Ernst, S. E., and Coauthors, 2024: A tale of two hazards: Studying broadcast meteorologist communication of simultaneous tornado and flash flood (TORFF) events. *J. Operational Meteor.*, **12** (1), 1-18, doi: https://doi.org/10.15191/nwajom.2024.1201.

Journal of Operational Meteorology
Article

A Tale of Two Hazards: Studying Broadcast Meteorologist Communication of Simultaneous Tornado and Flash Flood (TORFF) Events

SEAN R. ERNST
OU Institute for Public Policy Research and Analysis, Norman, OK
OU Cooperative Institute for severe and high-impact Weather Research and Operations, Norman, OK
NWS Storm Prediction Center, Norman, OK

JOSEPH T. RIPBERGER, JULIE KRUTZ, CAROL SILVA, HANK JENKINS-SMITH, ANNA WANLESS
OU Institute for Public Policy Research and Analysis, Norman, OK

DAVID NOWICKI
OU Institute for Public Policy Research and Analysis, Norman, OK
OU School of Meteorology, Norman, OK

KIMBERLY E. KLOCKOW-MCCLAIN
UCAR/Cooperative Programs for the Advancement of Earth System Science, Boulder, CO
NOAA/National Centers for Environmental Prediction, Boulder, CO

KODI L. BERRY
NOAA/OAR/National Severe Storms Laboratory, Norman, OK

HOLLY B. OBERMEIER
OU Cooperative Institute for severe and high-impact Weather Research and Operations, Norman, OK

MAKENZIE J. KROCAK
NOAA/OAR/National Severe Storms Laboratory, Norman, OK
OU Institute for Public Policy Research and Analysis, Norman, OK

(Manuscript received 16 November 2022; Review completed 16 October 2023)

ABSTRACT

Broadcast meteorologists are the primary source of weather information for the public, and thus are key to messaging the multiple weather hazards that can occur during simultaneous tornado and flash flood, or TORFF, events. Due in part to the challenge and cost needed to study broadcast coverage, there has been limited study into how broadcasters present these hazards to their viewers during TORFF events. To begin to address this knowledge gap, we developed the Coding Algorithm for Storm coverage Transcripts, or CAST.Bot, a simple algorithm that can efficiently and inexpensively compare the mentions of tornado and flash flood hazards made by meteorologists during on-air coverage.

For this study, we used CAST.Bot to quickly analyze 39 segments of coverage from eight TORFF events. Findings suggest that broadcasters generally favor mentions of tornadoes more than flash flooding during TORFF events with many tornado warnings, with more balanced coverage identified during events with similar numbers of tornado and flash flood warnings. Additional study of two cases, 1) the El Reno/Oklahoma City, Oklahoma, tornado and flash flood on 31 May 2013, and 2) Hurricane Harvey in Houston, Texas, on 26 August 2017, suggests that TORFF event coverage on television is subject to differences across stations and the way that the tornado and flash flood hazards in a TORFF unfold. Future work should seek to better understand how changes in the focus of messaging for TORFF events can impact viewers decisions and identify how context can influence TORFF message content. Options for use of the CAST.Bot algorithm to aid broadcasters during multi-hazard event coverage are also discussed.

Corresponding author address: Sean Ernst, 201 Stephenson Pkwy, Suite 2300, 5 Partners Place, Norman, OK 73019
E-mail: sean.ernst@ou.edu

1. Introduction

Simultaneous tornado and flash flood events, or TORFFs (Nielsen et al. 2015), present a complex threat to members of the public as well as a difficult communication challenge for safety messaging. These challenges are primarily due to the contradictory nature of the recommended actions for both threats; for tornadoes, the suggested protective action is to shelter in a basement or sturdy structure; for flash floods, the advice is to get to higher ground and avoid areas prone to high water (Ready.gov 2022a, 2022b). Further, although tornado hazards frequently attract greater attention because of their "sensational" nature, flooding hazards on average claim more lives each year. In 2021, flood deaths outpaced tornado deaths at 146 to 104 fatalities, and the 10- and 30-yr averages for annual fatalities for flooding also outpace those for tornado deaths (at 98 and 88 per year for flooding, and 49 and 71 for tornadoes, respectively; NWS 2023).

Despite the lack of available statistics on casualties specifically during TORFF events, individual TORFFs have resulted in fatalities and public concern. Flash flooding claimed more lives than tornadoes during the 31 May 2013 El Reno-Oklahoma City (OKC), Oklahoma, TORFF event, as many Oklahomans sought shelter from the widely televised tornado threat in drainage tunnels and other low-lying areas (NOAA, 2014). TORFF hazards were also highlighted in post-event reviews of the landfall of Hurricane Harvey in August 2017, as intense rainbands brought more than 50 in of rain and dozens of tornadoes to heavily populated areas of southeastern Texas (NOAA 2018; Burow et al. 2021). These benchmark disasters have resulted in accelerated study of the meteorology behind and communication of TORFF events, with the goal of reducing the impact these combined hazards have on members of the public.

Although prior work has investigated the climatology, communication, and public reception of tornado and flash flood warning overlaps (Nielsen et al. 2015; Henderson et al. 2020; First et al. 2022), no published study has yet investigated broadcast meteorologist coverage of TORFF events. This is a critical omission because broadcast meteorologists are the primary source of information about weather risks for the public and have been for decades (Lazo et al. 2009; Drobot et al. 2014; Ripberger and Silva 2022). To better understand how broadcasters cover the two major hazards in TORFF events, this study developed and applied a thematic coding algorithm to analyze broadcast coverage of eight separate TORFF events from 2013 to 2021 to identify which hazards broadcast meteorologists discuss most during their coverage. This manuscript will discuss the literature surrounding broadcast weather communication of tornadoes and flash flooding, as well as the methods behind the use of the Coding Algorithm for Storm coverage Transcripts (CAST.Bot) to analyze broadcast coverage.

a. TORFFs and their climatology

TORFFs are defined by Nielsen et al. (2015) as spatial intersections of tornado and flash flood warnings that are valid within 30 min of one another. Severe convective storms are a frequent cause of TORFF events, as the powerful updrafts that fuel strong thunderstorms are uniquely capable of producing both tornadoes and flash flooding (Nielsen 2019; Nielsen and Schumacher 2020). Flash floods generally occur where "the rainfall rate is the highest for the longest time" (Doswell et al. 1996). Thunderstorms can have high rainfall rates due to their ability to ingest large quantities of water vapor into their strong updrafts, especially when those updrafts are rotating mesocyclones in supercell thunderstorms (Doswell et al. 1996; Hitchens and Brooks 2013; Nielsen and Schumacher 2018; Nielsen 2019; Nielsen and Schumacher 2020). Simulated supercell rainfall production has been positively correlated with increased low-level (0–1km above ground level) shear, which is also a key ingredient for tornadoes (Markowski and Richardson 2014; Nielsen and Schumacher 2018; Nielsen 2019; Nielsen and Schumacher 2020). High low-level shear and moisture can also encourage the development of Mesoscale Convective Systems (MCS), which can produce tornadoes and heavy rain along the boundary between their outflow and the environmental air mass (Nielsen et al. 2015). Finally, high shear and moisture are frequently present in the outer bands of landfalling hurricanes, which can lead to smaller supercells that produce heavy rainfall and weaker tornadoes (Edwards et al. 2012; Burow et al. 2021; Mazurek and Schumacher 2023).

Climatological studies of TORFF events suggest that the distribution of TORFFs throughout the year in the United States can be explained by the yearly occurrences of the three major parent storms of tornadoes: supercells, MCS events, and hurricane landfalls (Nielsen et al. 2015; Krocak and Brooks 2018; Burow et al. 2021; First et al. 2022). TORFF warning overlaps in the contiguous United States generally occur east of the continental divide, although different storm morphologies dominate in different regions (Nielsen et al. 2015; Schumacher 2022). Most TORFFs occur across the South and Midwest United States (Fig. 1) during the climatological peak tornado months of April, May, and June, with most hazard overlaps caused by supercell thunderstorms (Krocak and Brooks 2018; Schumacher 2022). Although fewer in number, TORFF events also occur during the months of July through November within MCS events across the northern tier of the United States. There is a secondary annual peak in TORFFs during the fall months due to tropical cyclone landfalls along the East and Gulf coasts, particularly when stronger and slower-moving cyclones move inland (Burow et al. 2021). It is worth noting that TORFFs that occur with landfalling hurricanes or their remnants over land usually involve weaker tornadoes (<EF3) and significant, widespread flooding over multiple states as compared to their supercell-driven counterparts (Edwards et al. 2012; Nielsen et al. 2015). Finally, the few TORFF events that occur in December and January are generally associated with synoptically forced MCS events common in states bordering the Gulf of Mexico in winter (Nielsen et al. 2015; First et al. 2022; Schumacher 2022).

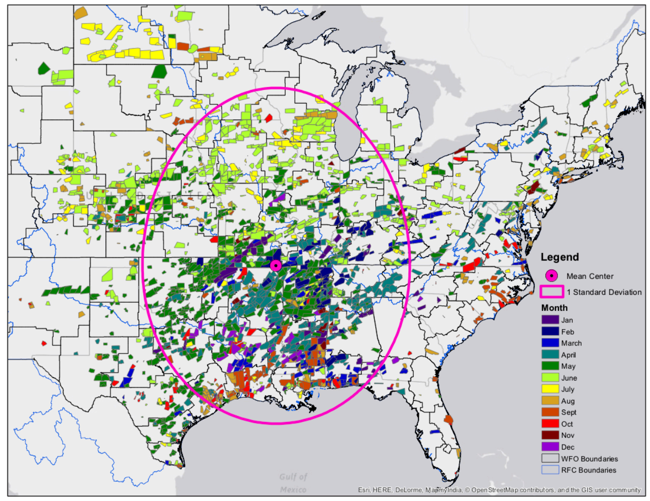

Figure 1. Map of all tornado and flash flood warning overlaps by month from 2008 through 2019, with the geographic mean center of all overlaps and one standard deviation distance from the centroid in pink. Image from Schumacher (2022). *Click image for an external version; this applies to all figures and hereafter.*

b. *Tornado and flood broadcast coverage*

When thunderstorms cause flash flooding and tornadoes, members of the public most frequently turn to broadcast meteorologists for updates on the weather (Ripberger and Silva 2022). The National Weather Service (NWS) considers broadcasters and other members of the electronic media to be core partners, with their role being to help disseminate NWS products and communicate crucial safety information to the public (NWS 2018). Surveys investigating public weather information sources have identified that members of the public hold meteorologists at local television stations in high regard and trust them as sources of generic weather information (Lazo et al. 2009; Drobot et al. 2014; Ripberger and Silva 2022). Targeted studies have also shown that a majority of the public relies on broadcast coverage as their primary source for life-saving severe weather warnings issued by the NWS (Daniels and Loggins 2007; Keul and Holzer 2013; Drost et al. 2016).

Studies of broadcaster communication during tornado threats show that these generalized conclusions about the public perception of television weather coverage can also apply to specific hazard coverage. Television coverage has been a key pillar of tornado warning coverage for decades, with “wall-to-wall” live coverage of tornado events an established practice nationwide by 2000 (Coleman et al. 2011). Wall-to-wall coverage has been related to viewers’ protective action behaviors, both in simulated tornado events and after real tornado impacts (Hammer and Schmidlin 2002; Zhao et al. 2019). Simulations using coverage from the 2013 Moore, Oklahoma, tornado found that media coverage increased risk perception and behavioral intent for viewers (Zhao et al. 2019). Furthermore, surveys of residents impacted by the 1999 Moore, Oklahoma, tornado found that nearly 90% of respondents listed television as their top source of warning information (Hammer and Schmidlin 2002). They also identified that, of the 47% of respondents that reported fleeing their homes in advance of the 1999 Moore tornado, 35% made the decision to flee based on television reports that told them to get out of the path of the storm. Other studies have shown that the likelihood of an individual taking shelter from a tornado is related to the trust they have in their local broadcast meteorologist (Sherman-Morris 2005).

Although flash flood broadcast coverage is less commonly studied than tornado coverage, research has shown that the public still relies on broadcasters to communicate flash flood hazards. One of these few studies surveyed individuals in Dresden, Germany, after severe floods in 2002 and 2006. Radio, television, newspaper, and internet sources were found to be ideal methods for communicating both river and flash flooding risk information to the public (Kreibich et al. 2008; Kellens et al. 2013). Other studies have found that the public frequently uses television for information about flash floods, compared to sources for information about slower river flooding (Hayden et al. 2007; Ryan 2013). Broadcast meteorologists have also reported that they are aware of the necessity of flash flood updates for the public and want to get flash flood warnings to their viewers before impacts begin (Morss et al. 2015). As an example, broadcasters played a key role in communicating flash flood hazards during Hurricane Harvey in Houston, acting as "storytellers" by using figurative and intense language to communicate information about the severity of water hazards to their viewers (Demuth et al. 2012; Prestley et al. 2020).

Despite the importance of broadcaster messaging during flash flooding and tornado events, broadcasters do not always have complete control of the story they share on air. Producers and other management staff often dictate to broadcast meteorologists what goes on air and what the focus of their coverage should be (Obermeier et al. 2022). Broadcast news coverage, including weather coverage, is heavily guided by consultant feedback that station management rarely shares with meteorologists (Henson 2010). One such example of market research inspired change is the "Code Red" language that many local stations across the United States have begun to adopt for communicating impactful weather days. These "Code Red" days feature a change to all station graphics that highlights weather hazards, suggesting that viewers should continue to watch the news for more information (Burnett 2016; Mojica 2019; CBS 4 News 2019). However, there are no standardized criteria or decision process that defines when "Code Red" days are issued. Some television stations that chose to start using "Code Red" days published announcements suggesting that the "forecast will show in red days when severe weather is expected" (Burnett 2016). Other stations were more specific and suggested that "Code Red" will be used for "dangerous conditions like tornadoes, flash flooding, severe storms or a downpour happening right now creating hazardous conditions for drivers" (Mojica 2019). News reports on "Code Red" use have suggested that broadcast meteorologists can only offer input on the final decision to declare a "Code Red" day, with station management making the final call (Stelter 2019). These managerial decisions can prevent broadcast meteorologists from presenting the weather story the way that they might prefer to, even during complex multi-hazard events like TORFFs.

c. *TORFF event coverage*

Although no published studies of broadcast meteorologist coverage of TORFF events yet exist, some research has sought to understand how TORFF events are communicated by the NWS and received by forecast users. In a study of the efforts made by one southeastern NWS office to message TORFF threats to the public, Henderson et al. (2020) identified that forecasts could unintentionally amplify tornado threats more than flash flood hazards in certain circumstances. For example, in advance of one TORFF event, the website of the forecast office presented graphical tornado forecast information as soon as viewers arrived on their homepage. Flash flooding information was accessed through clicking on a second tab on the site with the heading "heavy rain". Further, forecasters at this office amplified messaging on tornado potential in public forecast discussions for this TORFF by specifically mentioning "strong tornadoes" while using "heavy rain" to describe the simultaneous flash flood threat. Henderson et al. (2020) suggest that the forecasters felt that the tornado potential for this event was the most important hazard to message to the public, and so highlighted the tornado threat in their webpage organization and forecast discussions.

Henderson et al. (2020) further note that institutional factors may also contribute to unintentional amplification of tornado hazards before TORFF events. One such factor is that the collaboration between this southeastern NWS office, the convective-weather-focused Storm Prediction Center (SPC), and the precipitation-focused Weather Prediction Center (WPC) could be uneven at times. A forecaster at the southeastern NWS office expressed that their office has had a strong relationship with the SPC for much of their career, but that the same level of relationship has not existed with regards to the WPC and flash flood forecasts in the past (Henderson et al. 2020). Another possible factor mentioned by the researchers includes forecasters' assumptions and beliefs about their public, particularly that tornadoes are a more life threatening and salient threat for members of the public. Although these results should not be generalized across all NWS offices and forecasters, Henderson et al. (2020) suggest that future work should seek to better understand how the communication choices forecasters make can unintentionally magnify risks for recipients of forecast information.

Others have investigated how members of the public perceive the risks posed by flash floods and tornadoes, to see whether general assumptions about the publics' awareness of different threats are correct. In a survey of adults exposed to TORFF events of 25 and 27 March 2021 that occurred in Arkansas, Tennessee, Mississippi, and Alabama, First et al. (2022) found that increased tornado risk perceptions more often led to tornado-oriented protective actions, and that the same was true for flash flood risk perceptions and protective actions. However, when participants considered both hazards simultaneously, increased tornado risk perception led to less flash flood protective action, whereas increased flash flood risk perception had no effect on tornado protective actions. The authors suggest that increased tornado risk perception may increase the vulnerability of the public to flash flood impacts, particularly for those who live in vulnerable structures like mobile or manufactured homes. First et al. (2022) suggest that a better understanding of how the communication of TORFF events impact public threat perception is needed to identify strategies for improving TORFF messaging.

Based on this previous research and our evolving knowledge of TORFF hazard communication, we expect to find that broadcast coverage of TORFF events contains more mentions of tornado hazards than flash flood hazards. Such a preference for tornado messaging may be due to the institutionally reinforced perception that tornadoes pose a more significant threat to life. In theory, this pattern would be enhanced for events with a greater tornado threat than flood threat and muted for events with a greater flood threat. We will use a newly developed algorithm tool to perform a thematic coding analysis of televised TORFF coverage and identify whether or not this hypothetical pattern in TORFF coverage is consistent across TORFF events across different regions with varied storm morphologies.

2. Data and methods

a. Identification of TORFF events

The first step towards analyzing broadcast coverage of TORFF events was to establish a list of events to collect coverage from. We wanted to analyze coverage from two of the most "newsworthy" TORFF events in recent history: the 31 May 2013 TORFF in the El Reno/OKC metropolitan area, and the 26 August 2017 TORFFs in Houston, Texas, that were caused by Hurricane Harvey. These two events were of special interest because they generated a great deal of discussion among meteorologists and have recoverable YouTube clips of television coverage (Nielsen et al. 2015; NOAA 2018). It is important to note that both TORFFs occurred in extreme contexts; the El Reno/OKC TORFF occurred after a deadly EF5 tornado in Moore, Oklahoma; while Hurricane Harvey was a well-forecast and unusually slow-moving storm that brought heavy rain to Texas and Louisiana for a period of several days. Despite the importance of context to the newsworthy nature of both TORFFs, we decided to include these cases in our analysis to learn what differences might exist between coverage of these extreme and well-known events and more generic TORFF events.

After collecting data from the El Reno/OKC and Houston TORFFs, we sought to collect a larger sample of TORFF event coverage that we could use to identify patterns across events with different storm morphologies, locations, and stations. To narrow our search down to a manageable number of cases, we applied a set of criteria to the automated list of TORFF events generated by Schumacher (2022). First, we defined TORFF events using the definition proposed by Nielsen et al. (2015), which states that a TORFF occurs when a tornado warning and flash flood warning polygon overlap spatially within 30 min of each other. We do not define TORFF events as verified occurrences of tornado and flash flood reports, as issuance of warnings alone is enough to lead to broadcast coverage of both hazards. Second, our TORFF event search criteria were further defined by the limitations of our broadcast coverage aggregator. Archived TORFF coverage was sourced from Metro Monitor, a company that archives broadcast coverage for use in advertising studies and public relations research (Metro Monitor 2022). Unfortunately, Metro Monitor only collects coverage during set hours of the day when news blocks are usually scheduled and remove data from their collection after a period of several years. This limited our ability to investigate TORFF events that occurred before 2021 or during times outside of typical news coverage blocks.

Thus, to account for the limitations of the Metro Monitor database, we refined our search parameters for TORFF events to only identify TORFFs that occurred

Table 1. List of TORFF events selected for study and the number of television stations sampled for each event, as well as the maximum outlook tier for the Excessive Rainfall Outlook (ERO; WPC) and Convective Outlook (SPC) for the region impacted by the TORFF event for the three days leading up to the event. The level of that outlook on its respected scale is listed below the abbreviation for the scale's level, which are General Thunder (Gen. Thun.), Marginal (MRGL), Slight (SLGT), Enhanced (ENH), Moderate (MDT), and High (HIGH). Note that the ERO does not include the Enhanced Risk tier, leading it to be a 4-level scale, and that General Thunder in the SPC outlook is recorded as a zero out of five on that scale. Finally, the ERO debuted in 2014, after the Oklahoma City TORFF event of 31 May 2013 and thus is not included for that event.

Case	Date	DMA (State Impacted)	# Stations Sampled	D1 ERO	D2 ERO	D3 ERO	D1 SPC	D2 SPC	D3 SPC
A	29 July 2021	Philadelphia, Baltimore, New York (NJ)	11	SLGT (2/4)	MRGL (1/4)	MRGL (1/4)	ENH (3/5)	SLGT (2/5)	MRGL (1/5)
B	17 March 2021	Birmingham, Montgomery, Mobile (AL)	3	SLGT (2/4)	SLGT (2/4)	MRGL (1/4)	HIGH (5/5)	MDT (4/5)	ENH (3/5)
C	27 March 2021	Memphis, Little Rock (AR/TN)	4	MDT (3/4)	MDT (3/4)	SLGT (2/4)	ENH (3/5)	ENH (3/5)	SLGT (2/5)
D	18 May 2021	San Antonio, Austin, Houston (TX)	10	MDT (3/4)	MDT (3/4)	SLGT (2/4)	SLGT (2/5)	SLGT (2/5)	MRGL (1/5)
E	17 August 2021	Greenville, Charlotte (NC)	7	HIGH (4/4)	MDT (3/4)	SLGT (2/4)	SLGT (2/5)	SLGT (2/5)	Gen. Thun. (0/5)
F	1 September 2021	Philadelphia, New York (NJ)	2	HIGH (4/4)	HIGH (4/4)	MDT (3/4)	ENH (3/5)	ENH (3/5)	MRGL (1/5)
G	31 May 2013	Oklahoma City (OK)	1	NA	NA	NA	MDT (4/5)	MDT (4/5)	SLGT (ENH) (3/5)
H	26 August 2017	Houston (TX)	1	HIGH (4/4)	HIGH (4/4)	MDT (3/4)	SLGT (2/5)	SLGT (2/5)	MRGL (1/5)

in the year 2021 and during the daily "primetime" television hours of 1600 to 2300 local time. We also chose to limit our search to events where five or more TORFF warning overlaps occurred in a single NWS forecast office domain in one day. Limiting our search to events with a greater number of TORFF overlaps helped ensure that both tornado and flash flood hazards were present for many television viewers. Applying these search constraints resulted in the identification of seven TORFF events across 2021, which we then attempted to recover coverage transcripts from.

b. Recovery of coverage transcriptions and meteorological data

Using the Metro Monitor television coverage search tools and database, we sought out and recovered closed caption data for six of the seven 2021 TORFF events we identified for analysis (see Table 1). One of the seven events was not covered by the stations that were impacted by TORFFs, and so this event was not analyzed. It must also be noted that the closed caption data recovered for the six 2021 TORFF events suffered from some live transcription errors and missing sections of coverage, which could not be addressed in our data analysis. Further, the closed captions did not include timestamps for when a given line of coverage was presented, meaning that we were unable to match TORFF coverage to real-time events such as warning issuances and storm reports in our analysis.

Table 2. Table of the subjectively analyzed storm mode and number of warnings issued for each of the cases. Flash flood and tornado warning counts were recovered from the Iowa Environmental Mesonet Archived NWS Watch, Warnings, Advisories page (Herzmann 2023) and include the number of warning polygons for flash flood warnings and tornado warnings issued at the Warning Forecast Office (WFO) labeled during the 24 hr period starting at 1200 UTC on the date listed. The percentage of the total tornado and flash flood warnings that were flash flood warnings for each event is also calculated in the column "% FF Warnings." Storm mode was subjectively analyzed by viewing archived base reflectivity radar images from the UCAR image archive (Ahijevych 2023) and describes whether the dominant storm mode was of supercell thunderstorms, supercells transitioning into a Mesoscale Convective System (MCS), or a tropical cyclone or tropical cyclone remnant (with the name of the tropical cyclone at landfall that sourced the TORFF events in parenthesis).

Case	Date	WFO (State Impacted)	Flash Flood Warnings	Tornado Warnings	% FF Warnings	Storm Mode
A	29 July 2021	Philadelphia/Mount Holly (NJ)	6	14	30.0%	MCS to Supercell Transition
B	17 March 2021	Birmingham (AL)	4	38	9.52%	Supercells
C	27 March 2021	Memphis (AR/TN)	11	25	30.56%	Supercell to MCS Transition
D	18 May 2021	San Antonio (TX)	7	7	50.0%	Supercell to MCS Transition
E	17 August 2021	Greenville-Spartanburg (NC)	21	38	35.59%	Tropical (Tropical Storm Fred)
F	1 September 2021	Philadelphia/Mount Holly (NJ)	15	16	48.39%	Tropical (Major Hurricane Ida)
G	31 May 2013	Norman (OK)	6	11	35.29%	Supercell to MCS Transition
H	26 August 2017	Houston (TX)	31	49	38.75%	Tropical (Major Hurricane Harvey)

For the two "newsworthy" TORFF events, coverage was collected from YouTube uploads of local television live footage for both events. We were unable to use Metro Monitor to recover closed captioning from multiple stations for these events, as older saved coverage on their database is continuously deleted to make space for new coverage. Unfortunately, our limited access to coverage through YouTube and the need to use a separate tool to transcribe videos of television coverage prevented us from recovering coverage from more than one station for both the El Reno/OKC 2013 and Hurricane Harvey 2017 TORFF events. Finally, similar to the Metro Monitor closed caption transcripts, we did not have the time or resources to match coverage sentences to local time with the recovered YouTube coverage.

Despite our inability to match transcribed TORFF coverage to local time for either data source, we collected forecast products leading up to and during each of the eight TORFF events that could provide

Table 3. Table displaying the number of sentences coded by humans and used to train the CAST.Bot algorithm, by type of event sampled and coded coverage was for.

Event Type	Number of Sentences Coded
Convective (Thunderstorm Threat)	3224
Hurricane/Tropical Storm	3318
Winter Weather	9773

some meteorological context. First, we sought out the SPC and WPC outlook forecasts for the areas impacted by each TORFF event through their respective archival websites (SPC 2022; WPC 2022; Burke et al. 2022). We present the outlook level for each day for the three days leading up to each TORFF event in Table 1, although the WPC Enhanced Rainfall Outlook did not exist in 2013 and as such could not be collected for the El Reno/OKC 2013 TORFF. Second, we used the Iowa Environmental Mesonet warning product archive (Herzmann, 2022) to identify the number of flash flood and tornado warning polygons issued by the forecast offices impacted by our eight TORFFs. Warnings were collected for the 24 hr period starting at 1200 UTC on the day of each TORFF event (Herzmann 2022; Table 2). These data on forecast products provide further context about the forecast and observed balance of flash flood and tornado hazards during each of the TORFF events we studied coverage from.

Finally, we subjectively analyzed archived radar data to describe the dominant storm mode present for each TORFF event (Ahijevych 2023; Table 2). The subjective classifications we used to analyze storm mode were generally based on those described in Nielsen et al. (2015), although we did not analyze whether storms were "training," or repeatedly impacting the same area over time, in our analysis. Storm coverage in each TORFF was thus defined as either a "Supercell mode", "transitioning from an MCS to a Supercell mode", "transitioning from a Supercell to an MCS mode", or an "MCS mode". We also recorded whether each TORFF event was associated with a tropical cyclone landfall or tropical cyclone remnant, as tropical systems have a different morphology from typical continental thunderstorm complexes (Nielsen et al. 2015).

c. *Thematic coding and CAST.Bot*

We then analyzed our TORFF broadcast coverage transcripts through the use of an algorithm developed using human-defined "thematic codes". Qualitative data like our TORFF coverage transcripts are typically analyzed using thematic coding analysis, defined by Braun and Clarke (2006) as "a method for identifying, analyzing, and reporting patterns (themes) in data." For our study, this process involved applying thematic "codes," or labels, to sentences in the transcribed or closed caption broadcast coverage, then identifying common themes within the labeled data. We used a thematic coding scheme that was developed for a broader effort meant to produce a computer algorithm that could perform thematic coding analysis on large datasets. However, because this is the first publication to use this coding algorithm, we will describe its overall development here.

We first sought to develop a thematic coding scheme that could capture key messages present in broadcast weather coverage. In this particular study, we were interested in identifying what "Hazard" information broadcasters discussed, so that we could compare how often they spoke about flash floods versus tornadoes. As we had a clear idea of what themes we were looking for in our data, we utilized deductive or a priori thematic coding, where themes of interest are established based on the researchers' theories and research questions before beginning the coding analysis. We then used an inductive process to further refine our "hazard" codes through close reading of example broadcast coverage. This allowed us to develop codes for ideas that more naturally emerge from the data (Braun and Clarke 2006; Elliott 2018). As an example of this effort, analysts identified that when the words "flooding", "over its banks", and "high water" were used by broadcasters, the coverage was highlighting a flooding hazard. We defined a Flood code based on these mentions, where sentences like the previous examples that discussed flooding hazards were coded as including Flood hazards. To develop our inductive codes, we analyzed thousands of lines of broadcast coverage of thunderstorm, tropical storm, and winter weather coverage (see Table 3),

Table 4. Table displaying the codes under the Hazard category that the first version of the CAST.Bot algorithm identifies, as well as a description of what human thematic coders developed the code to capture in coverage transcripts.

Category Name	Code	Description
Hazard	Flood	For mentions of inundation or rising water levels, but not from Storm Surge.
	Rain	For mentions of liquid, non-freezing precipitation.
	Wind	For mentions of winds or blowing air, but not wind chill.
	Hail	For mentions of hail.
	Snow	For mentions of snow or blizzard conditions.
	Ice	For mentions of frozen or freezing precipitation, including freezing rain, sleet, and wintry mix.
	Cold	For mentions of dangerously cold air, freezing, and wind chill.
	Surge	For mentions of ocean-related storm surge flooding, but not river or inland flooding.
	Tornado	For mentions of tornadoes or storm rotation that might suggest a tornado threat.

resulting in a list of codes for the "hazard" theme as seen in Table 4.

Our qualitative analysis differed from a typical procedure at this point, as we used our analyst-created coding scheme to build a computer algorithm that could perform thematic coding analysis on massive datasets at high speed. We have named this algorithm the Coding Algorithm for Storm coverage Transcripts, abbreviated as CAST.Bot. The algorithm performs a simple check for words, identified by the analyst team, that were commonly associated with each of the codes under the "hazard" theme (further codes are being developed for overarching themes of "impacts" and "protective actions" that are mentioned by broadcasters, but these codes were not ready for use during this study). Continuing with the Flood code example from before, the CAST.Bot algorithm is designed to flag sentences of broadcast coverage that include the words "flooding", "over its banks", and "high water" with the Flood code (see Fig. 2 for an example). Sentences without those words do not receive a Flood tag.

Tests of the performance of CAST.Bot's coding of the "hazard" theme against analysts' coding of broadcast transcriptions identified that the algorithm performs well outside of its training datasets. The algorithm was tested on 7056 lines of TORFF coverage

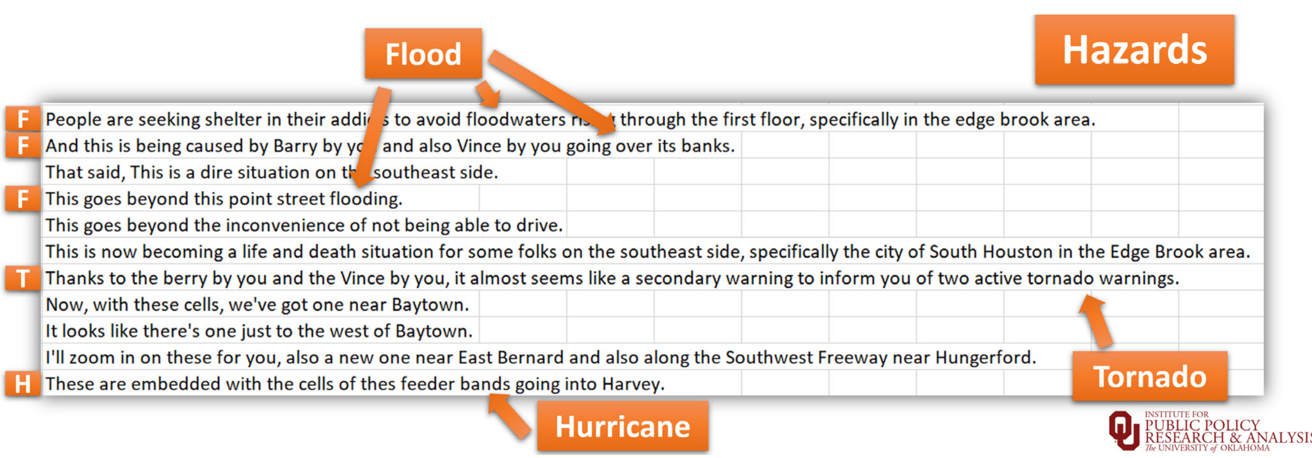

Figure 2. Diagram displaying an example of the coding process used to train the CAST.Bot algorithm on how to apply a set of codes under the Hazard theme.

Table 5. Table displaying the Probability of Detection (POD), Success Ratio (SR), False Alarm Ratio (FAR), and Critical Skill Index (CSI) values for each of the five convective hazard codes used in the CAST.Bot algorithm when compared to the performance of human coders.

Hazard Code	POD	SR (FAR)	CSI
Flood	0.808	0.969 (0.031)	0.787
Rain	0.973	0.995 (0.005)	0.968
Tornado	0.924	0.951 (0.049)	0.882
Hail	1.000	1.000 (0.000)	1.000
Wind	0.911	0.719 (0.281)	0.672

coded by human researchers, which translates to roughly 30% of our human-coded coverage (23 371 lines total). We identified that the algorithm achieved a high success ratio, which is equal to one divided by the false alarm ratio (FAR, which is the number of times that the algorithm suggested a code was present, and a human indicated a code was not present, divided by the total number of times the algorithm indicated a code was present). The algorithm was also found to have a high probability of detection for the "hazard" codes (POD, the number of times that both the algorithm and the human coders suggested a code was present, divided by the total number of times the human coders indicated that code was present, see Table 5). Combined, these findings suggest that the algorithm has high skill at identifying the occurrence of "hazard" codes that a human coder would also identify in TORFF event coverage.

Finally, we used CAST.Bot to compare the amount of coverage dedicated to Flood, Tornado, and Rain hazard codes in broadcast coverage of our eight TORFF events. Both the Flood and Rain codes were used in this analysis, instead of only the Flood code, because the two codes capture distinct concepts that are both important to flash flood messaging. The Flood code highlights mentions of rising water and inundation of normally dry areas whereas the Rain code is applied when broadcasters discuss falling liquid precipitation, which broadcasters often use to message the potential for future flash flooding. Note also that the Flood code captures mentions of both river and flash flooding, as the descriptions of these two threats are difficult to parse using an algorithm like CAST.Bot. Along with the Tornado code, these three codes allowed us to compare the ways that different broadcasters covered hydrological and tornadic threats during TORFFs.

3. Analysis

a. 2021 TORFF events

After processing the six 2021 TORFF coverage transcriptions through the CAST.Bot algorithm, we compared the sum of all lines flagged with Tornado, Flood, and Rain codes to the counts of each code for each station's coverage. These proportions were then averaged across all coverage from each event to find the average proportion of TORFF coverage that each

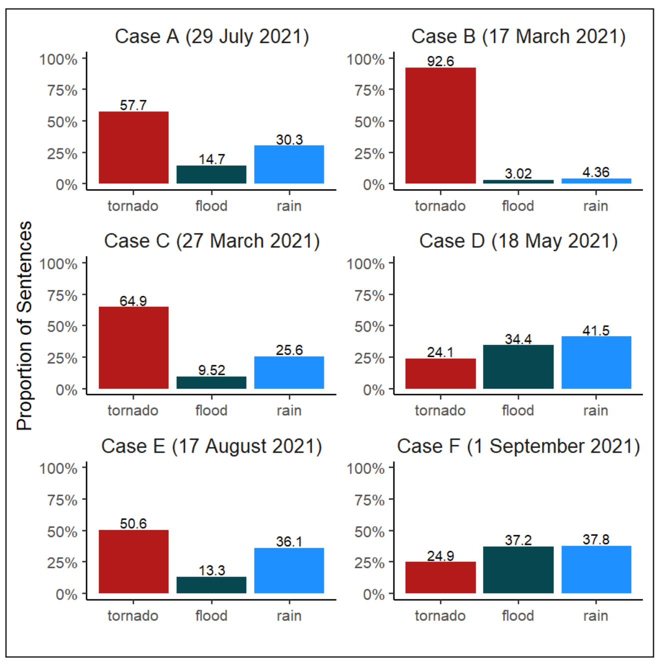

Figure 3. Plots displaying the average proportions of tornado, flood, and rain coverage versus the sum of tornado, flood, and rain coverage across all coverage for each of the six 2021 TORFF events sampled for this study. Numbers above each bar list the average proportion of TORFF coverage dedicated to that hazard.

hazard received (Fig. 3). The cases shown in Fig. 3 are organized by whether the SPC or WPC outlook was forecast to be a higher risk level (Table 1) and the observed primary storm mode (Table 2). As a result, the first two cases (A and B) describe supercell-driven events with higher SPC outlook risks, the middle two (C and D) present supercell-to-MCS driven events with higher WPC outlook risks, and the final two cases (E and F) highlight remnant tropical storms over land with high WPC outlook risks. Cases A and B also had the two lowest proportions of flash flood warnings across the cases collected here (Table 2), with a much more widespread tornado threat in Case B than any of the other cases. The middle group of cases (C and D) varied in their proportion of flash flood warnings versus all TORFF-associated warnings (30.56% and 50.0% respectively) despite their similar storm morphology. This was also the case for the two remnant tropical cyclone events in Case E and F (35.59% and 48.39% respectively).

When comparing broadcast coverage across TORFFs of similar storm morphology in the six 2021 cases, several interesting patterns emerge. The two supercell-driven TORFF events, Cases A and B, were both found to have larger proportions of Tornado codes than Flood and Rain codes combined. However, Case A was closer to a 50% proportion of Tornado codes than Case B, where more than 90% of TORFF-related “hazard” codes were Tornado codes (Fig. 3). Cases C and D, where TORFF events occurred due to supercells transitioning into an MCS, were also dissimilar in coverage proportions. On average broadcasters covering Case C mentioned tornadoes most frequently, whereas in Case D both the Flood and Rain codes made up a greater proportion of “hazard” codes than Tornado codes (Fig. 3). This pattern continued for the tropical remnant TORFFs in Cases E and F, where Case E coverage on average had a larger proportion of lines coded as mentioning the Tornado threat compared to more Flood and Rain coded sentences in Case F (Fig. 3).

Although there is less consistency in coverage between events of similar storm morphology, patterns do appear to emerge across the case groups. First, Cases D and F, despite being supercell-to-MCS and tropical remnant events, had nearly identical proportions of Tornado, Flood, and Rain codes on average across their coverage (Fig. 3). The two cases had similar forecasts in advance of their onset, as a Slight Risk of severe thunderstorms and a Moderate Risk of excessive rainfall was issued for Case D, while Case F was preceded by forecasts of an Enhanced Risk for severe thunderstorms and a High Risk of rainfall (Table 1). Both events also saw the highest proportion of flash flood warnings as compared to the total of TORFF-related warnings, at 50.0% and 48.39% of the total for Cases D and F respectively (Table 2). In contrast, the other supercell-to-MCS and tropical remnant cases (Cases C and E), which also had higher maximum WPC outlook risks versus SPC outlook risks, had more Tornado mentions than Flood and Rain mentions across their coverage (Fig. 3). It is worth noting that Cases C and E also had proportions of flash flood warnings that were closer to Case A (30.56 and 35.59% versus 30.0%, respectively) than the morphologically similar Cases D and F (50.0% and 48.39% respectively, see Table 2). Combined, these patterns in coverage suggest that the proportions of tornado and flash flood warnings issued during a TORFF event have a greater impact on TORFF coverage than the forecasts leading up to or the morphology of the storms causing the event.

In addition to comparing the average proportions of different hazards in TORFF coverage, CAST.Bot output can be displayed as the difference between the sum of Tornado-coded lines and the sum of Flood-coded lines across the duration of event coverage (see Fig. 4). We can observe that during the two events that had a greater average number of Flood mentions in coverage (i.e., Cases D and F), most stations had a near equal number of Tornado and Flood mentions throughout the duration of coverage. (Fig. 4). In contrast, the three stations that covered the tornado-oriented TORFF Case B mentioned Tornado hazards far more than Flood hazards, with the difference in total mentions increasing nearly linearly with time. Some of the stations covering Cases A, C, and E, which on average covered Tornado hazards more often than Rain or Flood hazards (Fig. 3), also displayed a nearly linear increase in the difference in mentions across their coverage (Fig. 4). However, other stations covering Cases A and E had nearly equal mentions of Tornado and Flood hazards, suggesting that individual differences between stations and broadcast meteorologists on air can have an impact on TORFF coverage breakdowns even within events.

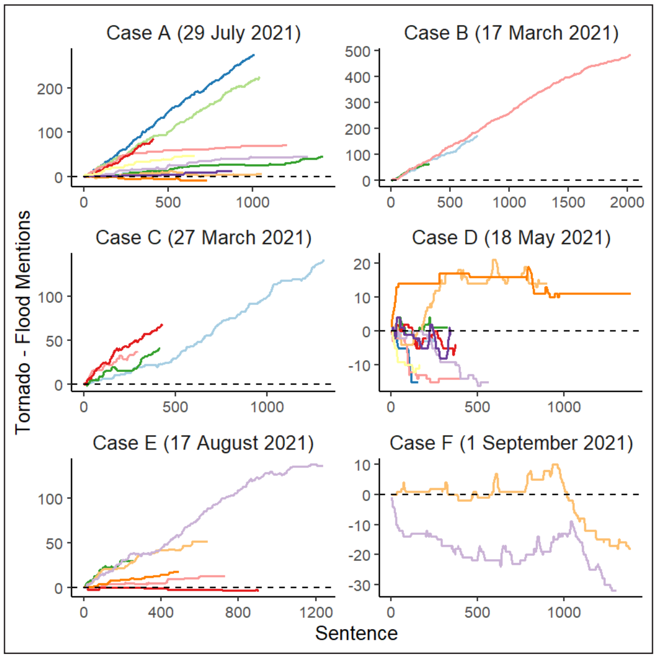

Figure 4. Plots displaying the total number of sentences coded as mentioning Flood hazards subtracted from the total number of sentences coded as mentioning Tornado hazards by sentence number for coverage of the six 2021 TORFF events in this study. Colors in these plots are used to differentiate individual stations from one another in each case; this means that colors do not indicate the same station across different events, only within each case. Positive values mean more tornado mentions are present in the coverage than flood mentions, while negative values mean more flood mentions have occurred across the coverage than tornado mentions.

b. *Case studies*

1. *The 31 May 2013 El Reno/Oklahoma City (OKC) Event*

We then compared the 2021 TORFF event coverage analysis to previous high-impact TORFF event coverage, starting with coverage of the infamous El Reno/OKC TORFF of 31 May 2013 (Case G). Although this event occurred before the existence of the WPC enhanced rainfall outlook, a Moderate Risk for severe thunderstorms was issued for this event (Table 1) and the NWS Norman office prioritized tornado safety information in their tweets leading up to the event (NWS 2013). It is worth noting that this TORFF event occurred at the end of a historic tornado sequence in central Oklahoma, including the highly televised and deadly Shawnee and Moore tornadoes on 19 and 20 May 2013. About 35% of the TORFF-related warnings for this event were flash flood warnings, the majority of which were caused by supercell thunderstorms that merged into an MCS (Table 2).

Coverage from one station was collected for this event, which overall displayed a preference for presenting the tornado threat (Fig. 5). This pattern is also reflected in the difference between Tornado and Flood mentions for the 31 May 2013 coverage, as the sum of Tornado mentions was consistently larger than the sum of Flood hazard mentions (Fig. 6). Interestingly, the difference plot does begin to trend slightly downwards after about 1000 sentences into the coverage, suggesting that the messaging of this TORFF event began to shift towards flooding coverage with time. This may be partly explained by the transition of this event from supercells with a significant tornado threat to an MCS that produced widespread heavy rains. Overall, the data from Case G is similar to coverage from the higher flood risk events in 2021 that prioritized tornado coverage (i.e., Cases B and C).

The similarity of the El Reno/OKC event to the 2021 coverage cases in its breakdown of Tornado, Flood, and Rain mentions is somewhat unexpected considering the context of this event and the general focus on tornado coverage found in retrospective analyses. Cases B and C both had higher average proportions of Tornado mentions than the station covering Case G (92.6% and 64.9%, versus 52.2%), and there is a larger proportion of Flood mentions in Case G than the average across the coverage sampled in Cases A and E (17.9%, versus 14.7% and 13.3%). These similarities suggest that despite the meteorologically extreme nature of, and the context of repeated deadly tornadoes leading up to, the El Reno/OKC TORFF event, coverage of this TORFF was not particularly exceptional compared to generic TORFF event coverage. Given that the breakdown of Tornado, Flood, and Rain mentions for Case G are so similar to the cases from 2021, and the known examples of Oklahoma City residents prioritizing tornado safety actions during this event, this finding suggests that flash flood hazards may not receive the same attention from viewers when Tornado mentions are outpacing Flood mentions even at more modest rates.

2. *The 26 August 2017 Hurricane Harvey Event*

The other major TORFF case study, which we have titled Case H, was coverage of Hurricane Harvey in

Houston, Texas. This event saw more than 40 tornado and flash flood warning overlaps on 27 August 2017 (Schumacher 2022). Unfortunately, we were only able to recover coverage from Houston from the afternoon of 26 August, as many stations flooded on 27 August and were taken off the air. The WPC issued a High Risk of excessive rainfall for southeastern Texas two days before 26 August 2017, while the SPC issued a Slight Risk for the region because of the threat of tornadoes in the storm's convective rainbands. Interestingly, although more flash flood warnings were issued for this event than any other case we collected, Case H also had the highest number of tornado warnings (49 in the 24 hr period starting at 1200 UTC on 26 August). Flash flood warnings thus only made up 38.75% of the total warnings issued by the NWS during this event (Table 2). Despite the lower proportion of flash flood warnings compared to other cases studied here, CAST. Bot analysis of coverage from Case H identified a much greater coverage focus on discussing Flood and Rain hazards, more so than any of the 2021 TORFF Cases (Fig. 5). Further, the difference plot for this event highlights the overwhelming focus on Flood mentions more than Tornado mentions, with the difference between the two steadily trending negative across the coverage (Fig. 6).

The multi-day TORFF event from Hurricane Harvey is easily the most extreme event captured in this study, with an unparalleled number of tornado and flash flood warnings issued over the 24 hr period on 26 August 2017 and multiple days of High ERO forecasts from the WPC (Table 1, Table 2). Despite the number of tornado warnings outnumbering the number of flash flood warnings, no other case in this study had a higher proportion of Flood or Rain mentions in coverage (Fig. 5, 40.3% and 42.7%), or a more negative value of Tornado-Flood mentions (Fig. 6). Though the flash flood amplification in this coverage is likely related to the fact that most tornadoes were weaker and were occurring within a historic and well-forecast flood threat, comparison of this case to coverage of the other tropical cyclone remnant TORFF events from the 2021 sample reveals important nuance. Both of the 2021 TORFF events classified as tropical storm remnants (Cases E and F) also led the WPC to issue High Risk areas for flash flooding in their ERO, the same risk level that was issued for the Houston area during Case H (Table 1). However, hazard coverage for Case E was more similar to the supercell-driven TORFF Case A than to Cases F and H (Fig. 3). Although the lower proportion of flash flood warnings during Case E as compared to Cases F and H is likely related to why tornadoes were mentioned more often in Case E, another possible reason for this discrepancy is that Cases F and H saw significant and deadly flash floods that were widely captured on film by residents of densely populated cities (New York City and Houston, respectively). The effect of video capture and population density on TORFF events is difficult to capture with a small sample of events, but it may affect coverage patterns on a station-to-station basis as seen in Fig. 4. Overall, study of Case H in comparison to our six 2021 events suggests that the narrative leading up to a major TORFF event can play a role in the way that the event is covered on television, but that local and meteorological context adds nuance that can further shape the nature of coverage.

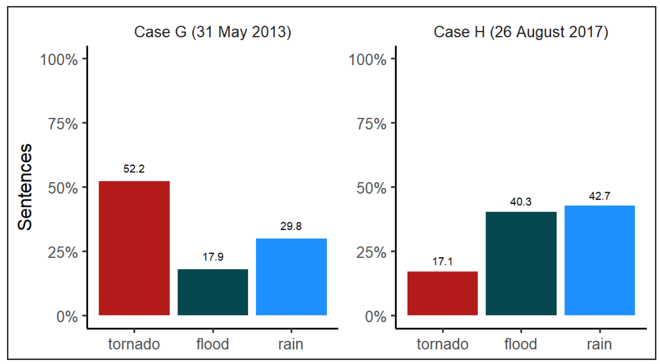

Figure 5. Same as in Fig. 4, but for coverage sampled from the 31 May 2013 El Reno/OKC tornado and flood event and from the impact of Hurricane Harvey in Houston, Texas, on 26 August 2017.

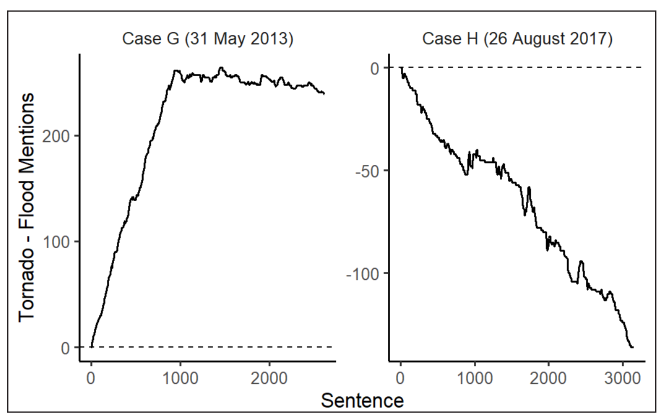

Figure 6. Same as in Fig. 5, but for coverage sampled from the 31 May 2013 El Reno/OKC tornado and flood event and from the impact of Hurricane Harvey in Houston, Texas, on 26 August 2017. Only one line is presented for each plot, as only one station was sampled for each event.

4. Discussion

Using the CAST.Bot algorithm, we have investigated how broadcast meteorologists balance coverage of flash flooding and tornado hazards during TORFF events. Our results suggest that television coverage of TORFFs can vary widely, but that the proportions of Tornado and Flood hazard mentions generally varied most across events with different proportions of issued tornado and flash flood warnings and across television stations within events. TORFF events with a greater forecast severe weather risk and a more discrete supercell thunderstorm morphology (Cases A and B) had coverage that generally focused more on tornado threats, although variation in coverage patterns was observed. In contrast, events with higher forecast flash flood threats and a supercell-to-MCS or remnant tropical cyclone morphology had coverage that ranged from amplifying tornado hazards (Cases C, E, and G) to a greater focus on flash flood and rain hazards (Cases D, F, and H). We did find that there was a higher proportion of flash flood warnings compared to the total number of TORFF-related warnings for Cases D, F, and H versus Cases C and E, which may explain why the latter two cases had a greater tornado focus in their coverage. Finally, by comparing the difference between the number of Tornado and Flood mentions across coverage from different stations and events, we identified that different stations covering the same TORFF can have substantial variation in the balance of their coverage.

Our findings suggest that the balance between flash flood and tornado coverage during TORFFs is not only dependent on the hazards present during the event, but also on the human factors present in local television stations covering storms. The latter point is a difficult one to address, as while broadcast meteorologists themselves make important coverage decisions, they can also be affected by management practices like "Code Red" language and consultant guidelines (Henson 2010; Stelter 2019; Obermeier et al. 2022). Future work should study differences across television stations' coverage policies and individual broadcasters' approaches to TORFF coverage, and how those differences relate to how tornado and flash flood hazards are presented during TORFF coverage. Our findings also suggest that broadcasters overall appear to amplify tornado threats more than flash flood hazards when proportionally more tornado warnings are issued than flash flood warnings. The amplification of tornado hazards in TORFF coverage with a higher tornado threat appears to be similar to the amplification and de-amplification of hazards found in TORFF messaging from one NWS office (Henderson et al. 2020). Further, given the decrease in flash flood protective action found by First et al. (2022) when tornado risk perceptions are heightened, we can speculate that viewers may deprioritize actions that could protect them from flash flooding hazards during TORFF events with a greater perceived tornado threat. It is important to recognize, however, that we do not understand how the balance of different hazards in TORFF events relates to measured impacts and casualties, and as such we cannot assert that a given balance of tornado and flash flood mentions in television coverage is "better" than any other. Our results merely suggest when tornado hazards may be amplified, and that differences across television stations appear to impact the balance of hazard coverage during TORFFs.

Case studies of coverage from TORFFs that occurred during the El Reno/OKC tornado and flash flood of 31 May 2013 (Case G) and Hurricane Harvey in Houston on 26 August 2017 (Case H) further highlight the complexity of broadcast coverage for extremely impactful tornadoes and flash floods. Coverage in Case H was by far the most Flood- and Rain-focused of the events we sampled in this study, despite having the highest number of tornado and flash flood warnings out of all the cases in this study. In contrast, coverage of Case G was oriented more towards tornado coverage, but not as much as some of the 2021 cases we studied. Given the complex contexts behind these two events, including the preceding tornadoes in May 2013 (NOAA, 2014) and the dire flooding forecasts ahead of Hurricane Harvey in Houston (NOAA 2018; see Table 1), we were surprised to find the proportional mentions of Tornado, Flood, and Rain hazards during coverage of both events were similar to broadcaster coverage from some of the 2021 events. Our findings suggest that TORFF coverage has not seen major changes since TORFFs became a better-known risk communication challenge in the aftermath of both Cases G and H.

For coverage of Hurricane Harvey in Case H, the general similarity of coverage proportions to cases we collected from 2021 (Cases E and F in particular) suggests broadcasters were working to reflect the severe nature of expected and ongoing flooding while keeping audiences updated on tornado threats. However, the similarity of coverage proportions in Case G to other TORFF events with tornadic supercells, as well as some of the 2021 tropical cyclone remnant and MCS transition cases (Cases C and E) suggest that coverage choices may at times de-amplify flash flood threats in a way that could lead to reduced public risk perception of those threats. Additionally, coverage of Case G shifted from Tornado-focused messaging to more balanced coverage of both the flash flood and tornado risk midway through the event, which could have important impacts on viewers' risk perceptions as long as they were still watching television or had not anchored more to the initially amplified tornado hazard. The two pre-2021 case studies highlight the importance of understanding the effects that amplification of different hazards during coverage of evolving TORFF events, as previously identified by Henderson et al. (2020) and First et al. (2022), can have on members of the public. Understanding the effects of coverage preferences is especially important given public reliance on television coverage for information during tornado and flash flood events (Hammer and Schmidlin 2002; Hayden et al. 2007; Ryan 2013; Zhao et al. 2019).

This study presents an early attempt to understand how simultaneous tornado and flash flood events are communicated to the public, but more work is needed to apply these conclusions to public response. One potential confound that this study did not investigate is the relative salience of hazard messaging leading up to a TORFF event for both broadcasters and the public, and whether or not the narrative that emerges during a TORFF event is predicated on the narrative that forms in the days leading up to an event. Future studies should seek to study broadcast coverage of TORFFs in this lead-up period, to identify how narratives serve to shape broadcast coverage on the day of the event. Further, future work could attempt to replicate the findings of First et al. (2022) by identifying whether viewer protective action decisions for flash flooding decrease after they are shown tornado-amplifying TORFF coverage, compared to more balanced hazard coverage. This study was also limited by access to television broadcast transcriptions through Metro Monitor, and our findings could be supplemented by future research that analyzes a wider selection of TORFF event coverage. Future studies might also study broadcast coverage of TORFF events using more traditional qualitative analysis techniques, as human-driven analysis is able to analyze the content and visual presentations of television coverage that the CAST.Bot algorithm cannot. Further, CAST.Bot in its current form is only able to analyze English transcripts of storm coverage, and future studies should consider the use of a Spanish version of the algorithm to better understand the TORFF coverage seen by the Spanish-speaking population of the Unites States. Finally, it would be worth investigating how broadcast meteorologists react to an algorithm, like CAST.Bot, providing live updates on what hazards they are prioritizing during coverage of multi-hazard events like TORFFs, and whether those updates lead them to modify their broadcast coverage in meaningful ways or present an overwhelming information burden.

5. Conclusions

The preliminary findings of this study on TORFF event broadcast coverage contribute to the conversation in the weather communication community on how complex, multi-hazard threats are messaged to those at risk. Coverage of TORFF events driven by supercell thunderstorms appears to generally focus on tornado hazards, although large variations in the balance of coverage for TORFF events was observed within other storm morphologies. Whether TORFF coverage was more balanced across the two hazards or amplified tornado hazards appeared to be somewhat related to whether there were similar numbers of flash flood warnings and tornado warnings issued during the TORFF. We also identified that coverage varied greatly from station to station across single TORFF events, and that some broadcasters evolved their coverage from amplifying tornado hazards to more balanced coverage of flash flood and tornado hazards as the event progressed. However, our findings alone do not suggest what the ideal coverage for these complex events should look like. Future work should seek to learn more about how variations in coverage for a given TORFF event can impact public risk perceptions, as well as how broadcast meteorologists and station management can work together to address potential institutional biases during coverage of simultaneous hazard events like TORFFs. Additionally, the CAST.Bot tool we used to complete this study could serve to aid broadcast meteorologists looking to rebalance their coverage and ensure that all life-threatening hazards that occur with a weather event receive the coverage that broadcasters feel they are due. Use of CAST.Bot to review coverage statistics after an impactful weather event may give broadcasters a powerful tool to better understand their own messaging and how they cover weather events with simultaneous hazards, potentially improving public messaging of TORFF events.

Acknowledgments. This project was funded under NOAA Award No. NA18OAR4590360. The authors acknowledge the efforts of the OU IPPRA student coding team for their work performing thematic coding analysis on the datasets collected for this study, as the CAST.Bot algorithm could not have been developed without their aid in developing training and testing data. The authors also thank Dr. Russ Schumacher and Dr. Erik Nielsen for sharing their database of TORFF events online and through email correspondence. Finally, the authors thank the support team for the broadcast coverage aggregator Metro Monitor for their assistance in teaching the authors how to use their aggregator to collect data for this study.

REFERENCES

Ahijevych, D., 2023: Image Archive. NCAR Mesoscale and Microscale Meteorology Division, accessed 16 March 2023. [Available online at: https://www2.mmm.ucar.edu/imagearchive/]

Braun, V. and V. Clarke, 2008: Using thematic analysis in psychology. Qual. Res. Psychol., **3** (2), 77–101. CrossRef.

Burke, P. C., A. Lamers, G. Carbin, M. J. Erickson, M. Klein, M. Chenard, J. McNatt, and L. Wood, 2022: The Excessive Rainfall Outlook at the Weather Prediction Center: operational definition, construction, and real-time collaboration. Bull. Amer. Meteor. Soc., **104** (3), E542–E562. CrossRef.

Burnett, A. J., 2016: 'Impact weather days' alert viewers to potential severe weather. WCVB-TV. Accessed 31 October 2022. [Available online at: https://www.wcvb.com/article/impact-weather-days-alert-viewers-to-potential-severe-weather/8235816]

Burow, D., K. Ellis, and L. Tran, 2021: Simultaneous and collocated tornado and flash flood warnings associated with tropical cyclones in the contiguous United States. Int. J. Climatol., **41** (8), 4253–4264. CrossRef.

CBS 4 News, 2019: What is a 'Code Red' day? Accessed 31 October 2022. [Available online at: https://www.valleycentral.com/news/local-news/what-is-a-code-red-day/]

Coleman, T. A., K. R. Knupp, J. Spann, J. B. Elliott, B. E. Peters, 2011: The history (and future) of tornado warning dissemination in the United States. Bull. Amer. Meteor. Soc., **92** (5), 567–582. CrossRef.

Daniels, G. L. and G. M. Loggins, 2007: Conceptualizing continuous coverage: A strategic model for wall-to-wall local television weather broadcasts. J. Appl. Comm. Res., **35** (1), 48–66. CrossRef.

Demuth, J. L., R. E. Morss, B. H. Morrow, and J. K. Lazo, 2012: Creation and communication of hurricane risk information. Bull. Amer. Meteor. Soc., **93** (8), 1133–1145. CrossRef.

Doswell, C. A. III, H. E. Brooks, and R. A. Maddox, 1996: Flash flood forecasting: An ingredients-based methodology. Wea. Forecasting, **11** (4), 560–581. CrossRef.

Drobot, S., A. R. S. Anderson, C. Burghardt, and P. Pisano, 2014: U.S. public preferences for weather and road condition information. Bull. Amer. Meteor. Soc., **95** (6), 849–859 CrossRef.

Drost, R., M. Casteel, J. Libarkin, S. Thomas, and M. Meister, 2016: Severe weather warning communication: factors impacting audience attention and retention of information during tornado warnings. Wea. Climate Soc., **8** (4), 361–372. CrossRef.

Edwards, R., A. R. Dean, R. L. Thompson, and B. T. Smith, 2012: Convective modes for significant severe thunderstorms in the contiguous United States. Part III: tropical cyclone tornadoes. Wea. Forecasting, **27** (6), 1507–1519, CrossRef.

Elliott, V., 2018: Thinking about the coding process in qualitative data analysis. The Qualitative Report, **23** (11), 2850–2861. CrossRef.

First, J. M., K. Ellis, and S. Strader, 2022: Examining public response and climate conditions during overlapping tornado and flash flood warnings. Natural Hazards Center Weather Ready Research Report Series WR1. Natural Hazards Center, University of Colorado, Boulder, CO. [Available online at: https://hazards.colorado.edu/weather-ready-research/examining-public-response-and-climate-conditions-during-overlapping-tornado-and-flashflood-warnings]

Hammer, B. and T. W. Schmidlin, 2002: Response to warnings during the 3 May 1999 Oklahoma City Tornado: reasons and relative injury rates. Wea. Forecasting, **17** (3), 577–581. CrossRef.

Hayden, M. H., S. Drobot, S. Radil, C. Benight, E. C. Gruntfest, and L. R. Barnes, 2007: Information sources for flash flood warnings in Denver, CO and Austin, TX. Environ. Hazards, **3**, 211-219. CrossRef.

Henderson, J., E. R. Nielsen, G. R. Herman, and R. S. Schumacher, 2020: A hazard multiple: overlapping tornado and flash flood warnings in a National Weather Service Forecast Office in the Southeastern United States. Wea. Forecasting, **35** (4), 1459–1481. CrossRef.

Henson, R., 2010: Weather on the Air: A History of Broadcast Meteorology. American Meteorological Society, Boston, MA, 241 pp.

Herzmann, D., 2022: Archived NWS Watch, Warnings, Advisories. Iowa Environmental Mesonet, Iowa State University. Accessed 23 May 2022. [Available online at: https://mesonet.agron.iastate.edu/request/gis/watchwarn.phtml]

Hitchens, N. M. and H. E. Brooks, 2013: Preliminary investigation of the contribution of supercell thunderstorms to the climatology of heavy and extreme precipitation in the United States. Atmos. Res., **123**, 206–210. CrossRef.

Kellens, W., T. Terpstra, and P. De Maeyer, 2012: Perception and communication of flood risks: A systematic review of empirical research. Risk Anal., **33** (1), 24–49. CrossRef.

Keul, A. G. and A.M. Holzer, 2013: The relevance and legibility of radio/TV weather reports to the Austrian public. Atmos. Res., **122**, 32–42. CrossRef.

Kreibich, H. and A. H. Thieken, 2009: Coping with floods in the city of Dresden, Germany. Nat. Hazards, **51**, 423–436. CrossRef.

Krocak, M. J. and H. E. Brooks, 2018: Climatological estimates of hourly tornado probability for the United States. Wea. Forecasting, **33** (1), 59–69. CrossRef.

Lazo, J. K., R. E. Morss, and J. L. Demuth, 2009: 300 billion served: sources, perceptions, uses, and values of weather forecasts. Bull. Amer. Meteor. Soc., **90** (6), 785–798. CrossRef.

Markowski, P. M., and Y. P. Richardson, 2014: The influence of environmental low-level shear and cold pools on tornadogenesis: insights from idealized simulations. J. Atmos. Sci., **71** (1), 243–275. CrossRef.

Mazurek, A. C. and R. S. Schumacher, 2023: Quantifying the relationship between embedded rotation and extreme rainfall rates in observations of Tropical Storm Imelda (2019). Mon. Wea. Rev., **151** (5), 1109–1128, CrossRef.

Metro Monitor, 2022: Who we are and what we do. Accessed 23 June 2022. [Available online at: https://metromonitor.com/company/]

Mojica, A., 2019: Code Red explained. FOX 17 Nashville. Accessed 31 October 2022. [Available online at: https://fox17.com/weather/tracking-code-red-days/code-red-explained]

Morss, R. E., J. L. Demuth, A. Bostrom, J. K. Lazo, and H. Lazrus, 2015: Flash flood risks and warning decisions: a mental models study of forecasters, public officials, and media broadcasters in Boulder, Colorado. Risk. Anal., **35** (11), 2009–2028. CrossRef.

Nielsen, E. R., G. R. Herman, R. C. Tournay, J. M. Peters, and R. S. Schumacher, 2015: Double impact: when both tornadoes and flash floods threaten the same place at the same time. Wea. Forecasting, **30** (6), 1673–1693. CrossRef.

____, and R. S. Schumacher, 2018: Dynamical insights into extreme short-term precipitation associated with supercells and mesovorticies. J. Atmos. Sci., **75**, 2983–3009. CrossRef.

____, 2019: Insights into extreme short-term precipitation associated with supercells and mesovorticies. Dissertation, Department of Atmospheric Science, Colorado State University, 183 pp.

____, and R. S. Schumacher, 2020: Observations of extreme short-term precipitation associated with supercells and mesovorticies. Mon. Wea. Rev.., **148** (1), 159–182. CrossRef.

NOAA, 2014: May 2013 Oklahoma Tornadoes and Flash Flooding Service Assessment, National Oceanic and Atmospheric Administration – National Weather Service, 63 pp. [Available online at: https://www.weather.gov/media/publications/assessments/13oklahoma_tornadoes.pdf]

____, 2018: August/September 2017 Hurricane Harvey Service Assessment, National Oceanic and Atmospheric Administration – National Weather Service, 78 pp. [Available online at: https://www.weather.gov/media/publications/assessments/harvey6-18.pdf]

NWS, 2013: The May 31-June 1, 2013 Tornado and Flash Flooding Event. Accessed 27 June 2022. [Available online at: https://www.weather.gov/oun/events-20130531]

____, 2018: National Weather Service (NWS) Service Description Document (SDD): Impact-Based Decision Support Services for NWS Core Partners April 2018. National Weather Service, 24 pp. [Available online at: https://www.weather.gov/media/coo/IDSS_SDD_V1_0.pdf]

____, 2023: Weather related fatality and injury statistics. Accessed 16 March 2023. [Available online at: https://www.weather.gov/hazstat/]

Obermeier, H. B., K. L. Berry, K. E. Klockow-McClain, A. Campbell, C. Carithers, A. Gerard, and J. E. Trujillo-Falcón, 2022: The creation of a research television studio to test probabilistic hazard information with broadcast meteorologists in NOAA's Hazardous Weather Testbed. Wea. Clim. Soc., **14** (3), 949–963. CrossRef.

Prestley, R., M. K. Olson, S. C. Vos, and J. Sutton, 2020: Machines, monsters, and coffin corners: broadcast meteorologists' use of figurative and intense language during Hurricane Harvey. Bull. Amer. Meteor. Soc., **101** (8), E1329–E1339. CrossRef.

Ready.gov, 2022a: Tornadoes. Department of Homeland Security. Accessed 15 April 2022. [Available online at: https://www.ready.gov/tornadoes?gclid=Cj0KCQjwr-SSBhC9ARIsANhzu15yCVev82VlsoTpVjVx6TidJO0uY9aRS5GK-HIkjVuSWK11DHp5-_kaAtCDEALw_wcB]

____, 2022b: Floods. Department of Homeland Security. Accessed 15 April 2022. [Available online at: https://www.ready.gov/floods?gclid=Cj0KCQjwr-SSBhC9ARIsANhzu16e-wpZRHdyUb7cniWtp5A-fSQMZksoETmFdIW9DTwBMGCu_mM1aTQaAjMQEALw_wcB]

Ripberger, J., and C. Silva, 2022: WxDashExp. Accessed 18 April 2022. [Available online at: https://crcm.shinyapps.io/WxDashExp/]

Ryan, B., 2013: Information seeking in a flood. Disaster Prev. Manag., **22** (3), 229–242. CrossRef.

Schumacher, R., 2022: Monitoring of concurrent, co-located tornado and flash flood (TORFF) warnings. Colorado State University. Accessed 18 April 2022. [Available online at: http://schumacher.atmos.colostate.edu/weather/TORFF_rt/]

Sherman-Morris, K., 2005: Tornadoes, television, and trust – A closer look at the influence of the local weathercaster during severe weather. Glob. Environ. Change Part B: Env. Haz., **6** (4), 201–210. CrossRef.

SPC, 2022: SPC Severe Weather Events Archive, NOAA/NWS Storm Prediction Center. Accessed 23 June 2022. [Available online at: https://www.spc.noaa.gov/exper/archive/events/]

Stelter, B., 2019: Weatherman who defied 'Code Red' alerts is out of a job. CNN. Accessed 23 June 2022. [Available online at: https://www.cnn.com/2019/06/13/media/joe-crain-sinclair-code-red/index.html]

WPC, 2022: WPC's Excessive Rainfall Outlook Archive. Accessed 23 June 2022. [Available online at: https://www.wpc.ncep.noaa.gov/archives/web_pages/ero/ero.shtml]

Zhao, M., H. Rosoff, and R. S. John, 2018. Media disaster reporting effects on public risk perception and response to escalating tornado warnings: a natural experiment. Risk Anal., **39** (3), 535–552. CrossRef.