Contextualizing Disaster Phases Using Social Media Data: Hurricane Risk Visualizations during the Forecast and Warning Phase of Hurricane Irma

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ABSTRACT: Common disaster-phase models provide a useful heuristic for understanding how disasters evolve, but they do not adequately characterize the transitions between phases, such as the forecast and warning phase of predictable disasters. In this study, we use tweets posted by professional sources of meteorological information in Florida during Hurricane Irma (2017) to understand how visual risk communication evolves during this transition. We identify four subphases of the forecast and warning phase: the hypothetical threat, actualized threat, looming threat, and impact subphases. Each subphase is denoted by changes in the kinds of visual risk information disseminated by professional sources and retransmitted by the public, which are often driven by new information provided by the U.S. National Weather Service. In addition, we use regression analysis to understand the impact of tweet timing, content, risk visualization and other factors on tweet retransmission across Irma's forecast and warning phase. We find that cone, satellite, and spaghetti-plot image types are retweeted more, while watch/warning imagery is retweeted less. In addition, manually generated tweets are retweeted more than automated tweets. These results highlight several information needs to incorporate into the current NWS hurricane forecast visualization suite, such as uncertainty and hazard-specific information at longer lead times, and the importance of investigating the effectiveness of different social media posting strategies. Our results also demonstrate the roles and responsibilities that professional sources engage in during these subphases, which builds understanding of disasters by contextualizing the subphases along the transition from long-term preparedness to postevent response and recovery.

SIGNIFICANCE STATEMENT: Visual information is an important tool for communicating about evolving tropical cyclone threats. In this study, we investigate the kinds of visualizations posted by professional weather communicators on Twitter during Hurricane Irma (2017) to understand how visual information shifts over time and whether different visuals are more retweeted. We find that visual information shifts substantially in the days before Irma's impacts, and these shifts are often driven by changes in Irma's strength or forecast track. Our results show that cone, satellite, and spaghetti-plot visualizations are retweeted more frequently, while watch/warning imagery is retweeted less. These results help us to understand how visual information evolves during predictable disasters, and they suggest ways that visual communication can be improved.

KEYWORDS: Social science; Tropical cyclones; Communications/decision-making; Emergency preparedness; Emergency response; Societal impacts

1. Introduction

High-impact disasters are often conceptualized as occurring in phases, corresponding to different patterns of activities undertaken by risk management entities and members of the public (Neal 1997). These disaster-phase models often include four phases: mitigation and preparedness are conceptualized as occurring before a storm, and response and recovery are conceptualized as occurring during or after a disaster (National Governors' Association 1979). This conceptualization of disaster phases helps guide practitioners in managing disasters, and it also provides a theoretical basis for understanding, at a high level, how information needs, risk perceptions, and behaviors and responses vary as disasters unfold.

While these conceptualizations offer a useful starting point, they do not fully represent the types of activities undertaken in the hours and days leading up to hazardous meteorological events such as floods, tornadoes, and tropical cyclones, which can now be forecast with longer lead times (e.g., Alley et al. 2019; Bauer et al. 2015; Brotzge and Donner 2013; Cangialosi et al. 2020). Specifically, these conceptualizations do not include the transitions between phases (Wolbers et al. 2021), such as the forecast and warning phase (see section 2a). This phase exists along the transition from preparedness to response when forecasts and warnings are issued and uncertainty lessens over time. As such, professional sources of meteorological information, such as the U.S. National Weather Service (NWS) and weather media, play a central role in communicating risk during this phase (Demuth et al. 2012; Bostrom et al. 2016; Morss et al. 2022b; Sherman-Morris 2005; Prestley et al. 2020).

To communicate evolving and uncertain information during the forecast and warning phase, professional sources rely on visual risk information to synthesize complex information about an evolving disaster into a dense visual package (see section 2b). One commonly used example in the context of tropical cyclone

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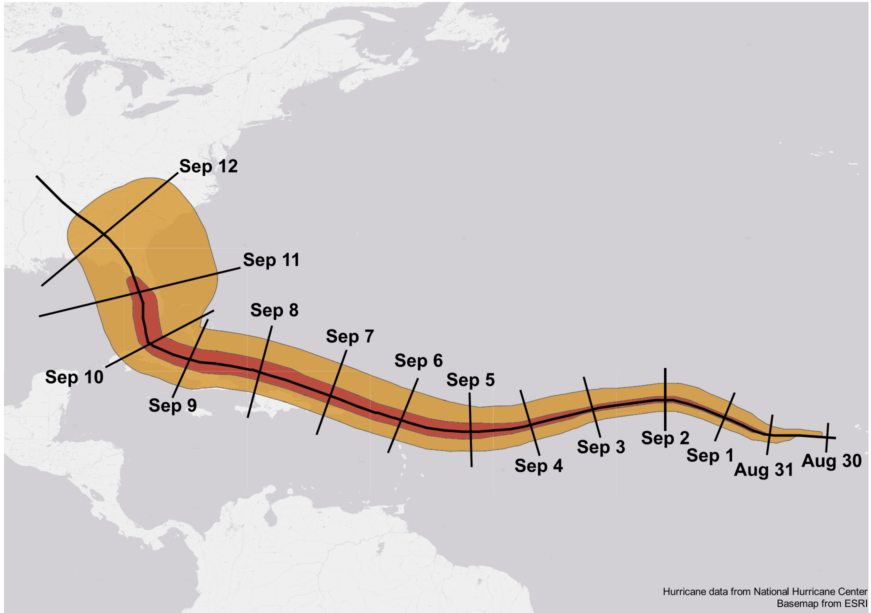

FIG. 1. Track and wind extent of Hurricane Irma. The black line represents the National Hurricane Center's best-track forecast. Shading represents Irma's wind extent, where light orange represents Irma's tropical storm–force wind extent [>39 mi h^{-1} (17.4 m s^{-1})] and dark red represents Irma's hurricane-force wind extent [>74 mi h^{-1} (33.1 m s^{-1})]. The labeled lines crossing the track denote Irma's location at 0000 EDT on the labeled date. The hurricane data are from the National Hurricane Center, and the base map is from ESRI.

disasters is the National Hurricane Center (NHC) track forecast cone, which depicts a map of a tropical cyclone's forecast track, track forecast uncertainty, and other attributes (NHC 2023; Fig. S1 in the online supplemental material). These risk visualizations can be customized to emphasize specific aspects of a disaster using coloring, shading, hatching, or other visual cues. This flexibility, combined with the nature of the modern risk information and communication environment (Morss et al. 2017), allows for the proliferation of numerous types of visual risk information as disasters evolve during the forecast and warning phase.

To understand how visual risk information is disseminated by professional sources and retransmitted by members of the public during the forecast and warning phase of a disaster, we use data from social media networks (see section 2c). Social media networks make up one part of the modern risk information system whereby risk information produced by professional sources is transformed and propagated through multiple information channels in order to reach a wide range of actors and end users (Morss et al. 2017; Kogan et al. 2015). This process of transformation and propagation occurs multiple times a day as new information about a disaster is received. By carefully selecting and filtering data from social media networks like Twitter (rebranded as X in July 2023 but referred to here by the original name), we can tap into a "natural laboratory" that provides a temporally detailed log of how different professional sources disseminate information (Sutton et al. 2015a; Houston et al. 2015; Vos et al. 2018; Bica et al. 2019) and how this information is retransmitted via sharing functions like retweets (Starbird and Palen 2010; Sutton et al. 2015b).

We study these processes in the context of Hurricane Irma, a 2017 hurricane that made landfall in southwestern Florida but caused damaging wind, storm surge, rainfall, and tornado impacts throughout the Florida peninsula. Irma offers an interesting case study, given the storm's 11-day-long forecast and warning phase (Fig. 1) and the numerous interrelated threats posed by Irma, which varied substantially across space and time. These factors led to the proliferation of visual risk representations to help disaster managers and at-risk members of the public make informed decisions as Irma continually evolved.

Specifically, we study the dissemination and retransmission of information provided by NWS and weather media Twitter accounts, focusing on Miami and Tampa, Florida's largest coastal metropolitan areas, which were affected by Irma in different ways and on different time scales. To better understand how these professional sources of meteorological information provide visual risk information during the forecast and warning phase of a tropical cyclone disaster, we pose the following questions:

1) What types of visual risk information do professional sources of meteorological information disseminate on Twitter during the forecast and warning phase of Hurricane Irma, and how does this dissemination evolve throughout Irma's forecast and warning phase?
2) What factors, including the types of visual risk information present in tweets, influence retransmission of information about Irma on Twitter during Irma?

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In the following section, we review three aspects of the disaster literature that are relevant to this study: the forecast and warning phase (and disaster phases broadly), risk visualizations, and social media. We then describe our Twitter data collection and analysis methodology (section 3) before providing results (section 4) and discussion (section 5), in line with our research questions.

2. Background

a. *The forecast and warning phase of predictable disasters*

As noted in the introduction, the four-phase (mitigation, preparedness, response, and recovery) disaster-phase model originated as a way of organizing the key activities and processes that disaster managers engage with as disasters evolve. While this model provides a useful heuristic for organizing disaster activities, the reality is that many activities and processes occur across several phases (Neal 1997). Disaster scholars, however, continue to rely on this heuristic in structuring their analyses, often focusing on a single phase (Wolbers et al. 2021). Thus, there is a clear need for research that focuses “on multiple phases, or the transitions from one phase to the other” (Wolbers et al. 2021, p. 383).

In this analysis, we seek to understand one such transition by focusing on what we call the forecast and warning phase for predictable disasters. This phase incorporates the warning timeline of disasters (Mileti and Sorensen 1990; Sorensen 2000), when disaster managers provide advanced notice of an impending disaster and protective action advice to take to mitigate personal risk (Sorensen 2000), and the forecast timeline of disasters, when disaster managers may be actively monitoring a potential threat but remain unsure whether to issue warnings due to high uncertainty about impacts. As such, the forecast and warning phase represents an interesting transition between the preparedness and response phases of the four-phase disaster model, especially for predictable disasters.

In studying this transition, we can highlight the ways in which traditional preparedness and response activities overlap during the forecast and warning phase of meteorological disasters, as well as shed light on additional activities that may only occur during the transitions between preparedness and response. For instance, previous literature has demonstrated the unique roles and responsibilities of professional sources of meteorological information during the forecast and warning phase of tropical cyclones, including monitoring updated information, making decisions about issuing evacuations, ordering supplies, activating shelters and emergency operations centers, and communicating with the public (Morss et al. 2022b; Bostrom et al. 2022).

Communication from professional sources is especially important during this phase, as members of the public interrogate information from different sources, grapple with multiple possible scenarios, and make difficult decisions under uncertainty. As such, previous literature has explored how professional sources of risk information might use different types of language to present information about a hazard’s strength (Perreault et al. 2014; Williams et al. 2022) and uncertainty (Joslyn and LeClerc 2012; Demuth et al. 2009), as well as information about protective actions to take in response to a hazard (Mileti and Sorensen 1990; Sutton et al. 2018, 2021), to different audiences (Sherman-Morris et al. 2020; Trujillo-Falcón et al. 2022) during the forecast and warning phase of meteorological hazards. We build on this literature by investigating how multiple forms of information, such as risk visualizations, are used by professional weather communicators as the forecast and warning phase evolves.

b. *Visualizations during the forecast and warning phase*

Professional weather communicators use risk visualizations during the forecast and warning phase to summarize complicated, uncertain information into compact visual displays (Spiegelhalter et al. 2011). These visualizations may denote different levels of risk, uncertainty, or threat, spatially or over time, for different kinds of hazards (MacEachren et al. 2005; Klockow-McClain et al. 2020; Shivers-Williams and Klockow-McClain 2021; Carr et al. 2016; Sutton et al. 2020; Sutton and Fischer 2021; Gulacsik et al. 2022).

Tropical cyclone visualizations have been a frequent topic of study, given the variety of threats posed by tropical cyclones and high uncertainty about impacts. To underscore this point, the NWS currently issues several visual products for each tropical cyclone threat. These include track forecast cone maps, maps that display wind speed probabilities and expected arrival times, storm-surge inundation maps, excessive rainfall outlooks, convective outlooks, hurricane threat and impact graphics, and key messages graphics (Morss et al. 2022b; Figs. S1–S5 in the online supplemental material). Each graphic in this suite of products attempts to communicate different aspects of a tropical cyclone’s potential threat, from when it will impact population areas to where the worst surge inundation will be (Sherman-Morris et al. 2015; Morrow et al. 2015), in order to provide complementary information about a tropical cyclone’s multifaceted threat.

While the NWS creates numerous visuals as part of the tropical cyclone product suite, some of these visuals may be used by professional weather communicators more frequently. For instance, results from Broad et al. (2007) and Morss et al. (2023, manuscript submitted to *Nat. Hazards Rev.*) suggest that the track forecast cone may be a particularly salient tropical cyclone visualization. As such, in this analysis, we seek to understand how different tropical cyclone risk visualizations are communicated by professional sources and how the public engages with these visualizations.

c. *Social media during disasters*

Social media networks have become an invaluable tool for communication and information-gathering during disasters. As such, analysis of social media data has been used to provide insight on how members of the public gather and retransmit information during disasters (e.g., Procopio and Procopio 2007; Palen et al. 2009). Social media data from public users have also been used to construct disaster narratives, which can help inform how risk perceptions and behaviors change

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TABLE 1. Summary of Irma-relevant tweet and retweet (RT) statistics for professional weather communicators with different affiliations and scopes of responsibility.

Source type	No. of sources	No. of tweets	Percent of tweets	Avg No. of tweets per account	Median RTs
National NWS	5	374	6.8	74.8	239.5
National weather media	2	321	5.8	160.5	215
Miami NWS	1	231	4.2	231.0	60
Miami weather media	18	2638	47.9	146.6	5
Tampa NWS	1	328	6.0	328.0	8
Tampa weather media	20	1611	29.3	80.6	4
All	*47*	*5503*	*100.0*	*117.1*	*7*

over the course of evolving disasters (Anderson et al. 2016; Demuth et al. 2018; Bica et al. 2023).

Here, we focus on how professional sources use social media during disasters, in line with previous research on information dissemination by these sources. Results from these analyses highlight the ways in which disaster managers use social media (Houston et al. 2015; Wukich 2016), or highlight the range and frequency of expressions used by disaster managers on social media (St. Denis et al. 2014; Hughes et al. 2014; Sutton et al. 2014, 2015a,b; Vos et al. 2018; Olson et al. 2019).

Studies of professional communication on social media additionally analyze how members of the public engage with disaster information by sharing messages from professional sources among their social networks. This process has been described with different terms, including diffusion (Rane and Salem 2012), message passing (Sutton et al. 2019), and serial transmission (Sutton et al. 2014). Here, we use what Sutton et al. (2014, p. 766) call retransmission, which is described as a form of message amplification, wherein "retransmitted messages are likely to be seen by a large number of persons [and] are likely to have been seen a larger number of times by any given person." Thus, studying patterns of retransmission offers value in providing recommendations for how professional sources can reach as many people as possible during disasters. For instance, social media studies have indicated that including media attachments or hashtags (Sutton et al. 2015a, 2019; Zheng et al. 2022), or posting during highly salient times (Vos et al. 2018) can increase retransmission.

However, many questions regarding social media dissemination and retransmission of disaster information remain unanswered. For one, only a handful of studies have investigated the role of visual risk representations on social media (Bica et al. 2019; Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*). In addition, social media research has focused primarily on how professional sources use social media in the response and recovery phases of disaster (Houston et al. 2015; Wukich 2016), with less attention paid to prestorm phases and the overlaps, transitions, and connections between phases [see Olson et al. (2019) and Sutton et al. (2019) for a few notable exceptions]. Thus, in this analysis, we seek to bridge these theoretical gaps to better understand the dissemination and retransmission of visual risk information during the forecast and warning phase of a tropical cyclone disaster, in line with our research questions.

3. Methods

a. Data collection and filtering

Consistent with our research focus, we collected tweets from accounts associated with two groups of weather communication professionals: the NWS and weather media. These include local NWS Weather Forecast Offices and individual and organizational accounts for media organizations that focus on producing or providing weather information for the Miami and Tampa areas. We also collected tweets from several high-profile national NWS and weather media accounts, since these sources also provide locally relevant weather information for some members of the public (Table 1); a full list of sources ($N = 47$) can be found in Table S1 in the online supplemental material and in Prestley and Morss (2023). We focus on these types of accounts based on previous research that found that they posted the majority of tropical cyclone forecast and warning information during Hurricane Harvey (Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*).

We used the Twitter-V2 (Academic) application programming interface to collect all original tweets (i.e., not retweets, replies, or quote tweets) posted by each source from 2000 eastern daylight time (EDT) (UTC − 4 h) 30 August to 1700 EDT 12 September 2017. This spans the time between the first and last NHC advisories issued for Irma, with a small buffer at the beginning to collect any earlier relevant tweets; this corresponds to Irma's forecast and warning phase, as well as the initial transition to response and recovery poststorm. This collection yielded 7719 original tweets (Fig. 2).

We then coded tweets based on relevance to Irma, defined as mentioning Irma or any of its associated threats and impacts (in either the tweet text or media attachments) (Prestley and Morss 2023). To test and refine the Irma-relevance definition, two coders cross-coded 778 randomly selected tweets (10% of the dataset) in three rounds. After each round of coding, the coders discussed and adjudicated disagreements and revised the coding scheme. Intercoder reliability was calculated for both coders over all three rounds using Krippendorff's alpha-reliability (Krippendorff 2011). Given high reliability ($\alpha = 0.94$), the primary coders coded the rest of the data. This yielded 5503 Irma-relevant tweets, which form the basis of our analysis (Fig. 2).

b. Data collection and filtering

Next, we categorized the Irma-relevant tweets to investigate patterns of dissemination and retransmission across a

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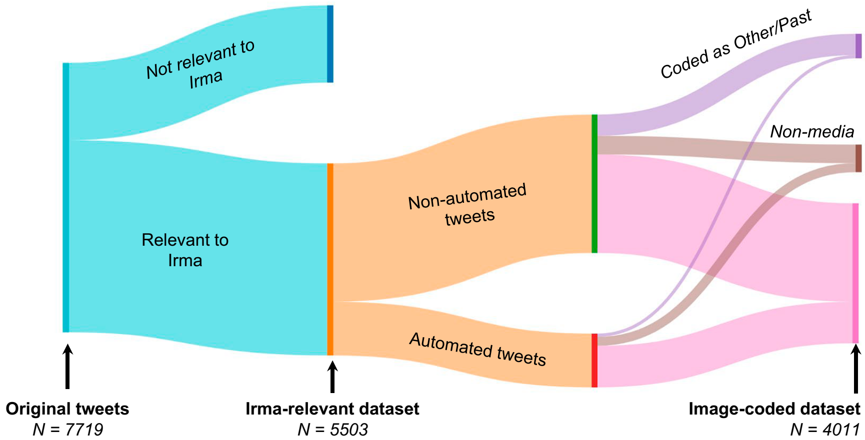

FIG. 2. Flow diagram illustrating the data coding and filtering process discussed in section 3b.

variety of categories. Three categorizations were based on metadata provided by Twitter during collection:

- Time of day: 3-h time bins based on the time of day tweets were posted, in EDT (e.g., 0000–0300, 1500–1800).
- Storm subphase: Time periods representing different subphases of Irma's forecast and warning life cycle, identified as part of our analysis (section 3c) and discussed further in section 4b.
- Media type: Type of multimedia attached to a tweet (single photograph, multiple photographs, animated GIF, or video), or no media attachments (text only).

We also used manual coding to categorize the tweets in several additional ways, which are summarized below.

1) Automated tweet identification

The data include sets of tweets that use identical or similarly formatted text phrases, often accompanied by similar visualizations. We refer to these as automated tweets, based on the source field in the Twitter metadata suggesting that many of them are automatically posted by third-party apps or "bots." These tweets are often posted after the issuance of an NWS warning or other product, as shown in the examples in Fig. 3.

We define automated tweets as tweets that include text phrases or formats that are repeated over at least five other tweets and that are posted on at least two different days during Irma's threat period (Prestley and Morss 2023). To identify these tweets, we grouped Irma-relevant tweets by the first 15 characters of the tweet text. Tweets that started with the same characters and met the other criteria were automatically coded as an automated tweet. One author then manually investigated tweets that did not start with the same characters for similarities that met the criteria (e.g., starting with a date and time, and thus starting with different text but following the same format). In total, we identified 24 distinct text patterns from 21 professional sources, accounting for 1539 automated tweets (28% of all Irma-relevant tweets). Both automated and nonautomated tweets were included in subsequent coding, as shown in Fig. 2.

2) Hazard and time reference coding

To investigate how professional sources discussed different types of tropical cyclone–related hazards, we coded each Irma-relevant tweet based on the meteorological hazard(s) represented and the time reference(s) of the information in the tweet (Tables 2 and 3; Prestley and Morss 2023). Both sets of codes were applied at the tweet level, based on whether the codes appeared in any of the major components of a tweet. Major components include sentences or sentence clauses in the tweet text, or distinct pieces of any multimedia attachment that occupy at least 20% of the media attachment, excluding titles, headers, and background information. Because tweets can contain multiple major components, tweets could be coded as more than one hazard or time reference.

To test and refine the hazard and tense coding schemes, two coders coded randomly selected subsets of nonautomated, Irma-relevant tweets. We chose to not include automated tweets during this process because their homogeneity might have artificially propped up intercoder reliability. In total, 600 tweets (~15% of the sample) were coded over four rounds, with discussion of disagreements and revisions to the coding scheme after each round. After establishing sufficiently high intercoder reliability ($\alpha > 0.75$) for all hazard and tense codes, one coder then coded the remaining nonautomated, Irma-relevant tweets, as well as all Irma-relevant automated tweets (Fig. 2).

3) Image type and branding

Given our focus on visual risk information, we also developed and implemented coding schemes for image type and image branding (Prestley and Morss 2023). These codes were applied to each Irma-relevant tweet that included at least one media attachment (photograph, animated GIF, or video), with tweets solely coded as "other" or "past" in the hazard and time reference coding excluded; this image-coded dataset consisted of 4011 tweets (Fig. 2). These latter tweets were not included for image coding because "other" tweets do not provide hazard- or time-reference-specific information, while

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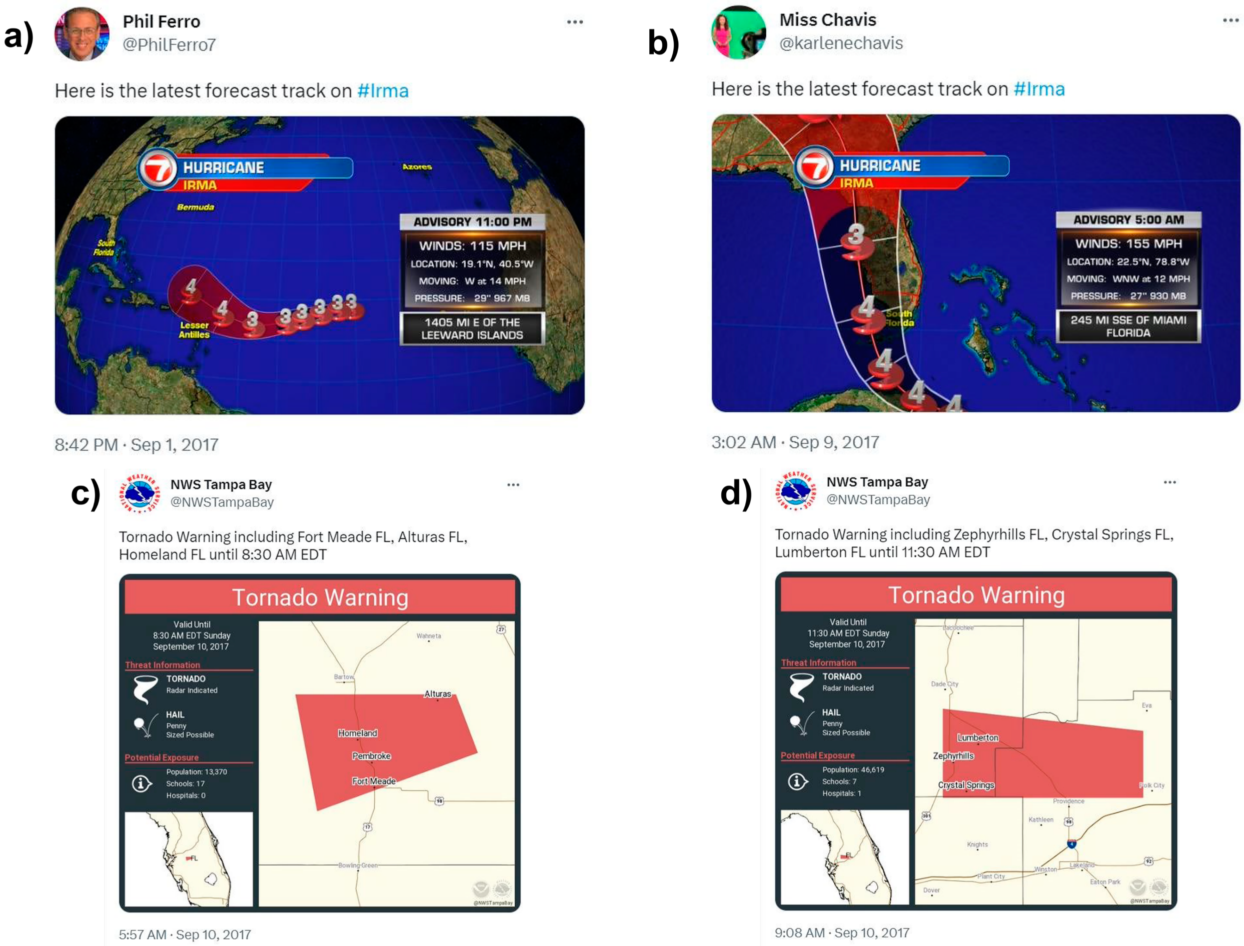

FIG. 3. Examples of automated tweets: (a),(b) automated tweets using the exact same tweet text and an identical visualization design, although they are posted by different professional sources (affiliated with the same television station) on different dates, and (c),(d) automated tweets that do not share the same tweet text, although they do use a similar text format.

"past" tweets occur outside of the primary forecast and warning communication window (see section 4b). Both image coding schemes were applied to the major visual components of media attachments.

The image-type coding scheme included the 15 codes shown in Table 4, which are based on the NWS suite of tropical cyclone risk visualizations (Morss et al. 2022a, 2023, manuscript submitted to *Nat. Hazards Rev.*), along with other image types that were either observed frequently in prior related analyses (Bica et al. 2019; Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*) or emerged in earlier coding. Image-type codes were applied at the tweet level, based on whether the codes appeared in any of the major components of any multimedia attached to a tweet.

TABLE 2. Definitions of hazard codes, along with a summary of tweets coded in each category among Irma-relevant tweets ($N = 5503$). Each tweet could be assigned one or more of the four hazard codes or could be categorized as "other."

Tweet code	Definition	No. of tweets	Percent of tweets
Tropical cyclone	Provides information about Irma's location; movement; visual appearance; strength, intensity, or wind speeds; or size	3948	71.7
Convective	Provides information about severe thunderstorms due to Irma, especially Irma's tornado threat	583	10.6
Heavy rain/inland flooding	Provides information about heavy rain or inland flooding due to Irma	501	9.1
Storm surge	Provides information about coastal flooding due to Irma	367	6.7
Other	Does not fit into any of the categories above	610	11.1

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TABLE 3. Definitions of time reference codes, along with a summary of tweets coded in each category, among Irma-relevant tweets ($N = 5503$). Each tweet could be assigned one or more of the four time reference codes or could be categorized as "other."

Tweet code	Definition	No. of tweets	Percent of tweets
Forecast (nonwatch/nonwarning)	Provides information about Irma's future threat or impact that is not related to an NWS watch or warning	2871	52.5
Watch/warning forecast	Provides information about one or more NWS watches and/or warnings issued as a result of Irma	1174	21.3
Observational/near past	Provides information about Irma's ongoing or very recent (e.g., within the past hour) threat or impact	2079	37.8
Past	Provides information about Irma's past (e.g., not ongoing, beyond 1 h) threat or impact	141	2.6
Other	Does not fit into any of the categories above	610	11.1

We also coded for image branding, which describes how names, symbols, and logos are used to organizationally brand visual risk information. We included three codes:

- *NWS/NOAA branding*, which includes imagery with the names, logos, and/or symbols of NOAA, NWS, or any NOAA or NWS entities,
- *non-NWS/non-NOAA branding*, which includes imagery with the names, logos, and/or symbols of organizations other than NOAA or NWS, including other weather information sources (such as The Weather Channel) or governmental entities (such as FEMA or CDC), and
- *no branding*, which includes imagery with no organizational names, logos, or symbols.

Each tweet was assigned at least one of these image-branding codes and could include any combination of these three codes.

To test and refine the image-type and branding coding schemes, two coders coded randomly selected subsets of the image-coded dataset, excluding automated tweets, as in section 3b(2), over two rounds of coding. The 282 tweets (10%) coded in these two rounds indicated sufficiently high intercoder reliability ($\alpha > 0.75$) for all image codes, other than "convective" (which did not appear in the test-coding subsets). One coder then coded the remaining nonautomated tweets in the image-coded dataset, as well as any automated tweets.

c. Analysis

Our analysis proceeds in two parts. To answer our first research question, we describe the dissemination of Irma-relevant tweets during Irma, with a focus on subphases of Irma's forecast and warning phase that we identified using top-down and bottom-up approaches. We first interrogated how dissemination and/or retransmission of content changed over time, which led to the identification of broad periods of interest. We then integrated knowledge of changes in Irma's meteorological characteristics and the types of information available at different times during Irma to further identify and characterize the subphases and their breakpoints.

To answer our second research question, we model retransmission using mixed-effects negative binomial regression. This distribution is appropriate for overdispersed count data (Green 2021) and thus has been used to model Twitter data in numerous previous studies (Sutton et al. 2014, 2015a,b; Vos et al. 2018; Sutton et al. 2019). Given our focus on retransmission during the forecast and warning phase, our regression analyses only include data from the four forecast and warning subphases, excluding tweets posted during the initial transition to response and recovery (section 4b).

Because retweet patterns can vary widely across professional sources, especially among sources with different audiences (Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*), we included each source as a predictor in the regression models as a control for other effects. We model the sources as random effects, as in prior work by Vos et al. (2018) and Sutton et al. (2019). All other effects—storm subphase, time of day, media type, automated tweet, hazard, time reference, image type, and image branding—are included as fixed effects. Categories with more than two mutually exclusive categories have dummy codes for each value, excluding a reference category (set to the category that occurs most frequently in our dataset).

We provide two regression models: one to assess retransmission effects across the full dataset, including tweets without multimedia attachments, and one to assess retransmission effects for specific types of visual risk information. The first model includes all predictors except image type and branding, analyzed for all 5156 tweets posted during Irma's forecast and warning phase. The second model includes the same predictors as in the first model, but replaces the hazard and time reference categories with image-type and branding categories, analyzed for the 3899 tweets with imagery posted during Irma's forecast and warning phase. We exclude hazard and time reference categories in this model because of numerous overlaps between hazard and time reference categories and image type categories; for instance, nearly all cone-image tweets are also coded as tropical cyclone for hazard and nonwatch/nonwarning forecast for time reference. This approach eliminates many, but not all, common overlaps; for instance, many tweets include both cone and advisory imagery. We explored adding interaction effects to account for these overlaps, but we found that adding interaction effects did not lead to meaningful changes to our models, so we do not report them here. Given the number of predictors tested in the regression models, we set a threshold of $p < 0.01$ for statistical significance. All regression analyses were conducted in R (version 4.2.1) using the glmmTMB (version 1.1.4) package (Brooks et al. 2017).

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TABLE 4. Definitions of image-type codes, along with a summary of tweets coded in each category, among image-coded tweets (N = 4011). Tweets could be assigned one or more of the image codes. Tweets were coded as "other" if they included imagery outside these codes and if no other image type (with the exception of "text," to represent the combination of text and imagery in infographics) was coded. Examples of each image type are shown in Figs. S1–S5 in the online supplemental material.

Image code	Definition	No. of tweets	Percent of tweets
Advisory	Text component (often part of a map) summarizing a tropical cyclone's current location and attributes (including wind speed, pressure, location, and movement)	1451	36.2
Cone	Map depicting a tropical cyclone's forecast track, surrounded by a track uncertainty cone	1440	35.9
Spaghetti plots	Map depicting possible tropical cyclone forecast tracks as individual lines or color-coded density maps	136	3.4
Probability of storm-force winds	Map depicting the probability of tropical storm– or hurricane-force winds	103	2.6
Arrival of storm-force winds	Map depicting the earliest reasonable or most likely time of arrival for tropical storm–force winds	36	0.9
Watch/warning	Map depicting NWS-issued watches, warnings, and/or advisories for a tropical cyclone–related hazard that is not an NWS impact watch/warning image	927	23.1
NWS impact watch/warning	NWS-branded map format for short-fused watches and warnings that includes a map of the warning area along with threat or safety and potential exposure information	118	2.9
Satellite	Map displaying satellite imagery (visible, infrared, or water vapor) of a tropical cyclone or atmospheric variables that influence a tropical cyclone	588	14.7
Radar	Map displaying radar imagery (reflectively or velocity) that depicts Irma or any of its related hazards	512	12.8
Text	Text or table that conveys hurricane risk or protective action information about a tropical cyclone in an image	428	10.7
Model output	Map or graph depicting output from numerical weather forecast modeling of a tropical cyclone or its attributes, including storm center location, mean sea level pressure, wind speed, or rainfall/reflectivity	72	1.8
Surge inundation	Map depicting the level of storm surge inundation from a tropical cyclone for fine-grained or general geographic areas along the coast	59	1.5
Convective	Map depicting thunderstorm and/or tornado-threat areas using color coding or other symbology	51	1.3
Rainfall	Map or graph depicting heavy rainfall-threat areas or forecast rainfall/flooding amounts or levels using color coding or other symbology	51	1.3
Threat/impact	Map depicting qualitative threat and impact levels for several Irma-related hazards, using color coding	41	1.0
Other	Does not fit into any of the categories above	357	9.0

Social media data have limitations, including unrepresentative user bases (Palen and Anderson 2016), the range of audiences contributing on social media in different ways (Kogan et al. 2015), and the large differences that can result from small changes in tweet collection and filtering decisions (Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*). Thus, it is important to carefully consider how generalizable the results of quantitative analyses of retweets counts are before making broader interpretations. To provide more meaningful insights from these data, our quantitative analysis is informed by in-depth descriptive analysis, complementary research on hurricane risk communication (e.g., Demuth et al. 2012, 2018; Bica et al. 2019; Lazrus et al. 2020; Demuth 2023; Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*), and contextualized knowledge in relevant fields of study (Balog-Way et al. 2020; Palen and Anderson 2016; Silver 2019; Williams and Eosco 2021; Wisner et al. 2004).

4. Results

a. *Dissemination and retransmission during Irma's forecast and warning phase*

We first review the types of information disseminated across Irma's forecast and warning phase. Table 1 shows that the vast majority of Irma-relevant tweets in the dataset are disseminated by local weather media sources in Miami (48%) and Tampa (29%). However, on a per-account basis, local NWS weather forecast offices in Tampa and Miami tweet most

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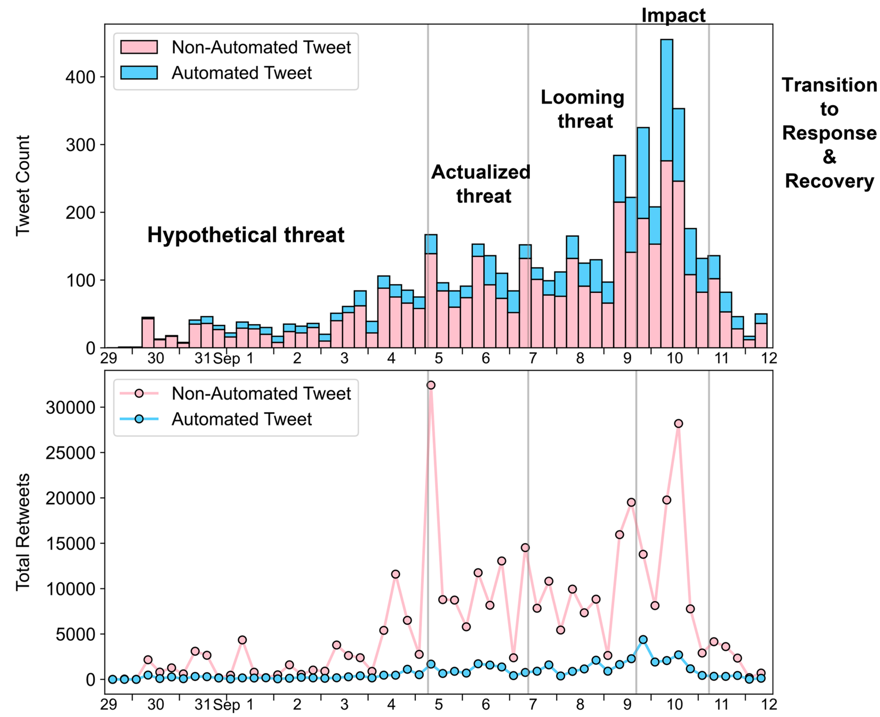

FIG. 4. (top) Tweet count and (bottom) total retweet count for automated tweets (blue) and nonautomated tweets (pink) in each 6-h period from 1800 EDT 29 Aug to 1200 EDT 12 Sep 2017. Ticks represent midnight on each day, and gray vertical lines delineate the four subphases of the forecast and warning phase, as well as the transition to the response and recovery phases.

prolifically, which reflects the key role of local NWS forecast offices in communicating during tropical cyclones. Most tweets (79%) include at least one multimedia attachment; these attachments are most commonly a single photograph (87%), with richer media types, like multiple photographs (6%), animated GIFs (5%), and videos (2%), used more sparingly.

As shown in Table 2, the majority of tweets disseminate general information about Irma (e.g., its size or location) or its wind speeds, with fewer tweets conveying information about other hazards associated with the storm. Table 3 shows that approximately 75% of tweets include either forecast or watch/warning information, with a significant minority including information about Irma's current conditions. Fifteen percent of Irma-relevant tweets contain both forecast and observational/near-past information, demonstrating the complementary nature of these two types of information. Past information is much more rare, and most of these tweets focus on contextualizing Irma's historic strength or reporting on Irma's impacts in the Caribbean.

Table 4 demonstrates that more than one-third of all Irma-relevant tweets include cone or advisory imagery, due, in part, to the large number of cone and advisory overlaps, which constitute 21% of all Irma-relevant tweets. Other common image types include watch/warning and radar imagery, which are also frequently paired together. Professional sources also disseminate text imagery at a high rate, which could reflect tweet text character limits, which might lead to more detailed forecast information being posted in multimedia attachments. Most imagery features non–NWS/NOAA branding (68.1%), with roughly equal proportions of imagery with NWS/NOAA branding (18.5%) or no branding (17.3%). This likely reflects the large number of local weather media sources in our collection relative to NWS- and NOAA-affiliated sources.

As shown in Fig. 4, professional sources use automated tweets throughout Irma to disseminate forecast and warning information as it is released. Some professional sources use automated tweets more than others. For instance, NWS Tampa automates tweets that provide standardized and impersonal text descriptions and a link each time a new text product is issued by the weather forecast office (WFO). NWS Miami uses automated tweets to post NWS impact watch and warning graphics (Fig. 3). Accounts associated with television station WSVN 7 weather in Miami also automate tweets, posting cone and advisory imagery with each new release of advisory information from the NHC.

Figure 4 also demonstrates how the dissemination and retransmission of information vary across Irma's forecast and warning phase. Dissemination follows a diurnal cycle, wherein more tweets are posted during the day than late at night. Layered on top of this cycle, we observe a general trend toward higher dissemination as Irma approaches and directly impacts Florida, followed by a decline as the storm's impacts

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TABLE 5. Summary of the four storm subphases identified within Irma's forecast and warning phase, discussed in section 4b (RT indicates retweet).

Storm subphase	Start time (EDT)	End time (EDT)	Length (h)	Tweet count	Tweets per hour	Median No. of RTs
Hypothetical threat	2000 29 Aug	0730 5 Sep	155.5	1088	7.0	5
Actualized threat	0730 5 Sep	1030 7 Sep	51	972	19.1	9
Looming threat	1030 7 Sep	1730 9 Sep	55	1400	25.5	9
Impact	1730 9 Sep	0630 11 Sep	37	1696	45.8	7

wane. We observe similar trends for retransmission, with spikes in retransmission on 5 and 10 September 2017. Embedded within these general trends, we identify four subphases of Irma's forecast and warning phase, which are described in the following sections and summarized in Table 5 and Figs. 5–8.

1) THE HYPOTHETICAL THREAT SUBPHASE: 30 AUGUST–5 SEPTEMBER 2017

Irma developed as a tropical storm on 30 August 2017 and rapidly strengthened to a major hurricane within 2 days. However, the storm remained well out to sea and was not a direct threat to the United States during this period. Therefore, it is unsurprising that professional sources post fewer Irma-relevant tweets during this time relative to subsequent subphases (Table 5). Virtually all of the tweet content during this subphase focuses on Irma's current conditions and forecasts (Fig. 7) related to the storm's size, strength, or location (Fig. 6). This is clear in the image content as well (Fig. 8), in which professional sources disseminate forecast and observational tropical cyclone information via cone, advisory, and satellite imagery.

2) THE ACTUALIZED THREAT SUBPHASE: 5–7 SEPTEMBER 2017

On 5 September 2017, two factors usher in a shift in dissemination and retransmission on Twitter. The first is meteorological; by early morning, Irma had strengthened to a category-5 storm, the highest category on the Saffir–Simpson hurricane strength scale. The second factor is related to Irma's forecast information, as portions of south Florida were now included in the NHC's 5-day track forecast cone. Thus, this period represents the transition from a hypothetical threat to a more actualized threat for the Florida coast.

In line with this shift, professional sources disseminate Irma-relevant information more frequently during this period (Table 5), especially national and Miami-oriented weather media sources (Fig. 5). However, the types of tweet content disseminated are generally similar as professional sources continue

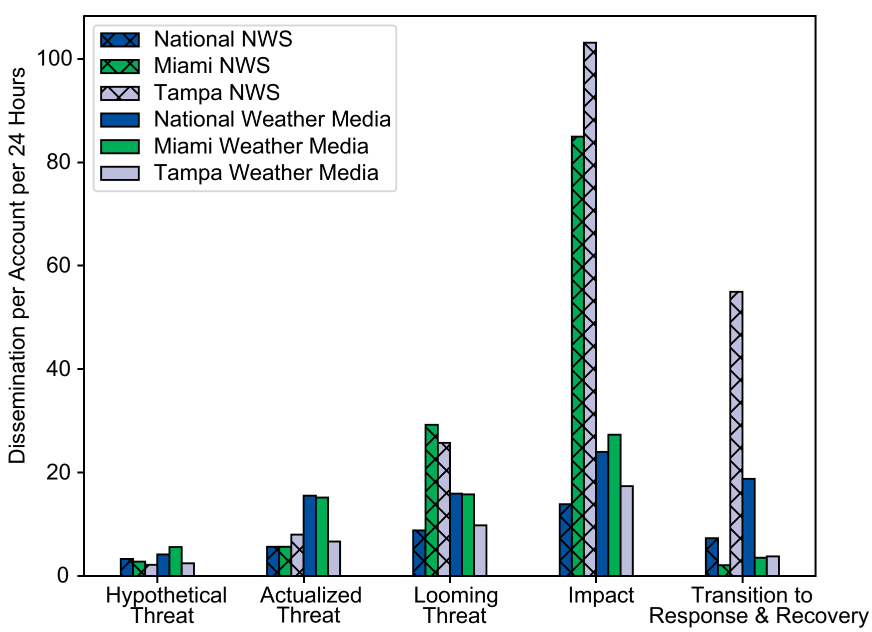

FIG. 5. Dissemination rates for tweets posted by different professional sources, grouped on the basis of their scope of responsibility and affiliation, during each subphase of Hurricane Irma's forecast and warning phase as well as the transition to the response and recovery phases. Colors correspond to different scopes of responsibility, and cross hatching identifies NWS-affiliated sources. Dissemination is presented as a rate per 24 h per account to normalize dissemination by the length of each subphase and the number of professional source accounts in each group.

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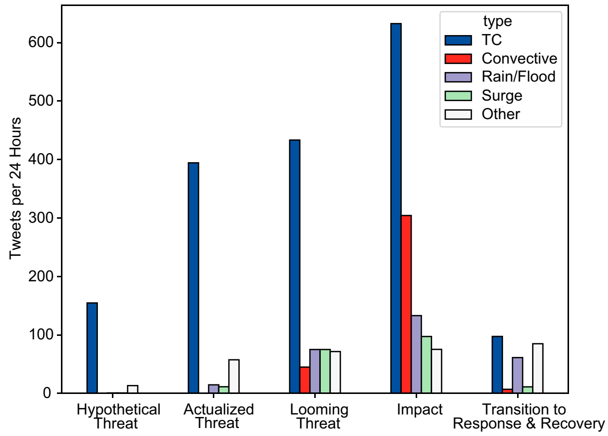

FIG. 6. Dissemination rates for tweets with each hazard type during each subphase of Hurricane Irma's forecast and warning phase, as well as the transition to the response and recovery phases.

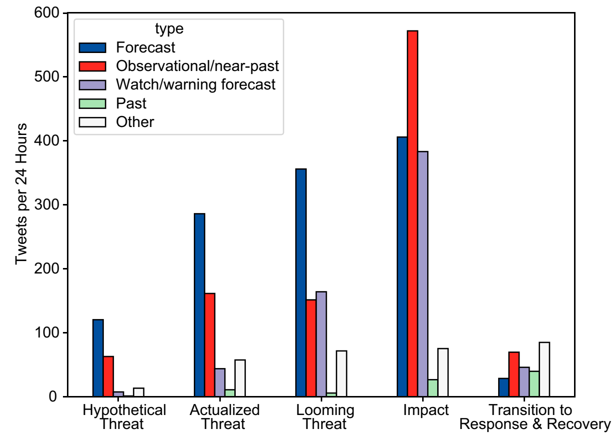

FIG. 7. Dissemination rates for tweets with each time reference type during each subphase of Hurricane Irma's forecast and warning phase, as well as the transition to the response and recovery phases.

to focus on the tropical-cyclone threat (Fig. 6) using forecast and observational/near-past time references (Fig. 7), with visual displays like cone, advisory, and satellite imagery disseminated at or near their highest rates during this subphase (Fig. 8). While less common, professional sources also disseminate spaghetti plots as an alternate approach for visualizing track forecast uncertainty.

However, we do see shifts among other image types. For instance, professional sources disseminate watch/warning imagery 5 times as frequently during this subphase as in the hypothetical forecast subphase. Most of this imagery (78%) is included as an element in cone or advisory graphics as tropical storm and hurricane watches and warnings are issued for parts of the Caribbean. Professional sources increasingly disseminate text imagery as well, which is used to communicate several kinds of information, including educational infographics that provide protective action information and explainers of key terms (like watch and warning), screenshots of NHC forecast discussions, and bullet-point lists of key forecast points, often implicitly or explicitly emphasizing forecast uncertainty. Taken together, these results characterize the actualized subphase as a period when professional sources provide more information at increasing specificity while still highlighting the uncertainties inherent in forecasts at these lead times.

3) THE LOOMING THREAT SUBPHASE: 7–9 SEPTEMBER 2017

The next subphase begins as the first hurricane watches are issued for parts of the Florida peninsula and local NWS offices become more active in disseminating Irma-relevant information (Fig. 5). As Irma's potential hazards and impacts come into sharper focus, much of the information disseminated during this period continues the trend of increasing specificity. For instance, professional sources disseminate tweets containing surge, rainfall/flooding, and convective hazard information at much higher rates than in previous subphases (Fig. 6). This information is often communicated using hazard-specific visualizations produced by the NWS, including surge inundation and threat/impact imagery, which are disseminated at much higher rates during this period than during the actualized threat subphase (Fig. 8). Other imagery also sees increased dissemination during this period. This category includes a diverse range of idiosyncratic visuals, such as wind extent and wave height visualizations, power outage indexes, evacuation zone maps, and long-form video (Prestley and Morss 2023). These results demonstrate the diversity of content being posted during this period as standardized hazard-specific guidance from the NWS comes online and professional sources find creative ways to visualize the complex web of forecast information now available to them.

The other major shift during this period is a continued increase in watch/warning forecast content (Fig. 7) and watch/warning imagery (Fig. 8). This content focuses primarily on new tropical storm and hurricane watches and warnings issued for parts of the Florida peninsula, although a growing portion of watch/warning imagery provides information about storm surge, convective, and rainfall/flooding watches and warnings. Much of this content is posted automatically by weather media sources in Tampa and Miami.

4) THE IMPACT SUBPHASE: 9–11 SEPTEMBER 2017

Dissemination and retransmission again increased during the impact subphase, as Irma's feeder bands began to move over southern Florida and continued as Irma made landfalls in Cudjoe Key and Marco Island. In total, this subphase includes the time frame of Irma's most severe wind, storm surge, flooding, and tornado impacts in Florida.

Professional sources disseminate several types of content during the impact subphase. The first type of content represents a continuation of the tropical cyclone–focused information common in previous subphases, as tropical cyclone hazard information (Fig. 6) and cone and advisory imagery (Fig. 8) continues to be disseminated at a high rate. However, information about Irma increasingly uses observational/near-past time references,

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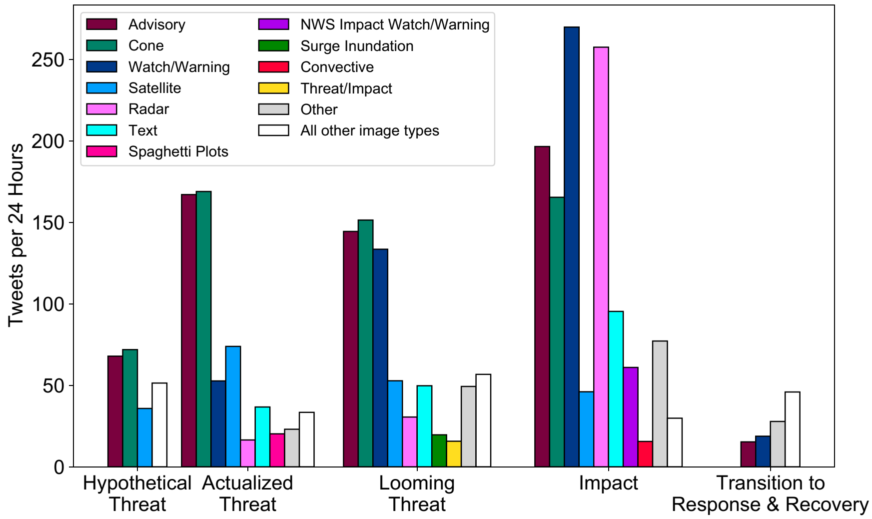

FIG. 8. Dissemination rates for tweets with each image type during each subphase of Hurricane Irma's forecast and warning phase, as well as the transition to the response and recovery phases. Within each subphase, only image types that occur at a rate greater than 15 tweets per 24 h are plotted separately; image types that occur at rates below this threshold are merged into the "all other image types" group.

as more observations from Irma become available. Professional sources often use text imagery (Fig. 8) to communicate observational/near-past information about Irma, via textual summaries of key forecast details for specific areas or lists of observations (e.g., maximum wind gusts).

As in the looming threat subphase, information about other hazards continues to proliferate during this subphase, including information about Irma's storm surge, rainfall, and convective threats. In particular, professional sources disseminate convective hazard information nearly 7 times more during the impact subphase than during the looming-threat subphase (Fig. 6). The vast majority of these convective tweets provide information about short-fused tornado warnings, which are communicated with the watch/warning forecast time reference (Fig. 7) and watch/warning, NWS impact watch/warning, and radar imagery (Fig. 8).

Professional sources often post about these sorts of short-fused warnings in real time using automated tweets (as described in more detail in section 4a), which contributes to an increase in the dissemination of automated tweets during the impact subphase (Fig. 4). Combined with an increase in the dissemination of nonautomated tweets (Fig. 4), professional sources disseminate far more information during this subphase than any other (Table 5). This is especially the case for NWS offices in Tampa and Miami, which tweet much more frequently than other sources (Fig. 5) and rely the most on automated tweets during this period (65% of NWS Miami tweets and 80% of NWS Tampa tweets are automated).

These results show the ways in which professional sources respond to constantly evolving information about Irma's threats and direct impacts, using automated and nonautomated approaches to keep up with regular releases of tropical cyclone information about Irma in addition to the near-steady stream of short-fused convective watches and warnings issued by local NWS offices.

5) TRANSITION TO LONGER-TERM RESPONSE AND RECOVERY: 11–12 SEPTEMBER 2017 AND BEYOND

The final period in our data collection represents the initial transition from the forecast and warning phase to longer-term response and recovery phases. For this analysis, we consider this transition to begin when hurricane warnings are replaced with tropical storm warnings for Tampa and points south as Irma weakens and moves out of the area. This period extends until the end of our data collection period, when Irma dissipated over the inland southeastern United States.

As the storm's impacts wind down, so too does the Irma-related Twitter dissemination of the selected professional sources, especially among Miami NWS sources, as well as weather media sources in both Miami and Tampa (Fig. 5). Dissemination from national weather media and Tampa NWS sources decreases less, which may reflect the later transition out of impacts for Tampa and points north.

The information disseminated during this time highlights the transition between the forecast and warning phase and the response and recovery phases. Professional sources continue to disseminate information about Irma and its rainfall/flooding threats (Fig. 6), including observational/near-past information (Fig. 7) such as advisory imagery (Fig. 8) and river flood warnings (Figs. 7 and 8). At the same time, the sources provide other and past information (Fig. 7), which includes forecasts for cleanup, updates from affected communities, damage photographs and videos, charts and maps of peak wind gusts or rainfall amounts, and summaries of Irma's track and satellite/radar presentation over its entire lifetime. Through these types of content, the professional

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TABLE 6. Results of mixed-effects negative binomial regression model predicting retweets for Irma-relevant tweets with and without imagery ($N = 5156$). This model includes random effects for each professional source, which are reported in Table S1 in the online supplemental material. Statistically significant effects ($p < 0.01$) are in boldface type. The Akaike information criterion (AIC) = 39 187.

Fixed effects	Est	SE	p	IRR (95% CI)
(Intercept)	**3.00**	**5.00**	—	—
Storm subphase (reference = looming threat)				
Hypothetical threat	**−0.75**	**0.02**	**<0.001**	**0.47 (0.43, 0.52)**
Actualized threat	0.04	0.05	0.35	1.05 (0.95, 1.15)
Impact	**−0.19**	**0.04**	**<0.001**	**0.83 (0.76, 0.90)**
Time of day (EDT; reference = 0900–1200)				
0000–0300	−0.15	0.06	0.04	0.86 (0.74, 0.99)
0300–0600	**−0.18**	**0.05**	**0.002**	**0.83 (0.74, 0.93)**
0600–0900	−0.03	0.05	0.52	0.97 (0.87, 1.07)
1200–1500	−0.04	0.06	0.53	0.96 (0.86, 1.08)
1500–1800	0.07	0.06	0.15	1.08 (0.97, 1.19)
1800–2100	0.10	0.07	0.09	1.11 (0.98, 1.24)
2100–0000	0.09	0.06	0.10	1.10 (0.98, 1.22)
Media type (reference = single photograph)				
Text only	**−0.44**	**0.03**	**<0.001**	**0.65 (0.59, 0.71)**
Multiple photographs	0.11	0.09	0.16	1.12 (0.96, 1.30)
Animated GIF	**0.74**	**0.17**	**<0.001**	**2.10 (1.78, 2.47)**
Video	0.18	0.14	0.12	1.20 (0.95, 1.51)
Automated tweet	**−1.05**	**0.02**	**<0.001**	**0.35 (0.32, 0.39)**
Hazard				
TC	0.01	0.07	0.90	1.01 (0.90, 1.14)
Surge	0.06	0.07	0.34	1.07 (0.94, 1.22)
Rain/flood	**−0.57**	**0.03**	**<0.001**	**0.57 (0.50, 0.64)**
Convective	−0.05	0.07	0.50	0.95 (0.82, 1.10)
Time reference				
Nonwatch/nonwarning forecast	**0.14**	**0.05**	**0.002**	**1.15 (1.05, 1.25)**
Watch/warning forecast	**−0.27**	**0.04**	**<0.001**	**0.76 (0.69, 0.84)**
Observational/near past	0.01	0.04	0.85	1.01 (0.93, 1.09)
Past	0.25	0.16	0.05	1.28 (1.00, 1.63)
Other hazard/time reference	**−0.73**	**0.04**	**<0.001**	**0.48 (0.40, 0.58)**

sources are able to relay and reflect on Irma's impacts to their communities.

b. *Regression results*

We now turn to the results of regression modeling to understand how different factors, including tweet and image content, influence the retransmission of tweets during the four main subphases identified in section 4a. We report on two regression models, as described in section 3c and summarized in Tables 6 and 7. For both models, we provide estimated model coefficients (Est) and standard errors (SE), in addition to incidence rate ratios (IRRs) and their 95% confidence intervals (CI), which provide an additive frequency interpretation of the model coefficients (Vos et al. 2018). For instance, tweets that include a GIF have an IRR of approximately 2 (Table 6), meaning these tweets are retransmitted twice as much as tweets with a single photograph. Correlations between the fixed effects in each model are available in Figs. S6–S9 in the online supplemental material.

1) MODEL 1: METADATA, HAZARD, AND TIME REFERENCE RESULTS

Results from this first model (Table 6) indicate that tweets posted during the hypothetical threat subphase or posted in the early hours of the morning (0000–0600 EDT) tend to be retransmitted at lower rates relative to other storm subphases and times of day. These results highlight the diurnal cycle in retransmission (Fig. 4) and reflect less public attention early in Irma's life cycle. However, tweets posted during the impact subphase when dissemination is highest also garner fewer retweets when controlling for other effects.

These results demonstrate that tweets with media attachments are retransmitted more than tweets without media attachments, in line with previous research (Vos et al. 2018; Sutton et al. 2019). We also find that tweets with GIFs are retransmitted significantly more than tweets with single photographs.

Automated tweets are retransmitted less than nonautomated tweets, as is evident from Fig. 4. This could be related to the repetitive nature of automated tweets or their tendency to include language in the tweet text that comes across as impersonal and nondialogic (Kent and Taylor 2021).

Among hazard codes, tweets with rain/flood information tend to have fewer retweets. This suggests that rainfall and rain-induced flooding may have been a less salient hazard during Irma in the regions studied in this analysis; we do not necessarily anticipate this result to extend to other types of storms. Tweets

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TABLE 7. As in Table 6, but for Irma-relevant tweets with imagery ($N = 3899$). The AIC = 29 566.

Fixed effects	Est	SE	p	IRR (95% CI)
(Intercept)	**2.84**	**4.60**	—	—
Storm subphase (reference = looming threat)				
Hypothetical threat	**−0.71**	**0.03**	**<0.001**	**0.49 (0.44, 0.55)**
Actualized threat	0.00	0.06	0.98	1.00 (0.90, 1.11)
Impact	**−0.23**	**0.04**	**<0.001**	**0.79 (0.72, 0.87)**
Time of day (EDT; reference = 0900–1200)				
0000–0300	−0.12	0.08	0.18	0.89 (0.74, 1.06)
0300–0600	**−0.23**	**0.05**	**<0.001**	**0.80 (0.70, 0.91)**
0600–0900	−0.03	0.06	0.58	0.97 (0.86, 1.09)
1200–1500	−0.03	0.07	0.71	0.97 (0.85, 1.11)
1500–1800	−0.01	0.06	0.81	0.99 (0.88, 1.11)
1800–2100	−0.02	0.07	0.78	0.98 (0.86, 1.12)
2100–0000	−0.04	0.06	0.56	0.96 (0.85, 1.09)
Media type (reference = single photograph)				
Multiple photographs	−0.13	0.08	0.14	0.88 (0.74, 1.04)
Animated GIF	**0.84**	**0.21**	**<0.001**	**2.33 (1.95, 2.78)**
Video	0.26	0.17	0.05	1.30 (1.00, 1.68)
Automated tweet	**−1.07**	**0.02**	**<0.001**	**0.34 (0.30, 0.39)**
Image branding				
NWS/NOAA	0.06	0.11	0.58	1.06 (0.87, 1.29)
Non-NWS/Non-NOAA	0.06	0.13	0.64	1.06 (0.83, 1.36)
No branding	0.17	0.16	0.21	1.19 (0.91, 1.56)
Image type				
Advisory	0.05	0.06	0.40	1.05 (0.94, 1.18)
Cone	**0.48**	**0.10**	**<0.001**	**1.61 (1.42, 1.82)**
Spaghetti plots	**0.37**	**0.15**	**<0.001**	**1.45 (1.18, 1.78)**
Probability of storm-force winds	0.02	0.13	0.87	1.02 (0.80, 1.30)
Arrival of storm-force winds	0.15	0.23	0.43	1.17 (0.80, 1.71)
Watch/warning	**−0.21**	**0.04**	**<0.001**	**0.81 (0.74, 0.90)**
NWS impact watch/warning	−0.12	0.15	0.48	0.89 (0.64, 1.23)
Satellite imagery	**0.25**	**0.09**	**<0.001**	**1.28 (1.12, 1.47)**
Radar imagery	0.14	0.08	0.05	1.15 (1.00, 1.31)
Text imagery	−0.08	0.06	0.25	0.92 (0.81, 1.06)
Model output	−0.02	0.14	0.91	0.98 (0.75, 1.30)
Surge inundation	−0.10	0.14	0.50	0.90 (0.67, 1.22)
Convective	−0.13	0.23	0.62	0.88 (0.52, 1.48)
Rainfall	−0.11	0.18	0.58	0.90 (0.61, 1.32)
Threat/impact	0.06	0.18	0.74	1.06 (0.76, 1.48)
Other	0.17	0.09	0.04	1.18 (1.01, 1.38)

that include nonwatch/nonwarning forecast information tend to have greater retransmission, while those including watch/warning information have less retransmission (even controlling for other effects like automated tweets). This could be related to the large number of short-fused convective watches and warnings that are only relevant for short periods (less than an hour) disseminated by professional sources.

2) Model 2: Image type and branding results

As Table 7 demonstrates, the patterns of significance for metadata predictors (including storm subphase, time of day, and media type) and automated tweets in model 2 are identical to the patterns in model 1.

Image branding does not have a significant effect on retransmission. This result is in contrast with results from Bica et al. (2019), who found that tweets with NWS/NOAA branding had higher diffusion rates. These results suggest that image branding may not be a critical factor for retransmission during the forecast and warning phase of a disaster, or for the sources collected for this analysis, especially when controlling for other factors. However, we anticipate that image branding likely influences retransmission in some contexts and thus may be important for further analysis.

Image type, on the other hand, does influence retransmission. In particular, these results highlight three image types that positively influence retransmission: satellite, spaghetti-plot, and cone imagery. These results align with previous research that has established the importance of the track forecast cone (Broad et al. 2007; Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*), satellite imagery (Bica et al. 2019), and spaghetti plots (Bostrom et al. 2022) in the communication of a tropical cyclone's strength, current location, and forecast track. In contrast, the inclusion of watch/warning imagery leads to less retransmission, in line with results from Morss et al. (2023, manuscript submitted

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to *Nat. Hazards Rev.*). This, again, suggests that information about Irma's watches and warnings was retransmitted less than other types of information, possibly due to the short warning time frames of frequently disseminated convective watches and warnings.

5. Discussion

This analysis uses Twitter data to explore the dissemination and retransmission of visual risk information during Hurricane Irma. We find that the types of content disseminated by professional sources of meteorological information vary substantially across Irma's forecast and warning phase, as the storm's meteorological attributes and information about the storm evolve. Additionally, we use regression modeling to identify message attributes that increase message retransmission, which allows information to reach broader audiences on social media.

These findings demonstrate the value in exploring forecast and warning communication during disasters in greater depth. In doing so, we find that professional weather communicators engage in preparedness activities typically discussed in the hazards and disasters literature, as well as activities that fall outside of the traditional preparedness and response umbrellas. For instance, we see that these sources must manage forecast uncertainty across the forecast and warning phase by using visual and textual information to emphasize this uncertainty to their audiences in the actualized subphase, and by shifting to more hazard-specific, impact-based content and warnings in the looming subphase. We also observe how professional sources manage rapidly changing and updating information during the impact phase, using automated approaches to communicate Irma's ongoing impacts and convective warnings. These activities, manifest in the professional sources' communication, demonstrate the wide range of roles and responsibilities during the forecast and warning phase that are currently unaccounted for in the four-phase disaster-phases model described in sections 1 and 2 (Neal 1997; Wolbers et al. 2021). As such, this analysis advances our understanding of disasters by characterizing subphases of this critical transition from preparedness to response and recovery for predictable disasters.

These results also help to elucidate what events lead to changes in dissemination and retransmission during the forecast and warning phase. We find that these shifts in communication and response are consistent with the action and decision timelines of professional meteorological sources, as described in Morss et al. (2022a), which, in turn, are driven not just by Irma's meteorological development but also by updates in information provided by the NWS and NHC. For example, we observe how changes in professional sources' dissemination and public retransmission are associated with the release of major changes in the NWS forecast [section 4a(2)] or new types of NWS products [section 4a(3)] as the storm evolves. These results affirm the key role of these sorts of professional sources of meteorological information, which can drive the cadence and tenor of activity on social media during the forecast and warning phase of tropical cyclones (Demuth et al. 2012; Bostrom et al. 2016; Morss et al. 2022b, 2023, manuscript submitted to *Nat. Hazards Rev.*). Practically, these results can be used by disaster managers who use social media and could monitor for these types of shifts and anticipate higher levels of retransmission when they occur.

We next turn to our results on how different types of imagery were disseminated and retransmitted during Irma. These results show that cone imagery is both highly disseminated by professional sources and highly retransmitted by members of the public, which underscores the salience of information in the current NHC track forecast cone product during tropical cyclones. This is despite an accumulation of research that has identified flaws in the cone's design (Drake 2012; Broad et al. 2007) and attempted to redesign or replace it (Radford et al. 2013; Ruginski et al. 2016; Bica et al. 2020; Millet et al. 2020; Witt et al. 2023). However, our results suggest that these efforts will have to provide alternative depictions of storm-track forecasts and associated uncertainties that will be as usable for professional sources and as appealing for public audiences, while also communicating key information effectively.

Watch/warning imagery faces the inverse problem: professional sources disseminate this imagery frequently, but these tweets are retransmitted less. This may be a result of some sources in our dataset who, with the help of automated scripts, disseminate watch and warning information for all watches and warnings issued for a storm event. These warnings are often short-lived (from 15 min to 1 h) and geographically focused on small, low-population areas (Morss et al. 2023, manuscript submitted to *Nat. Hazards Rev.*), which may limit retransmission in comparison with tweets with information that remains relevant longer. Future analyses could thus investigate whether watches and warnings for longer-fused hazards lead to similar patterns of retransmission.

More generally, we found that tweets posted automatically are retransmitted much less than nonautomated tweets. As such, we would recommend future research that investigates the effectiveness of different strategies for automated forecast and warning tweets. We also recommend that professional sources explore ways in which automated tweets can be improved to provide information in more accessible formats or relied upon less extensively for forecast and warning communication.

Our results illuminate two unmet informational needs during the forecast and warning phase of tropical cyclone disasters. First, we note that professional sources generally do not disseminate information about Irma's storm surge and rainfall-induced flooding threats until the looming-threat subphase, which can likely be linked to the lack of official hazard-specific guidance available before this period. Thus, additional standardized forecast guidance for these hazards is needed at longer lead times so that professional sources can provide a more holistic picture of the suite of hazards posed by tropical cyclones (Morss et al. 2022b). This could take the form of new or extended hazard-specific visualizations, as predictability constraints allow, or improved summary visualizations that provide information about all hazards (Millet et al. 2022).

Second, these results highlight the need to move beyond the track forecast cone and design additional ways of visualizing forecast confidence or uncertainty in key storm attributes, especially at longer lead times. For instance, professional sources use spaghetti plots and text imagery to contextualize Irma's forecast uncertainty during the actualized threat

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subphase, and members of the public retransmit this information at high rates. However, professional sources vary in their use of different visual styles or text phrasings in these images, which could lead to inconsistency and confusion (Williams and Eosco 2021). Thus, this represents another opportunity for the NWS to provide more standardized output that can be used in conjunction with the current product suite to support effective communication of forecast uncertainty at longer lead times.

One limitation of this study is its focus on a single storm; additional analyses are needed to understand how patterns of dissemination and retransmission of visual information play out for disasters with different threat profiles and lead-times. Such analyses could focus on additional visualizations that NWS has developed and refined since Hurricane Irma, or explore the interactions between more focused sets of imagery and other factors. Future work could extend these sorts of analyses to understand which aspects of the forecast and warning phase are important in other disasters with less lead time, such as earthquakes, or explore additional transitional periods in the disaster phase model.

We caution that these results precede recent changes in Twitter's ownership and subsequent changes to many aspects of the Twitter experience, which may threaten the usability of Twitter for professional disaster managers and hamper access to Twitter data for disaster researchers. These changes highlight the ephemerality of Twitter data and the need for research investigating other social media networks, as well as novel methodological approaches for collecting and analyzing societal data in real time during weather threats (Demuth 2023). That being said, we hope that Twitter continues to be a vibrant and useful resource for disaster response and research, and that iteratively developing and scaling up our methodological approach can provide a pathway to real-time social media data analysis. Such analyses could allow researchers to assess how recent changes to forecasts and warnings have impacted dissemination and retransmission of disaster information, and could give practitioners the opportunity to monitor and respond to changing public engagement in real time as disasters evolve.

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Data availability statement. Protocols for collecting the data analyzed in this study and codebooks for data analysis are available in a DesignSafe-CI data repository (Prestley and Morss 2023).

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