Information Dissemination, Diffusion, and Response during Hurricane Harvey: Analysis of Evolving Forecast and Warning Imagery Posted Online

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Abstract: This article aims to build interdisciplinary understanding about modern hazard communication by investigating visual information dissemination, diffusion, and response leading up to and during a weather-related disaster. The study analyzes data from online social media posts by authoritative sources during Hurricane Harvey, focusing on forecast and warning tweets containing hurricane risk imagery. The research integrates quantitative and qualitative analysis of tweets, retweets, and replies to explore how the roles of different information content and sources evolved with Harvey's threat. Building on the work of Mileti and other warning scholars, the results illustrate the complexity of dynamic multisource, multimessage, and multihazard forecast and warning situations, including hurricanes. In such situations, people can engage in different hazard response processes simultaneously and near-continuously, as they are exposed to, attend to, and make sense of an evolving, heterogeneous collection of available information. The analysis also finds that during Harvey, authoritative sources used a mix of tweeting strategies to disseminate and amplify emerging information. Different types of sources led the creation of forecast and warning content at different times, with other sources playing complementary roles in communicating potentially important or salient content to broader audiences. Overall, the study provides updated models of hazard warning communication and response and associated processes such as milling, along with new methodological approaches for utilizing social media and other online data to understand these processes. In addition to these theoretical and methodological contributions, the analysis points to opportunities for the National Weather Service and others to improve tropical cyclone risk communication. **DOI: 10.1061/NHREFO.NHENG-1802.**

Introduction

In hazard contexts, forecasts and warnings are designed to inform people about a threat and support effective responses. As described by Mileti and Sorensen (1990), hazard warning response involves multiple interconnected subprocesses, including hearing (or seeing) the warning; understanding, believing, personalizing, and confirming the information; and deciding on and taking action. Multiple factors, including recipient attributes and warning message source, content, and style, influence these processes (Mileti and Sorensen 1990; Mileti 1995).

Research on a variety of hazards utilizes this framework developed by Mileti and colleagues, which is referred to as the Warning Response Model (e.g., Mileti and Sorensen 1990; Sorensen 2000; Bean et al. 2015; Wood et al. 2018; NASEM 2018; Sutton et al. 2018, 2023; Kuligowski et al. 2023). However, warning creation, communication, and response has changed significantly over the last few decades. For weather-related hazards, scientific and technological advances have markedly improved forecasts (Bauer et al. 2015; Cangialosi et al. 2020). At the same time, advances in information and communication technology, such as the Internet, mobile phones, and social media, have transformed how people access, share, and interact with hazard information (Gladwin et al. 2007; Sutton et al. 2008; Fraustino et al. 2012; Bean et al. 2015; Morss et al. 2017). These advances enable more skillful forecasts and warnings for weather-related hazards, issued further in advance, as well as more rapid and widespread forecast and warning dissemination. They also enable extensive use of visuals in weather and other hazard communication (Lindell 2020; Millet et al. 2020; Prestley and Morss 2023; Wilhelmi et al. 2024). Along with such opportunities for hazard risk communication, these changes bring challenges, including the potential for rapidly spreading false information and amplification of low-credibility sources (Starbird et al. 2014; Shao et al. 2018; Vosoughi et al. 2018; Swire-Thompson and Lazer 2020).

The research presented here aims to advance empirical and theoretical understanding about how modern forecast and warning systems function. This includes updating Mileti's and others' work on warnings to reflect the dynamic modern information environment, improved forecast and warning skill, and new forms of communication described above (Mileti and Sorensen 1990; Sorensen 2000; Basher 2006; Gladwin et al. 2007; NASEM 2011, 2018; Lindell and Perry 2012; Morss et al. 2017; Anderson-Berry et al. 2018). To do so, we investigate how visual forecast and warning communication evolved in real time leading up to and during a

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complex disaster with multiple types of embedded hazards, viewed through the lens of data from social media posts.

The study focuses on Hurricane Harvey, which caused more than 100 deaths and $125 billion in damage in the U.S. in August 2017 (National Oceanic and Atmospheric Administration 2018). As illustrated by the timeline in Fig. 1, Harvey was a dynamic situation that presented multiple interconnected hazard threats—including strong winds, storm surge inundation, heavy rainfall and associated flooding, and tornadoes—in different areas of south Texas and Louisiana over the course of more than a week. By studying Hurricane Harvey from this perspective, we seek to elucidate communication and response processes for a variety of types of hazards that pose spatially and temporally varying risks.

As a tropical cyclone such as Harvey evolves, weather forecasters, media personnel, and public officials generate and communicate updated information about the threat multiple times each day (Mileti and Sorensen 1990; Lindell et al. 2007; Demuth et al. 2012; Bostrom et al. 2016). This evolving information propagates through social and information networks and is interpreted and used in a variety of ways (Morss et al. 2017). Visuals can play important roles in these processes, for example, by influencing attention, message passing, risk personalization, and response (Keib et al. 2018; Sutton et al. 2019; Clive et al. 2021; Wilhelmi et al. 2023, 2024; Prestley and Morss 2023). Thus, we use hurricane risk imagery conveyed by these types of sources as an entry point for analysis. Although these sources communicate across multiple media, the

Evolution of Harvey and its hazards (blue) and associated forecasts and warnings (red)

17 August
- Tropical Depression Nine forms over the Atlantic Ocean; NHC issues first track and wind speed forecasts for the system; system strengthens into a tropical storm and is named Harvey

18–19 August
- Tropical Storm Harvey moves westward in the Caribbean and weakens

20–21 August
- Harvey's remnants continue westward; NHC stops issuing track and wind speed forecasts for the system but indicates medium-high likelihood that it will redevelop into a tropical storm over the next few days

22 August
- NHC forecasts high likelihood of the system redeveloping over the next 48 hours and that it could produce storm surge, strong winds, and prolonged heavy rainfall along and near the Texas coast

23 August
- ~07:00: Remnants of Harvey redevelop into a Tropical Depression in the Gulf of Mexico
- ~10:00: NHC issues first track and wind speed forecasts for Harvey in the Gulf of Mexico, indicating that Harvey is likely to make landfall along the Texas coast on August 25 as a tropical storm that is expected to produce storm surge, strong winds, and 10-20" of rainfall; NHC issues Hurricane, Tropical Storm, and Storm Surge Watches for parts of the Texas coast
- ~22:00: NHC forecasts that Harvey is expected to strengthen into a hurricane prior to landfall
- ~23:00: Harvey strengthens into a tropical storm

24 August
- ~04:00: NHC issues Hurricane, Tropical Storm, and Storm Surge Warnings for areas of Texas
- ~06:00: NWS WFOs begin issuing Flash Flood Watches for areas of Texas, which are extended into the Houston area later in the day
- ~10:00: NWS forecasts Harvey to strengthen to a major hurricane prior to landfall and then move slowly, producing up to 30" of rainfall over several days with potential for life-threatening flooding. A few Texas communities begin announcing evacuations, closures, and disaster declarations.
- ~12:00: Harvey strengthens into a hurricane
- ~13:00–17:00: Additional evacuations, closures, and disaster declarations announced; NHC extends Hurricane and Storm Surge Warnings northeast along the Texas coast

25 August
- Additional evacuations announced throughout the day, along with orders to shelter in place
- ~11:00: NWS WFOs begin issuing Tornado Warnings in Texas
- ~14:00: Harvey strengthens into a major (Category 3) hurricane
- ~17:00: NWS rainfall forecasts for Harvey increase to up to 40" in some areas; NWS Corpus Christi WFO issues Extreme Wind Warning as Harvey's eye approaches land
- ~22:00: Harvey makes first U.S. landfall near Corpus Christi, Texas, as a Category 4 hurricane
- ~23:00: NWS WFOs begin issuing Flash Flood Warnings in Texas

26 August
- Harvey remains over Texas and weakens to a tropical storm while continuing to cause tornadoes, heavy rainfall, and flooding; NWS WFOs continue issuing Tornado and Flash Flood Warnings; additional evacuations announced
- ~21:00: NWS WFOs begin issuing Flash Flood Emergencies due to severe life-threatening flooding in southeast Texas, including the Houston area

27–29 August
- Harvey continues to meander over Texas and the nearby Gulf of Mexico, causing tornadoes, heavy rainfall, and extensive flooding; NWS WFOs continue issuing Tornado and Flash Flood Warnings; additional evacuations announced, as well as do-not-travel and civil emergency messages due to flooding; rainfall totals from the storm exceed 45" in some areas

30 August – 2 September
- Harvey makes a final landfall in southwestern Louisiana, weakens to a tropical depression, and moves out of the region

Fig. 1. Timeline of the evolution of Harvey and its hazards and associated forecasts and warnings, compiled from Blake and Zelinsky (2018), National Oceanic and Atmospheric Administration (2018), NWS product archives, and the Twitter data set. All times are approximate and in local time (CDT). NWS = U.S. National Weather Service; NHC = NWS National Hurricane Center; NWS WFOs = NWS local Weather Forecast Offices.

Internet—especially social media—provides a rich view of the visual information landscape at different times. Twitter, in particular, provides near-real-time, temporally detailed data about the online content that emerges during hazards, as well as about how Twitter users engage with information in this multidimensional communication space (Starbird and Palen 2010; Wu et al. 2011; Sutton et al. 2014; Anderson et al. 2016; Veltri and Atanasova 2017; Fellenor et al. 2018; Reuter et al. 2018; Silver and Andrey 2019; Netzel et al. 2021).

Mileti and colleagues noted that hurricanes present complex risk communication situations. However, much of their work focuses on simpler textual warning messages designed to notify populations at risk about a specific hazard and motivate protective actions (Mileti and Sorensen 1990; NASEM 2011, 2018; Bean et al. 2015). Here, we extend Mileti's work by focusing on visual risk communication. This is important because a variety of maps and other forms of imagery are now commonly used to convey complex, geospatially detailed information about hazard threats, but visual warning messages have been less frequently studied (Liu et al. 2017; Bica et al. 2019; Clive et al. 2021; Sutton et al. 2023).

We also expand prior work by investigating individual warning messages in the context of an evolving multimessage, multihazard forecast and warning situation. The Warning Response Model and some other warning systems research conceptualize predictions as precursors to warnings. However, forecast and warning information is now regularly updated and communicated during hurricane threats, beginning days before impacts reach land (Gladwin et al. 2007; Demuth et al. 2012; Bostrom et al. 2016; Morss et al. 2017). We integrate this reality into our analysis by examining warning messages together with the forecast information that is communicated preceding and concurrent to warnings. In addition, research shows that many people now obtain hurricane forecasts from multiple sources and use that information to assess risk and make protective decisions—along with traditional warning messages such as evacuation orders (Dow and Cutter 1998, 2000; Gladwin et al. 2001; Dash and Gladwin 2007; Zhang et al. 2007; Morss and Hayden 2010; Demuth et al. 2023). Bringing these concepts together, we contribute to the hazards literature by taking a multisource, integrated forecast and warning approach, which incorporates the broader context of modern hurricane forecast and warning, risk communication, and response processes.

Building on the body of research studying how authoritative sources use Twitter to communicate and engage with different audiences (e.g., Neiger et al. 2013; Hughes et al. 2014; Sutton et al. 2014, 2020; Eriksson 2018; Vos et al. 2018; Olson et al. 2019; Rufai and Bunce 2020), this study explores what hurricane-related forecast and warning information was disseminated during Harvey's threat, by whom, when, and how. More specifically, we combine qualitative and quantitative analysis of Twitter data to address three research questions:

1. How did authoritative sources communicating with populations in areas at risk convey visual forecast and warning information on Twitter during Harvey?
2. To what extent were different types of visual forecast and warning information, disseminated by different sources, diffused on Twitter?
3. How did these processes change over Harvey's lifetime, as the hazard threats posed by the storm and associated forecast and warning content evolved?

We study dissemination and diffusion because both influence who is exposed to information. These processes therefore provide a critical bridge between the creation of information and subsequent hearing or seeing, understanding, personalizing, believing, and confirming that information as described in the Warning Response Model (Mileti and Sorensen 1990).

To investigate dissemination, we analyze what types of forecast and warning information are tweeted by which types of authoritative sources as the threat progresses. To investigate diffusion—in other words, whether and how information passes through formal and informal networks and is potentially amplified to reach different audiences—we analyze patterns of retweets of authoritative sources' original tweets (Toriumi et al. 2013; Kogan et al. 2015; Vos et al. 2018; Bica et al. 2019; Sutton et al. 2020). In addition, we examine how diffusion occurs through information originated by one source propagating into others' communications. For example, during weather threats, the U.S. National Weather Service (NWS) issues a variety of meteorological forecast and warning products, in textual and graphical formats. As NWS creates this information, it disseminates both the products and underlying data outside of Twitter for others to use. We incorporate this into our analysis by investigating how other authoritative sources further diffuse NWS-generated information by including it in their own tweets. We also use retweets as markers of the salience of different information from different sources and of people's attention to and amplification of that information (Ripberger et al. 2014; Vos et al. 2018; Silver and Andrey 2019; Sutton et al. 2019). Finally, we use the content of replies to forecast and warning tweets to explore how people in areas at risk interpret, make sense of, and respond to Harvey's evolving threat. We examine all of these processes at multiple times during Harvey, taking a longitudinal approach (Siegrist 2014; Demuth et al. 2023, Forthcoming).

When analyzing the types of forecast and warning information communicated during Harvey, we incorporate Mileti's findings on five topics important to include in warning messages—hazard or risk, guidance, location, time, and source—and associated stylistic aspects such as specificity and clarity (Mileti and Sorensen 1990; Bean et al. 2015; Wood et al. 2018; Kuligowski et al. 2023; Sutton et al. 2023). We also explore how our results intersect with the confirmation and milling processes discussed in the warning response literature, where people seek additional information from others to verify warning messages (Mileti and Sorensen 1990; NASEM 2011, 2018; Sutton et al. 2023) and make sense of emerging, uncertain situations (Wood et al. 2018; Carlson and Barbour 2023). Social media data enables us to see multiple aspects of these complex processes, which are well known in the hazards community but difficult to observe and analyze as they unfold (Chung 2011; Lachlan et al. 2014; Sutton et al. 2014; Spence et al. 2015; Veltri and Atanasova 2017; Reuter et al. 2018). By integrating concepts and knowledge from hazard warning, weather prediction and predictability, and risk and crisis communication and studying how they manifested in a real tropical cyclone event, we aim to advance understanding about public warnings and alerts from an interdisciplinary perspective (Gall et al. 2015; Peek et al. 2020; Morss et al. 2021; Sherman-Morris et al. 2021).

We start by describing the research methods, which use Twitter data collected for an earlier study of hurricane risk imagery by Bica et al. (2019), but here with a different goal: studying forecast and warning communication with people in areas at risk from a specific hurricane threat. Thus, prior to analysis, we filtered the Bica et al. data set to focus on image tweets that convey forecast and warning information for Hurricane Harvey, posted by authoritative sources communicating with populations in areas at risk from this storm. Next, we present results, starting with the overall roles of different types of imagery and authoritative sources in Twitter forecast and warning communication during Harvey. This is followed by analysis of how hazard communication evolved throughout Harvey's lifetime. To explore this evolution in greater depth, we then

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examine dissemination, diffusion, and response in three 3-h periods during Harvey's threat, analyzing changes within and across these periods. We close with a summary of key findings, areas for further research, and suggestions for improving hazardous weather risk communication.

Methods

This section presents key aspects of the research methods important for understanding the study results. To help advance the design of rigorous, replicable methodologies for using social media data to study forecast and warning communication, we provide additional details about the study's methods and the reasons underlying different methodological choices in Supplemental Materials. The coding schemes used in the study are available in Prestley and Morss (2024).

Data Collection and Original Image Tweet and Time Filtering

The study uses data collected by a team at University of Colorado Boulder in collaboration with researchers at the National Center for Atmospheric Research, as part of a larger project studying dynamic hazard prediction, risk communication, and decision making in the modern information environment (Morss et al. 2017). Bica et al. (2019) previously used these data to investigate global diffusion of and reactions to hurricane risk images that authoritative sources of hurricane risk information tweeted during the 2017 Atlantic hurricane season. To identify relevant Twitter accounts for data collection, Bica and colleagues started with two public lists of Twitter accounts providing official information for Hurricanes Harvey and Irma [see Bica et al. (2019) for details]. Members of the research team then manually added national, regional, and local NWS, other government, weather media, and news media Twitter accounts providing reliable hurricane information during four of the season's major hurricane threats to the U.S.: Harvey, Irma, Maria, and Nate. These 796 Twitter accounts provided the starting point for data collection. However, as subsequently described, we later narrowed the data set to tweets from a smaller, more curated set of sources.

Bica and colleagues collected data that included all tweets posted by these 796 accounts from August 17, 2017 to October 10, 2017. Here, we start with the set of original tweets posted by these accounts, filtered to tweets containing at least one still image, video, or animated GIF (collectively referred to as *image* or *imagery*). We also use retweet counts that Bica et al. (2019) calculated for these tweets, overall and during specific time periods after posting, and the content of replies to these tweets. Additional details about the data collection and image filtering are provided in Bica et al. (2019) and section S1.

Given this study's focus on Hurricane Harvey, we filtered these original image tweets to those posted during the period when Harvey was a potential or active threat: 00:00 UTC on August 17, 2017 (19:00 CDT on August 16) to 15:00 UTC on September 2, 2017 (10:00 CDT on September 2); all subsequent times are provided in local time (Central Daylight Time, CDT). The resulting *time-filtered data set* contains 47,342 original image tweets (Fig. 2).

Authoritative Source Coding, Categorization, and Filtering

We coded authoritative source accounts for two purposes: (1) to filter the data set to tweets from sources communicating about Harvey with populations in areas at risk from the storm, and (2) to categorize source accounts for analysis. During the coding process, we confirmed that all accounts included in the data set were credible information sources. We coded the accounts along three dimensions: geographic area of responsibility, representation as an individual or organizational account, and type of professional role. Two researchers (R. Prestley and R. Morss) independently coded each account and then adjudicated differences to develop a consensus coding.

For geographic area, we categorized sources according to whether their area of responsibility or primary coverage was national or international (*National*); local or regional to the primary areas threatened or affected by Harvey (south, southeast, or central Texas or southwest Louisiana; *Local*); or sub-national, not well defined, or local or regional to a different area (Other). We coded accounts as *organizational* if their username or profile indicated an

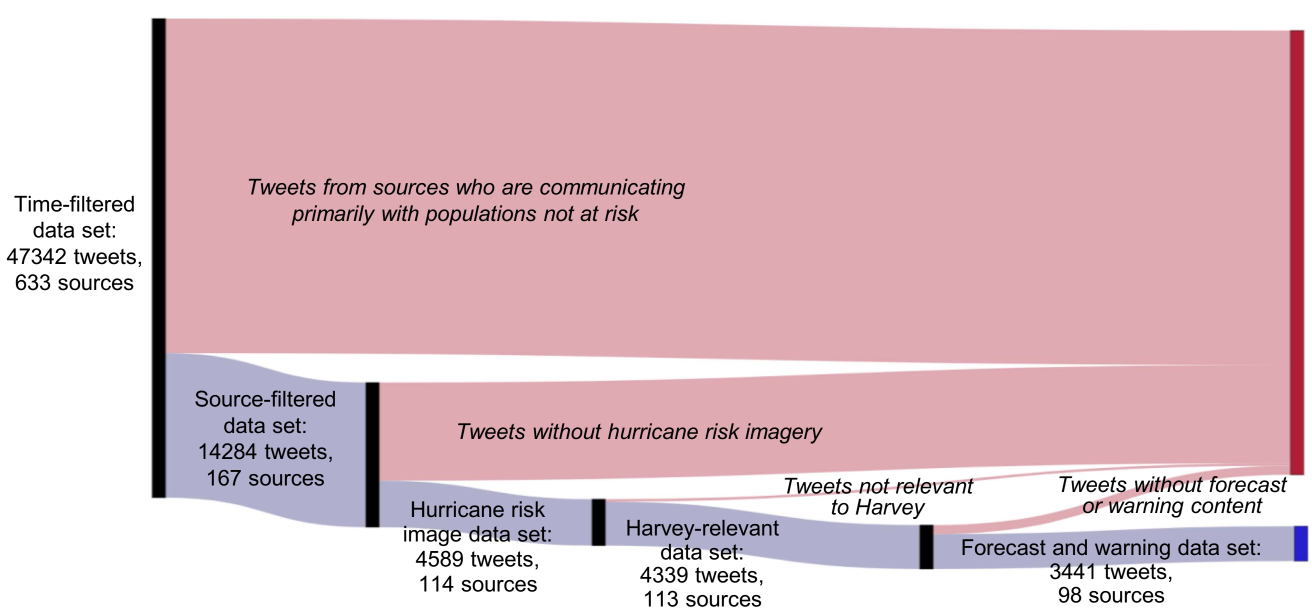

Fig. 2. Filtering steps used to derive the Harvey forecast and warning data set analyzed in this study, starting with the initial Bica et al. (2019) data set filtered to original image tweets posted during the period when Harvey was a potential or active threat.

Table 1. Descriptions of the seven types of authoritative sources analyzed in this study

Source type	Description	# of accounts	Most active disseminator(s) during Harvey (excluding NWS Impact Watch/Warning tweets)
National NWS	Includes national NWS organizational accounts, along with individual accounts of meteorologists working at these organizations	11	Organizational accounts for the NWS Storm Prediction Center (@nwsspc, 35% of tweets posted by this source type) and NWS National Hurricane Center (@nhc_atlantic, 31%)
Local NWS	Includes regional NWS organizational accounts in Texas and southwest Louisiana	7	Organizational accounts for three NWS Weather Forecast Offices in Texas: @nwshouston (36% of tweets), @nwssanantonio (22%), and @nwscorpus (16%)
National Weather Media	Includes accounts for national broadcast meteorologists and national media organizations focused on weather	17	Accounts for three national weather media organizations: The Weather Channel (@weatherchannel, 26% of tweets), AccuWeather (@breakingweather, 12%), and Weather Nation (@weathernation, 12%)
Local Weather Media	Includes accounts for local broadcast meteorologists and weather accounts for local television stations	13	@hellerweather (16% of tweets), a Chief Meteorologist at a Houston television station at the time of Harvey
Local News Media	Includes accounts for local television stations and newspapers, along with individuals working at these organizations	25	Organizational accounts for two Houston television stations: @fox26houston (32% of tweets) and @kprc2 (16%)
Local Non-NWS Government	Includes accounts for local emergency management, police, fire, and other governmental organizations; individuals working at these organizations; and local politicians	22	@jefflindner1 (a meteorologist working for a Texas county, 17% of tweets) and two accounts for Texas county government or emergency management organizations: @brazoriacounty (16%) and @fbcoem (14%)
Local Weather Bloggers	Includes accounts associated with Texas weather blogs	3	@txstormchasers (53% of tweets)

official organizational affiliation and *individual* if these indicated a personal account (see section S2 for details).

For professional role, we categorized accounts associated with media organizations (television, radio, print, and/or online) as *Weather Media* if they focused on producing or providing information about the weather and *News Media* if they focused primarily on providing other news content. We categorized accounts associated with government organizations as either *NWS* or *Non-NWS Government*, and the remaining accounts as Other. We then combined the geographic area and professional role codes into a single set of source type categories (see section S2).

Because the Bica et al. (2019) Twitter data collection included a variety of sources posting throughout the 2017 hurricane season, the time-filtered data set contains many sources local to areas not at risk from Harvey, and many tweets unrelated to Harvey (or to weather at all). Therefore, to help narrow the data to tweets of interest for this study, we filtered the data set to include only tweets from seven types of National and Local Harvey sources, shown in Table 1. We developed this source filtering approach using knowledge about hurricane risk and social media communication, along with results from preliminary analysis as described in section S2. The resulting *source-filtered data set* contains 14,284 original image tweets (Fig. 2).

Hurricane Risk Image, Harvey Relevance, and Forecast and Warning Coding and Filtering

Although the time and source filtering processes described previously removed many tweets not relevant to this study, the source-filtered data set still contains many tweets not relevant to hurricane forecasts and warnings or to Harvey. Thus, we used tweet content—both text and imagery—to further filter the data to tweets of interest for our research questions.

First, as described in Bica et al. (2019) and section S3, we filtered the data set to include only tweets with hurricane risk images (Fig. 2). Next, we coded tweets in this *hurricane risk image data set* according to whether they were *relevant to Harvey.* Relevance was defined as either the tweet text or imagery referencing Harvey by name or mentioning or visually representing the storm's threat, its impact, or related protective action information. Using this coding, we filtered the data to contain only Harvey-relevant tweets, generating a *Harvey-relevant data set* (Fig. 2). We then coded these tweets according to whether they contained *Harvey forecast or warning information*, defined as either the tweet text or imagery conveying Harvey-relevant threat, impact, or protective action information in future terms. Tweets that included only observational data, such as depictions or descriptions of recent storm evolution, were not coded as forecast or warning information (Rosen 2019).

We tested the Harvey relevance and forecast/warning code definitions as described in section S3; intercoder reliability was high for both Harvey relevance (Krippendorff's $\alpha = 0.97$) and forecast or warning information ($\alpha = 0.93$). The two coders discussed and adjudicated differences, and one coded the remaining tweets. After coding, we filtered the data to retain only tweets that contained Harvey forecast or warning information. The resulting *forecast and warning data set* contains 3,441 tweets, as shown in Fig. 2.

Image Categorization

After the filtering steps described previously, we categorized each tweet in the Harvey forecast and warning data set by image type and branding, for use in the analysis. We developed the initial set of image type codes (Table S1) based on the analysis in Bica et al. (2019), images observed in earlier rounds of coding, and the research team's knowledge about commonly used hurricane forecast and warning visuals. It includes 14 codes representing common visualizations of hurricane risk information, along with two Other codes. Two researchers tested and revised this coding scheme through several initial rounds of cross-coding, including calculating intercoder reliability as described in section S4. One researcher then coded the remaining data.

During the coding process, we identified three additional image types in the data and added them to the coding scheme (Table S2). In addition, as discussed further in the results, during coding we found that the majority of images in the data set depicting NWS Watches or Warnings were in the format of the example in Fig. 3(a), an experimental NWS product referred to as Severe Weather Impact Graphics (National Weather Service 2016; Walawender et al. 2017). Given the prevalence of these images, we separated them out of the *Watch/Warning* code into their own category, called *NWS Impact Watch/Warning* (or *NWS Impact W/W*). We then revised the image type codes into a more compact, mutually exclusive categorization to combine infrequently used codes and account for common overlaps, as described in section S4 and shown in Table S2.

The resulting image type categorization used in the analysis contains 13 categories, described in Table 2 with examples shown in Figs. 3–6. This categorization includes image types that NWS, media, and other authoritative sources frequently use to convey hurricane forecast and warning information across multiple communication platforms, including television, the Internet, and social media [see, e.g., Morss et al. (2022b) and Bostrom et al. (2022)];

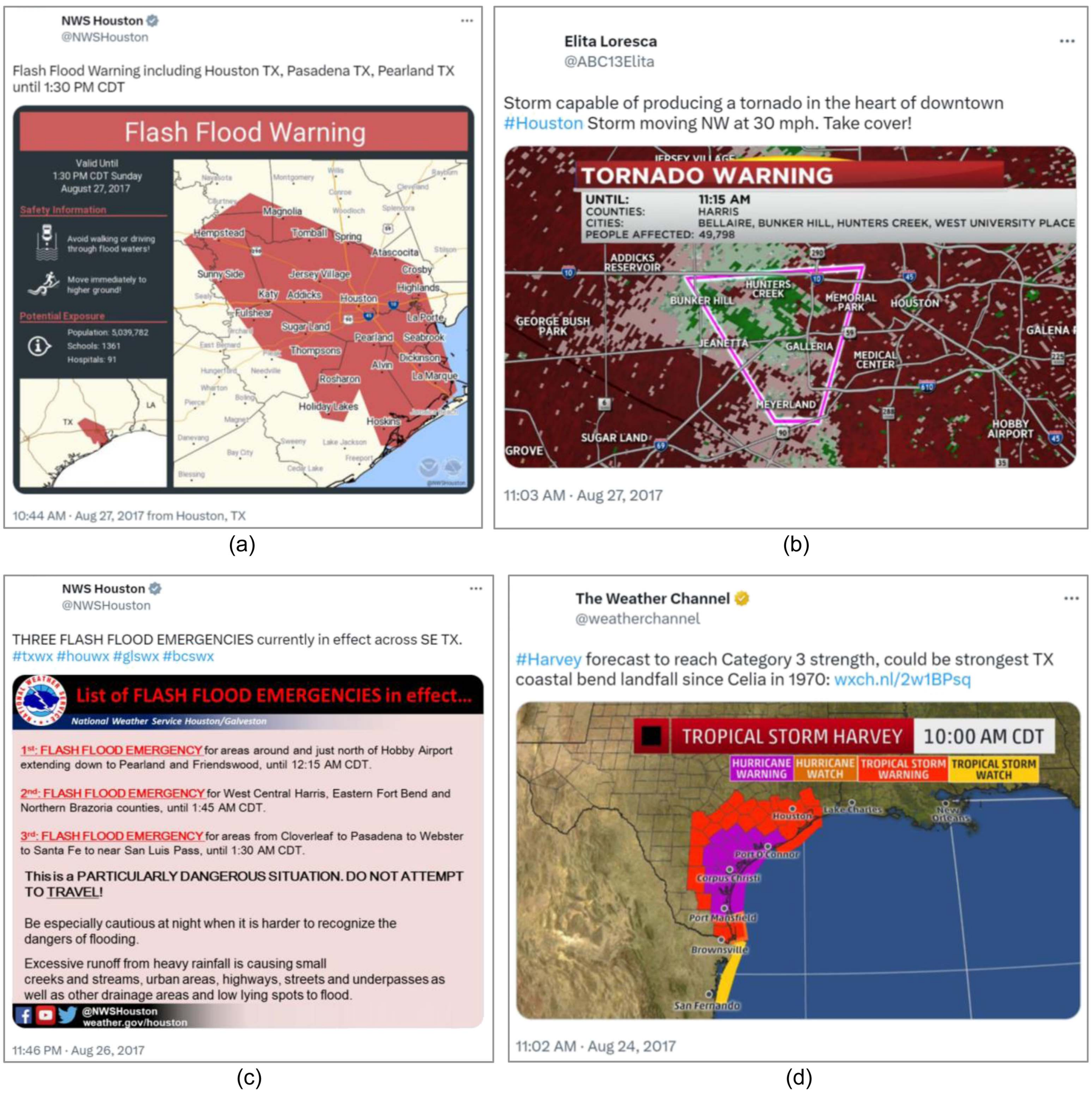

Fig. 3. Example tweets illustrating the image types analyzed in this study, part 1: (a) NWS Impact Watch/Warning conveying an NWS-issued Flash Flood Warning; 73 retweets (reprinted from NWS Houston 2017i); (b) Watch/Warning conveying an NWS-issued Tornado Warning; 94 retweets (reprinted from Loresca 2017); (c) Watch/Warning conveying several NWS-issued Flash Flood Emergencies; 222 retweets (reprinted from NWS Houston 2017j); and (d) Watch/Warning conveying NWS-issued Hurricane and Tropical Storm Watches and Warnings; 442 retweets (reprinted from The Weather Channel 2017m). All tweet times are shown in CDT (local time).

Table 2. Descriptions of the 13 image type categories analyzed in this study

Image type	Description	Example(s)
NWS Impact Watch/Warning (NWS Impact W/W)	Image generated by the NWS that includes a map depicting the area covered by an NWS-issued Severe Thunderstorm, Tornado, or Flash Flood Watch, Warning, or Advisory, accompanied by textual information about potential population exposure and threat type or safety recommendations	Fig. 3(a)
Watch/Warning	Image with map and/or text about an NWS-issued Watch, Warning, or Advisory in a format other than NWS Impact Watch/Warning image; an NWS Watch indicates increased risk of a weather-related hazard, and an NWS Warning indicates that a hazard is occurring, is imminent, or has a very high probability of occurring (National Weather Service 2023)	Figs. 3(b–d)
Cone	Map depicting a tropical cyclone's forecast track and track uncertainty, often along with forecast intensity and other information	Figs. 4(a and b)
Model Output	Map or chart depicting output from numerical weather forecast modeling	Fig. 4(c)
Tropical Outlook	Map depicting the probability of tropical cyclone formation in different areas	Fig. 4(d)
Rainfall	Map depicting forecast rain amounts or areas at risk from heavy rainfall using color coding or other symbology	Fig. 5(a)
River Flood	Image depicting forecast river flooding, usually in the form of a hydrograph (chart displaying water level over time at a specific location) or a map depicting forecast flooding at different locations	Fig. 5(b)
Convective	Map depicting areas at risk from thunderstorms, tornadoes, or other severe weather using color coding or other symbology	Fig. 5(c)
Key Messages	Image generated by the NWS National Hurricane Center that includes two embedded hurricane risk images and text summarizing key information about a tropical cyclone	Fig. 5(d)
Text	Image that uses text to convey hurricane risk or protective action information and is not in the Watch/Warning category	Fig. 6(a)
Other Forecast	Image containing hurricane risk, evacuation, or other protective action information that is not in any of the above categories	Fig. 6(b)
Other Non-Forecast	Image that does not contain Harvey forecast or warning information, usually a satellite or radar map or other observations of current or recent conditions	Fig. 6(c)
Multiple	Category for tweets that includes more than one of the 12 image types above	Fig. 6(d)

here, we observe them on Twitter. In two of these categories—*NWS Impact Watch/Warning* and *Key Messages*—all images are in a similar NWS-generated format [Figs. 3(a) and 5(d)]. Many of the other categories include images in both NWS and non-NWS formats, often with the non-NWS formats generated using the data underlying a corresponding NWS graphical product [see, e.g., Figs. 4(a and b)]. The *Other Forecast* group contains images that included Harvey forecast or warning information, but that were not prevalent in the data set or for which we could not reliably define distinguishing criteria (section S4). The *Other Non-Forecast* group contains tweets that include Harvey forecast and warning information, but not in the imagery. The *Multiple* group contains tweets that included two or more distinct types of imagery, either combined into one media attachment [as in Fig. 6(d)] or in multiple attachments.

The image branding coding scheme included two codes (section S4). We tested the code definitions as described in section S4 and obtained excellent intercoder reliability ($\alpha > 0.95$). We then categorized each tweet using a binary scheme: *NWS-branded* if any image has an NWS logo, symbol, or name or is in an NWS format, and *Non-NWS-branded* otherwise.

Data Analysis

As shown in Fig. S1 and discussed further in section S5, the data set described above contains two outlier tweets with anomalous retweet and reply behavior. Together, these two tweets account for 19% of retweets and 34% of replies in the data set. In addition, many of the replies to these tweets focused on climate change or U.S. politics. This indicates that much of people's interactions with them on Twitter is not related to communication about Harvey's threat with populations potentially exposed to the storm. We therefore removed these two tweets from the data set used in the analysis, leaving 3,439 tweets.

Our integrated forecast and warning approach requires simultaneously understanding individual pieces of information and processes and examining how these evolve and intersect. To do so, we combined multiple forms of qualitative and quantitative analysis. To understand dissemination, we conducted an in-depth investigation of what types of information different sources tweeted as Harvey's threat evolved. To understand diffusion and response, we coupled this investigation with in-depth analysis of retweets of and replies to different types of information tweeted by different sources at different times. We then used these in-depth analyses to inform how we structured the higher-level integrated analyses presented in this article. We also used the in-depth analyses to help us interpret the results of higher-level analyses.

In the results presented in this article, we use counts of original tweets as the primary quantitative metric of dissemination, and we use counts of retweets as the primary quantitative metric of diffusion. We also examine diffusion by tracking whether and how imagery and other information content generated by one authoritative source propagated into other sources' tweets, through online and offline mechanisms. In addition, we use retweets as a measure of how Twitter users responded to authoritative sources' tweets, including the salience of the information and their attention to it.

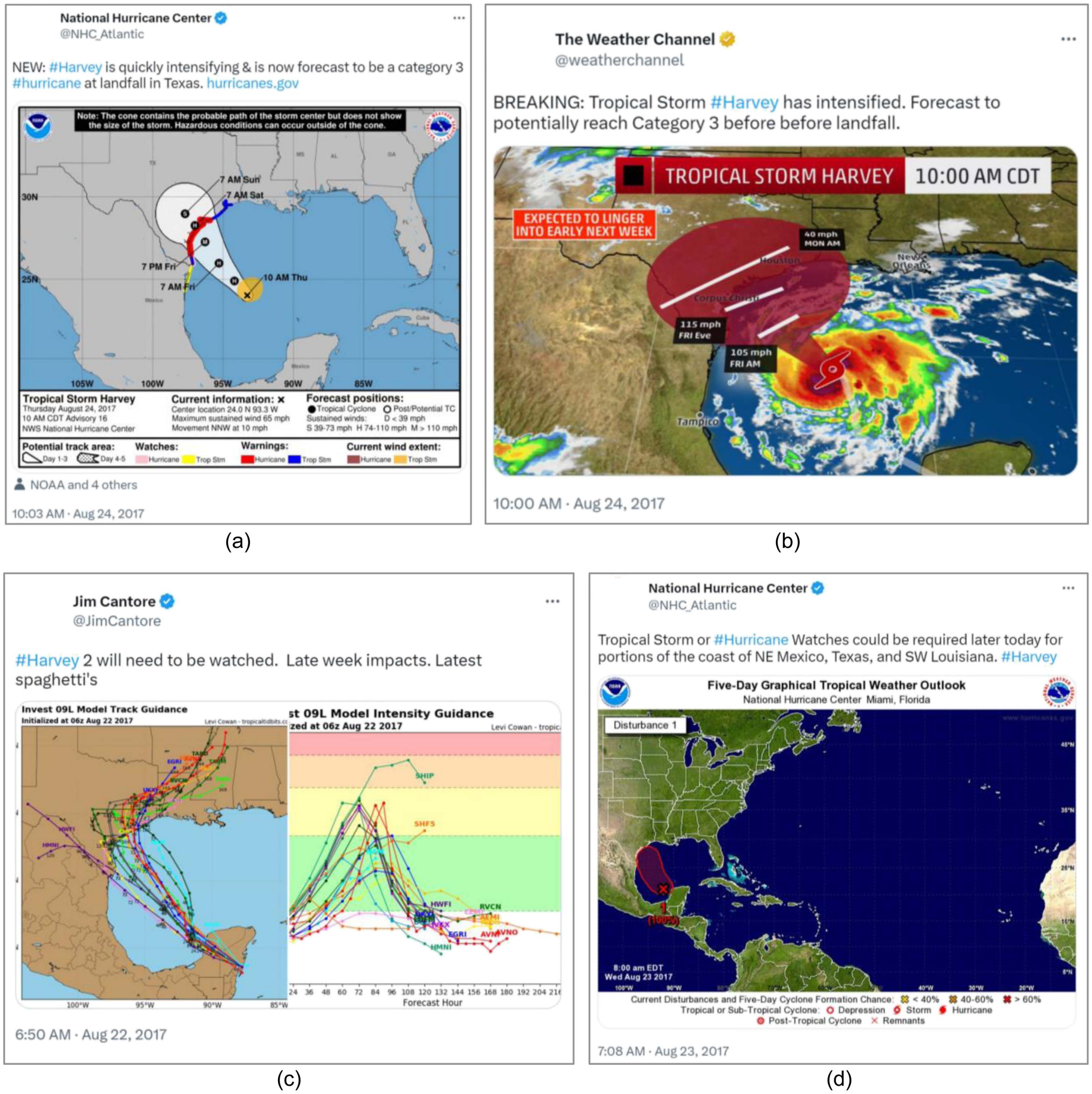

Fig. 4. Example tweets illustrating the image types analyzed in this study, part 2: (a) Cone, NWS-branded; 1327 retweets (reprinted from National Hurricane Center 2017a); (b) Cone, Non-NWS-branded; 2208 retweets (reprinted from The Weather Channel 2017n); (c) Model Output, multi-image tweet; 102 retweets (reprinted from Cantore 2017); and (d) Tropical Outlook; 150 retweets (reprinted from National Hurricane Center 2017b).

Finally, to explore additional aspects of people's responses to the evolving forecast and warning information that authoritative sources tweeted during Harvey, we incorporated reply content into the analysis. Given our research questions, we focused on replies from people whose Twitter content and/or location in their Twitter profile at the time of Harvey indicated that they are members of the public either located in or communicating with people in an area at risk. Although the replies provide some data of interest, the data set contains a limited number of interpretable, relevant replies. Moreover, the reply data are from Twitter users engaging with authoritative sources, which is a limited sample. Thus, we only incorporated brief analyses of reply content into this article, using that content to reveal some of the different ways that people responded to Harvey's evolving forecasts and warnings.

Results

Roles of Different Image Types and Sources in Harvey Forecast and Warning Dissemination

First, we examine what types of forecast and warning imagery the sources studied here tweeted during Harvey, and what types of content these images typically include (Research Question 1). Each source and image type is described in Tables 1 and 2, with statistics and additional information in Tables 3 and 4.

As shown in Table 3, more than one-third of the tweets in the data set disseminated NWS Impact Watch/Warning images, which convey certain types of NWS-issued Watches and Warnings in an NWS-designed graphical format [Fig. 3(a)]. Most of these tweets convey NWS Tornado or Flash Flood Warnings, consistent with the

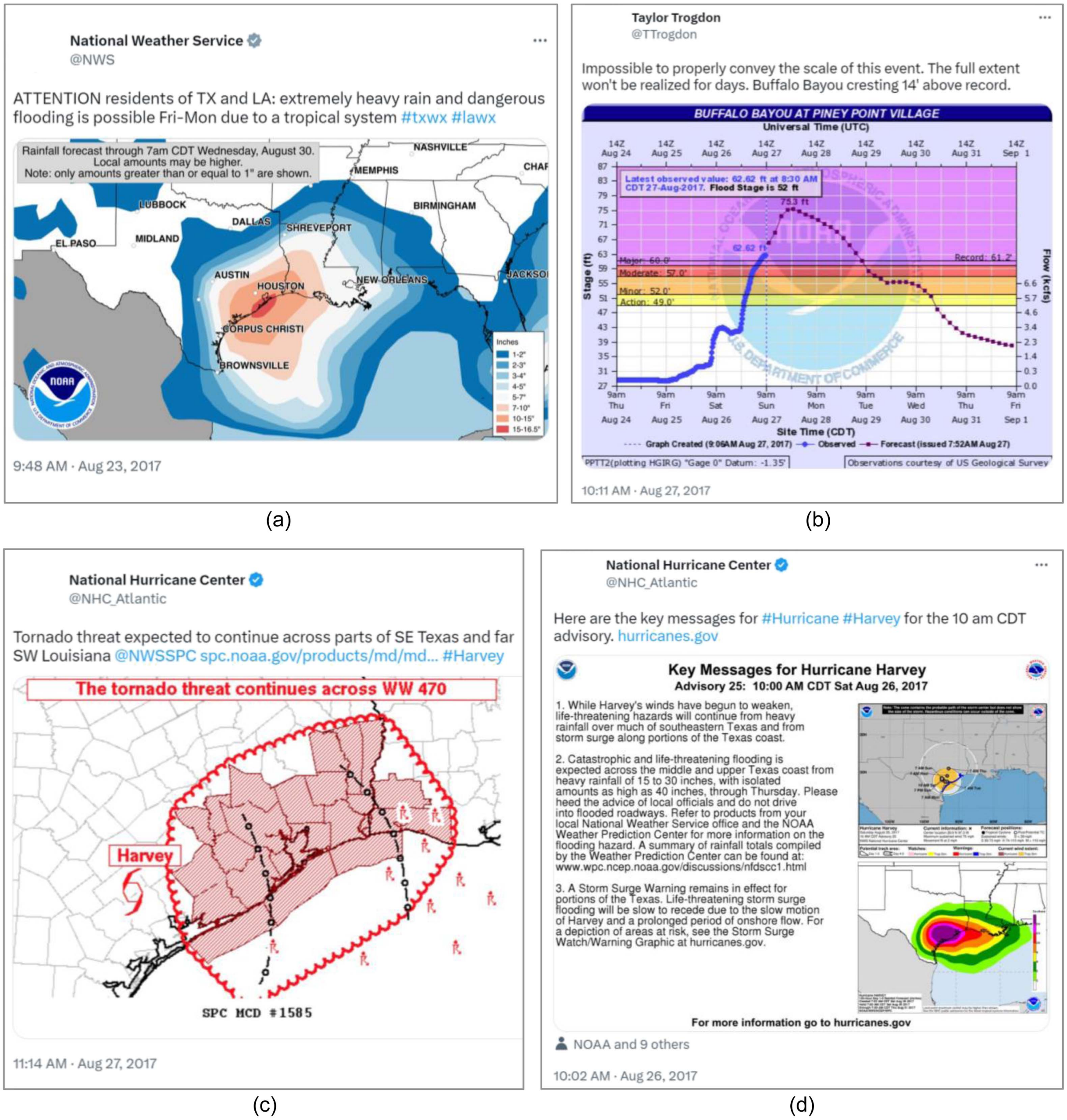

Fig. 5. Example tweets illustrating the image types analyzed in this study, part 3: (a) Rainfall; 346 retweets (reprinted from National Weather Service 2017); (b) River Flood; 1142 retweets (reprinted from Trogdon 2017); (c) Convective; 264 retweets (reprinted from National Hurricane Center 2017c); and (d) Key Messages; 396 retweets (reprinted from National Hurricane Center 2017d).

large number of these warnings issued in areas affected by Harvey (National Oceanic and Atmospheric Administration 2018). At the time of Harvey, the NWS automatically tweeted NWS Impact Watch/Warning images in parallel from two Twitter accounts: the account of the local NWS Weather Forecast Office issuing the relevant NWS product, and one of the two NWS Twitter accounts (@nwstornado, @nwsflashflood) that focus on distributing these images (National Weather Service 2016). Nearly all (99.5%) of the NWS Impact Watch/Warning images in the data set were tweeted by these Local and National NWS accounts.

In addition, the data set contains approximately 600 Watch/Warning tweets. As shown in Figs. 3(b and c), many of these tweets also convey NWS Tornado or Flash Flood Warnings; in other words, they are based on the same NWS products as NWS Impact Watch/Warning tweets, but use different imagery. The Flash Flood Emergencies in Fig. 3(c) are rare, higher-end Warnings that NWS issues when flash flooding poses a severe threat to human life and catastrophic damage is anticipated. However, as shown in Fig. 3(d), some Watch/Warning tweets convey other types of NWS Watches and Warnings associated with Harvey, e.g., for tropical-storm or hurricane-force winds. As the three examples in Figs. 3(b–d) illustrate, the Watch/Warning images tweeted during Harvey use a variety of formats. In addition, many of them are Non-NWS-branded, and more than two-thirds were disseminated by non-NWS accounts. Together, these results illustrate how a variety of authoritative sources disseminate NWS-issued Warning messages during tropical cyclone threats, using heterogeneous map-based and textual imagery.

Additional analysis found that, as shown in the example in Fig. 3(a), NWS Impact Watch/Warning tweets for flash flooding include all five types of warning message content recommended

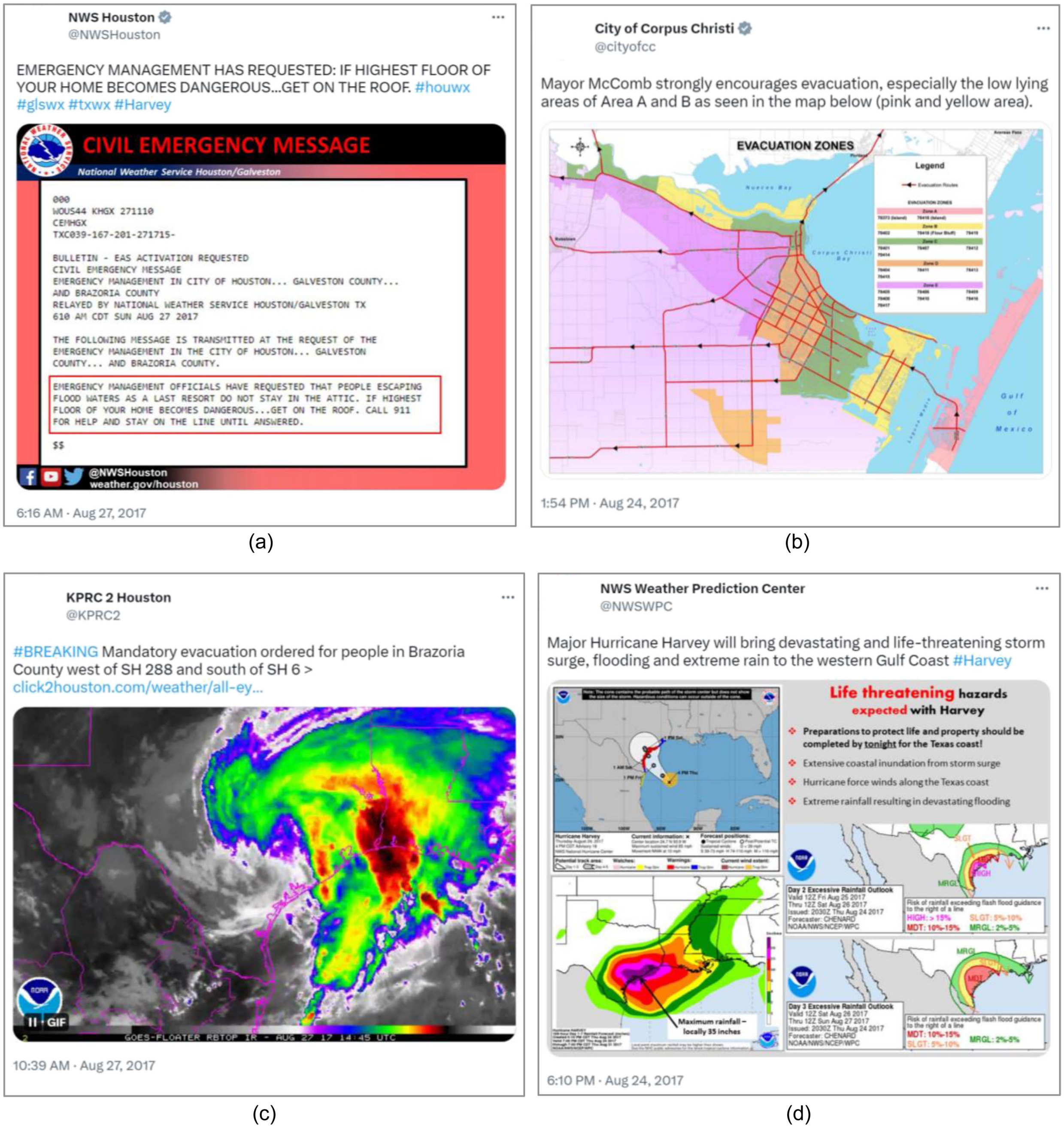

Fig. 6. Example tweets illustrating the image types analyzed in this study, part 4: (a) Text; 5239 retweets (reprinted from NWS Houston 2017k); (b) Other Forecast; 653 retweets (reprinted from City of Corpus Christi 2017); (c) Other Non-Forecast, frame from animated gif; 416 retweets (reprinted from KPRC 2 Houston 2017); and (d) Multiple; 376 retweets (reprinted from NWS Weather Prediction Center 2017).

by Mileti and Sorensen (1990). However, NWS Impact Watch/Warning tweets for tornadoes do not include guidance information. Moreover, some of the NWS Impact Watch/Warning tweets lack the specificity and clarity recommended by Mileti and Sorensen (1990), e.g., because the maps lack place names or other easily recognizable geographic references. Across the text and imagery, some of the Watch/Warning tweets also include the five types of recommended content. However, although the full text products that NWS issues for NWS Watches and Warnings typically include all five types of content, many of the Watch/Warning tweets focus on conveying the location and timing of the warned-for hazard. This includes Watch/Warning tweets posted by NWS and non-NWS sources.

The next most common image type in the data set is Cone imagery. Cone images convey a tropical cyclone's potential location over the next several days, often along with other information about the storm's threat (Tables 2 and 3). They are based on a graphic generated by the NWS National Hurricane Center (NHC), the Track Forecast Cone [Fig. 4(a)]. However, additional analysis found that about 40% of the Cone images in this data set are in non-NWS formats that other authoritative sources created using the underlying NWS data [Fig. 4(b)]. In addition to the count of Cone image tweets in Table 3, many of the Key Messages and Multiple image tweets also include Cone images [e.g., Figs. 5(d) and 6(d)].

As these results illustrate, Track Forecast Cones are a common form of hurricane risk imagery that a variety of authoritative

Table 3. Statistics and typical image content for tweets with different image types

Image type	# of tweets	Typical image content	Median retweets
NWS Impact Watch/Warning	1,214	Hazard, location, time, source; also includes guidance for some hazard types	*7*
Watch/Warning	584	Hazard, location, time; may also include guidance, source	16
Cone	316	Hazard, location, time; NWS-branded formats also include source	24
Model Output	83	Hazard, location, time	19
Tropical Outlook	45	Hazard, location, time; NWS-branded formats also include source	16
Rainfall	169	Hazard, location; often also includes time, source	*64*
River Flood	107	Hazard, location; often also includes time, source	24
Convective	95	Hazard and location; often also includes time, source	9
Key Messages	33	Hazard, location, time, source; may also include guidance	*268*
Text	98	Evacuation and emergency messages: guidance, location, source; often also include hazard, time. Content of other images varies.	22
Other Forecast	241	Content varies	27
Other Nonforecast	266	Content varies	25
Multiple	188	Content varies	33
All image types	3,439		14

Note: Image types are organized in the order discussed in the text. Typical image content is based on the five categories of content that Mileti and Sorensen (1990) discussed as important to include in warning messages: hazard or risk, guidance, location, time, and source. Median tweet values in italics indicate that the image type's retweet distribution is statistically different from that of all other image types (Mann-Whitney U test, $p < 0.01$).

Table 4. Statistics for tweets posted by different types of authoritative sources, with National NWS and Local NWS sources partitioned into NWS Impact Watch/Warning tweets and all other tweet types

Source type	# of tweets	Average # of tweets per account	Median retweets
	High retweet distribution		
National NWS (all other tweet types)	271	30	47
Local NWS (all other tweet types)	405	68	46
National Weather Media	500	29	39.5
Local Weather Bloggers	106	35	38
	Medium–high retweet distribution		
Local Non-NWS Government	195	9	14
	Medium–low retweet distribution		
Local Weather Media	352	27	11
Local News Media	401	16	9
Local NWS (NWS Impact Watch/Warning tweets)	687	172	9
	Low retweet distribution		
National NWS (NWS Impact Watch/Warning tweets)	522	261	5
All source types	3,439	35	14

Note: Source types are organized from highest to lowest median retweets. Source types with statistically similar retweet distributions are grouped together (Mann-Whitney U test, $p < 0.01$).

sources use when communicating about hurricane risk. However, Cone images have several limitations. One is that they focus on the probable track of the center of a tropical cyclone, and thus do not convey the types of hurricane-related hazards that people in different locations may experience. Another is that some people inaccurately infer that areas outside the track swath depicted in the cone are not at risk (Broad et al. 2007; Evans et al. 2022; Morss et al. 2022b). As indicated in Table 3, most Cone images also do not include guidance about recommended actions. Thus, Cone images usually do not, on their own, provide enough information for people to understand the risks that a tropical cyclone poses and decide what protective actions to take when.

Along with Cone images, authoritative sources tweeted a number of Model Output images during Harvey, many of which convey possible storm tracks and/or intensities [e.g., Fig. 4(c)]. They also tweeted Tropical Outlook images, which are based on an NHC-generated graphic that depicts locations of current and potential future tropical cyclones [Fig. 4(d)]. Like Cone images, many Model Output and Tropical Outlook images indicate areas that a tropical cyclone may affect, but they often provide little or no information about associated risks and recommended actions.

In addition, Tables 2 and 3 show that during Harvey, authoritative sources disseminated several other image types focused on communicating information about hurricane-related hazards. The most common are Rainfall images depicting the forecast rain threat from Harvey [Fig. 5(a)]. A variety of sources tweeted such images, often accompanied by text conveying the danger posed by Harvey's forecast rain. A variety of sources also tweeted River Flood images conveying forecast flooding in one or more locations [Fig. 5(b)]. Related to Harvey's tornado threat, the data set includes nearly 100 Convective images [Fig. 5(c)]. However, most of these were tweeted by one source, @nwsspc (the NWS Storm Prediction Center). As shown in Table S2, the authoritative sources studied here also tweeted several images focused on conveying Harvey's potential wind speeds in different locations or storm surge inundation, but these were uncommon and so were combined into the Other Forecast category. Most of these hurricane-hazard images focus on conveying the hazard and its location, although some include information about source and timing (Table 3). Only a few include guidance about recommended protective actions.

Another image type in the data set is Key Messages, which NHC uses to convey graphical and text highlights about a tropical cyclone threat. @nhc_atlantic (NHC's primary official Twitter account) typically tweets Key Messages at 6-h intervals, after NHC releases a new set of forecast products and associated data (referred to as a *forecast package*). As indicated in Table 3, some Key Messages images include information about recommended protective actions, as in the example in Fig. 5(d). However, many focus on communicating meteorological information about the threat.

Interestingly, authoritative sources also tweeted nearly 100 images during Harvey that contain primarily textual information. These Text images convey a variety of types of information, including evacuation notices, NWS text products, government press releases, and text highlights about the threat. They also vary widely in format and complexity. For example, some Text images are black and white, while others add color or simple graphics for emphasis or visual appeal [Fig. 6(a)]. Some contain a lot of text, while others are brief. As summarized in Table 3, when authoritative sources used Text images to convey evacuation orders or other emergency messages during Harvey, the image typically includes information about guidance, location, and source, often along with hazard and time (although not necessarily with the specificity and clarity recommended by Mileti and Sorensen 1990). The content of other Text image tweets varies, as does the content of images in the Other Forecast, Other Non-Forecast, and Multiple categories.

Overall, these results illustrate the variety of imagery that authoritative sources used to communicate forecast and warning information on Twitter during Hurricane Harvey. A few of the image types prevalent in the data set focus on notifying people about an imminent or ongoing hazard and motivating protective action, like the warning messages that Mileti and colleagues focused on in much of their work with the Warning Response Model (Mileti and Sorensen 1990; Bean et al. 2015; Wood et al. 2018; Sutton et al. 2018; Kuligowski et al. 2023). However, many of the images in the data set focus on conveying longer-term or broader scale forecast information about Harvey's threat.

Diffusion of Harvey Forecast and Warning Tweets

Next, we examine the extent to which Twitter users retweeted the different image types that authoritative sources disseminated during Harvey (Research Question 2). Most of the image types exhibit wide variability in retweets, depending on attributes such as source, timing, content, and style. However, a few clear patterns emerged, summarized in the right column of Table 3.

First, Key Messages images had, by far, the highest median retweets. This high diffusion and attention could be influenced by the Key Messages format and content, which combines text highlights about the tropical cyclone threat with graphics. However, this likely occurs at least in part because the highly retweeted @nhc_atlantic account posted nearly all of the Key Messages images in the data set.

Second, Rainfall images were on average more retweeted than all other image types except Key Messages. As noted above, a variety of accounts tweeted Rainfall images. In addition, nearly all of the Key Messages images tweeted during Harvey included an embedded Rainfall image [e.g., Fig. 5(d)]. Together these results suggest that at least at an aggregate level, authoritative sources and a number of other Twitter users attended to the significant threat posed by Harvey's rainfall and sought to share that information.

Third, Twitter users tended to retweet NWS Impact Watch/Warning graphics less than all other image types studied here. Along with the previously noted result that few non-NWS sources tweeted these images, this finding suggests that most of these images did not gain significant attention or amplification on Twitter during Harvey. Many of these images cover small or less populated areas, and most of the more retweeted NWS Impact Watch/Warning images convey threats for metropolitan areas that cover a large population [such as the Houston-area example in Fig. 3(a)]. This suggests that NWS Impact Watch/Warning images may tend to garner fewer retweets at least in part because many of the underlying NWS Warnings affect a small number of people and cover a short time period. However, some people may still see and use images with few retweets.

To explore retweet patterns from another perspective, Fig. 7 shows how different tweet types accumulated retweets over time. Key Messages tweets were retweeted hundreds of times, on average, within the first several hours after posting, and they continued to accumulate retweets beyond 6 h [Fig. 7(a)]. Many of the other tweet types accumulated retweets in a similar pattern, continuing beyond 6 h [Figs. 7(a and b)]. In contrast, Watch/Warning and Convective tweets tended to accumulate most of their retweets

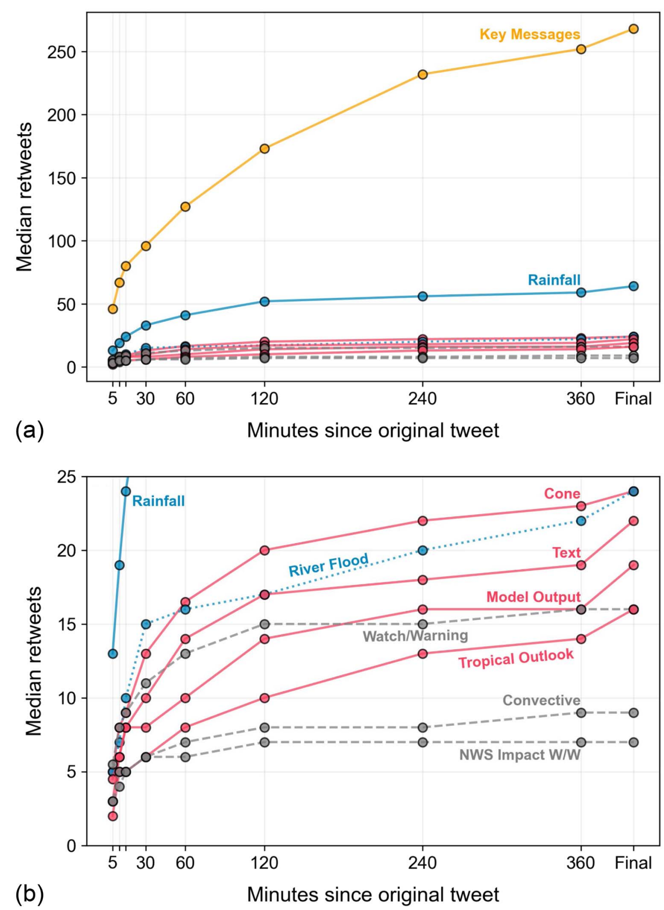

Fig. 7. Evolution of the median number of retweets with time elapsed since a tweet was posted, for tweets with different image types. (a) and (b) show the same data, with different y-axes so that different tweet types are visible; Key Messages is included in (b) but is not visible on the plot because its median retweets are greater than 25 for all times shown. For clarity, Multiple, Other Forecast, and Other Non-Forecast are not shown; these three image types have curve shapes similar to that for Cone, but with higher median retweet values at each time.

more quickly, with little retweeting after the first 120 min. NWS Impact Watch/Warning tweets accumulated most of their retweets even earlier, within 30 min. In other words, these latter three tweet types typically had a shorter diffusion and amplification lifetime. NWS Impact Watch/Warning tweets tended to have an especially short lifetime, likely in part because many of them convey short-term hazards. However, our in-depth analysis of August 27th, provided below, suggests that other factors contributed, including authoritative sources' choices about how to use Twitter to diffuse and amplify NWS-issued Warning information.

Finally, we examine how often Twitter users retweeted Harvey forecast and warning tweets posted by different types of authoritative sources, summarized in Table 4. National and Local NWS sources were two of the most retweeted source types, but only when we separated out NWS Impact Watch/Warning tweets. If these automated tweets are not separated out, NWS sources are on average among the least retweeted. As this example illustrates, at multiple stages of analysis, we found that choices about how to categorize the data and structure quantitative analyses affected results. This highlights how pairing qualitative with quantitative inquiry can help analysts obtain meaningful results from *big data* (Palen and Anderson 2016).

Table 4 also shows that NWS Impact Watch/Warning tweets from the two National NWS accounts that regularly posted these images (@nwsflashflood and @nwstornado) were typically less retweeted than those posted by Local NWS accounts. One possible explanation is that these two national accounts only posted these automated tweets, without a broader Twitter engagement strategy (Eriksson 2018; Olson et al. 2019). More generally, these results illustrate how information source and content intersected to influence social media attention and diffusion.

Within the most retweeted source types, several accounts—including @nhc_atlantic, @nwshouston, and @nws (NWS sources) and @weatherchannel and @jimcantore (National Weather Media sources)—received especially high diffusion and attention. As we illustrate by several of the tweet examples in Figs. 3–6 and explore in more depth later in the article, these sources tweeted forecast and warning information that they created, and they tweeted in ways that amplified forecast and warning content created by other sources. This suggests that these sources act as "amplification stations" discussed in the Social Amplification of Risk Framework (Kasperson et al. 1988, 2022), here in a short-term hazard situation. Although Local Non-NWS Government, Local Weather Media, and Local News Media sources tended to have fewer retweets, more in-depth analysis found that some tweets from these groups garnered many retweets. In other words, despite the overall quantitative results, some sources in these less-retweeted groups actively contributed to Twitter forecast and warning communication.

Collectively, these results provide an overall picture of the multisource, multimessage, and multihazard nature of forecast and warning communication during Hurricane Harvey. They also begin to illustrate how source and imagery play intersecting roles in Twitter dissemination and diffusion of hurricane forecast and warning information, which we investigate in further depth below.

Evolution of Forecast and Warning Communication during Harvey

This section examines how dissemination and diffusion of forecast and warning image tweets evolved over the lifetime of Harvey's threat (Research Question 3). These results provide a longitudinal perspective on the roles that different types of forecast and warning content and sources played in hazard communication during Harvey. Building on related work (e.g., Wood et al. 2018; Carlson and Barbour 2023), this analysis also augments knowledge about how the confirmation and milling processes discussed in the hazard warning literature operate in the modern information environment.

We start with the synthesis in Fig. 8, which partitions the data set into three groups informed by the analysis above:

- NWS Impact Watch/Warning tweets
- Watch/Warning tweets
- All other tweet types combined (referred to as Non-Watch/Warning).

To understand how and why these different types of communication evolved, we interpret the Twitter data results in the context of how the storm, its impacts, and meteorologists' ability to predict different aspects of the threat evolved, which is summarized in Fig. 1.

Fig. 8(a) shows that authoritative sources began disseminating Non-Watch/Warning tweets on August 17th, but tweet volume remained low through August 21st. Once forecasts began indicating the high likelihood of the storm redeveloping and tracking toward Texas, the volume of Non-Watch/Warning tweets began increasing, and it continued to increase with the storm's threat to the U.S. After landfall on August 25th, Non-Watch/Warning tweets gradually decreased until the storm dissipated.

Authoritative sources began actively disseminating Watch/Warning tweets on August 23rd, when NWS began issuing Hurricane, Tropical Storm, and Storm Surge Watches for Texas, followed by related Warnings. Midday on August 25th, the number of Watch/Warning tweets increased dramatically, as NWS began issuing Tornado and Flash Flood Warnings related to Harvey. At the same time, NWS also began tweeting a large number of NWS Impact Watch/Warning images for the same hazards. Dissemination of both types of imagery remained high for several days, as NWS continued issuing Tornado and Flood Warnings for Harvey, before decreasing.

Also visible in Fig. 8(a) is a diurnal pattern in Non-Watch/Warning tweets, with authoritative sources tweeting these images more frequently during the day (6:00–18:00 CDT), during their and their audiences' typical waking hours. In contrast, for much of Harvey's threat, Watch/Warning and NWS Impact Watch/Warning tweets do not exhibit a diurnal pattern. This indicates that dissemination of this information was driven primarily by how Harvey's hazards evolved and when NWS issued associated Watches and Warnings.

Through most of Harvey's lifetime, total retweets for Non-Watch/Warning images [Fig. 8(b)] evolved similarly to tweet volume [Fig. 8(a)]. An exception is the morning of August 27th, when retweets of Non-Watch/Warning tweets peaked. This peak likely occurred because of increased attention to Harvey's emerging devastating impacts and associated amplification of Twitter messages. Retweets of Watch/Warning images peaked at a similar time, as NWS continued issuing Warnings for the life-threatening flooding that began overnight in and near the highly populated Houston area [Figs. 1 and 3(c)].

Fig. 9 examines the evolving roles of different types of images and sources in more depth by depicting time series of individual tweets in the data set. Again, we interpret these data in the context of how the event and the available meteorological information evolved. During the period August 17th through 19th, as Harvey formed and then moved westward in the Caribbean, authoritative sources tweeted mostly Cone images, satellite images, and other map-based graphics depicting areas at risk from the storm. This was followed by several days with few Cone image tweets, when Harvey weakened into a tropical wave and NWS stopped issuing the track and intensity forecasts underlying the Cone. On August 20th and 21st, to fill the gap left by the lack of NWS track forecasts,

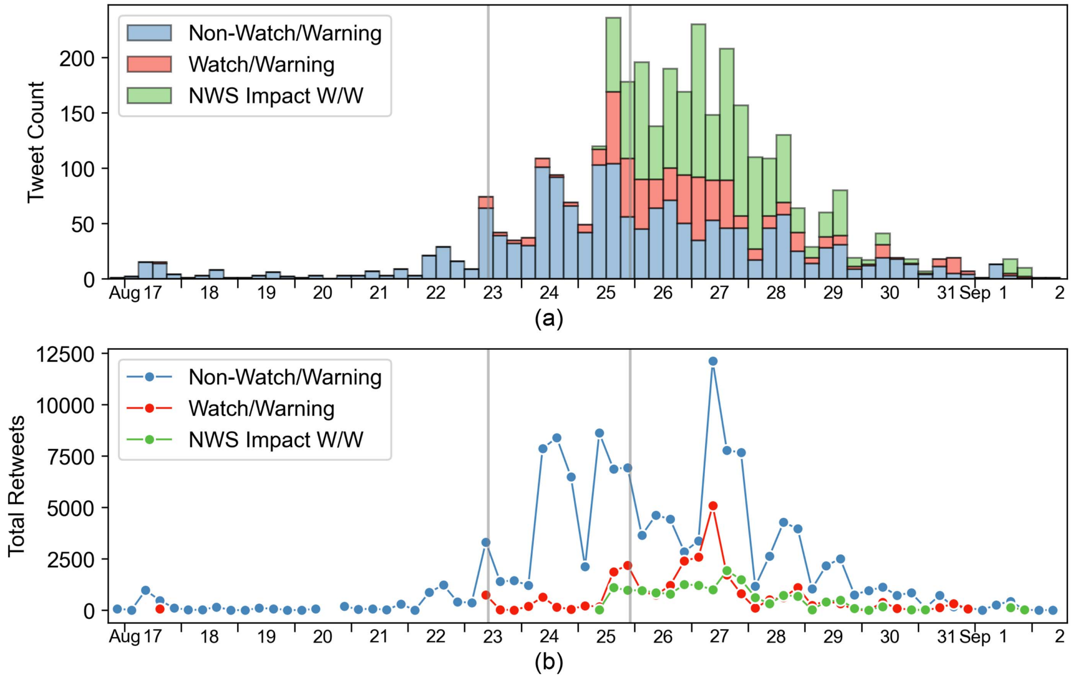

Fig. 8. (a) Time series of the number of tweets in the data set posted during 6-h time bins throughout Harvey's lifetime, partitioned into Non-Watch/Warning, Watch/Warning, and NWS Impact Watch/Warning tweets. (b) Time series of the total number of retweets for the Non-Watch/Warning, Watch/Warning, and NWS Impact Watch/Warning tweets posted in each 6-h time bin. In each panel, the tick marks on the x-axis represent 0:00 CDT on the corresponding date; in (b) statistics are shown for the time when a tweet was posted (not when it was retweeted). The vertical gray lines indicate, from left to right, the times when NHC issued its first forecast package for Harvey in the Gulf of Mexico (10:00 CDT on August 23) and when Harvey made its first landfall in Texas (22:00 CDT on August 25). N = 3,439.

authoritative sources tweeted primarily Tropical Outlook images indicating that Harvey might redevelop and Model Output images indicating that the redeveloped storm might track toward Mexico and the U.S. In addition, Fig. 9 indicates that from August 18–20, NWS sources tweeted little Harvey forecast and warning imagery. Instead, most of the tweets during this period were posted by National and Local Weather Media (non-NWS) sources.

As the risks to the U.S. increased, both NWS and non-NWS sources began tweeting more frequently about the storm. They also began disseminating a greater variety of imagery. On August 23rd, authoritative sources restarted tweeting Cone images as Harvey redeveloped into a Tropical Depression and NHC restarted issuing the track and intensity forecasts underlying the Cone graphic. At this time, local officials had not yet issued evacuation orders. However, the forecast information communicated during this period of a hurricane threat helps set the stage for how people interpret subsequent warning messages (Dash and Gladwin 2007; Zhang et al. 2007; Morss and Hayden 2010; Lazrus et al. 2020).

Between August 24–28, as Harvey approached and then caused major impacts in the U.S., all source types actively tweeted a variety of Harvey forecasts and warning imagery. The circle sizes indicate that some of these tweets were widely retweeted. Together, these results indicate that throughout this period multiple types of forecast information were disseminated and diffused on Twitter, along with warning messages. Although here we observe these processes on Twitter, other research indicates that authoritative sources also communicate a large volume of hurricane forecast and warning information via other mechanisms, including television, other Internet and social media platforms, radio, mobile phones, and in-person communication (Dash and Gladwin 2007; Morss and Hayden 2010; Morss et al. 2017; Lazrus et al. 2020; Prestley et al. 2020; Bostrom et al. 2022). In other words, for a period of several days or longer during a dynamic hurricane threat such as Harvey, people in areas at risk frequently—and sometimes near-continuously—hear and see evolving forecast and warning information. After this active forecast and warning period, as the immediate threats from Harvey subsided, Figs. 8 and 9 show that authoritative sources tweeted less forecast and warning information and a smaller variety of imagery.

This analysis suggests that it is important to update understanding of warning communication and response processes to reflect the "ever-evolving context where information is disseminated on various levels by a multitude of sources" (Dash and Gladwin, p. 70). During complex, dynamic hazardous situations like Harvey, many people may not engage in confirmation or milling in response to individual warning messages. Rather, they can *continually access and interpret forecast and other risk information leading up to and alongside the receipt of warnings*, as they seek to make sense of an evolving, uncertain situation and decide what to do (Morss et al. 2017; Wood et al. 2018; Carlson and Barbour 2023). In such situations, the seeing or hearing, understanding, believing, personalizing, confirming, and deciding processes described by Mileti and Sorensen (1990) may not be distinct processes or stages that people go through in response to individual pieces of information, as conceptualized several decades ago. Instead, people can engage in these processes simultaneously, in response to an evolving collection of information about a threat.

In-depth Analysis of Three Time Periods

To further characterize how hazard communication and response processes function in the modern information environment, next we analyze in greater depth how authoritative sources' tweets and their retweets and replies evolved during three periods within the

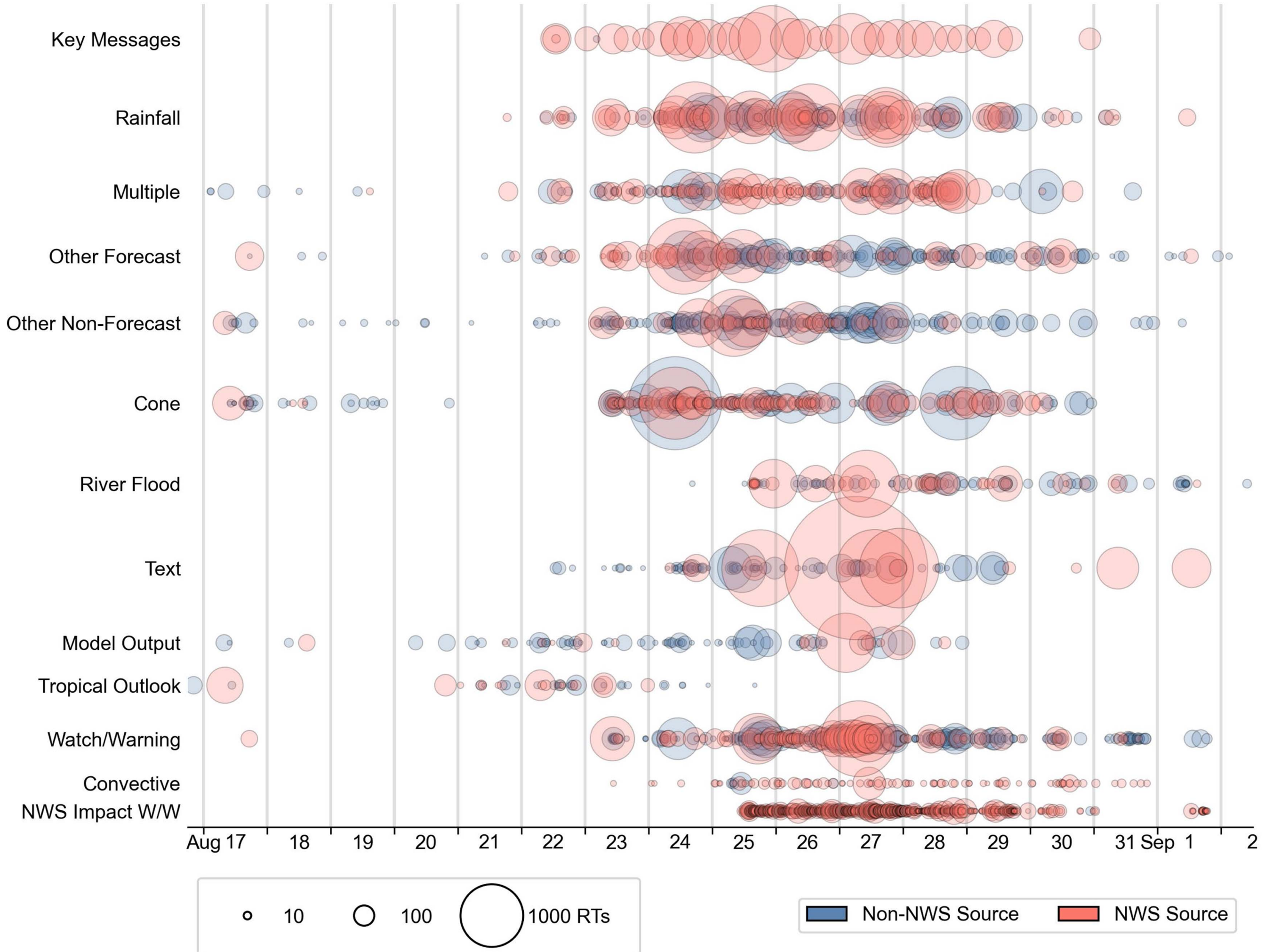

Fig. 9. Temporal evolution of tweets with different image types throughout Harvey's lifetime, with each circle representing one tweet. Each circle's size indicates that tweet's number of retweets (RTs), and its color indicates whether that tweet was posted by an NWS or non-NWS (Weather Media, News Media, Non-NWS Government, or Other) source. The tick marks on the *x*-axis represent 0:00 CDT on the corresponding date. Image types are organized from highest to lowest median retweets. N = 3,439.

data set: 9:00–12:00 CDT on August 23, 24, and 27. Key features of each period are synthesized in Figs. 10–12 and discussed below. As in previous sections, we present selected results, informed by additional in-depth analysis.

We chose these three periods because they represent times when different types of information were available about Harvey's threat (Fig. 1), when dissemination and diffusion peaked (Fig. 8), and when the analyses presented above indicated patterns of interest to further explore. Time of day influences dissemination, diffusion, and response through multiple mechanisms, including forecast release schedules, media coverage timelines, and ebbs and flows in attention and response. Thus, we analyzed the same period on each day, and we selected a time of day with a standard NHC forecast release time (10:00) partway through the period.

August 23, 09:00–12:00 CDT: Harvey as an Actualized Threat

This period began shortly after Harvey redeveloped into a tropical depression, and it coincided with NHC issuing its first forecast package for Harvey in the Gulf of Mexico (Fig. 1). This NHC package included the first forecasts of storm track and intensity—in other words, the first release of an NWS Cone image and underlying data—in the Gulf region. It also included newly issued Hurricane, Tropical Storm, and Storm Surge Watches for the Texas coast.

During the first 50 min of this period, this set of authoritative sources tweeted only four Harvey forecast images (Fig. 10). Starting at 9:50, as NHC released the forecast package and associated data, authoritative sources began tweeting Harvey forecast information much more frequently. The first few tweets, from National and Local Weather Media sources, contain text about Harvey redeveloping as a tropical depression and/or the just-issued Watches, accompanied by satellite imagery (Other in Fig. 10). This indicates that these sources could access and use some of the new NHC information, but not yet the graphical products or underlying data. This changes at 9:55, when authoritative sources began tweeting a flurry of Cone images. Starting at around 10:30, these sources shifted to tweeting maps depicting areas under Hurricane and Tropical Storm Watches (Watch/Warning in Fig. 10) along with Cone images. After this hour-long burst of Cone and Watch/Warning images derived from the newly released NHC forecast package, authoritative sources tweeted a wider variety of image types between 11:00 and 12:00.

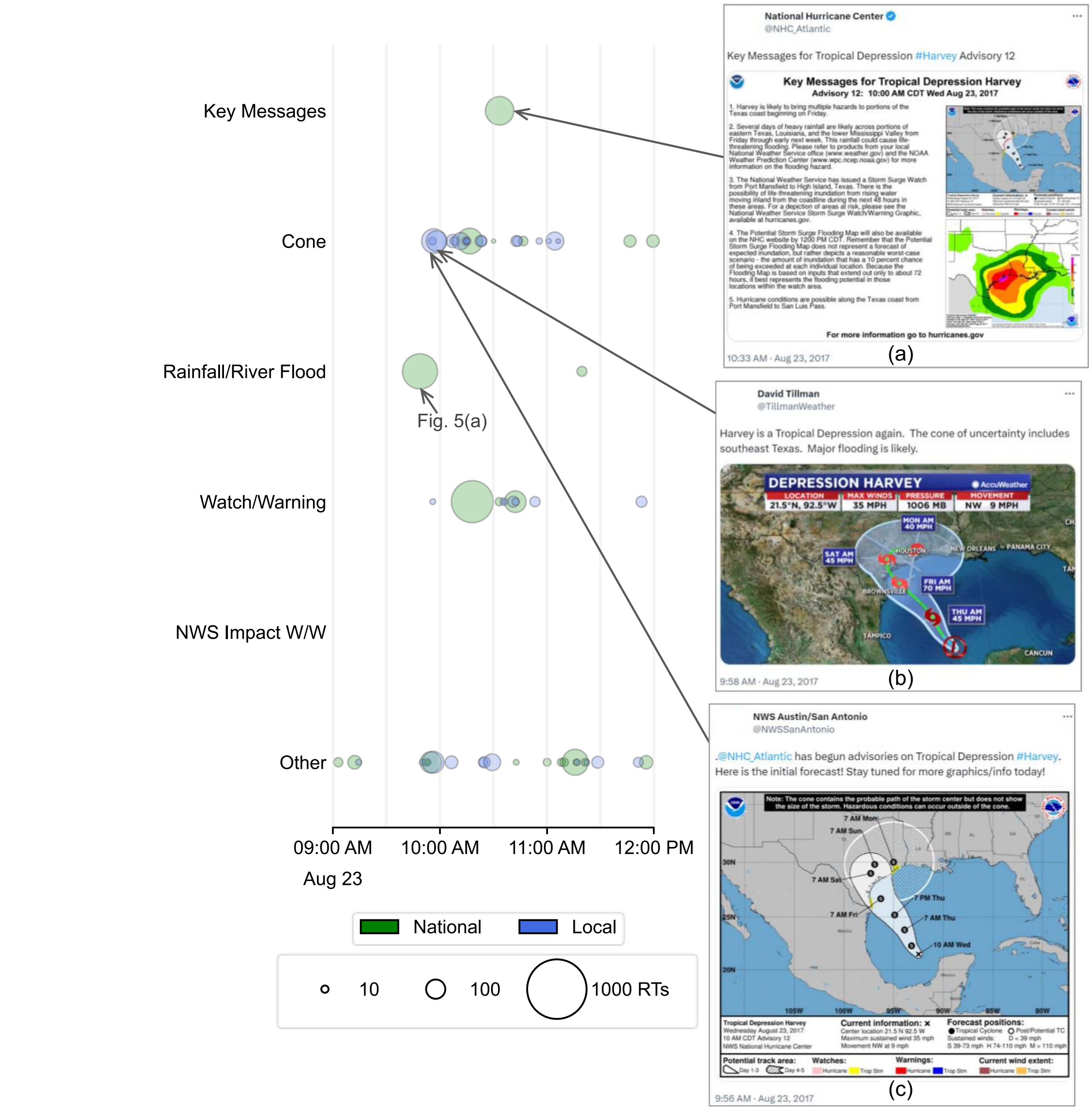

Fig. 10. Temporal evolution of tweets with different image types during the period 09:00–12:00 CDT on August 23, 2017. Each circle represents one tweet, with the circle's size indicating that tweet's number of retweets and its color indicating whether that tweet was posted by a National or Local source. Key Messages, Cone, Rainfall and River Flood, Watch/Warning, and NWS Impact Watch/Warning tweets are depicted separately, and the seven other image types are combined (Other). On the right, three example tweets posted during this period are shown: (a) Key Messages (reprinted from National Hurricane Center 2017e); (b) Cone (reprinted from Tillman 2017); and (c) Cone (reprinted from NWS San Antonio 2017). The timing of the example tweet shown in Fig. 5(a) (Rainfall) is also indicated.

Thirty-seven percent of the tweets in the data set during this period featured Cone images. These Cone images were tweeted by 20 different authoritative source accounts, in a mix of NWS and non-NWS formats. Authoritative sources also tweeted additional Cone graphics as part of other image types, as well as maps of possible storm tracks. These results indicate that communication about forecast storm track and intensity was prevalent during this period.

Since NHC generates the Cone graphic and underlying track and intensity data, these results also elucidate the importance of National NWS sources in driving forecast and warning communication during this period. This is further underscored by how NHC releasing a new forecast package influences the timeline of authoritative sources' tweets. The impacts of forecast and warning information generated by National NWS entities—especially NHC—are evident in both National and Local sources' tweets.

Although Cone imagery was most common during this period, additional analysis found that about half of the Cone image tweets included textual information about the risk of strong winds, storm surge, rainfall, and/or flooding posed by the storm. Moreover, several of the most retweeted tweets during this period used imagery to convey Harvey's potential rainfall or other hazards. Thus, authoritative sources did use Twitter during this period to communicate about the different hazards posed by Harvey. However, much of

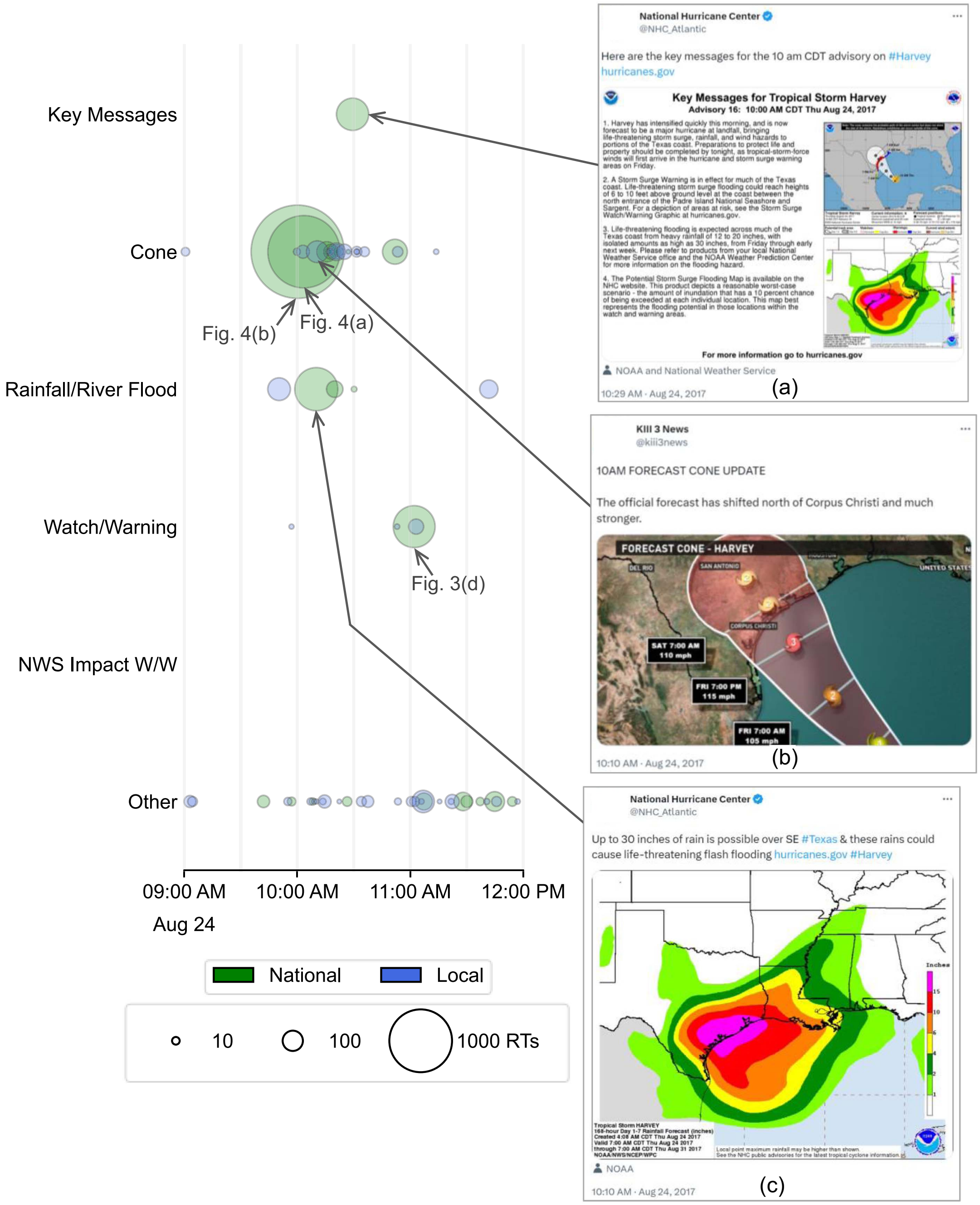

Fig. 11. As in Fig. 10, for the period 09:00–12:00 CDT on August 24, 2017. Three example tweets are shown: (a) Key Messages (reprinted from National Hurricane Center 2017f); (b) Cone (reprinted from KIII 3 News 2017); and (c) Rainfall (reprinted from National Hurricane Center 2017g). The timing of the example tweets shown in Figs. 4(a and b), and 3(c) (two Cone images and one Watch/Warning) is also indicated.

their communication focused on conveying higher-level information about the storm, given the rapidly evolving threat and significant forecast uncertainty.

In their replies to authoritative sources' forecast and warning tweets during this period, several people indicated disbelief in the forecasts or made humorous comments, for example, about the region at risk needing rain. This suggests that during this period, some people in areas at risk downplayed or potentially discounted the risk, and others used humor as a coping mechanism (Parkhill et al. 2011; Morss et al. 2017; Demuth et al. 2018). However, more replies expressed worry about the storm or asked questions about the storm's anticipated track or its impacts in certain areas. A few expressed concern for friends or family in at-risk areas or used an added @mention to draw their attention to the authoritative sources' tweet. Others expressed confusion about an aspect of the forecast, or discussed or asked questions about preparing for the storm. Several of these types of responses signify people engaging in self-organizing, information-seeking, and sense-making behaviors during Harvey's threat, as observed in prior disaster research using social media data (Sutton et al. 2008; Houston et al. 2015; Anderson et al. 2016; Demuth et al. 2018; Reuter et al. 2018; Silver and Andrey 2019; Silver 2019).

August 24, 09:00–12:00 CDT: Harvey's Threat Increases

During the hours leading up to the second period, Harvey strengthened into a tropical storm, and NHC began forecasting that the

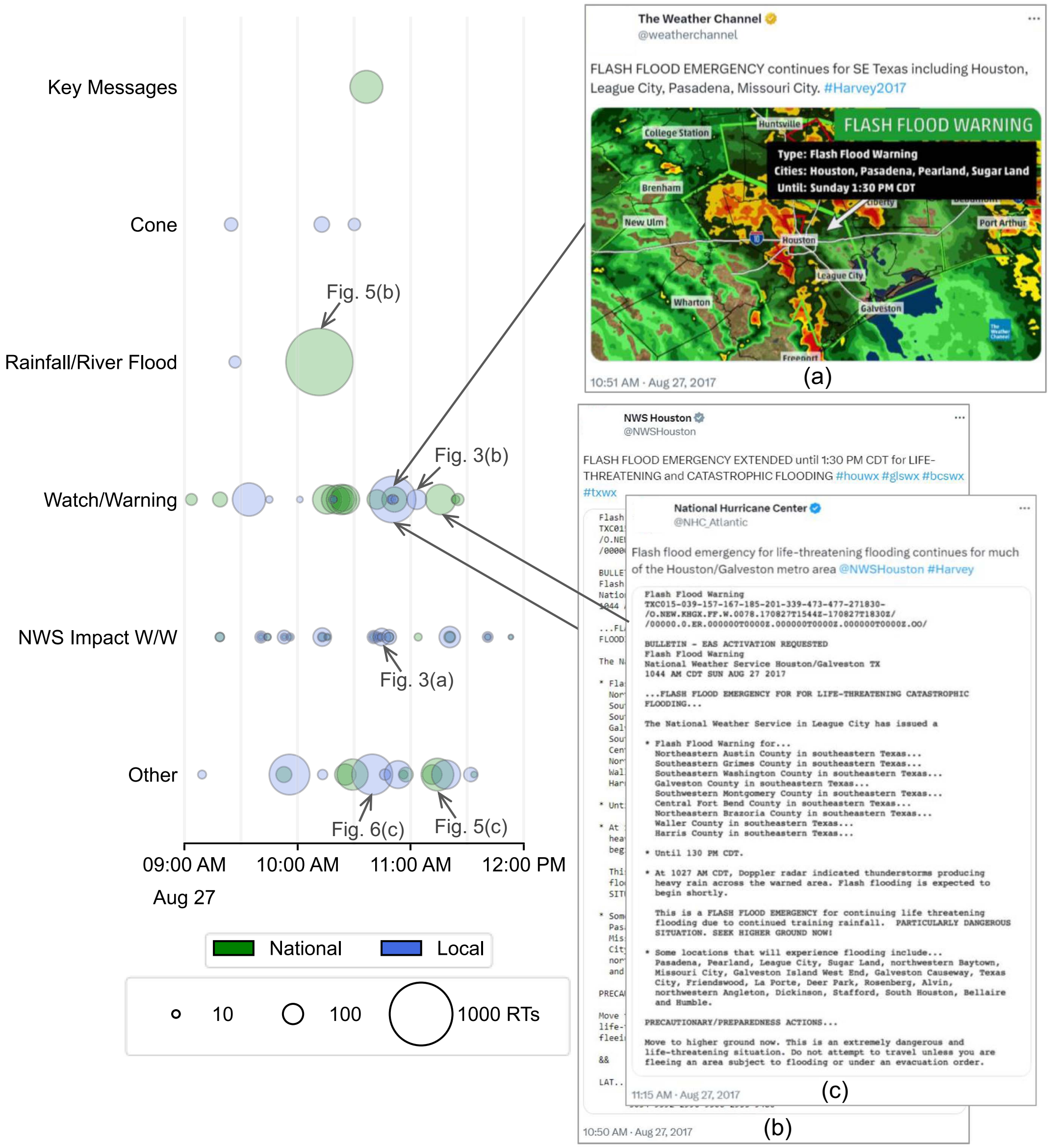

Fig. 12. As in Fig. 10, for the period 09:00–12:00 CDT on August 27, 2017. Three example tweets are shown: (a) Watch/Warning (reprinted from The Weather Channel 2017o); (b) Watch/Warning (reprinted from NWS Houston 2017l); and (c) same (truncated) Watch/Warning image as (b) (reprinted from National Hurricane Center 2017h). The timing of the example tweets shown in Fig. 5(b) (River Flood), Fig. 3(b) (Watch/Warning), Fig. 3(a) (NWS Impact Watch/Warning), Fig. 6(c) (Other Non-Forecast), and Fig. 5(c) (Convective) is also indicated.

storm would make landfall as a Category 1 hurricane (Fig. 1). NWS also began issuing hurricane-related Warnings for parts of Texas as well as Flash Flood Watches. During this period, NHC issued a new forecast package, which increased the storm's predicted intensity at landfall to a Category 3 (major) hurricane. And, with the storm intensifying and forecast to make landfall in about 36 h, a few communities began announcing evacuations and closures.

The Twitter timeline during this period began in a similar way to August 23rd, with authoritative sources tweeting few forecast and warning images during the first 50 min (Fig. 11). At 9:55, as information from NHC's new forecast package was released, they started tweeting more frequently. For the next hour, this set of authoritative sources tweeted primarily Cone images. After this flurry of Cone tweets, starting at 11:00, they again tweeted a wider mix of images.

As on August 23rd, Cone images remained prominent, comprising 35% of tweets. A variety of accounts tweeted these Cone images, using both NWS and non-NWS formats. Additional analysis found that many of these Cone image tweets included text emphasizing Harvey's recent and/or predicted intensification [see, e.g., Figs. 3(a and b)], as did as a number of other tweets. In other words, authoritative sources amplified this aspect of the newly released NHC forecast by posting a variety of types of original tweets, which Twitter users then further spread through retweets. The salience of storm intensity information is further demonstrated just after the end of this period, when NHC provided an update that Harvey had intensified into a hurricane (Fig. 1). This update led to a series of Media tweets between 12:00 and 12:10 conveying this intensification (not shown in Fig. 11).

NWS versions of the Cone include a depiction of Hurricane and Tropical Storm Watches and Warnings [e.g., Fig. 4(a)]. However, one difference from the previous day is that authoritative sources tweeted few images focused on NWS Watch and Warning information during this period. NWS had issued several

Watches and Warnings earlier that were still in effect, and a few authoritative sources redisseminated them [e.g., Fig. 3(d)]. Overall, however, this information was not prominent in authoritative sources' tweets.

Another difference from August 23rd was an increase in tweet text and imagery conveying rainfall, storm surge, and associated flooding threats. In addition, a few tweets disseminated information about evacuation or other preparatory actions. Thus, during this period authoritative sources did tweet information about the storm's potential hazards, associated warnings, and protective guidance—and a few even emphasized the importance of paying more attention to Harvey's flood threat than its specific track or intensity. However, storm track and intensity information remained prevalent, especially in imagery.

Analysis of reply content during this period found similar themes to the previous day. One new theme was replies focusing on Harvey's current or forecast intensity, including surprise at the rapid change. This is consistent with prior research findings that storm intensity is a salient concept for many members of the public (e.g., Zhang et al. 2007; Camelo and Mayo 2021). However, it is likely also related to authoritative sources' emphasis on intensity in their tweets. In addition, more Twitter users in at-risk areas expressed worry, and more asked questions about the forecasts for different locations and recommended actions. As on August 23rd, this illustrates how social media data can help researchers observe how people engage in the information gathering and interpretation processes described in the Warning Response Model.

Figs. 8 and 11 show that some of the Non-Watch/Warning tweets during this period were highly retweeted, which suggests widespread diffusion of and attention to the information. For many people in areas at risk, this forecast information therefore likely provided important context for the evacuation and other protective action information issued on the afternoon of August 24th and later, as the storm's threat increased and expanded to additional locations. In addition, as on August 23rd, National NWS sources played an important role in driving the forecast and warning conversation during this period. Our analysis again found this occurring through tweets posted by National NWS accounts and through National NWS-originated information propagating into other sources' tweets. It is also visible in the timeline of authoritative sources' tweets before and after the NHC forecast package release.

August 27, 09:00–12:00 CDT: Ongoing Harvey-Related Hazards and Impacts

The third period is after Harvey's landfall in Texas. The storm's winds had weakened, but it continued to produce heavy rain, leading to dangerous flooding in and near Houston beginning late on August 26th and continuing into August 27th [Figs. 1, 3(c), and 6(a)]. Along with warnings for flash flooding, during this period NWS also issued warnings for tornado threats caused by Harvey [e.g., Fig. 3(b)]. These co-occurring threats introduced additional complexities, as the two types of threats require different types of protective actions.

In contrast to August 23 and 24, the August 27 period did not begin with a relative lull in tweets leading up to the release of the NHC forecast package, nor did it contain many Cone image tweets (Fig. 12). Instead, during this period authoritative sources tweeted primarily Watch/Warning and NWS Impact Watch/Warning images (74% of tweets). All of these Watch/Warning tweets conveyed Tornado or Flash Flood Warnings for imminent or occurring hazards. Authoritative sources disseminated these in bursts throughout the period, interspersed with a mix of other image types, most of which conveyed the ongoing rain, flood, or tornado threats and associated recommended actions [e.g., Figs. 12(a), 5(c), and 6(c)].

As discussed earlier, the 40 NWS Impact Watch/Warning tweets during this period were posted automatically when the NWS issued a relevant Watch or Warning product. Most of these had few retweets. The 23 Watch/Warning image tweets focused on communicating the same NWS products as the NWS Impact Watch/Warning tweets. However, the Watch/Warning images evolved in a different temporal pattern, and they were tweeted by a wider variety of sources. They also tended to have more retweets.

Further analysis revealed that during this period, most of the Watch/Warning image tweets were authoritative sources redisseminating certain NWS Warnings by communicating the warning information in a new original tweet. For example, Fig. 3(a) indicates that at approximately 10:44 AM, the NWS Houston Weather Forecast Office (a Local NWS source) issued a Flash Flood Warning for the highly populated Houston area. Fig. 12 shows that this was first tweeted as an NWS Impact Watch/Warning image. Six minutes later, @nwshouston (the Twitter account for the NWS Houston Weather Forecast Office) tweeted an image of the corresponding NWS text product [Fig. 12(b)]. One minute later, @weatherchannel (a National Media source) tweeted a different map conveying the same NWS Warning [Fig. 12(a)]. Approximately 25 min later, @nhc_atlantic (a National NWS source) tweeted an image of the same NWS text product [Fig. 12(c)]. As this sequence illustrates, during this period National sources tweeted in ways that amplified warning information originated by Local NWS sources.

As shown in Fig. 12, this period also includes several highly retweeted tweets in the Other category. These tweets focus on locally originated evacuation information, recommendations to avoid affected areas, or the ongoing nature of Harvey's flood or tornado threat. One example is the tweet shown in Fig. 6(c), in which a Local Media source uses tweet text to communicate information about an evacuation order, accompanied by a satellite image of Harvey (Other Non-Forecast). The highly retweeted River Flood and Key Messages tweets in Fig. 12 similarly convey the ongoing local threat and associated local officials' recommendations, although in these cases through posts from National accounts. Together with the Watch/Warning discussion above, these results illustrate how on August 27th—after Harvey's landfall when the storm is causing major local impacts—information from Local NWS and Non-NWS Government sources drove much of the forecast and warning conversation. National and other Local sources played important roles by helping this locally originated information reach a wider audience.

Much of the reply content on August 27th comments on how bad the flooding is or asks questions about it. This includes questions about what is happening in specific areas, when the impacts will end, and what people should do in response to the impacts or warnings. Some of these replies are from people in affected areas. Other replies are from people who are concerned about or requesting assistance for friends or family in affected areas, as observed in previous Twitter research (Hughes et al. 2014; Houston et al. 2015). These themes are similar to those in the two earlier periods, with more distress and urgency as people try to make sense of the complex ongoing situation and decide how to navigate the mix of rapidly evolving threats.

The reply content on August 27 also indicated that some people were confused about what actions to take given concurrent Tornado and Flash Flood Warnings [see, e.g., Henderson et al. (2020)]. This suggests that, as discussed by Mileti and Sorensen (1990), improved communication strategies are needed for complex multihazard situations like hurricanes. Such strategies are especially important when multiple types of threats co-occur in the same area, or within a region where many people will receive the same forecast and warning messages.

Overall, this period differs from the two earlier periods in that Harvey's hazards and impacts have already arrived, and so exposed populations are hearing or seeing warning messages that they must rapidly interpret and respond to. Thus, the information that authoritative sources communicated during this period most closely corresponds to the types of situations characterized by the Warning Response Model. However, our analysis of this period illustrates the complexity of modern warning messaging for a hazardous situation such as Harvey, with multiple sources conveying warnings about multiple hazards alongside other forecast information.

Summary and Conclusions

This study developed a mixed-method approach for using near-real time data from online social media posts to investigate evolving hazard forecast and warning communication with populations in areas at risk. We implemented this approach to study forecast and warning dissemination, diffusion, and response leading up to and during Hurricane Harvey, which posed a complex set of interconnected, spatially and temporally varying risks. The entry point for analysis was original image tweets posted by authoritative sources of weather risk information. We focused in particular on dissemination and diffusion because being exposed to, attending to, and engaging with information about a threat are important aspects of risk communication and decision making (e.g., Mileti and Sorensen 1990; Griffin et al. 1999; Lindell and Perry 2012; Silver 2019; Kasperson et al. 1988, 2022).

Our analysis found that along with warning messages of the type examined in Mileti and colleagues' Warning Response Model, authoritative sources tweeted a variety of types of forecast information during Harvey, beginning days before warnings. On average, forecast tweets were retweeted more than warning tweets and for a longer period, suggesting greater attention to and diffusion of the information. Our analysis of replies also found that, consistent with other research, members of the public were interpreting and responding to this forecast information (Dow and Cutter 1998, 2000; Zhang et al. 2007; Morss and Hayden 2010; Morss et al. 2017; Demuth et al. 2018). These results indicate that for hazards that can be predicted hours or days in advance, including hurricanes, the forecast information communicated about a threat provides important context for people's interpretations of and responses to warning messages. Understanding how people attend to, perceive, and respond in these types of hazardous situations therefore requires reconceptualizing warning response—expanding it to encompass a broader forecast and warning perspective. As the meteorological, earth system, and other communities continue to improve prediction capabilities, updating hazard and disaster research models to incorporate these new developments will grow even more important.

The study's findings also demonstrate the large volume and variety of frequently updated forecast and warning information that was available to members of the public during Harvey, as the risks evolved in space and time. This illustrates how, in complex, dynamic hazardous situations such as hurricanes, warning communication and response are part of a larger risk information ecosystem. In this ecosystem, hearing or seeing, understanding, personalizing, believing, and confirming information are still important, as are milling processes. However, our analysis suggests that these may not be distinct processes that people proceed through in response to specific forecast and warning information. Instead, these processes can occur simultaneously and continually, as people access the evolving collection of information about a threat, perceive risks, make sense of the situation, and decide what to do.

Another key finding from this study is how different types of authoritative sources played complementary, changing roles in communication as Harvey evolved. From August 18–20, when Harvey was not an active tropical cyclone, NWS sources tweeted little forecast information about the potential threat, and Weather Media sources filled this gap. As the threat to the U.S. increased and then Harvey redeveloped, National NWS sources led the generation and dissemination of new forecast and warning content, with other sources diffusing this content and providing additional interpretations. Then, as the situation transitioned to ongoing impacts and warnings for imminent hazards after landfall, Local NWS and other Local Government sources led the generation of new locally relevant forecast and warning content, with National NWS and Media sources using Twitter to help this information reach a larger audience. In these different phases, we observed how purposeful social media posting by multiple types of authoritative sources, using similar or different imagery, helped gain attention for, amplify, and augment forecast and warning messages. This provides evidence of how, as discussed in Demuth et al. (2012), the different types of authoritative sources studied here work together to collectively create and communicate hurricane forecast and warning information. Although these sources operate on an increasingly crowded and fragmented information landscape, they continue to serve important, complementary roles in providing reliable hazard information.

Our analysis also reveals the important roles that information originated by NWS plays in other authoritative sources' hurricane forecast and warning communication. One example is how, during Harvey, both NWS and non-NWS sources tweeted many images conveying NWS-issued Tornado and Flash Flood Warnings. Social media can help rapidly disseminate such warnings—if the information gains traction. However, many of the NWS tweets with this content disseminated NWS Impact Watch/Warning images, most of which had few retweets. Another example of NWS's role in driving forecast and warning communication is our finding that despite the Cone's well-known limitations, a variety of sources tweeted Cone images after NHC releases of new forecast packages. These examples underscore the importance of NWS providing visuals and data that help other communicators effectively convey the most important aspects of a threat at any given time.

Regarding forecast and warning messaging, we found that many of the tweets in this data set do not contain all five types of content that Mileti and Sorensen (1990) recommended including in warning messages: hazard or risk, guidance, location, time, and source. In particular, many of the common visuals found in this data set contain little or no guidance about recommended protective actions. This contravenes Wood et al.'s (2012) findings on communicating actionable risk, as well as work on the importance of efficacy in risk communication and decision making (e.g., Bourque et al. 2013; Ruiter et al. 2014; Demuth et al. 2016; Morss et al. 2016). Those creating and communicating warning messages may therefore benefit from using Mileti and Sorensen's (1990) recommendations about message content and style. However, much of the information studied here is communicated when key aspects of the threat are uncertain. Moreover, a growing body of research indicates that rather than obtaining comprehensive warning messages from one authoritative source, many people access multiple types of hurricane risk information from a variety of sources and synthesize it to make sense of the situation and decide what to do (Zhang et al. 2007; Morss and Hayden 2010; Demuth et al. 2018, 2023; Lazrus et al. 2020). People can therefore access important content collectively, from multiple sources and messages. Thus, it is important to update Mileti and Sorensen's recommendations to reflect the larger volume and longer lead times of information now available for weather-related hazards and the greater complexity of modern hazard risk communication and response.

One goal of this research was advancing methods for studying the complex, evolving dynamics of modern forecast and warning communication and response. Online posts produce vast amounts of potentially informative data, but we found that choices about structuring data collection, filtering, and analysis influence what is learned. In order to obtain meaningful results about our research questions, we needed to sample, categorize, filter, and analyze the data carefully (Palen and Anderson 2016). This included conducting in-depth qualitative analysis to support and help guide quantitative analysis. In addition, to develop robust results relevant to the study domain, we needed to analyze the data from multiple perspectives, informed by knowledge of the information content and communication context. This type of deep content-based knowledge can help researchers build up to analyses with larger data sets involving more quantitative and automated methods.

Along with the theoretical and methodological contributions discussed above, our analysis leads to several practical recommendations:

- The gap in NWS Twitter communication from August 18–20 provides further support for recent recommendations that NWS develop new products and strategies for communicating tropical cyclone scenarios at longer lead times, before NHC provides the track and intensity forecasts used in Cone images (Morss et al. 2022a).
- Our results on how different sources play complementary roles in Twitter forecast and warning communication suggest the potential for NWS, public officials, media sources, and others to develop new ways of coordinating online to quickly communicate critical information to a variety of audiences.
- The prominence of Cone image tweets during Harvey provides additional support for recent recommendations that NWS update the Track Forecast Cone graphic or develop an improved tropical cyclone threat summary product that more effectively communicates hurricane risks to different populations (Evans et al. 2022; Henson 2022; Morss et al. 2022a).
- Our related finding that some authoritative sources emphasized newly released information, e.g., about Harvey's rapid intensification on August 24th, suggests that NWS develop improved strategies to highlight the most important information at any given time, across their product suite.
- Our findings on Watch/Warning tweets, including the lack of protective action guidance in many Watch/Warning tweets and the few Watch/Warning tweets on the morning of August 24, suggest that NWS may want to develop new approaches for communicating Watch and Warning messages—approaches that prominently feature the key information NWS is trying to convey and facilitate other sources diffusing and amplifying this information.
- These Watch/Warning results, together with our results on NWS Impact Watch/Warning tweets, suggest that NWS develop revised visuals for communicating longer- and shorter-term Watches and Warnings. To be effective, these visuals should be developed in collaboration with other weather information communicators, so that the imagery can readily be diffused or adapted for others' communications.

These recommendations were developed by interpreting this study's findings in the context of current knowledge about hurricane forecast and warning communication research and practice.

One limitation of this study relates to our aim of studying forecast and warning communication with people in areas at risk. Although we structured our methods with this aim in mind, the retweets in the data set are from a mix of populations. Moreover, many people are not on or not active on Twitter, and some populations are not engaged with the types of authoritative source communications that we analyzed. Thus, it is important to complement this type of research with work that uses other approaches to understand how people interact with and use hazard information, including sociodemographically diverse populations and those who may be more susceptible to harm (e.g., Dash and Gladwin 2007; Lazrus et al. 2012, 2020; Anderson et al. 2016; Huang et al. 2016; Wilhelmi et al. 2023, 2024).

Another limitation is that we only analyzed tweets that included hurricane risk imagery, based on our use of Bica and colleagues' data set and our interest in visual communication. Future work could extend these methods to analyze forecast and warning content more broadly and to investigate the interplay between text and imagery. In addition, Harvey was a unique tropical cyclone with an atypical evolution; to develop more generalizable findings, it is important to study other events. To begin addressing these limitations, two members of our research team conducted a follow-on study of tweets with and without imagery posted by professional sources during Hurricane Irma (Prestley and Morss 2023). Compared to Harvey, Irma had a longer predictive lead time. In addition, Irma and its impacts evolved differently from Harvey and affected a region with different geography, which led to a Twitter data set less dominated by short-fused, post-landfall warnings in a major metropolitan area. This allowed the Irma study to build on the analysis presented here in several ways, including identifying forecast and warning sub-phases and using regression analysis to understand how tweet timing, content, and other factors affect retweets.

In addition, after we conducted our analysis, Twitter went through major changes, leaving its future role in hazard forecast and warning communication uncertain. We do not yet know whether Twitter will continue to be a robust, trusted platform for conveying risk messages, or whether Twitter will continue to provide valuable data for research. Nevertheless, we anticipate that aspects of our findings are relevant beyond Twitter specifically, and social media more broadly, to modern multisource, multiplatform, and multimessage communication.

Overall, the processes we see in these data connect to those in Mileti's and others' work on hazards and warnings. Yet during the last few decades, the Internet, social media, and other advances have dramatically increased the volume, heterogeneity, and complexity of information available during times of threat. They have also opened up new opportunities to observe in depth how information communication and response processes evolve and interact. It is challenging to simultaneously investigate multiple aspects of these processes during dynamic, uncertain situations, as information about a threat evolves. Yet approaching data collection and analysis from this perspective, guided by relevant knowledge from multiple fields, enabled this study to update current understanding about real-world hazard forecast and warning systems. The findings can be used to contextualize other research that focuses on subsets of the topics studied here, guide additional work, and improve forecast and warning communication.

Data Availability Statement

The data coding schemes that support the findings of this study are published in the DesignSafe Data Depot Repository (Prestley and Morss 2024). Additional information is available from the corresponding author upon reasonable request.

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Supplemental Materials

Tables S1–S2 and Fig. S1 are available online in the ASCE Library (www.ascelibrary.org).

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