving body of information about an approaching hurricane that propagates through society, transforms across many people, and is used

[1] For further details, see, for example, Garriott (1900).

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in protective decisions, all in ways that could not have been imagined even a decade ago.

As these examples illustrate, scientific and technological advances over the last century have revolutionized humans' capabilities to anticipate and warn for weather-related risks. Moreover, advances in information and communication technology have transformed the ways in which many people access, share, and use information. In particular, the Internet and the social computing platforms it supports are creating new relationships among individuals, their social networks, and information during times of threat (Palen et al. 2010; Fraustino et al. 2012).

Together, these advances are fundamentally changing how information about weather and climate risks is created, communicated, and used. Yet, we know little about how people interact with and interpret the vast, complex collection of weather-related information available in today's world. Without this understanding, it is difficult to develop effective strategies for improving weather forecasts, warnings, and information communication in ways that benefit diverse populations.

To help build this understanding, this article synthesizes knowledge across atmospheric science, computer and information science, and social sciences to articulate a new framework for conceptualizing hazardous weather prediction, risk communication, and decision-making in the modern information environment. The framework integrates uncertain predictive information that evolves as a hazardous weather threat approaches, information flow and social interactions in the physical and digital worlds, and people's evolving risk perceptions, vulnerabilities, and decisions. It conceives of these as interconnected processes within a natural–human dynamic system. Using this perspective as an analytical starting point, we then present two complementary research approaches for examining these interconnected processes in greater depth: analysis of social media "big data" streams and coupled natural–human system modeling.[2]

The framework and research approaches build on existing knowledge and tools from multiple fields of study. By connecting and combining ideas across these fields, we develop an integrative perspective that extends beyond the contributions of the individual fields as well as new methodological approaches for studying the system within this expanded frame. To demonstrate the research approaches, we present examples from our ongoing research investigating how evolving information and social interactions influence people's risk interpretations and decisions as a hurricane approaches the U.S. coastline. The results of this research will be discussed in detail elsewhere; here, we use the research examples to show how the methods help ground and support the broader frame and how this type of research can open up novel research directions.

Building on other work that challenges simplified, one-way models of risk communication focused on "educating" members of the public [e.g., National Research Council (NRC) 1989; Fischhoff 1995; Lewenstein 1992; Michael 1996; Bauer et al. 2007; Welsh and Wynne 2013], we conceive of weather risk communication and decision-making as an interactive experience among people who are working within their own evolving, uncertain worlds, embedded in larger sociotechnological contexts. In doing so, we seek to lay the groundwork for a hazard prediction, communication, and response system that acknowledges and capitalizes on new scientific capabilities, networked communication, and socially distributed information, while also accounting for the vulnerabilities and capacities of different populations.

RECONCEPTUALIZING CREATION, COMMUNICATION, INTERPRETATION, AND USE OF WEATHER RISK INFORMATION.

In the atmospheric science community, weather risk communication and decision-making is often conceptualized as a largely linear process: meteorologists or public authorities create and disseminate a forecast or warning message, which individuals at risk then receive and use to decide whether to evacuate, take

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[2] The research presented here is part of a larger project entitled Communicating Hazard Information in the Modern Environment (www.mmm.ucar.edu/chime).

SOCIAL MEDIA, HAZARD EVENTS, AND WEATHER RISK COMMUNICATION

Since the mid-2000s, the rise of social media, text messaging, and other forms of computer-mediated communication has dramatically expanded opportunities for peer-to-peer and one-to-many communication. During times of threat, when disruption to everyday activities is accompanied by more intensive information seeking and sharing, people are increasingly going online to interact. Over the last decade, social computing use during hazard events has continued to grow, event after event and across the world (Fraustino et al. 2012). This rapid expansion in online communication and the new behaviors it enables have important implications for weather risk communication and responses.

New information and communication technologies can be powerful conduits for disseminating information about hazard warning and response [Mass 2012; Department of Homeland Security (DHS) 2013; Hughes and Palen 2014]. Thus, when meteorologists and emergency management professionals enter social media environments, they often focus on sending messages "out." This emphasis on using social media for dissemination leads information producers and communicators to ask certain types of questions. For example: What should messages contain? How often should they be issued? How many "followers" are needed for a message to be effective?

A next step is realizing that people in social media environments are not simply passive recipients of information; instead, they are active participants in communication. During hazard threats, for example, members of the public use social media to message "in" to meteorologists and emergency management professionals, to ask questions, request help, and share on-the-ground information (DHS 2013; Hughes et al. 2014). People also use social media extensively to pass on messages from others and contribute their own observations and opinions. For meteorologists, these social media messages have potential value as new sources of data for prediction, warning, and research (Hyvärinen and Saltikoff 2010; Mass 2012). Importantly, they are also indicators of how people are participating in the process of weather risk communication, interpretation, and response.

A further step is recognizing that when people interact on social media, they can engage in creative behaviors beyond the types of two-way information exchange and individual decision-making discussed above. Social computing enables new forms of information processing and social problem solving during times of threat (Palen et al. 2010; Palen and Anderson 2016). During and after disasters, for example, new volunteers and groups emerge—connecting people locally and across the globe—to filter, consolidate, integrate, and relay needed information and organize other activities to help affected populations (Sutton et al. 2008; Starbird and Palen 2011; DHS 2013; White et al. 2014; Meier 2015). Our ongoing research suggests that these types of networked online behaviors also occur during the preevent (forecast, warning, and preparation) stage. For example, in our analyses of Twitter data as Hurricane Sandy approached, we find people interacting online to access, interpret, and share information and to seek and provide help in protective decision-making (Anderson et al. 2016; Demuth et al. 2017, manuscript submitted to *Wea. Climate Soc.*).

When considering messaging to or from members of the public on social media, atmospheric scientists and emergency management professionals often ask questions about the accuracy or trustworthiness of information or its source (Hyvärinen and Saltikoff 2010; Castillo et al. 2011; Tapia et al. 2011; NRC 2013; Silva et al. 2015). Although such questions are important, the world of online communication is much more complex and dynamic than these questions suggest. The rapid advancement of social computing and the behaviors it facilitates are pushing our understanding of how information is and will be created, communicated, and used as hazardous weather approaches and arrives. Acknowledging these behaviors and appreciating their potential value can help atmospheric scientists engage more effectively with social media to improve weather forecasting, warning, and risk communication.

shelter, or engage in other preparedness action. This framing reflects the limited predictive skill of the past as well as a view that hazard information is created by a few formal sources and transmitted through a limited set of channels to a passive, waiting audience. It also reflects a belief that people respond (and should respond) to risks based primarily on information provided by people and organizations with formal scientific or other professional expertise.

These simplified depictions of information creation, communication, and use have never been accurate, neither for experts nor for the public. Hazard warning communication and response are social processes in which members of the public have always played active roles (Mileti and Sorensen 1990; Drabek 1999; Tierney et al. 2001; NRC 2006; Dash and Gladwin 2007). People are often innovative consumers and disseminators of hazard information. Moreover, they do not interpret and decide how to respond to risks based solely on scientific and technical information originated by official experts. Instead, these processes are influenced by many interconnected factors—including past experiences, risk perceptions, emotions, attitudes and beliefs, and situational motivations and constraints—and are deeply embedded in their social and cultural contexts (Slovic 1987; Loewenstein et al. 2001; Slovic et al. 2004; Gladwin and Peacock 1997; Sorensen 2000; Dash and Gladwin 2007; Taylor et al. 2009; Lindell and Perry 2012; Lazo et al. 2015; Morss et al. 2016a; Demuth et al. 2016).

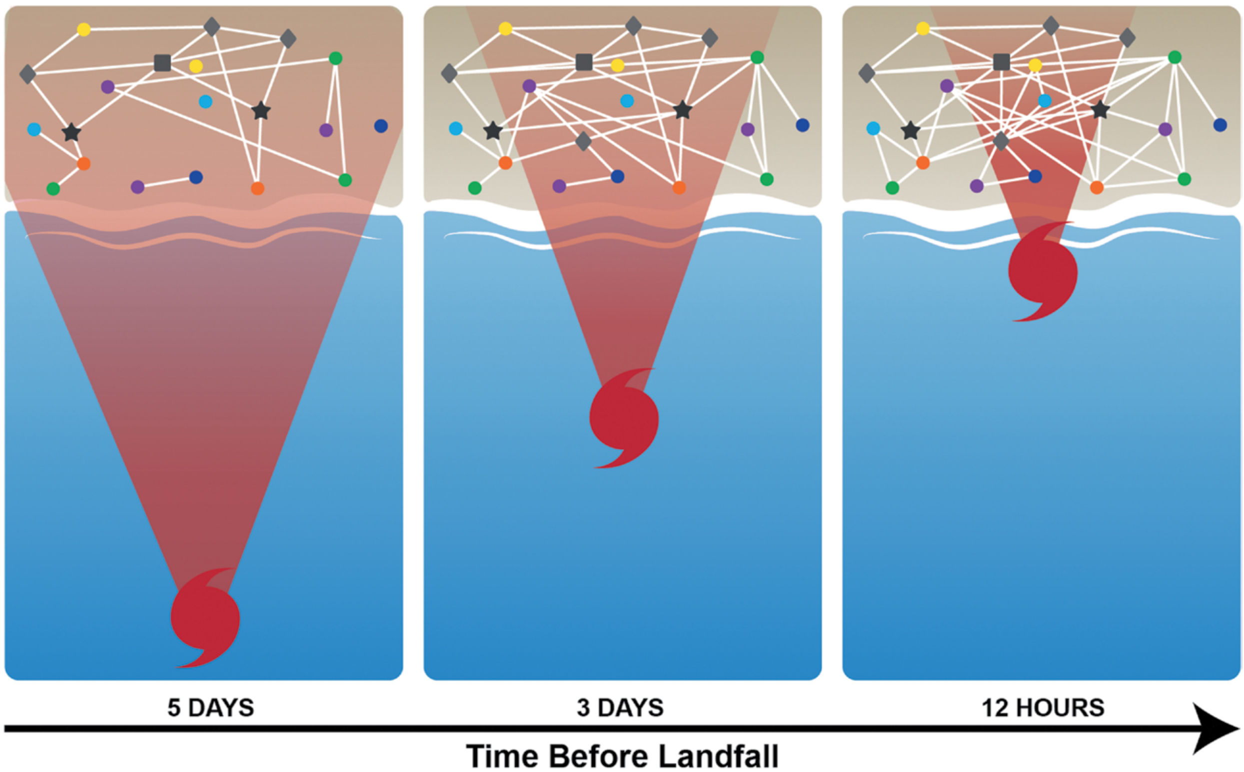


Fig. 1. Simplified depiction of several of the processes that intersect to form the modern dynamic hazard information system, for the example of an approaching hurricane. The evolving hazard is represented by the red hurricane symbol, and the evolving forecasts of the threat and associated uncertainty are represented by the changing area of risk (red shading) as the hurricane approaches the coast. The evolving networks through which people interact to create, communicate, interpret, and use information are represented by the interconnected symbols over land. The symbols represent different actors, including forecasters (square), public officials (stars), information intermediaries (including broadcast and digital media outlets; diamonds), and diverse members of the public (different colored circles). The white lines connecting the symbols represent information flow among actors through connections in the physical and digital worlds.

Although warning communication and response have always been complex processes, recent evolutions in information and communication technology have dramatically increased that complexity. In today's multisource, multimessage communication environment, people can obtain much more and a wider variety of information (Gladwin et al. 2007; Neeley 2013). They can also access and broadcast information more easily, quickly, and frequently, through a rapidly growing array of information networks and digital media. With modern communication technologies, people often receive information even when they are not seeking it because it is pushed to them (e.g., through alerts on wireless devices) or they accidentally encounter it (e.g., by seeing a social media post). New technologies have also expanded the scale and form of interpersonal interactions, transforming how people interact with information and each other. Moreover, these changes are enabling new types of online socially networked groups that allow people to combine, interpret, and generate information in new ways during times of threat (Liu and Palen 2010; Starbird et al. 2010; see sidebar on "Social media, hazard events, and weather risk communication").

Another important evolution during the last few decades is the dramatic improvements in the skill of weather forecasts and warnings (Bauer et al. 2015). Depending on the phenomena involved, potential weather-related threats can now often be identified hours, days, or sometimes even a week or more in advance. As a threat approaches, these predictions evolve to provide more localized, more detailed forecasts and warnings. This forecast information is now accessed and used by many members of the public to help them evaluate the risks posed by approaching hazardous weather (Dow and Cutter 2000; Zhang et al. 2007; Lee et al. 2009). Today's forecast and warning information is not only more accurate, more specific, and available further in advance, it is also more complex and updated more frequently

(Bostrom et al. 2016). Accompanying this rapid expansion in forecast information and its use, the number of forecast interpretations available—especially from the private sector and other nongovernment sources—has exploded. These changes, in conjunction with information and communication technology advances, have transformed the preevent warning and preparedness stage for weather hazards.

The complexities and changes raised by each of these perspectives—from social sciences, computer and information science, and atmospheric science—modify our understanding of how weather forecasts and warnings are created, communicated, interpreted, and used in today's world. Together, they produce a hazard information system that is fundamentally different than it was even a decade ago and that continues to change with new developments in science, technology, and society. Several of the key processes that contribute to the dynamics of this system are depicted in simplified form in Fig. 1.

In Fig. 1, information about an approaching hazard evolves as the hazard and knowledge about it develop. As a hurricane approaches a coastline, for example, uncertainties in forecasts of the hurricane's track are typically reduced, narrowing down the geographic area that is most likely to be at risk. At the same time, predictive information about the likelihood of specific weather phenomena in different areas, such as winds of a certain strength, typically improves. As landfall approaches and uncertainty in the atmospheric predictions decreases, forecasting hurricane-related hazards (such as coastal and inland flooding) and associated impacts at different locations becomes more feasible, although still uncertain. These capabilities for predicting weather-related risks and the predictability limits that bound them are important influences on the system.

As the threat evolves, so do the social interactions (Fig. 1) that influence how information flows through society, is interpreted and reinterpreted, and gets translated into decisions. Enabled by advances in information and communication technology, today's social networks are complex, evolve rapidly, and exhibit emergent behaviors during a threat. As indicated in Fig. 1, forecasters and public officials play important roles in the system by providing new forecast information about the threat and recommendations for protective actions. However, this information typically is not translated directly into protective decisions. Instead, it propagates across social networks and is interpreted and used in combination with the vast quantities of other information from different sources flowing through the system. Moreover, as new forecast and warning information enters the system, it becomes available to many others to disseminate, interpret, and use, and it is often revised or substantively changed in the process. Information about hazard risks can now be created and conveyed not only by formally trained experts but also by millions of interconnected intermediaries and Internet-engaged citizens.

The perspective presented here builds on models of warning response and protective decision-making that include social interactions and feedback loops as people seek or obtain new information (Mileti and Sorensen 1990; Gladwin et al. 2001; Lindell and Perry 2012). It also builds on conceptions of forecast and warning communication that include complex information networks (Gladwin et al. 2007; Lindell and Perry 2012) as well as work that explores people's dynamic interpretations and behaviors as weather threats evolve (Morss and Hayden 2010; Meyer et al. 2013, 2014; Ruin et al. 2014; Morss et al. 2016b). We propose that people are immersed in a vast sea of continuously evolving risk information that they access and interpret through complex, evolving interactions across the physical and digital worlds. Although Fig. 1 depicts the system at distinct points in time, in reality it is a continuum; before people have time to digest and react to one new piece of information, they often have obtained more information to consider. As a threat evolves, people are continually interacting with their natural and social environments, filtering and processing new data, deciding how much to attend to the threat, and updating interpretations and decisions. These features of the modern hazard information system can alleviate or exacerbate people's vulnerabilities to weather hazards by enabling or constraining information access, risk interpretations, and protective decisions (see "Dynamic hazard vulnerability and risk communication" sidebar).

This integrative framework provides a more accurate and more comprehensive paradigm for thinking about and analyzing hazardous weather prediction, communication, and decision-making in the modern information environment. Next, we explore how this framework enables novel research that can yield new forms of knowledge about this system and the processes within it.

BUILDING UNDERSTANDING OF THE DYNAMIC HAZARD INFORMATION SYSTEM.

Studying this system requires approaches that can simultaneously follow individuals, their social and information networks, and system-level behaviors as a threat evolves. The processes we are interested in are nonlinear, rapidly changing, and distributed among a

DYNAMIC HAZARD VULNERABILITY AND RISK COMMUNICATION

When hazardous weather occurs, an important determinant of impacts is the vulnerability of affected populations, in other words, their susceptibility to harm. Not all people are affected equally by a hazard due to their different exposures, sensitivities, and capacities (Morss et al. 2011). Many factors contribute to population vulnerability; here, we focus on how risk communication as a hazard approaches can influence people's experiences and outcomes from hazardous weather events. By integrating concepts from vulnerability research into how we conceptualize the preevent forecast, warning, and preparedness stage, we can deepen our understanding of diverse populations in ways that shift the framing of weather forecast and warning communication.

Vulnerability is often characterized using aggregate population-level demographic and environmental characteristics, such as gender, race, socioeconomic status, and residence type or location (e.g., Cutter et al. 2000). However, in reality, vulnerability is malleable and changes with space, time, and circumstance (Hilhorst and Bankoff 2004; Dilling et al. 2015). Approaches that rely on demographic characteristics alone can describe potential vulnerability at a broad level. However, these approaches can miss important individual-level capacities and behavioral factors as well as hazard-specific aspects of vulnerability. The actual harm that people experience during and after a hazardous weather event depends on their capacities to prepare for and respond to perceived risks and on what they do as the threat unfolds (Adger et al. 2005; Wilhelmi and Hayden 2010; Engle 2011; Hayden et al. 2011). Although demographic characteristics are often associated with differences in capacities and behaviors, other factors, such as risk information and social networks, play important roles.

For example, residents of public housing typically have lower socioeconomic status, and so might be considered highly vulnerable. However, in focus groups conducted in New York City after Hurricane Sandy, we found that social connections enabled by public housing (e.g., with building managers and neighbors) helped some residents access important information about evacuation orders and transportation to shelters, supporting protective decisions (Lazrus et al. 2017). In contrast, some residents of nearby private housing did not receive key information, did not have informed social networks, and were unable to access transportation. This demonstrates how demographic characteristics alone are not adequate to assess population vulnerability. It also illustrates how information as well as the social networks that serve as conduits of that information (Eisenman et al. 2007; Taylor et al. 2009) can enhance people's capacities to manage risks.

The new modes of communication enabled by information technologies can also play important roles in alleviating or exacerbating vulnerabilities. As risk communication increasingly relies on digital platforms, those who are digitally disconnected (i.e., cannot themselves access much, or any, of the information available online) may have more difficulty obtaining important information, which could increase their susceptibility to harm from hazardous weather. However, Lazrus et al. (2012) found that data services on cellular phones have enabled new forms of access to hurricane information among those who are deaf or hard of hearing. Additionally, our post-Sandy focus groups in New York City indicate that some digitally disconnected individuals have other capacities that alleviate these potential vulnerabilities, such as members of their social networks who transmit key information to or from the online world and enable protective actions when needed (Lazrus et al. 2017). In other words, by helping people access and share important information, features of the modern information environment can facilitate social safety nets (Turner et al. 2003) that support behaviors to reduce harm.

These examples illustrate the nuanced, context-dependent nature of vulnerability to weather hazards and the dynamic ways that vulnerability intersects with the modern hazard information system. Approaching vulnerability as evolving and malleable expands our framing to ask how the content and communication of hazardous weather forecasts and warnings can be improved in ways that enable people's capacities to reduce harm, cope with impacts, and recover in the context of their actual situations.

diverse population, which makes obtaining the data needed to understand the full system challenging. For example, when hazardous weather threatens, it is difficult to collect data from a large number of people at risk about how they are interacting with each other and with information and then to follow them through the threat. After an event, it is difficult for people to accurately recall and explain all details about their social interactions, information exchange, perceptions, and decisions across the stages of a threat.

To begin addressing this knowledge gap, we are using two research approaches: analysis of real-world behaviors using social media data and computational experiments using coupled natural–human system modeling. We combine these approaches because they have complementary strengths and limitations; linked by our conceptual framework, they (and other approaches) can inform each other to develop a more comprehensive, deeper understanding.

The system we are studying continues to change rapidly, as science, technology, and society continue to evolve. Any analysis provides, at best, only a snapshot in time. With this in mind, our discussion of the research emphasizes larger-scale, conceptual findings that we anticipate will be relevant beyond the specific times and places studied.

ANALYZING REAL-WORLD BEHAVIORS USING SOCIAL MEDIA DATA STREAMS.

Social media posts offer new sources of first-person data that can help us understand how people are interacting with information and what they are thinking and doing during an event, such as a hazardous weather threat. Microblogging platforms, in particular, facilitate posting quickly and frequently and thus have potential to provide a rich source of near-real-time data for investigating topics such as information flow, information use, and decision-making as a situation evolves. Our current research analyzes data from the microblogging platform Twitter, which has been used to study a variety of sociobehavioral phenomena in hazard events (Hughes and Palen 2009; Houston et al. 2015).[3] We generate meaning from the vast Twitter data available by integrating quantitative and qualitative analyses, informed by our research questions, understanding of the nature of the data, and expertise in the relevant research domains (Kogan et al. 2015; Palen and Anderson 2016; Anderson et al. 2016; Stowe et al. 2016; Bica et al. 2017; Demuth et al. 2017, manuscript submitted to *Wea. Climate Soc.*).

Because social media platforms and their use change rapidly, our aim is not to study Twitter itself. Rather, we are using data from Twitter because it is currently one of the most popular microblogging platforms in the United States and other parts of the world, and the accessibility of its data makes it well suited for this type of research. Data from other social media platforms can be used to investigate similar questions. For example, in China, multiple platforms, including Sina Weibo and Tianya, have been popular and thus have been used for related research (Qu et al. 2009, 2011).

The types of big datasets that platforms like Twitter provide are often used to examine macroscale behavior, using quantitative analyses. For example, much of the current work using Twitter data for hazardous weather research focuses on questions about how many people are tweeting, where, and how frequently (Lachlan et al. 2014; Shelton et al. 2014; Ripberger et al. 2014; Silva et al. 2015; Kryvasheyeu et al. 2016). However, the power of social media data also lies in their potential to provide insight from those who are experiencing a threat through their near-real-time documentation about the experience. The goal of such analyses is not to analyze a representative sample. Rather, by sampling data carefully and then treating these "found" data similarly to data gathered using other ethnographic methods, we can develop in-depth understanding about processes of interest.

To demonstrate some of the ways that social media data can be analyzed and what these data can reveal, here we present examples from our ongoing analyses of Twitter data created during a recent hazardous weather threat: Hurricane Sandy.[4] We start with macroscale analyses of large Twitter datasets and then focus our attention inward to examine data from a significantly affected, socioeconomically diverse neighborhood and narratives from individual locals at risk. As a complement to the Twitter data analysis, we also conducted focus groups in neighborhoods of New York City, New York, that were significantly affected by Hurricane Sandy, with an emphasis on populations who are less likely to be active on social media (Lazrus et al. 2017). By combining Twitter analyses with these focus groups, we aim to address interrelated research questions using different data collection methodologies and complementary samples, integrated by our broader conceptual frame.

As an entry point for studying Hurricane Sandy, our research team collected Twitter data in real time using eight Sandy-related keywords (including hurricane, Sandy, Hurricane Sandy, and frankenstorm) starting on 24 October 2012, 5 days before Sandy's U.S. landfall (Kogan et al. 2015; Palen and Anderson 2016). As shown in Fig. 2, millions of people tweeted using Sandy keywords during the threat. The frequency of tweets containing Sandy keywords increased significantly on the day prior to landfall (28 October), as evacuation orders were announced for major populated areas such as New York City. It dipped during the overnight hours in the United States and then peaked near the time of landfall on the evening of 29 October. After another, smaller overnight dip, there was a secondary peak on the morning after landfall.

To identify the place of origin of a tweet, one can use the tweet's geolocation (latitude, longitude) information, although only a small subset of tweets is geotagged (typically less than 2%). As shown in Fig. 3, the Sandy keyword dataset includes tweets from around the world. An animation of these data (more information can be found online: https://doi.org/10.1175/BAMS-D-16-0058.2) shows that several

[3] Twitter communications (called tweets) are limited to 140 characters, but individual tweets can provide more than 140 characters' worth of data by linking to other online content, such as images, web pages, and posts on other social media platforms that allow longer formats.

[4] Although Sandy transitioned into a posttropical cyclone, for simplicity, we refer to the storm as Hurricane Sandy or simply Sandy.

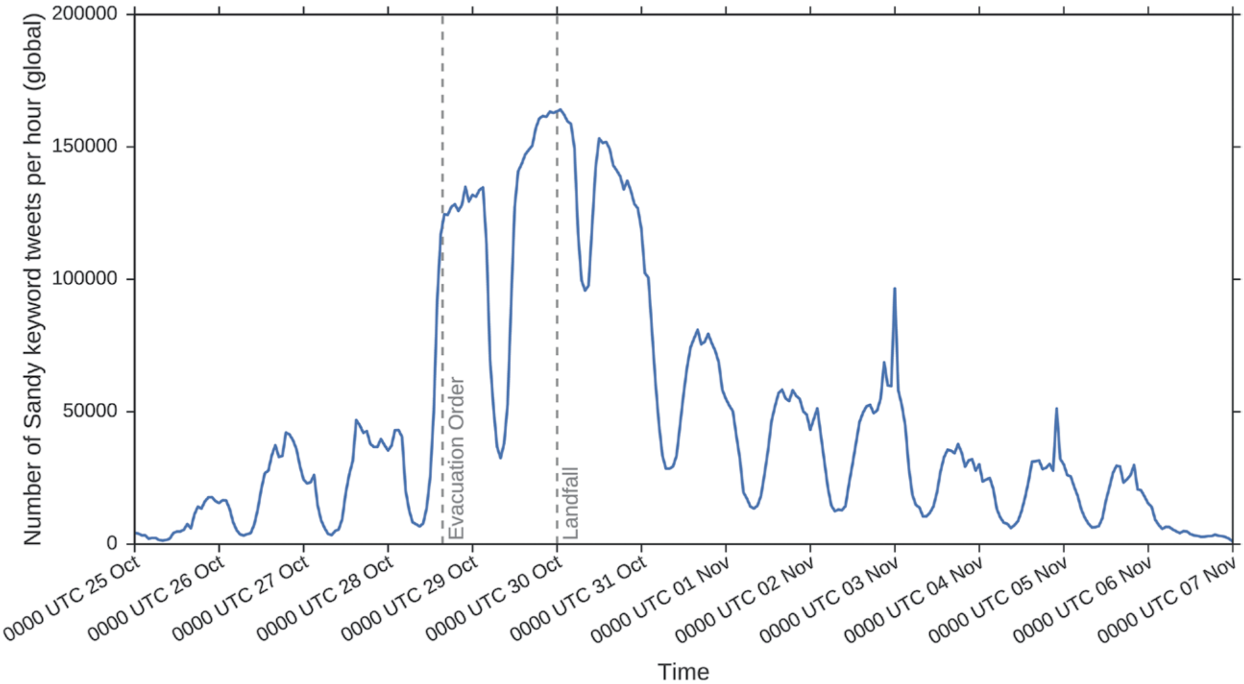


Fig. 2. Number of tweets in the Sandy keyword Twitter dataset, during each hour from 0000 UTC 25 Oct to 0000 UTC 7 Nov 2012. The dashed vertical lines indicate the approximate times when the mayor of New York City announced an evacuation order for areas of New York City (1530 UTC 28 Oct 2012) and when the center of Sandy made U.S. landfall (2330 UTC 29 Oct 2012). At landfall, local time [eastern daylight time (EDT)] is 4 h earlier than UTC. During the 13-day period shown, this dataset contains approximately 14.4 million tweets from 5.3 million Twitterers; 1.1% of the tweets are geotagged.

days before landfall, geotagged Sandy keyword tweets are generated primarily in the Caribbean and eastern coastal United States (in the areas directly at risk). As the storm approached and then affected the mainland United States, the Twitter conversation using Sandy keywords expanded across the United States and then quickly spread around the globe.

The data in Figs. 2 and 3 combine many different types of conversations about Sandy, from global to local. We are interested in extracting from these online conversations new understandings about how people interact with, interpret, and respond to evolving information about approaching weather threats. For this analysis, we must identify Twitterers who are evaluating the threat and deciding what to do. Approaches for narrowing large social media datasets such as those in Fig. 2 include random or opportunistic selection, searches for terminology representing concepts of interest, or use of geotagged tweets. However, none of these strategies yielded a suitable sample of Twitterers for our analyses.[5] Thus, we developed a sampling approach that focused on geographic areas at high risk, without relying on geotagged data.

Rather than examine individual tweets, we analyze Twitterers' full "contextual" tweet streams, in other words, their full sequence of tweets during the period of interest, regardless of the presence of a keyword (Anderson et al. 2016; Palen and Anderson 2016). We do so, first, because people often tweet about a topic without using specific researcher-defined keywords, and so limiting analyses to only tweets containing certain terms can introduce biases. In addition, individual tweets often have new meaning when viewed in the context of a Twitterer's narrative—the story that develops in their Twitter stream. Tweet streams also provide far richer data than individual tweets about how processes evolve and interact over time.

Here, we utilize Twitterer narratives from Far Rockaway, Queens, New York, which was in a

[5] Random selection of keyword tweets yields a dataset focused on the global response rather than those who are directly at risk. Terminology-based searches miss the large number of tweets about concepts of interest that do not use that (researcher defined) terminology (see, e.g., the example "stationary" tweet in Fig. 5 and the example "move somewhere safer" tweet in Fig. 6). Relying on geotagged tweets also misses the vast majority of data, and initial analyses using geolocated tweets to identify Sandy Twitterers in areas at risk yielded few people of interest for understanding risk interpretations and protective decision-making.

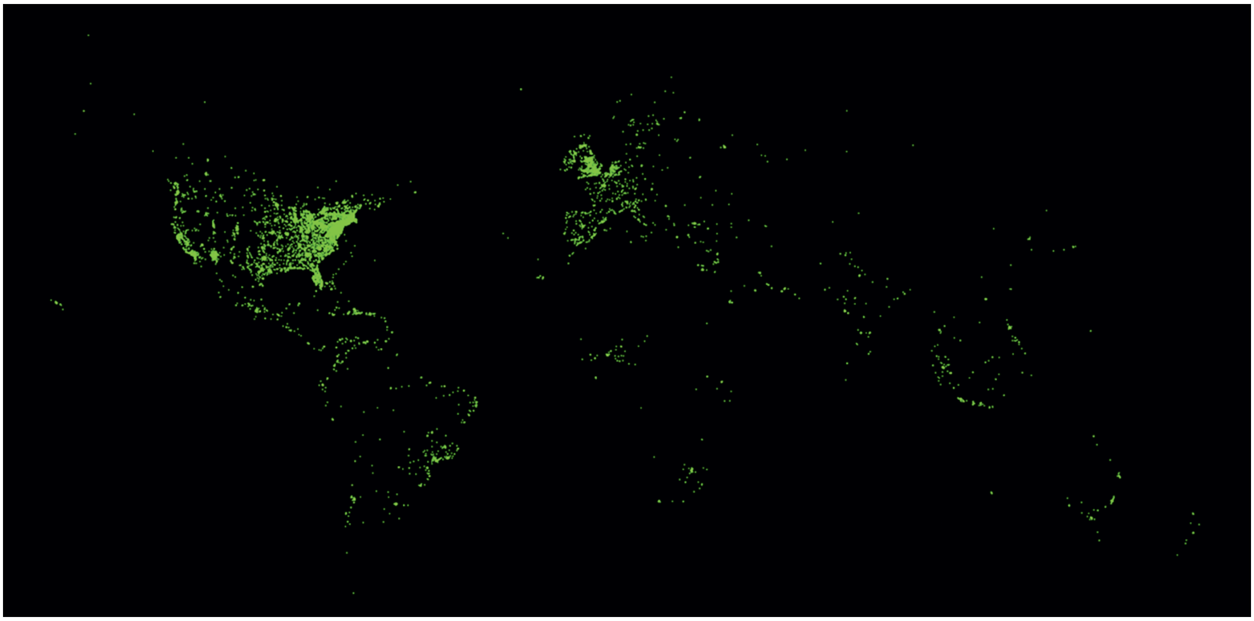


Fig. 3. Geographical distribution of the geotagged tweets in the Sandy keyword Twitter dataset shown in Fig. 2. During the period shown (0000 UTC 25 Oct–0000 UTC 7 Nov 2012), this dataset contains approximately 160,000 tweets from 92,000 Twitterers. (For an animation of the temporal evolution of these data, see the online supplement.)

mandatory evacuation zone for Sandy, experienced major flooding from storm surge, and is socioeconomically diverse. Using the methods discussed in Anderson et al. (2016) and Demuth et al. (2017, manuscript submitted to *Risk Anal.*), we examined contextual Twitter streams to identify a sample of Twitterers who lived in or very near Far Rockaway as Sandy approached. Each tweet in each of those streams was then coded as either relevant to Sandy or not, in the context of its narrative, as well as by the topics in a coding scheme that our interdisciplinary research team developed to help analyze how factors related to people's hazard information use, vulnerabilities, and decision-making are represented in social media data (Anderson et al. 2016; Stowe et al. 2016).

Figure 4 shows how the number of Sandy-relevant tweets in the Far Rockaway contextual dataset evolves over time, compared to the Sandy keyword tweets in this dataset. As this illustrates, adding the contextual tweets provides many additional relevant tweets that help fill in Twitterers' narratives, especially during and after landfall. Compared to the global keyword dataset in Fig. 2, the frequency of Sandy-relevant tweets from these Far Rockaway residents exhibits a similar peak as the evacuation order for Far Rockaway is announced and then a much sharper peak near the time of landfall, as Far Rockaway experiences the worst of Sandy's winds and flooding. Unlike the global Sandy Twitterers, many in the Far Rockaway dataset are relatively silent on Twitter after landfall because they lost power for an extended period or for other reasons as they dealt with Sandy's impacts.

To help illustrate what we can learn from examining these types of Twitter narratives in greater depth, Figs. 5 and 6 depict the evolution of two individual Far Rockaway Twitterers' tweet streams during a 7-day period around the time of Sandy's landfall. Figure 5 depicts a rare example in the Sandy Twitter data of a nonmeteorologist who explicitly references weather forecasts. He also gathers data from his own observations of what others are doing and, as landfall approaches, from natural and built environmental cues related to the storm. Although he sometimes uses humor when discussing Sandy, his tweets also indicate that he is aware of and worried about the potential for harmful impacts from Sandy, including life-threatening flooding. As the storm approaches, his tweets shift to focus more and more on Sandy compared to other topics, reflecting his concern. He discusses the threat of surge as well as wind, and he knows that he lives in an evacuation zone and about New York City's evacuation order. Nevertheless, he decides to stay in his home through the storm, for multiple reasons revealed in his tweet stream. Then, at landfall, his home floods, leaving him surprised and frustrated.

Figure 6 depicts a person who, like most in our Sandy Twitter data, does not explicitly reference a

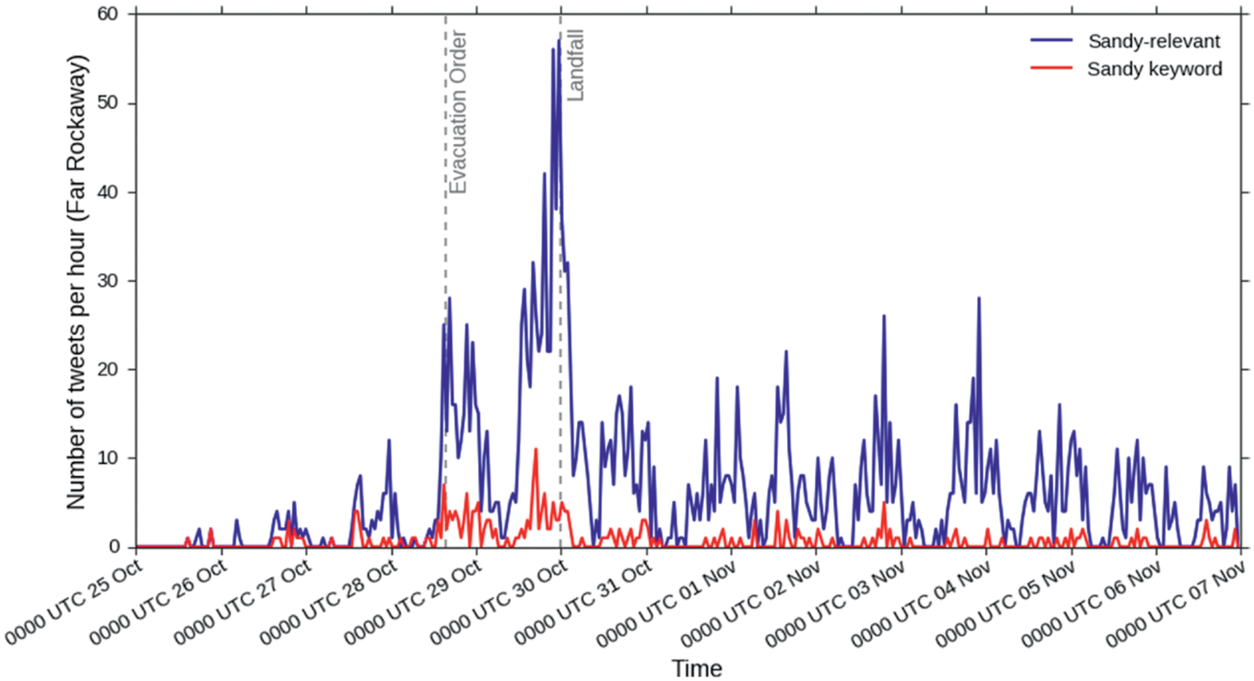
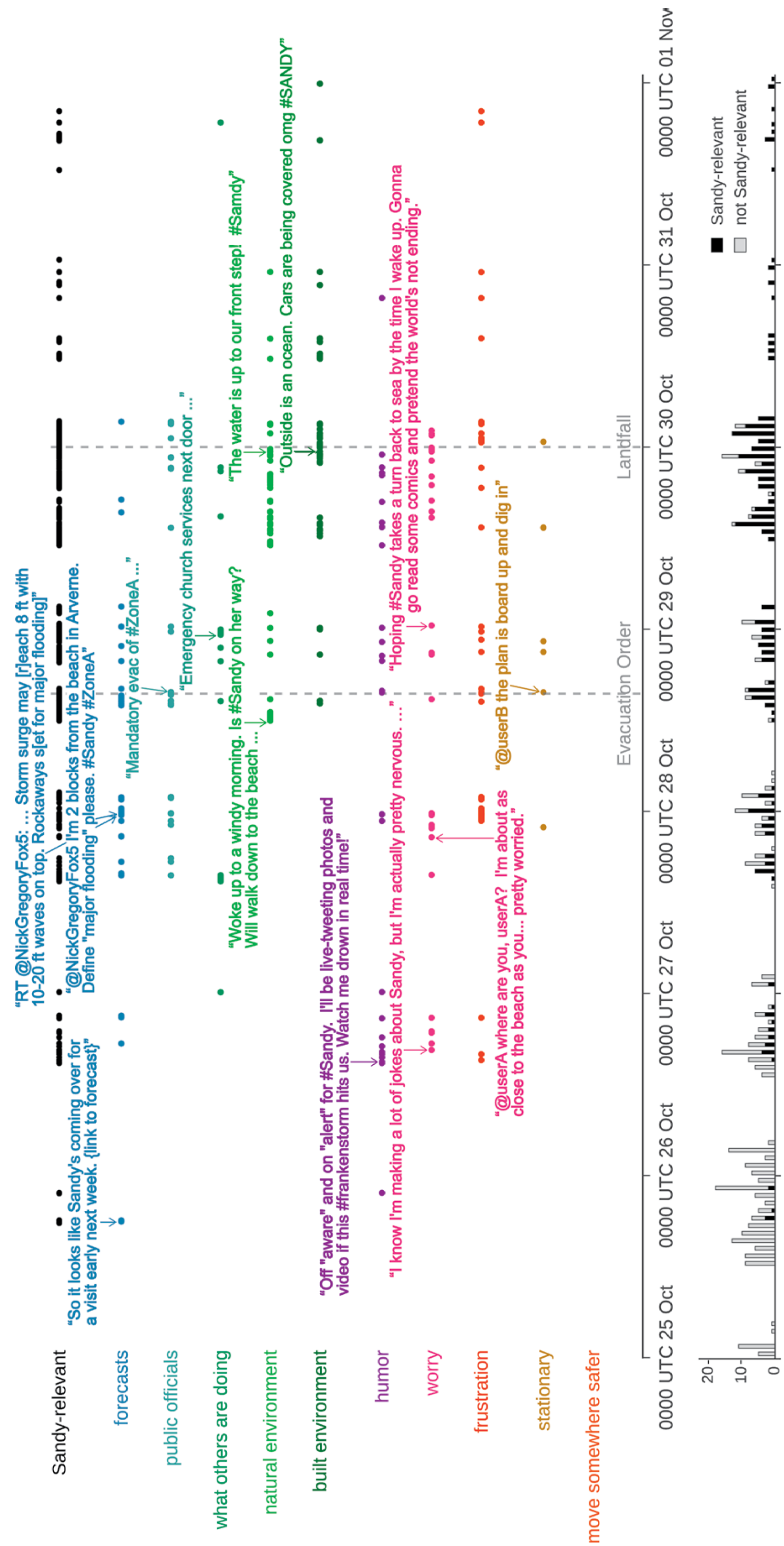


Fig. 4. As in Fig. 2, but for the number of Sandy-related tweets (blue line) and Sandy keyword tweets (red line) in the Far Rockaway (New York) contextual Twitter dataset. The dashed vertical lines represent the timing of the New York City evacuation order and Sandy's U.S. landfall, as in Fig. 2. During the period shown, this dataset contains 2,378 Sandy-related tweets from 58 Twitterers; only 268 of these tweets contain one of the Sandy keywords used in data collection, and only 70 Sandy-related tweets are geotagged.

weather forecast. However, the influence of forecast information is indirectly revealed by her tweets about Sandy beginning several days before landfall. She is aware of the risk to Far Rockaway and is worried about Sandy. Nevertheless, shortly after the evacuation order is issued, she tweets that she is not evacuating. The morning of landfall, she tweets about seeing high ocean waves and flooding in Far Rockaway. Her tweets then indicate that she has changed her decision to stay home and has moved to a sturdier building nearby where a relative lives.

These narratives show how social media data streams, carefully sampled and analyzed, can reveal new insights about the dynamic ways in which people evaluate and respond to approaching hazardous weather threats. For example, Figs. 5 and 6 illustrate how people gather and use different types of information and how they interact with others to evaluate a threat and decide what to do as a threat evolves. They also illustrate the complex evolution of people's interpretations of risks, emotional and other coping responses, and decisions. These and additional findings

► Fig. 5. Graphical depiction of an example tweet stream produced by a Far Rockaway resident as Sandy approached and arrived. (top) The temporal evolution of this Twitterer's Sandy-relevant tweets (black dots) and tweets related to 10 different topics related to Sandy (colored dots), along with sample content from individual tweets. The topics and sample tweets were selected to illustrate how attention to different types of information evolves in conjunction with Sandy-related sentiments and protective decision making. The topics represent, from top to bottom, Sandy-relevant tweet content that mentions weather forecasts or forecasters; mentions public officials or their information or actions; mentions what others are doing related to the threat (social cues); mentions natural or built environmental cues; indicates attempts at humor; indicates worry, fear, or anxiety; indicates frustration, anger, or defiance; mentions staying at home during the threat; or mentions moving somewhere safer related to the threat. Each tweet could be coded into multiple categories or none. The sample tweet content is represented using the color of one of the topics with which that tweet was coded; "RT" indicates a retweet, and "@" represents the mention of another Twitterer (@ mentions of members of the public were anonymized). (bottom) The temporal evolution of this Twitterer's tweet volume and Sandy-relevant tweet volume on the same time axis as in the top panel. Note that many tweets are quasi-real-time posts (indicating the Twitterer's current situation), but some tweets are summative or retrospective posts (indicating the Twitterer's past situation, reported after the fact). The dashed vertical lines represent the timing of the New York City evacuation order and Sandy's U.S. landfall, as in Figs. 2 and 4.



Sandy-relevant
forecasts
public officials
what others are doing
natural environment
built environment
humor
worry
frustration
stationary
move somewhere safer
"So it looks like Sandy's coming over for a visit early next week. {link to forecast}"
"RT @NickGregoryFox5: … Storm surge may [r]each 8 ft with 10-20 ft waves on top. Rockaways s[et for major flooding]"
"@NickGregoryFox5 I'm 2 blocks from the beach in Arverne. Define "major flooding" please. #Sandy #ZoneA"
"Mandatory evac of #ZoneA …"
"Emergency church services next door …"
"Woke up to a windy morning. Is #Sandy on her way? Will walk down to the beach …"
"The water is up to our front step! #Samdy"
"Outside is an ocean. Cars are being covered omg #SANDY"
"Off "aware" and on "alert" for #Sandy. I'll be live-tweeting photos and video if this #frankenstorm hits us. Watch me drown in real time!"
"I know I'm making a lot of jokes about Sandy, but I'm actually pretty nervous. …"
"Hoping #Sandy takes a turn back to sea by the time I wake up. Gonna go read some comics and pretend the world's not ending."
"@userA where are you, userA? I'm about as close to the beach as you… pretty worried."
"@userB the plan is board up and dig in"
Evacuation Order
Landfall
0000 UTC 25 Oct
0000 UTC 26 Oct
0000 UTC 27 Oct
0000 UTC 28 Oct
0000 UTC 29 Oct
0000 UTC 30 Oct
0000 UTC 31 Oct
0000 UTC 01 Nov
20
10
0
Tweets per hour
Sandy-relevant
not Sandy-relevant

are discussed further in Anderson et al. (2016) and Demuth et al. (2017, manuscript submitted to *Risk Anal.*).

The example results in Figs. 2–6 illustrate that finding robust, meaningful signals of interest about the complex hazard information system in the vast data available online is not an easy task. Decisions about how to collect, sample, and analyze social media data can inadvertently limit or skew a study's results. Therefore, it is important to design and implement each analytical step using knowledge about the processes being studied and the strengths and limitations of different analytic techniques. Quantitative and automated data processing techniques (such as natural language processing, text classification, and information diffusion analyses) can help build understanding (Verma et al. 2011; Imran et al. 2015; Kogan et al. 2015; Stowe et al. 2016; Bica et al. 2017). However, tweets use free-form language, including unique grammar and spellings and can contain embedded symbols, links, and images. By focusing in on locals at risk, without relying on tweets that are geotagged or use certain terminology, we uncover rich, diverse stories about people's thoughts, feelings, experiences, and actions as a threat evolves. Once we understand how the concepts and processes of interest are represented in the data and how to find them, we can use this knowledge to apply automated processing techniques and interpret the outputs of quantitative analyses in more valid, informative ways.

Like all data, social media data have important limitations that must be considered when performing analyses and interpreting results. One limitation is that social media provides data only from those who are online and posting on that platform, when and about what they are posting. While we do not present the Twitter analysis results as generalizable, we also take other steps to involve populations who may not be engaged with social media. In our research on Hurricane Sandy, we are complementing the Twitter analysis with focus groups with people from Spanish- and Russian-speaking communities, residents of public and senior housing, and other populations, investigating how risk communication related to Sandy interacted with population vulnerabilities (Lazrus et al. 2017). Insights from the focus groups help us identify indicators and discussions of vulnerability in the social media data that we may not have seen otherwise. They are also helping us understand the roles of information, social networks, and other factors in protective decision-making among people who do not personally use social media. By purposively designing and implementing this empirical mixed-method approach, we aim to develop new understandings from multiple investigative angles about how diverse populations are engaging with the dynamic hazard information system and making decisions as hazardous weather approaches.

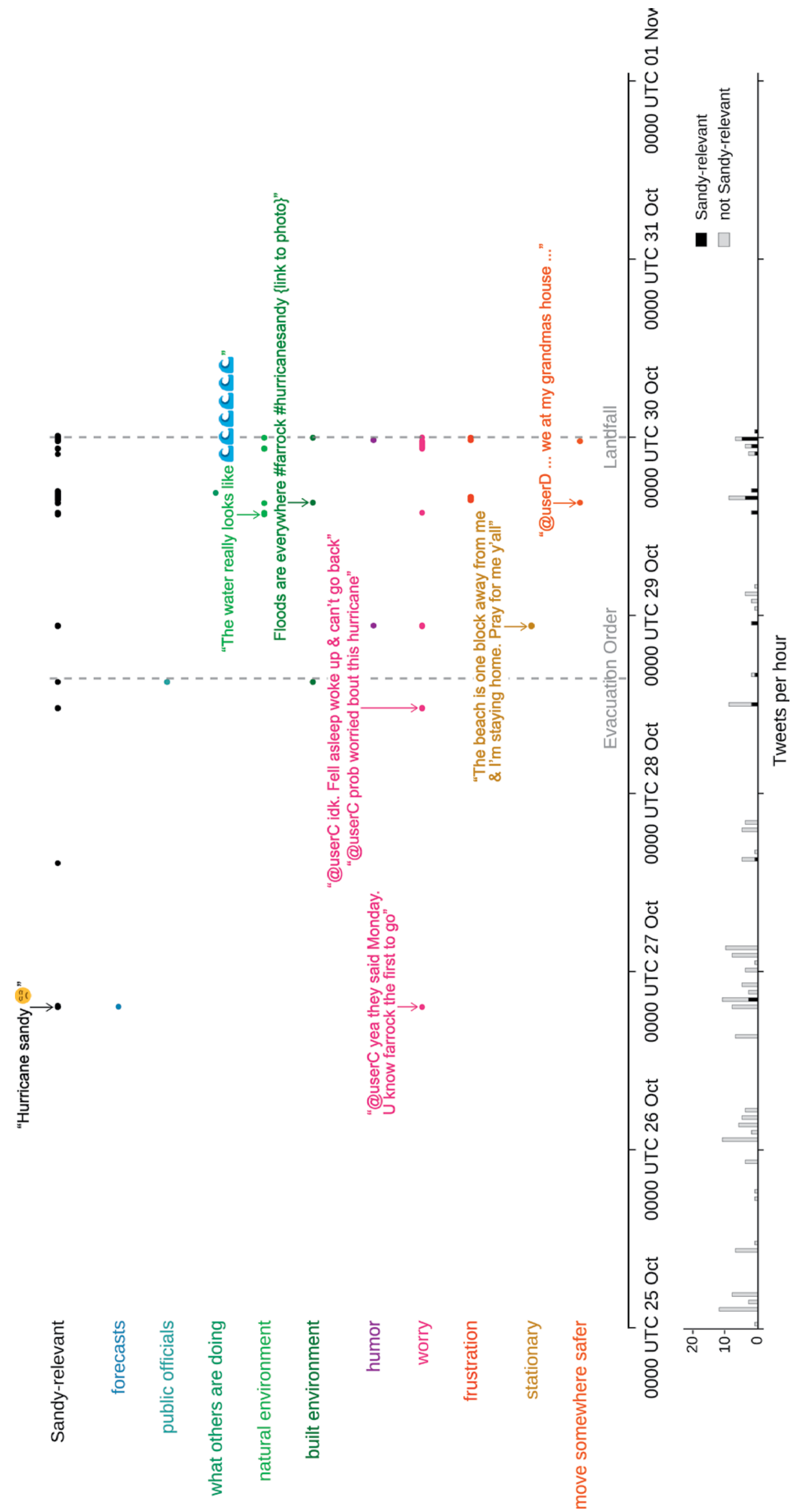
COMPUTATIONAL MODELING OF THE COUPLED NATURAL–HUMAN SYSTEM.

Coupled natural–human systems such as that examined here exhibit complex dynamics that are challenging to comprehensively investigate. Computational modeling can provide a laboratory for investigating the system's behavior in different scenarios by conducting experiments that would be impossible to perform in the real world. With computational modeling research, we are not attempting to predict the decisions of real people in real situations or to digitally recreate the complete behavior of the real system. Rather, we are using models to provide a controlled setting for exploring how the system's component processes interact and how they influence the system dynamics and outcomes of interest under different circumstances.

Computational natural–human system modeling can take multiple forms (Rounsevell et al. 2014; Barton et al. 2016; Verburg et al. 2016; Moss et al. 2016); the most appropriate modeling tools depend on the spatial and temporal scales, processes, and interactions of interest. The approach we use here combines geophysical modeling of hurricanes and hurricane-related hazards with a model of interactive human decision-making in response to evolving social and environmental information.

The geophysical component of the modeling laboratory couples atmospheric predictions of landfalling hurricanes with storm surge inundation modeling. Initially, we are using idealized representations of hurricane forecast uncertainty as input to the advanced circulation (ADCIRC; Luettich and Westerink 2004) storm surge model (Fossell et al. 2017); this can later be extended to also use numerical modeling for the atmospheric component. We are using this hurricane surge modeling, first, to investigate the practical predictability of storm surge by examining the propagation of uncertainty in atmospheric predictions into surge predictions. This research is building fundamental scientific knowledge about the predictability of coupled atmosphere–hazard systems. The findings can also be of practical use to forecasters and forecast users by indicating the potential for providing different types of hazard forecasts at different lead times

▶ **Fig. 6. As in Fig. 5, but for a second example tweet stream from a Far Rockaway resident.**



Sandy-relevant
forecasts
public officials
what others are doing
natural environment
built environment
humor
worry
frustration
stationary
move somewhere safer
"Hurricane sandy"
"The water really looks like"
Floods are everywhere #farrock #hurricanesandy {link to photo}"
"@userC idk. Fell asleep woke up & can't go back"
"@userC prob worried bout this hurricane"
"@userC yea they said Monday. U know farrock the first to go"
"The beach is one block away from me & I'm staying home. Pray for me y'all"
"@userD ... we at my grandmas house ..."
Evacuation Order
Landfall
0000 UTC 25 Oct
0000 UTC 26 Oct
0000 UTC 27 Oct
0000 UTC 28 Oct
0000 UTC 29 Oct
0000 UTC 30 Oct
0000 UTC 31 Oct
0000 UTC 01 Nov
20
10
0
Tweets per hour
Sandy-relevant
not Sandy-relevant

in different situations. For example, results from our coupled hurricane–surge experiments suggest that typical errors in current hurricane track forecasts severely limit the skill of location-based storm surge predictions beyond 12–24-h lead times, except for unusually large storms (Fossell et al. 2017). In addition, we are using the hurricane–surge modeling to help design and conduct modeling experiments investigating how evolving information about approaching hurricanes interacts with the human system.

The human component of the modeling laboratory is an agent-based model (ABM), a form of computational simulation in which autonomous "agents" are provided with simple rule sets for perceiving their environments and making decisions that influence subsequent model states (Bankes et al. 2002; Miller and Page 2007). In an ABM, agents can reside in different parts of a spatially explicit virtual world and have different social connections, and hence have different natural and social environmental experiences. Thus, agents with the same rule sets can obtain different information and make different decisions, resulting in emergent patterns at the aggregate system level. Different populations of agents can also be given different rule sets, and individual agents can have characteristics that vary across the population and influence their decisions.

Because of its adaptable, bottom-up approach to representing decisions and interactions of heterogeneous agents at multiple scales, agent-based modeling offers scientists a powerful toolkit for investigating complex social behaviors (Miller and Page 2007; Barton 2014). Increasingly, ABMs are being employed to represent interactions and feedbacks between natural and human systems (Parker et al. 2003; French 2010; Boone et al. 2011; Rounsevell et al. 2012; Farmer et al. 2015; Barton et al. 2016). In the weather and climate realm, however, most of this work emphasizes time scales of months, years, or longer, unlike the shorter time scales of interest here. Our research also extends this type of work by modeling agents that are influenced by information about the anticipated future weather or climate (i.e., forecasts) as well as the environmental conditions themselves. In the hazards arena, ABMs have been used to model human behaviors for approaching hurricanes (Chen et al. 2006; Zhang et al. 2009; Widener et al. 2013; Yin et al. 2014) and other natural hazards (Dawson et al. 2011; Wang et al. 2016). Our modeling advances this application of ABMs by taking a novel and sophisticated approach to studying hazard information flow and decision-making, simulating an imperfect, socially interactive, dynamic information environment.

The ABM we have developed includes a spatially explicit landscape, weather hazards that move across that landscape, forecasts that evolve with the hazards, and computational agents that are abstractions of people who obtain, process, and share information and make protective decisions as a hazard approaches and arrives. The ABM and its behavior are discussed further by Watts et al. (2017, manuscript submitted to *Environ. Modell. Software*), and the model code and detailed description are available for download in the Network for Computational Modeling for Socio-Ecological Science (CoMSES Network) model library online (www.openabm.org/model/5504). Here, we briefly describe key features of the ABM and then present an example model run to illustrate how this type of computational social science can be used for exploring natural–human system interactions.

The current version of the ABM contains several types of agents, representing the major actors in weather forecast, warning, and response systems (Demuth et al. 2012; Brotzge and Donner 2013; Morss et al. 2015; Bostrom et al. 2016). As in the real world, the majority of the agents in our simulations represent members of the public. These citizen agents can seek, receive, and transmit information; combine information from different sources; and process that information to decide whether to take protective action. Other agent types represent weather forecasters (who transmit forecast information into the model world), information intermediaries (including broadcast media and Internet information aggregators), and public officials (who can issue protective action information). We developed the rule sets for agent decision-making using the literature on how people obtain, interpret, and use information for hurricanes and other weather hazards (e.g., Dash and Gladwin 2007; Lindell and Perry 2012; Demuth et al. 2012), in conjunction with relevant expertise from members of our research team.

The ABM can carry out experiments with real or synthetic weather events and forecasts, and the virtual environment can be idealized or use real-world data about relevant natural (e.g., topography and coastlines) and social (e.g., census data, political boundaries) features. This flexibility allows researchers to compare the model's behavior with outcomes in real-world cases, while also allowing a wide range of experiments. The model is currently implemented for a hurricane making landfall along a U.S. coastline, but the modeling framework is designed to be adaptable to other types of weather hazards and regions.

Figure 7 depicts the temporal evolution of a single 5-day run of the current version of the ABM

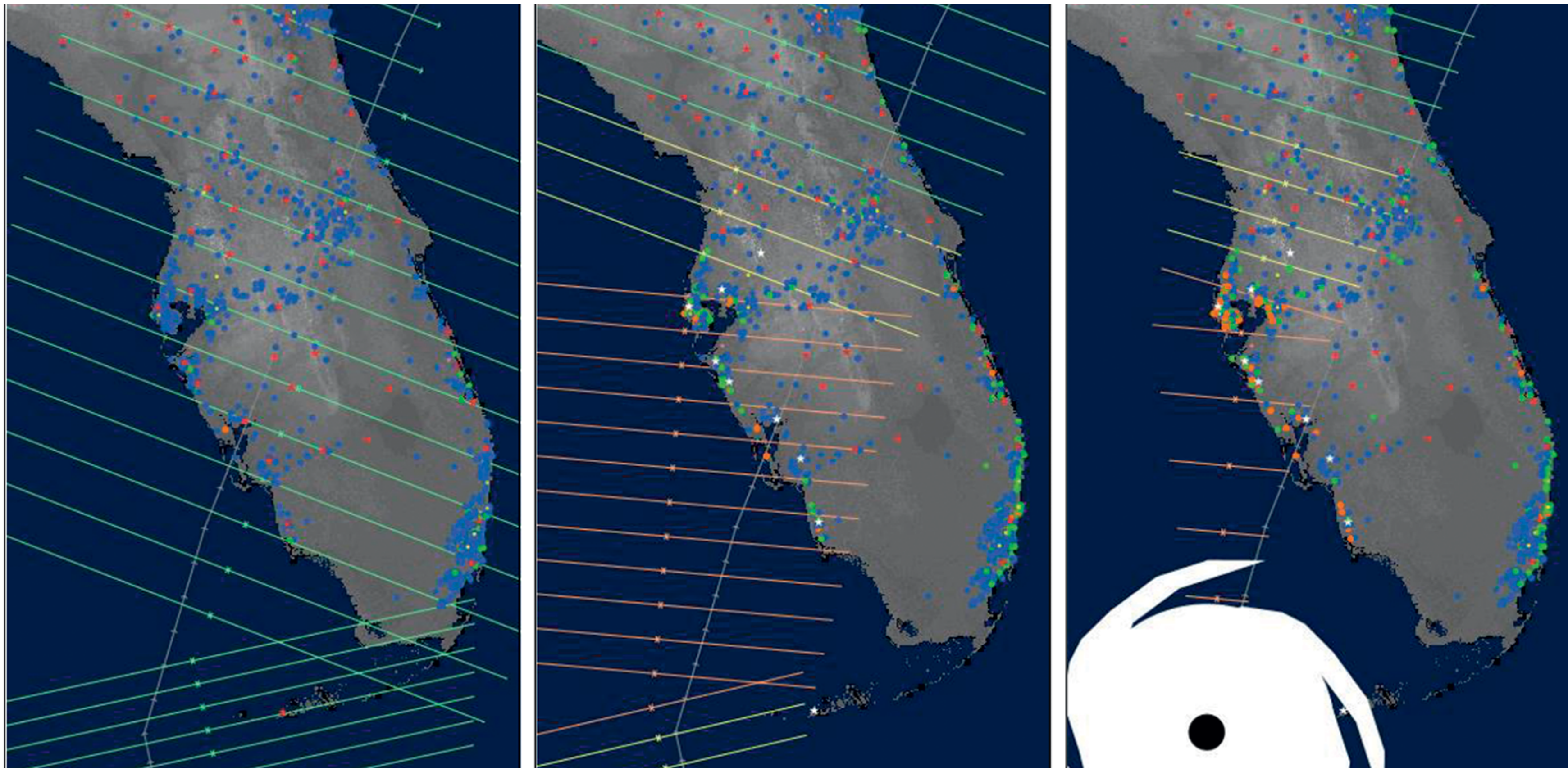


Fig. 7. Time series depicting the evolution of a single ABM run for a hurricane approaching and then crossing the state of Florida from southwest to northeast. In this example, the virtual world was generated using GIS data; a subset of the model domain is shown. The evolution of the hurricane, hurricane forecasts, and hurricane track forecast uncertainty were derived from Hurricane Charley (2004), using National Hurricane Center (NHC) best-track data, the NHC forecast archive, and the radii of the NHC forecast cone circles in 2004, respectively. Times shown are (left) 36, (middle) 60, and (right) 84 h after the start of the run, which begins approximately 92 h before the hurricane eye makes landfall. The purple line with hatch marks represents the hurricane's track; the storm's position at the current time and approximate size is depicted with a white tropical storm symbol, visible as it approaches the coast in the right panel. The series of different-colored lines represents the hurricane's forecasted track (cross at center of each line) and associated track uncertainty (lines, representing historical track forecast errors) for the most recent NHC forecasts available at each time, with the cross and line colors representing the storm's forecasted intensity at each forecast time (green = category 1, yellow = category 2, orange = category 3, and red = category 4 or 5 hurricane on the Saffir–Simpson scale). This run includes 1 forecaster agent, 10 broadcaster and 10 aggregator agents (small yellow and pink circles), and 67 public official agents (one for each Florida county, located at county seats; red stars changing to white if that agent issues evacuation orders). The run has 1,000 citizen agents (dark blue circles changing to green if an agent decides to gather information more frequently and orange if an agent decides to evacuate) distributed quasi realistically in the landscape based on U.S. Census data from the year 2000. (For an animation of the temporal evolution of the full ABM run, see the online supplement.)

(animation available in the online supplement). As the simulation evolves, public officials who perceive that their counties are at risk based on the forecasts decide to issue evacuation orders (white stars in the middle and right panels in Fig. 7). Before any evacuation orders are issued (left panel), a few citizen agents have decided to gather information more frequently (green circles) or evacuate (orange circles) based on their evaluations of the risk using the forecast information they have received up to that time. Once the evacuation orders have been issued and disseminated (right panel), this information, in conjunction with the evolving forecast information, contributes to more citizen agent evacuation decisions. As the storm begins to affect land (not shown in Fig. 7), environmental cues (such as strong winds) motivate additional citizen agents to decide to evacuate. As expected given the hurricane's track and the forecasts, evacuation orders and evacuating citizens are focused in coastal western Florida, near where the storm made landfall and to the north (where the storm was predicted to make landfall at 1–2-day lead times; middle and right panels). However, as in the real world, people's protective decisions vary both in and out of these areas.

Because the ABM includes stochastic elements (e.g., through randomly distributed parameters in the citizen agents' rule sets), it can exhibit different behaviors even under a single set of model parameters and conditions. Thus, each experiment is repeated multiple times to assess central tendencies and variability in the model's behavior. Multiple sets of experiments can then be run, varying the model parameters and inputs, to investigate how information flows through the computational system, assess how information transforms across time and space and is translated into decisions, characterize emergent system-level patterns, and compare outcomes of interest. In this way, the modeling laboratory can be used to investigate the effects of changing different aspects of the natural or human system or the couplings between them (J. Watts et al. 2017, unpublished manuscript). When performing such experiments, we can observe the model's behavior at multiple scales simultaneously, from the individual agent to the system level. Interpreted in conjunction with findings from empirical research, these modeling experiments can help develop new insights about the system's dynamics and the ways in which different processes interact.

THE FUTURE OF HAZARDOUS WEATHER RESEARCH, PREDICTION, AND COMMUNICATION. This article articulates an integrative framework for understanding the creation, communication, interpretation, and use of hazardous weather information as evolving, interconnected processes. It then demonstrates how these processes interact in a dynamic system using examples from novel research. The framework recognizes that weather hazards and information about them evolve, along with the associated uncertainties. It recognizes that risk communication likewise evolves and that it includes information created by and exchanged with many different sources in the physical and digital worlds. It recognizes that people's hazard-related risk perceptions and decisions evolve, as new information becomes available and is propagated and interpreted within its larger social and cultural context. And it recognizes that individuals and populations have different capacities to prepare for, respond to, and recover from hazards and that these capacities evolve based on risk communication, circumstances, and other factors.

The framework provides an important conceptual and analytical starting place; it allows us to see important features of the system, which then makes these features available for analysis. Without the framework, we could not have designed or implemented our research approaches, and we would have struggled to make sense of the dynamic, interconnected processes that are revealed by the social media, computational modeling, and other data. The research examples also illustrate and support the larger framework, which ongoing research will continue to refine and clarify.

The framework and research examples illustrate how interdisciplinary research can integrate different intellectual and methodological approaches rigorously to develop a broader, deeper understanding. At the same time, the interdisciplinary integration helps us articulate research directions—related to weather risk communication and decision-making in the age of social media, dynamic population vulnerability as a hazard approaches, coupled weather–hazard predictability, and other topics—that lead to novel contributions within multiple fields of study.

What are the implications of the reality of hazard communication as a dynamic, interconnected system? Our empirical analyses and computational experiments indicate that weather forecasts and warnings play critical roles in the hazard information system by initiating the threat recognition process and helping guide how information about the threat evolves. Public officials' evacuation orders also play critical roles by helping spur protective actions. However, these professionals and the information they provide are only a small subset of the many actors and pieces of information within the system. Once information enters the public sphere, it can rapidly propagate and transform; the information's original creators have limited control over how it is interpreted and used. As the Twitter narratives illustrate, even people who receive forecasts, warnings, and protective action recommendations for an approaching hazard and are aware of and worried about the risks may decide not to take protective action until they see first-hand evidence of the threat. There are also many contextual factors that influence people's access to information, their interpretations of risks, and their capacities to take protective action. The framework we present and these findings of our research can help atmospheric scientists and weather forecasters understand these realities and engage more effectively with the modern hazard information system.

What does this new paradigm mean for the future of hazardous weather prediction and communication? The scientific and sociotechnical revolutions of the last few decades have transformed the creation, communication, and use of information about hazard risks, setting the stage for new relationships among geophysical science, computer and information science, and risk and hazards research and practice. To take full advantage of these advances, it will be critical to incorporate the roles played by members of the public—including the complex, creative ways that they are using information and communication technologies—into how we approach creating and communicating hazardous weather information. People often have valuable knowledge about the risks that they are exposed to, and they can integrate, convey, and use information in ways that professionally trained meteorologists and emergency management personnel might never have imagined. As discussed by Fischhoff (1995, p. 138), effective risk communication requires moving beyond "get[ting] the numbers right" and "explain[ing] what we mean by the numbers" to incorporating those who may be affected by a risk—in other words, the intended audience—as partners. This is especially important because the scientific and technological drivers of the system are evolving rapidly, and so the system is changing faster than we can study and understand it. Thus, to intersect effectively with people's dynamic information interactions, risk interpretations, decisions, and vulnerabilities, future approaches to hazardous weather prediction and communication must be flexible and adapt quickly to new technologies and circumstances.

How can the knowledge developed through this type of research be used to improve forecast, warning, and communication strategies? On Twitter, in our focus groups, and in related empirical research, diverse people at risk are telling us what they need and want to know, and how they are accessing, interpreting, sharing, and using information as a threat evolves. The computational modeling research is building understanding about what types of predictions of weather-related hazards are possible on different time scales and about how evolving hazard information interacts with societal information flow and protective decisions. By bringing this knowledge together, we can identify new entry points for improving hazardous weather prediction and risk communication in the modern information environment in ways that help alleviate vulnerabilities and reduce harm.

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