Storms in the Screenome: An Analysis of Digital Information Acquisition During Extreme Weather Events

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Abstract

The intensity and frequency of extreme weather events is increasing. As the amount of time people are spending on their smartphones also increases, the “Weather Information Landscape” is shifting away from “traditional” communication sources like radio and television toward digital media, including social media and smartphone-enabled weather communication (Krocak et al., 2024). However, the content people see – and the sources of that content – in this new landscape are not yet well accessible or understood. Through detailed observation of individuals’ smartphone behavior, we investigate 1) where people source extreme weather information, 2) the sequence of how people acquire information, and 3) whether individuals are passively or actively acquiring information. Specifically, we leverage data collected by the Human Screenome Project (HSP) – millions of smartphone screenshots obtained every five seconds from 264 people in the United States between 2020 and 2021 (Reeves et al., 2020). After merging this dataset with NOAA’s Storm Events Database, we identified 10 participants that had experienced one or more of 12 high-casualty/damage weather events while participating in the HSP. Using qualitative coding of screenshots and phone-use metadata, such as time spent on specific apps or activities, we identified weather information encountered before, during, and after the weather events. Our findings support three key hypotheses: (1) non-expert weather sources are increasingly disseminating information via social media, (2) information-seeking behavior tends to occur in concentrated bursts, and (3) individuals often encounter weather risk information passively, scrolling past it while doing other activities. Overall, our analysis provides a detailed, holistic, and insider view into how people consume and act on risk communication during extreme weather events – from reacting to weather warnings to sharing disaster information and communicating with family and friends.

Introduction

The science is clear: climate change is increasing the severity and frequency of extreme weather events like floods, wildfires, and heat waves (Seneviratne et. al., 2021). In the United States in 2024, there were 27 billion-dollar disasters, totaling $189 billion in damages and 568 lives lost. In the span of three weeks, just two events – Hurricane Helene and Hurricane Milton – caused around $114 million in damages and claimed the lives of 251 people (Smith, 2025).

At the same time, access to information and technology is rapidly expanding. According to the Pew Research Center, in 2024 mobile phone and smartphone ownership also reached all time highs – 98% of Americans now own cell phones and 91% own smartphones (Mobile Fact Sheet). Each day, the average American spends over 4.5 hours on these cell-phones engaged in nonvoice activities (Laricchia, 2023).

Together, these trends present a critical inflection point for disaster preparedness and extreme weather communication. With a majority of Americans now carrying smartphones, governments and the weather enterprise have powerful opportunities to use real-time alerts and crowdsourced data to save lives and livelihoods. However, the tragic toll of recent events like Hurricanes Helene (2024) and Milton (2024) and the 2025 Los Angeles (LA) wildfires suggests that the digital advantage is not being fully harnessed.

LA Wildfire Case Study

The LA Wildfires in January 2025 caused between $28 billion and $53.8 billion in damages (Horton, 2025), and the deaths of over 30 people (Anguiano, 2025). Throughout the month of January, fire departments across LA issued evacuations of tens of thousands of people and pets (Lee, 2025).

During the crisis, it is difficult to measure the impact smartphones have on successful evacuations. However, one incident stands out in particular. On January 9th, 2025, an emergency alert for the Kenneth Fire was mistakenly sent to all 9+ million residents of Los Angeles County, warning, “An EVACUATION WARNING has been issued in your area.” This was only meant for the neighborhoods of Calabasas and Agoura Hills, an LA County Official later specified on the social media platform X. The county supervisor also clarified later on that this was due to a “technical error.” At the time, the incident caused a frenzy on social media and interrupted a Fox LA meteorologist’s live on-air broadcast (Zeff, 2025).

Months later, on May 12, 2025, US Congressman Robert Garcia issued a report focused on lessons learned from this incident and future research needed. In the report, he stressed the impacts of such a mistake: erosion of public trust, fatigue and wellbeing issues caused by unnecessary distress, public safety issues, and the risk that future alerts are downplayed or ignored. In an oversight inquiry by thirteen members of Congress representing the LA County area, Garcia and colleagues learned that 1) the issue came from a third party technology alert vendor, 2) the County acted quickly and swiftly to remedy the error, 3) wording within the message could be improved to include the affected areas (i.e. Calabasas and Agoura Hills), and 4) there were also repeat false messages due to technical errors. These findings inform Garcia's policy priorities moving forward – 1) increased funding for local government towards public alerts, 2) federal policy requirements on standardization for third-party technology providers, 3) coordination between the Federal Emergency Management Agency (FEMA) and the Federal Communications Commission (FCC) for requiring location-aware maps as part of mobile alert systems by December 2026 and 4) better FCC performance standards. Finally, Garcia and colleagues include a call to action for the federal government to close the gap on public communication during disaster – and to modernize the nation's alerting infrastructure (Garcia, 2025). It is exciting to imagine a world where people have accurate, geographically-informed extreme weather communication tailored to their individual needs, but it will take time and human-informed research to get there.

Significance

The Kenneth Fire false alarm incident emphasizes the importance of smartphone-enabled evacuations, hints at the scattered bureaucracies for crisis communication and response, and demonstrates potential ramifications of miscommunication. In a world with different digital channels vying for our attention, active misinformation, government delays, and questions of government legitimacy, it is more important than ever to understand the complex landscape of digital weather information.

These have been components of a research gap identified by the National Academies of Sciences, Engineering, and Medicine (NASEM) since 2018. Namely, the report "Integrating Social and Behavioral Sciences Within the Weather Enterprise" calls for research to understand "critical systems of connections" among different stakeholders in the weather enterprise. Additionally, it also calls for ways to improve "timing, content, and channels" of extreme weather information to better reach vulnerable populations (NASEM, 2018). The events and lessons from the Kenneth Fire are specific examples of why this research is important in practice. In addition to modernizing alert systems to ensure the Kenneth Fire incident does not repeat itself, NASEM and Congressman Garcia both emphasize that we also need to delve into more research broadly on improving public communication during disaster events (Garcia, 2025).

Risk Communication and Extreme Weather

A wealth of knowledge has been amassed on risk communication regarding extreme weather. A variety of studies have established the underlying psychological motivations underlying climate adaptation behaviors, such as disaster preparedness and information-seeking. For example, Domingos and colleagues (2018), using qualitative interviews, outlined a biopsychosocial model of challenge and threat (BPS) to describe how individuals frame extreme weather. When individuals interacted with information that framed extreme heat weather events as positive, they adopted an approach (pursuing something "good") tendency that reminded them of pleasant activities like going to the beach. On the contrary, when individuals were primed with a negative framing, they adopted an avoidance (avoiding something "bad") tendency that reminded them of staying at home and isolated from social contact. The conclusions stress the need for careful design of extreme weather risk messaging that takes into account internal framing models – and also provide citizens with informed, actionable resources.

The original Risk Information Seeking and Processing (RISP) Model model details that seven factors influence the extent an individual will seek out and critically analyze risk information: individual characteristics, perceived hazard characteristics, affective response to the risk, felt social pressures to possess relevant information, information sufficiency, personal capacity to learn, and beliefs about the usefulness of information in various channels (Griffin, 1999). This model has been the cornerstone to much weather risk communication research to date. For example, Rivera (2021) used national survey data and applied the RISP Model to describe individuals' information-seeking. They found that demographic factors such as education, income, race, and ethnicity had varying effects on active information-seeking, but *prior extreme weather experiences* motivated more active information-seeking. This work also expands on previous work done by Demuth and colleagues (2016), who found that prior experiences with hurricanes can influence self efficacy and evacuation intentions.

These studies demonstrated their importance in the Southeastern US during Hurricane Helene in September 24-27, 2024. Of the 45 counties affected by Helene, only one county

(Haywood County, NC) had prior exposure before being severely damaged by Tropical Storm Fred in 2021. The entire region was better prepared – with systems in place like river gauges, truck-mounted loudspeakers/warning systems, and Spanish-speaking deputies deployed to warn folks on the ground (Russell, 2024). Not only were infrastructure and governments better prepared, but individuals were in a better position as well. An emergency services spokesperson said in the New York Times, “Because of the previous storm, people were more keyed into the risk” (Russell, 2024). Rivera identified that future work should focus on further understanding sequences of behaviors – and in what particular order does absorbing, seeking, and sharing extreme weather information occur. Building from this work, I will examine how these processes manifest in digital spheres.

Digital and Social Media for Weather Information

As smartphones become an increasingly used and pervasive technology, many studies have examined the role of digital mediums in disaster communication and information-seeking. Yoder-Bontrager and colleagues (2017) used focus groups to qualify how people are interacting with such phone alerts. The authors present a smartphone as many sources of information funneled into one, meaning that it may be more difficult than ever to issue alerts effectively. Focus group participants had varying phone usage behaviors and diverse preferences for how they wanted alerts to be delivered. Overall, it seems that people want access to weather information and also the ability to personalize how it is communicated to them.

Armstrong and colleagues (2021) conducted an online survey of college students and distinguished between the uses of mediated (e.g., news, maps, social media) and non-mediated (e.g., friends, family) sources of information. The authors affirmed prior literature suggesting that prior exposure to extreme weather made people more worried and more adamant on seeking further information. They also found that information seeking, particularly with mediated sources, was a predictor of disaster preparedness.

Finally, Silver and Andrey (2019) conducted a content analysis of Tweets posted during an extreme weather outbreak in southern Ontario, Canada on September 10, 2016. The authors found that a majority of Tweets provided situational information and observations, but only a small number of Tweets actively sought information or asked questions. They suggested then that information-seeking is conducted on social media through reading and searching, rather than direct interactions or Tweeting.

Methodological Approaches

Thus far, a variety of different methods, from focus groups to qualitative interviews to online surveys, have been used to examine how people seek out and respond to extreme weather information. However, none of these methods provide objective information about *exposure* – when and how individuals actually engage with extreme weather information in their daily lives.

Krocak and colleagues (2024) affirmed that “traditional” weather sources like television were being replaced with digital sources like personal contacts, websites, notifications, and social media. However, they highlighted that it is not well understood if the information is coming from a local broadcast meteorologist, a government source, or “low-quality” sources like weather enthusiasts or people with malicious intent. The researchers observe that the recent surge in social media use and easier access to information reflects a trend where users prioritize convenience over credibility.

One key behavior overlooked by existing methods is the act of *sharing* weather information. It is understood that factors such as medium, prior extreme weather exposure, and personalization can affect individuals’ *seeking* of information, but it is not understood how information is shared between individuals. With increasing access to information and a wide degree of weather sources, there is a greater need to filter and develop strategies to counter low-quality weather communication. In doing so, the actual *stewards* of weather information need to be identified and studied.

Newly Available Data

The newly available data from the Human Screenome Project (HSP) – a research effort that collected smartphone use data and screenshots of screen content every five seconds from 264 people in the United States for a full year (Reeves et al., 2020) — provide complete records of what people actually see and engage with on their smartphones. This enables more holistic and detailed descriptions of individuals’ engagement with extreme weather information than has been available. Screenshot data is adept in capturing metrics not well-represented in prior research, such as read-time or clicks, social media searches, and direct communication with friends and family.

Implications

Researchers have amassed a wealth of information about digital and social media spheres in the last several years. We now know when designing for public communication of extreme weather hazards to take into account: subjective framing, prior exposure, personalization, information seeking, and definitions of active engagement. The next several sections leverage these takeaways and newly-available HSP data to design a study that examines the digital realms of extreme weather communication in greater depth. This analysis will be directly beneficial to government officials who increasingly have to compete with many digital sources for citizens' attention. Overall, through this project, I strive to illuminate the diverse ways people are exposed to extreme weather information on their phones.

The Present Study

This study examines how people engage with weather information and adapt to new weather extremes. Specifically, my research leverages data collected by the Human Screenome Project to characterize how people engage with weather information during extreme weather events. The HSP dataset presents a unique and holistic approach to studying human interaction with risk communication, such as weather warnings, watches, and advisories. Utilizing the highly granular smartphone metadata and screenshots, this study contributes to growing literature around how society interacts with extreme weather, with the goal to ascertain how we can better communicate extreme weather information and adapt to climate change. Specifically, I examine:

1) Who are the stewards of the extreme weather information individuals encounter in their everyday digital lives?
2) What are behavioral sequencing patterns of individuals' seeking and sharing of weather information?
3) What are the frequencies and qualities of individuals' passive and active information-seeking?

Methods

Data Sources

Storm Event Data. We leverage the National Center for Environmental Information's (NCEI) storm events database, which contains details of various extreme weather events collected by the National Weather Service (NCEI, 2024). The dataset's variables include relevant information such as storm start and end times, narrative descriptions, injuries and lives lost, property damage costs, and the counties in which the storm occurred. In 2020 and 2021, there were 122,668 such events in the database, ranging from winter weather to excessive heat to hail and thunderstorms.

HSP Data. Participants were recruited online and provided informed consent to participate before being enrolled in the research study (procedures approved by Institutional Review Board of Stanford University IRB-56430). After enrollment, participants installed software on their personal smartphones. The software took screenshots every 5 seconds while the phones were in use (Reeves, 2021). For this study, researchers accessed data through secure Google Cloud Platform storage buckets and only data from 12 events of 10 participants were queried. These events were chosen based on 1) quality of screenshot data – namely that the participants were not professional surveytakers and 2) the severity of the storm events, which are defined in the Results section. To further emphasize the anonymity of the participants, we assigned random non-identifying person identifiers (PIDs) labeled 1-10 to the 10 participants in our research. Table 1 contains the demographics of these participants.

Table 1

Participant data and demographics

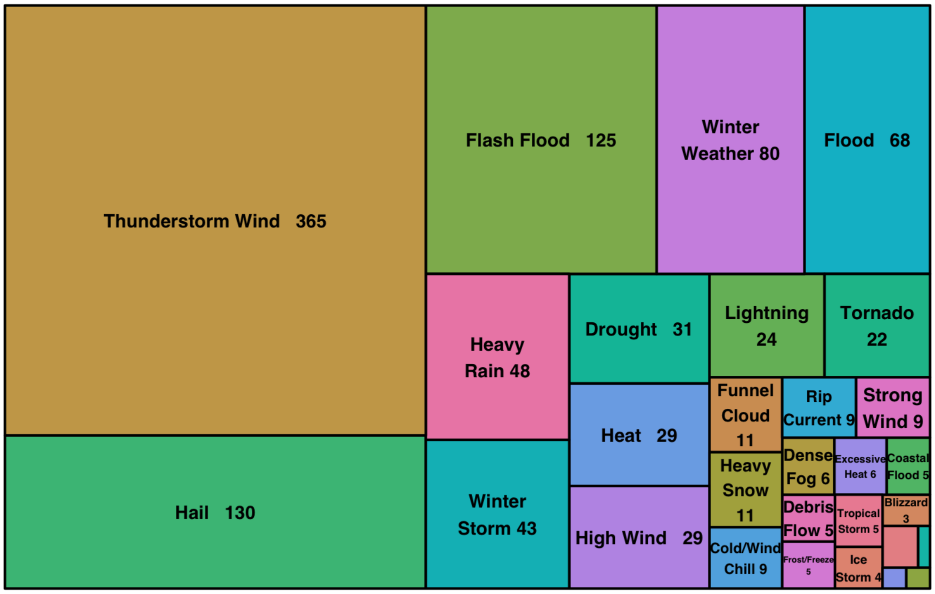
PID	Total Screenshots	Age	Gender	Race	Region	Residence Type
1	1,628,708	27	Female	Multiracial Hispanic	South	Urban
2	564,402	39	Female	Black	Midwest	Suburban
3	1,341,669	49	Female	White	Midwest	Urban
4	423,780	77	Male	White	South	Suburban

5	417,625	43	Male	Asian	Northeast	Suburban
6	1,092,037	38	Female	White	Midwest	Suburban
7	102,618	63	Male	Black	Midwest	Urban
8	194,235	70	Male	White	Southeast	Suburban
9	828,734	45	Female	Multiracial Hispanic	Southeast	Suburban
10	1,086,844	56	Female	White	South	Urban

Combined Data. Using R, we performed a series of merges of the NCEI data with the HSP data, with geographic locations at the county level and the screenshot dates as keys for the join. Altogether, this dataset contains information of 1088 storm events that occurred in the counties where 158 HSP participants were living, on various dates in 2020 and 2021. The diverse variety of the different types of storm events are shown in Figure 1. Additional demographic visualizations including geographic locations and NCEI-defined alert sources are shown in Appendix A.

Figure 1

A treemap of different types of extreme weather events occurring in the entirety of the Screenomics dataset.



Measures

Table 2

The definitions of different terms appearing in this paper.

Term	Definition
Extreme weather communication	The process of sharing timely, accurate, and actionable information about extreme weather events—such as hurricanes, floods, winter storms, or dust storms—to help individuals prepare for these events.
Passive interaction	The process of acquiring information without actively searching for it
Active interaction	The process of intentionally engaging with particular knowledge or answers.
Sequence	A series of consecutive screenshots that contains related content
Session	A single phone interaction lasting from unlocking to locking the phone
Episode	A set of dedicated and related actions within a session. For example: looking at a notification and texting about the notification are each defined as distinct episodes

Identification of Weather Communication and its Features. From this merged dataset, we then leverage Python to build a data preparation pipeline that identifies and compiles content that participants encountered related to the weather events, such as news media, Twitter posts, and text messages. This process involves manually viewing the screenshots and classifying weather-related information according to the codebook we created beforehand, displayed in Table 3. In the manual coding, we noted the sources of content and the interaction styles (RQ1 and RQ3). The pipeline is also designed to track timestamps of tagged screenshots (RQ2). Importantly, the manual coding was completed on my own behalf and – by nature of the exploratory analysis – was not verified by additional parties.

Table 3

A codebook contains the two research questions that are qualitatively answered, the associated measure (the source of information or passive/active), the definition of each measure, and screenshot examples that have been blocked out for privacy considerations.

Question	Categories	Definition	Examples (from pid in Arizona)
RQ1: Who are the stewards of the extreme weather information individuals encounter in their everyday digital lives?	Government	An organized agency through which political and weather authority is exercised.	NWS Phoenix, NWS Tucson
	Formal News Media	Established organizations that gather, produce, and distribute news content.	AOL, Whats Up Tucson, Arizona Daily Star, Brooke Wagner, ABC News, NPR, USA Today, NBC News
	Informal Entities	Loosely organized groups, individuals, or organizations that operate without formal structures, official recognition, or regulatory oversight.	Tim Brando sports, twitter replies
	Personal Contacts	Direct, personal relationships, such as friends, family members, colleagues, or acquaintances.	None related to weather, but could have included friends and the participant's partner.
RQ3: What are the frequencies and qualities of individuals' information acquisition?	Passive	The process of acquiring information without actively searching for it	Scrolled past a headline
	Active	The process of intentionally engaging with particular	Clicked into a Tweet, searched, or paused (2 screenshots)

knowledge or answers.

Notably, the codebook specifies possible categories of **sources** of weather information: government, formal media, informal entities, and personal contacts; it also specifies definitions for **passive and active** interaction.

In the HSP dataset, a screenshot is taken every five seconds. Expanding on Silver and Andrey's (2019) definitions of "active interaction," corroborated with Lewis and colleagues' (2017) distinctions of information "seeking" versus "scanning," we coded "active" if the current screen is shown for at least 2 images (at minimum 5 seconds of engagement), or if the user "clicked into" an interaction by entering a weather-related app or post. For all other screenshots, such as notifications that were dismissed, or news headlines that participants scrolled past, they were coded as "passive." Beyond the codebook, we also included two important tags created post hoc that were relevant to our research questions: first, if the participant was *sharing* the information or *receiving* the information. A large majority of the events were the participants *receiving* the information, but a small amount – 131 total screenshots – contained instances where participants were actively *sharing* the information. We also included tags of when the participants were interacting with information on distal and indirect extreme weather events. For example, one participant lived in Austin during the time of Gulf Coast hurricanes and storms, but clicked into a post detailing extreme weather events across the United States, including wildfires on the West Coast. There were only 34 such "indirect" screenshots across the entire dataset. These nuances become key behavioral distinctions that we examine closely in our detailed case study analysis.

Results

To narrow the scope of 1088 storm events across 158 participants, we identified a subset of 12 events that spanned the 7 largest in casualties and 5 largest in damages for 10 participants. Table 4 shows casualty and damage numbers for the 12 events, and a table containing media articles of the events can be found Appendix B. Figure 2 shows distributions of screentimes, episodes, sessions, and screenshots across all participants in this 12-event study.

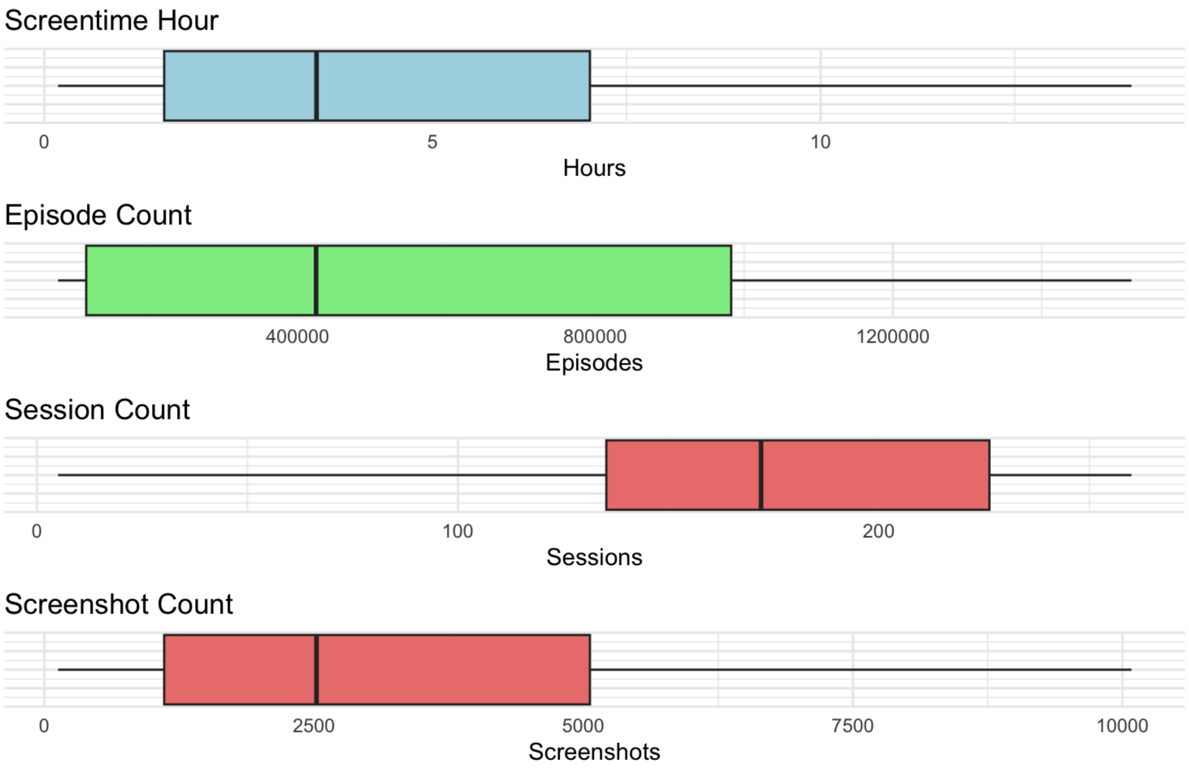
Table 4

The 12 events chosen for the study from 10 unique participants.

Event	Pid	Hazard	State	Date	Damage	Casualties
1	1	Winter Weather	TX	2021-02-11	$2,000,000	107
2	2	Cold/Wind Chill	OH	2021-02-01	$0	7
3	3	Winter Weather	IN	2021-01-30	$500,000	7
4	1	Tornado	TX	2020-11-24	$0	5
5	4	Flash Flood	AZ	2020-08-22	$10,000	5
6	5	Tornado	PA	2021-09-01	$5,000,000	3
7	6	Lightning	MN	2020-08-08	$10,000	3
8	7	Flash Flood	MI	2021-06-26	$139,000,000	0
9	1	Hail	TX	2021-03-24	$58,000,000	0
10	8	Strong Wind	NC	2020-10-29	$1,500,000	0
11	9	Thunderstorm Wind	FL	2021-09-01	$1,500,000	0
12	10	Thunderstorm Wind	TX	2020-08-22	$1,000,000	0

Figure 2

Summary screenshot statistics for 10 HSP participants during 12 extreme weather events



From our dataset of 152,898 screenshots over 10 participants, we used qualitative coding to collect a total of 1374 screenshots that contained relevant extreme weather content. In order to better measure the frequencies of passive versus active information-seeking, we define “sequences” as a series of consecutive screenshots that contain weather content. For example, if a participant saw a single screenshot – representing a weather notification – before moving on to other content, that would constitute a *passive sequence*. On the other hand, if a participant saw a weather notification, then clicked into a weather app, then clicked into a Doppler radar app, that group of screenshots would constitute a single *active sequence*. From the 1374 total screenshots, we identified 218 total sequences. This constituted 122 active sequences and 96 passive sequences.

For RQ1: *Who are the stewards of the extreme weather information individuals encounter in their everyday digital lives?* Using my manually coded data, we summarized how often and for what durations of time participants encountered and engaged with weather-related content.

Figure 3

a) Treemap of stewards across 1374 screenshots b) Treemap of stewards found within 218 sequences

Figure 3 shows a visualization of stewards in the dataset, first by screenshot count, then by sequence count. Figure 3(a) better represents the *accumulated time and exposure* to each steward. For example, if a participant monitored an air quality sensor for a long period of time, 3(a) is more informative to show the time that participant spent engaged with information from the steward. On the contrary, in that situation, 3(b) would only amount to one active sequence. This means 3(b) more clearly shows how many different sequences (activities) each steward is initiating for the participant. As another example, while The Weather Channel does not have the highest number of individual screenshot counts, it is responsible for the highest overall frequency of activities reaching the participant.

For RQ3: *What are the frequencies and qualities of individuals' passive and active information-seeking?* Using my manually coded data I summarized how often and for what durations of time participants were passively or actively engaged with the weather-related content.

Figure 4

a) Treemap of stewards in passive sequences b) Treemap of stewards in active sequences

In Figure 4, from the passive sequences, we see that out of 96 passive sequences, we observe a dominance in the Weather Channel – largely due to passive notifications later seen in Vignette A. The next five largest contributors to passive sequences were from CNN, FOX, and NBC (WTHR) news networks. On the contrary, Weather Channel, native weather apps, the Southeastern Pennsylvania Transportation Authority (SEPTA), air quality sensors, and radar apps constituted the majority of stewards from active weather sequences. This suggests that these participants largely interacted with stewards from those channels versus those from formal news networks.

Figure 5

Bar plot of passive and active sequences, separated by steward category on the y-axis (formal, government, informal, and personal)

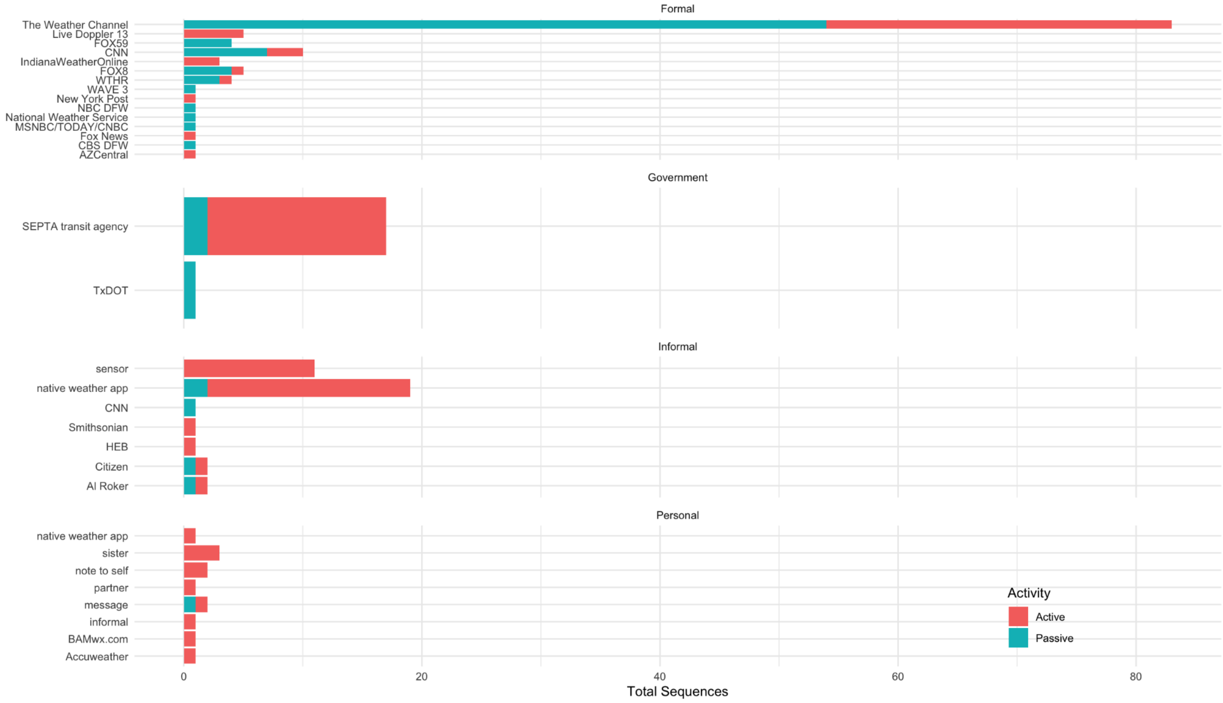


Figure 5 further suggests that active interaction comes with tailored stewards such as radar apps, government transit notices, personal sensors, and native weather apps. The stakeholders on the left represent the *original source* of extreme weather information, and the groupings represent the category of the *messenger* that communicated the information. Oftentimes, these were the same: Live Doppler 13 communicated information through the Live Doppler 13 (formal) app, which the participant primarily accessed. Other times, they were different. CNN sometimes communicated through formal messenger channels, such as through an article published by CNN. However, personal or informal contacts could often repost such information, resulting in distinct *source/messenger* channels.

Upon observation of the blue (passive) bars versus red (active) bars in Figure 4, one notices that the share of passive sources are increased in formal channels and the share of active sources are increased in informal and personal channels. Specifically, there are a higher proportion of blue bars in the formal channels like CNN and The Weather Channel and a higher proportion of red bars in informal (e.g. native weather app) and personal (e.g. sister, note to self). Although many of these results can be swayed with data from one participant, they match up with the expectation that people are more likely to engage with tailored and personalized information.

Case Studies

For RQ2: *What are behavioral sequencing patterns of individuals' seeking and sharing of weather information?* We turn to a set of "vignettes" as case studies – these illustrate select participants' specific behaviors over the course of: two days before the NCEI-identified event, the day of the event, and two days following the event. Recasting the timing and duration data into a collection of repeated events (encounters with weather-related content) and time until the next information event, I used a recurrent event analysis to understand the pattern of flow of discrete exposures to extreme weather content. The recurrent event analysis (an extension of Cox proportional hazard models that accommodates multiple events) allowed me to quantify the likelihood that a person will encounter or engage with weather-related content on their phone in the hours since the last encounter.

Figure 6

A bar plot illustrating passive and active sequence counts for each person 1 through 10. Person 7 did not exhibit any sequences in their data.

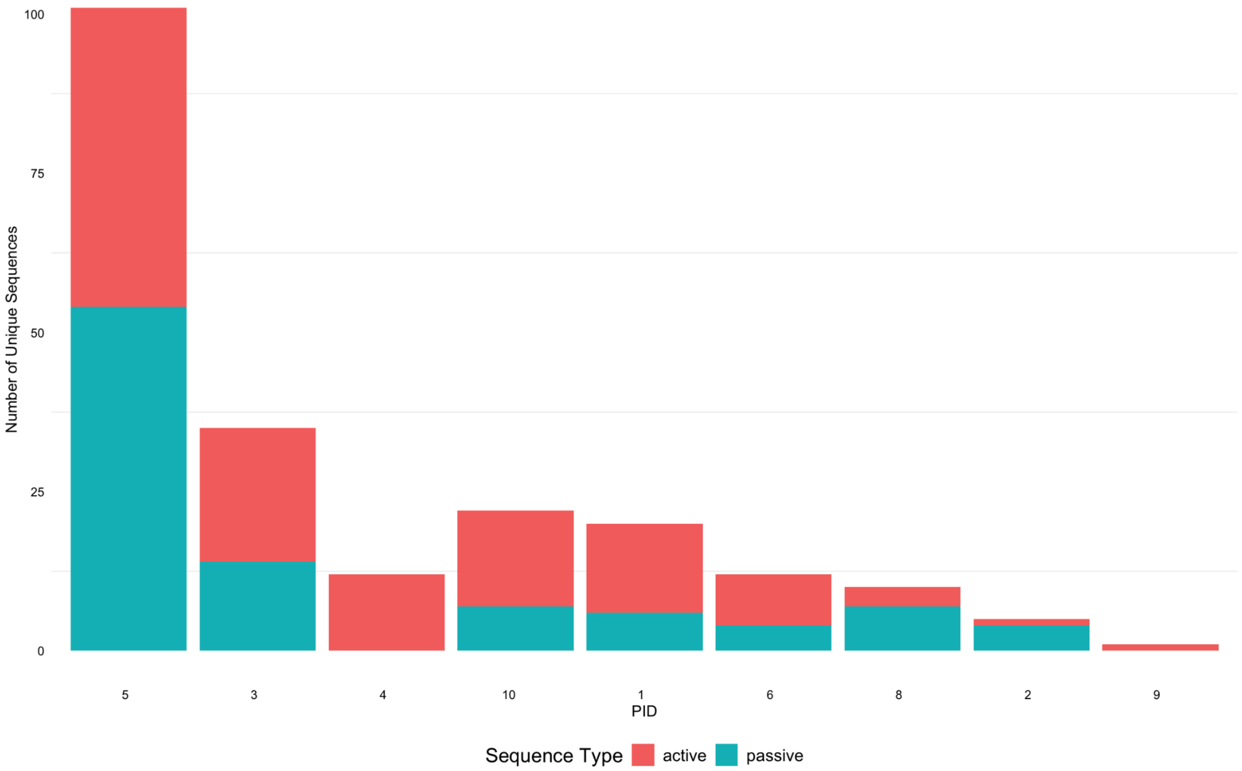
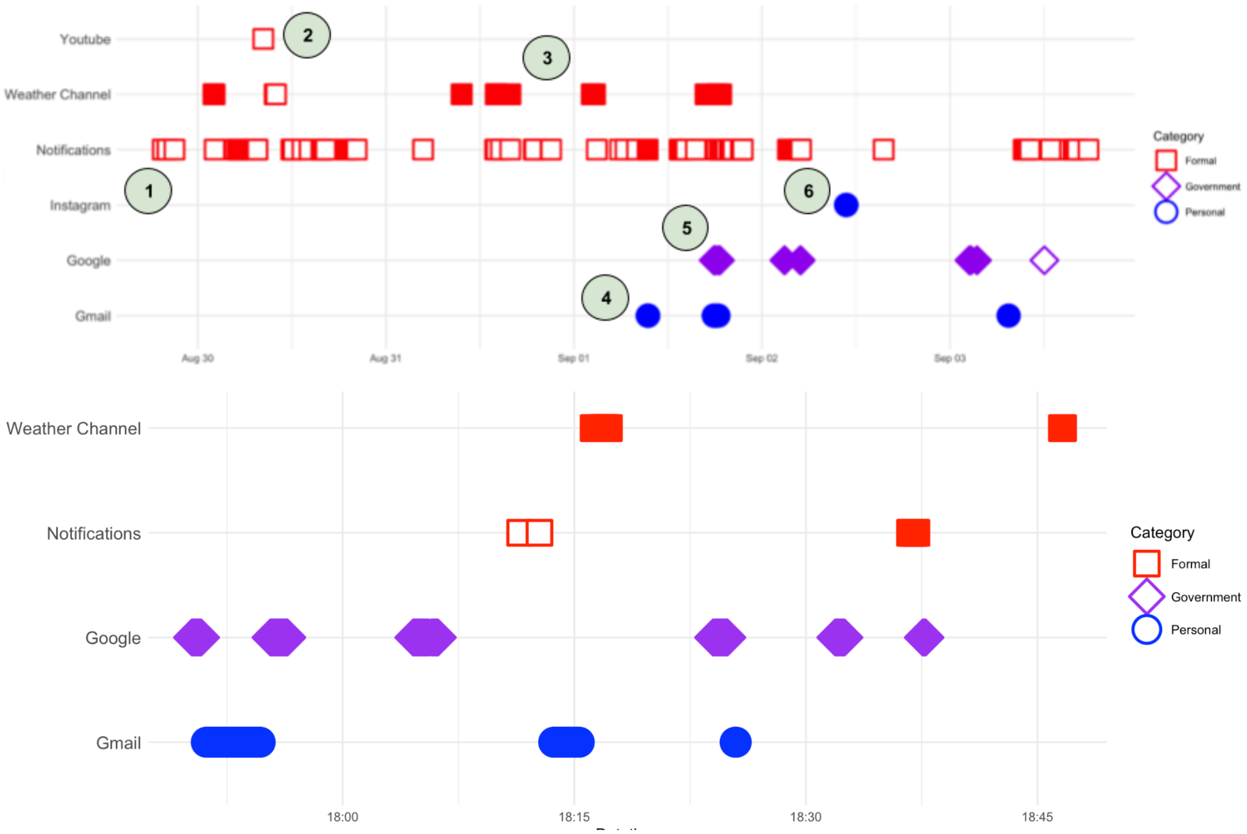


Figure 6 was used to dictate the three vignettes of choice for closer analysis. This includes person ID (PID) 5 from Philadelphia, PID 3 from Indianapolis, and PID 4 from Arizona comprising Vignettes A, B, and C. A and B were chosen for the two most sequences in total, and C was chosen as the participant with substantial data containing only active extreme weather sequences. The latter is especially interesting – not just for only containing active sequences, but also for the content that comprised the sequences themselves. In each section below, I further explain why the vignette was selected and the unique behavioral characteristics of the participant during the extreme weather events.

Vignette A

Figure 7

a) Sequenced event diagram b) Sequenced event diagram between the hours of 5:30pm and 7pm.



On September 1, 2021, the remnants of Hurricane Ida made its way through the mid-atlantic in the late afternoon hours, becoming what the Philadelphia/Mt Holly Weather Forecast Office calls, “one of the area’s worst natural disasters ever observed” (September 1: Remnants of Ida). Torrential rainfall, tornadoes, and catastrophic flooding culminated in 22 deaths in the local area and billions of dollars in damages. Montgomery County, PA is specifically mentioned in the report and featured an EF-2 tornado. According to the NOAA Storm Events Database, the storm dealt $5 million in damages and 3 casualties in the county.

For Vignette A, a sequenced event diagram is produced and shown in Figure 6. Vignette A was chosen to highlight a stunningly unique case study: a participant faces a natural disaster while stuck in commute. In today’s digital age, they relied on their phone for the latest information on the train status – leveraging government websites and preferred channels of information acquisition (Weather Channel) and dissemination (Gmail).

The participant amassed 7853 screenshots in the 5 days spanning the severe storm event: two days prior, the day of (September 1), and the two days following. At point 1 on the graph, notifications are presented to the participant, primarily originating from The Weather Channel app. These notifications continued throughout the days and hours preceding the event, with most being passive checks. At point 2 on the graph, YouTube's algorithm recommended content from large news networks, specifically from national news outlets of MSNBC, TODAY, and CNBC. Similar to the early notifications, this content was passively glossed over by the participant.

At point 3, the solid red squares indicate intentional and frequent checks of a formal source – the Weather Channel app. The participant browsed hourly conditions and radar maps. This happened in bursts and indicates the participant's primary preference of media and information acquisition during this storm event. At point 4, the solid blue circles indicate active interactions with personal contacts about weather. In this case, participant began sharing about their live circumstances regarding the storm, namely that they were on a Southeastern Pennsylvania Transportation Authority (SEPTA) train. Notably, they disseminated information to friends, a private religious contact, and through notes to self. In one particular sequence, they wrote an email to themselves, expressing that they were feeling worried about other personal contacts in the storm.

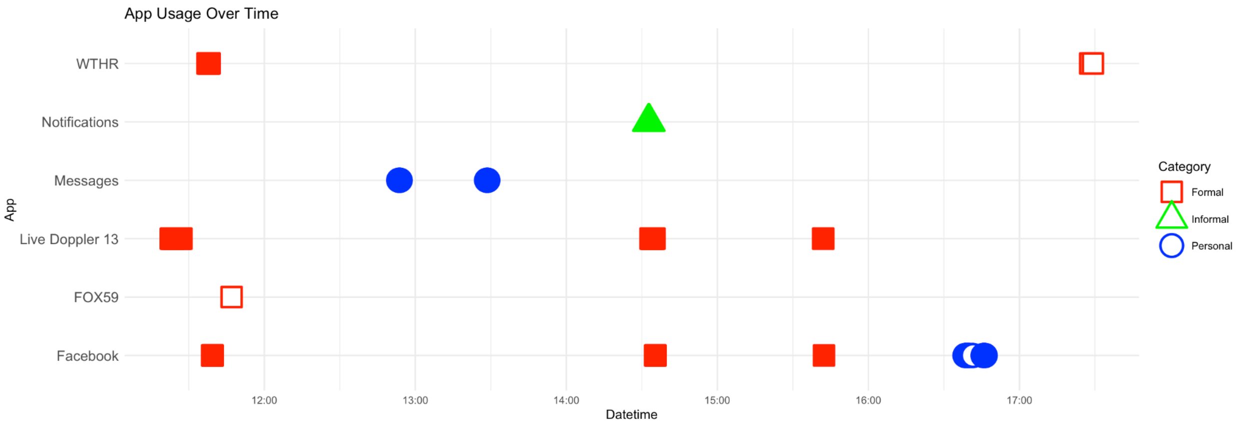
At point 5, something special happens – the participant is stuck on the train. According to the contents of the screenshot and through the government agency's communications, the participant learns that a tree had fallen onto the train tracks, causing delays to the route. In the span of around an hour, the participant then toggles between Gmail, The Weather Channel and Google (through *septa.org*) to acquire their information.

In the days following the event, the participant continues checking *septa.org* in the morning hours to learn of any storm-induced transit delays. At point 6, the participant sees visualizations of the damages from personal contacts in Philadelphia over Instagram. From these 6 points, the vignette displays not just the diversity of stewards of extreme weather information, but also uniquely how those stewards are crafted into a unique behavioral sequence for the participant.

Vignette B

Figure 8

a) Sequenced event diagram b) Sequenced event diagram between the hours of 10am and 7pm on January 31.



On January 31, a "significant snowfall event" occurred in Marion County, Indiana. The event caused reduced visibility, hazardous roadway conditions, and dumped around 7 inches of snow in different regions (January 30-31, 2021: Significant Snowfall Event…). According to the NOAA Storm Events Database, the storm dealt $500,000 in damages and 7 casualties in the county.

Vignette B was chosen to illustrate the personalization of weather information acquisition, the passive exposure to certain stewards such as FOX59, and most importantly the diversity of origins and channels that constitute information acquisition behaviors. In Vignette A, we observed passive interactions with news agencies and a preference for tailored weather information from various stewards. However, it wasn't until Vignette B that it became clear a single channel could encompass a rich variety of different stewards.

In Figure 8, Points 1, 2, and 3 emphasize the participant's primary sources of weather information during the event. 13WTHR – NBC's local news affiliate – was a key information source, with content accessed through both their news app and associated radar app. IndianaWeatherOnline, accessed via Facebook, was also a major source of information, particularly evident in the active and formal instances at point 3.

At Point 4, an hour later at 1pm, the participant begins sharing weather information with personal contacts. This included sharing real-time conditions and observations of snowfall coming in – thereby highlighting the diversity of digital and in-person collection of weather information.

At around 2:30 PM at point 5, the participant received a notification from the Citizen public safety app, an informal source for weather information which they actively read. Six screenshots later, they revert to toggling between IndianaWeatherOnline via Facebook and Live Doppler 13. An hour later, they check the same pair of IndianaWeatherOnline and Live Doppler 13 as the storm dies down. At point 6, the participant comes across Facebook images from friends and personal contacts of snowfall across the region – from buried rulers on backyard decks to snow piled atop cars. In part b of Figure X, points 1 through 6 and a passive point from local FOX59 are enlarged to show the participant's pattern of toggling between the radar app and IndianaWeatherOnline via Facebook. This supports literature – particularly focus group findings of Yoder-Bontrager and colleagues (2017) that individuals often have personalized communication channels.

At point 7, a personal contact on Facebook reposted information from BAMwx.com, a privatized weather intelligence app. This resulted in an active engagement by the participant. This example highlights the complex pathways through which weather information is often communicated to the public. In this case, the participant absorbs information from a personal contact on Facebook, but the origin of the information is BAMwx. It is thus key to know that there are different stewards with different responsibilities to originate and communicate the information. The screenshot data allows us to illustrate and better understand these distinctions.

At point 8, yet another steward of weather information shows up: Smithsonian. They shared on Facebook the impacts of the snowstorm on their parks. Points 3, 7, and 8 thus illustrate that a single app such as Facebook could be the channel for completely distinct types of stewards that are formal, informal, and personal.

Last, point 9 depicted information on Google, originated from FOX59. For the participant, all weather information originating from FOX59 were passively looked over – whether on the FOX59 news app or an intermediary such as Google. This suggests that, in this event, FOX59 was not as relevant an originating weather source as other formal news channels such as 13WTHR.

Vignette C

Figure 9

Sequenced event diagram

One of the most diverse weather hazard events in the dataset occurred in Maricopa County, Arizona in the days following August 20, 2020, when monsoon storms triggered lightning, flash flooding, and wildfires (Roman 2020). According to NOAA's database, the storm dealt an estimated $10,000 in damages and 5 casualties in the county. Although the participant living in Mesa only amassed 4546 total screenshots across the five-day period starting August 20, these screenshots told a rich story unlike any of our other participants.

This Vignette captures a wholly unique system for weather information acquisition – quantitative, individually generated data that is the most relevant and up-to-date information for the participant. It was supplemented with a single, active read-through of relevant wildfire information. This rich data point suggests the potential opportunity to leverage user-generated data as a channel for a highly personalized sense of weather risk communication.

Upon first glance of Figure 9, we observe that the participant only engaged actively with weather information. Despite limited phone usage throughout the event, this participant actively engaged in the aftermath of the events and pointed out crucial downstream impacts of extreme weather. Expanding on the RISP theory, this participant continued to assess their risk based on sufficient information available to them in the form of hazard-induced impacts such as poor air quality. In points 1 and 2, we are introduced to Flow and Ecobee, two apps that communicate air quality conditions through interior and exterior home sensors. In the days following the event, the participant frequently monitored the air quality around their home, which varied from poor to very good during the wildfire aftermath.

At point 3, the participant engaged with an article about the wildfire from AZCentral, a local formal news medium that used Gmail as a channel to get its content to the end-user. The user read the entirety of the article and did not immediately engage with other sources of weather information. This further illustrates how stewards utilize various channels for extreme weather information.

For this participant, it would be interesting to investigate other non-wildfire dates in their Screenome for if they engaged with air quality information at the same frequency. In the current study, we assume that the storm event (directly or indirectly) caused this behavior, but it would be important to analyze behavioral patterns outside the event.

Summary

Using qualitative case study analysis on quantitative timestamp data, we are able to meaningfully compare three very different events and behavioral patterns. Vignette A illustrated the experience of being stuck on a train during the remnants of a hurricane. Vignette B captured the exchange of snowy images, and Vignette C demonstrated a novel, self-initiated approach to data collection during wildfires. All three participants had far more content in their Screenome than what governments initially issued in warnings. Instead, they had access to a rich collection of information stewarded by diverse sources such as transit agencies, personal contacts, and air quality sensors. It is through such analysis that we can begin to understand the actual behavioral sequencing patterns – from taking in information through notifications, to researching the personalized impact, to finally communicating it back out to other Screenomes.

Discussion

Main Findings and Interpretations

From our investigation into the three research questions, we find that there are a diverse range of stewards, categorizable into formal news media, informal, government, and personal sources. Although a majority of the content on people’s screens came from formal media, participants had passive interactions with these sources and more active interactions with government, informal, and personal sources. From our three case study participants, close examination yielded three completely different profiles of information gathering and preparedness. From relying heavily on government sources, to keeping track of the snow radar, to looking at personal air quality sensors, each participant had their own flavor of extreme weather information acquisition. As such, there were no clear takeaways of how behavior is sequenced across all the different stewards. This affirms findings from prior literature that people prefer highly-personalized patterns of communication and information acquisition for extreme weather (Yoder-Bontranger et al., 2017).

Implications

For governments, this study emphasizes that there are a myriad of channels that *steward* information to its destination of the general public. A tweet originating from the National Weather Service may get retweeted and then referred to by a personal contact. In every step along the way, the perception of the information changes and governments can no longer regard themselves as the main stewards of the information. In this reality, official sources need to be able to leverage and get information out through informal and personal channels. This happens through understanding the different channels that exist and their unique features – such as personalities that reshare weather information or personal data collection devices. Additionally, governments also have to ensure the quality of information they disseminate themselves and advocate for better standards for public alerts. Garcia and other US representatives from Los Angeles County are first movers in this, and more work needs to be done so the weather enterprise is better prepared when the next disaster strikes (Garcia, 2025).

Limitations

This study has a variety of limitations. First is sample representativeness. This thesis presents a novel study design and we thus only examined 12 events across 10 participants. Because of this, each participant's weather-related Screenome highly affected results across the whole dataset. Future research should apply the present study design and expand it across the HSP data. Second is tagging and data collection. It is definitely reasonable to suspect biases when manually tagging the screenshots. Sometimes, for example, the screen would move down only a little bit between two still frames – and I would tag both frames as an active interaction. This level of subjectivity should ideally be confirmed by another third-party tagger in a future study. Third is the relevance of data. As there becomes more technological and smartphone innovations year to year, and extreme weather events also get more costly year to year, data collection needs to catch up in order to be relevant in evolving landscapes. This study investigates phone usage during hurricanes, storms, and wildfires that occurred in 2020-2021. In the last 4-5 years, many behaviors could have already changed, and future research should assess the relevancy of recent events.

For example, in the LA wildfires, a specialized wildfire-tracking app called Watch Duty came into the spotlight as a new and effective channel of communication (Sherwood Forestry Service, 2024). The app, started by a US nonprofit, takes in radio traffic from first responders and communicates wildfire dangers in real time through an interactive map interface. The app reportedly gained 750,000 users within just 12 hours during the LA wildfires and has been praised for providing real-time, actionable information that helped save countless lives and protect livelihoods (Peters, 2025).

This is a recent example of how the digital information sphere is rapidly evolving to keep up with the growing demands of a changing climate and the increasing frequency and intensity of extreme weather events. As a result, new modes of information – such as specialized apps – will become available, opening new channels that the weather information enterprise needs to understand and leverage. Overall, for this study, limitations exist on the spectrums of sample representativeness, how it was measured, and at what time scale, and future analyses should take these all into account for adapted study designs.

Conclusion

This thesis provides new insight into what kinds of stewards of weather information existed on people's phones during extreme weather events in 2020 and 2021. It offers initial answers to three of our key research questions:

For RQ1: *Who are the stewards of the extreme weather information individuals encounter in their everyday digital lives?* We found that there are a rich variety of stewards that span formal news media, government, informal entities, and personal contacts. Each participant in the study engaged with different kinds of stewards in different ways, corroborating prior research that people have their own preferences for weather communications.

For RQ2: *What are behavioral sequencing patterns of individuals' seeking and sharing of weather information?* From a passenger stuck on a train, to someone monitoring snow radars, to a participant collecting their own air quality information and readings, we were able to dive deep into individuals' unique behavioral sequencing patterns in the time of three severe storm events. We found that people have nuanced, often unpredictable patterns of collecting extreme weather-related information – as with the case of someone getting stuck in commute. This is important to understand for the development of tailored interventions and for trusted sources to better leverage various communication channels.

For RQ3: *What are the frequencies and qualities of individuals' passive and active information-seeking?* In our small dataset of ten participants, we found that people actively engaged more with The Weather Channel, native weather apps, radar apps, and transit agency websites. On the other hand, people scanned and glossed over news networks such as CNN, FOX and NBC. Although the dataset is small and very rudimentary, it provides frameworks to challenge news media as the best distribution channel for weather information that people actually engage with. By design of the *Human Screenome Project*, there were also many other limitations such as data size, data quality, and demographic representation. Further analysis should be conducted to collect more data points of various stewards and behavioral interaction patterns.

This thesis presents a first-of-its-kind study and visualization at the ever-evolving landscape of extreme weather communication. At the time of its writing, Hurricane Helene, Hurricane Milton, and the LA wildfires are still relatively fresh in mind for the American public as disasters that occurred in the last several months. With climate change, we know that there will be more, stronger disasters in store for the future. It is imperative that the weather enterprise better understand communication channels – so that we're all better prepared when the next one hits.

Acknowledgements

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Appendix

Appendix A

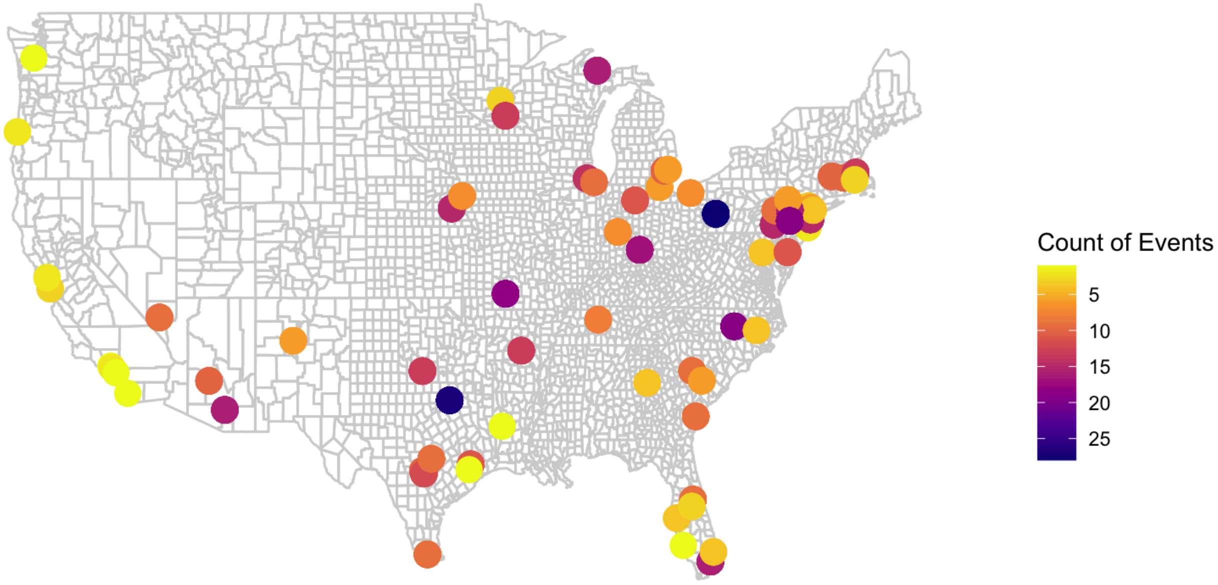


Figure 1: A map visualization of storm events that coincided with HSP data collection.

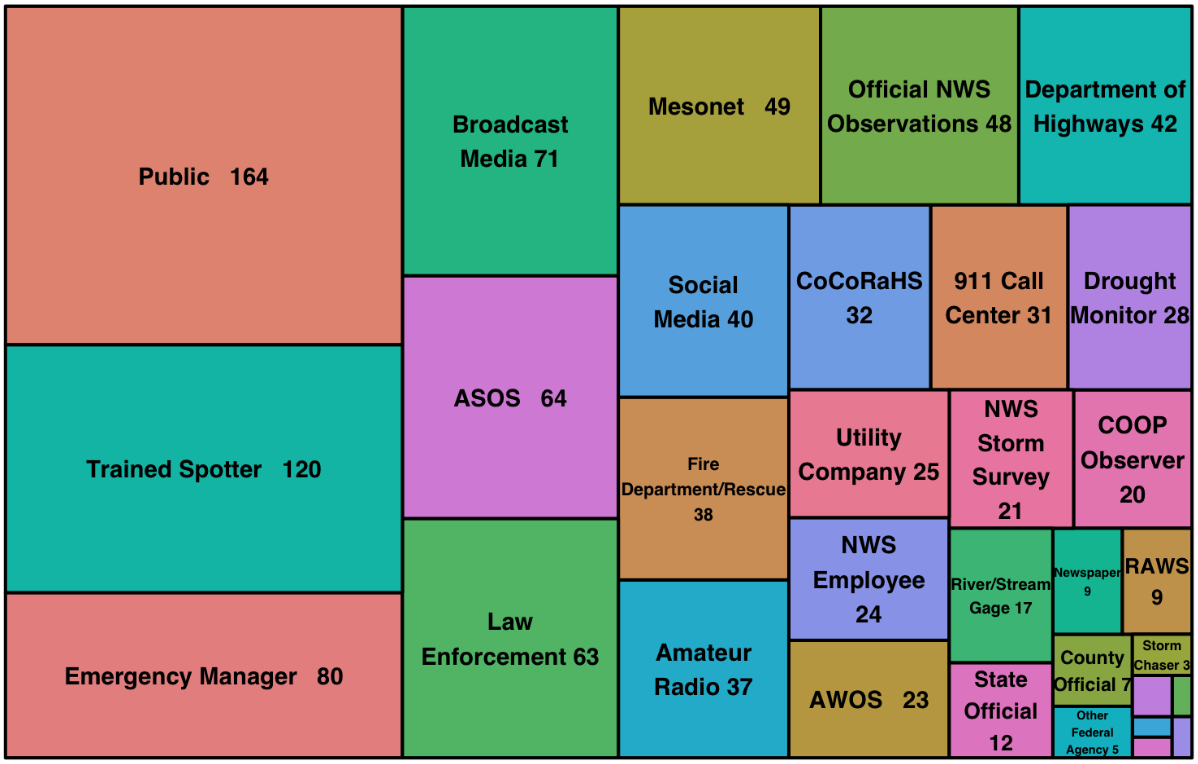


Figure 2: a treemap containing NOAA-defined sources of information for the storm events

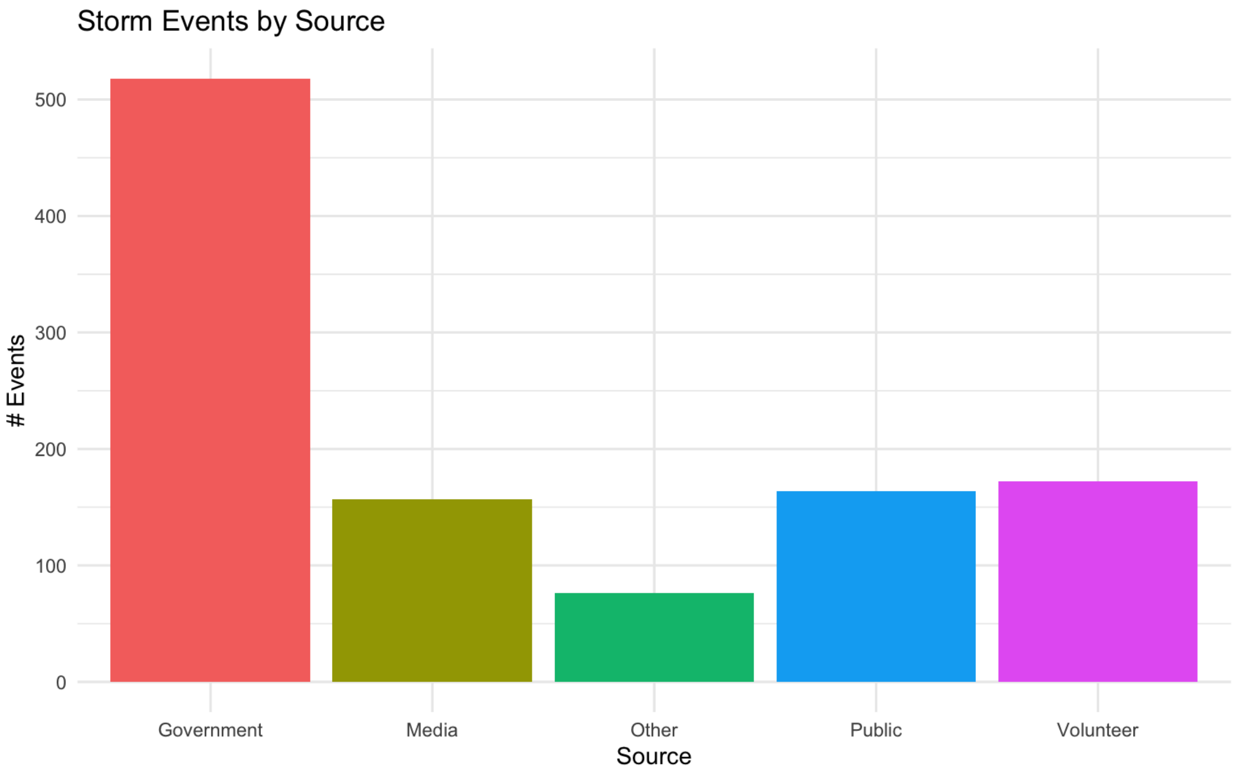


Figure 3: a barplot containing distribution of sources initially defined in the NOAA/HSP combined dataset

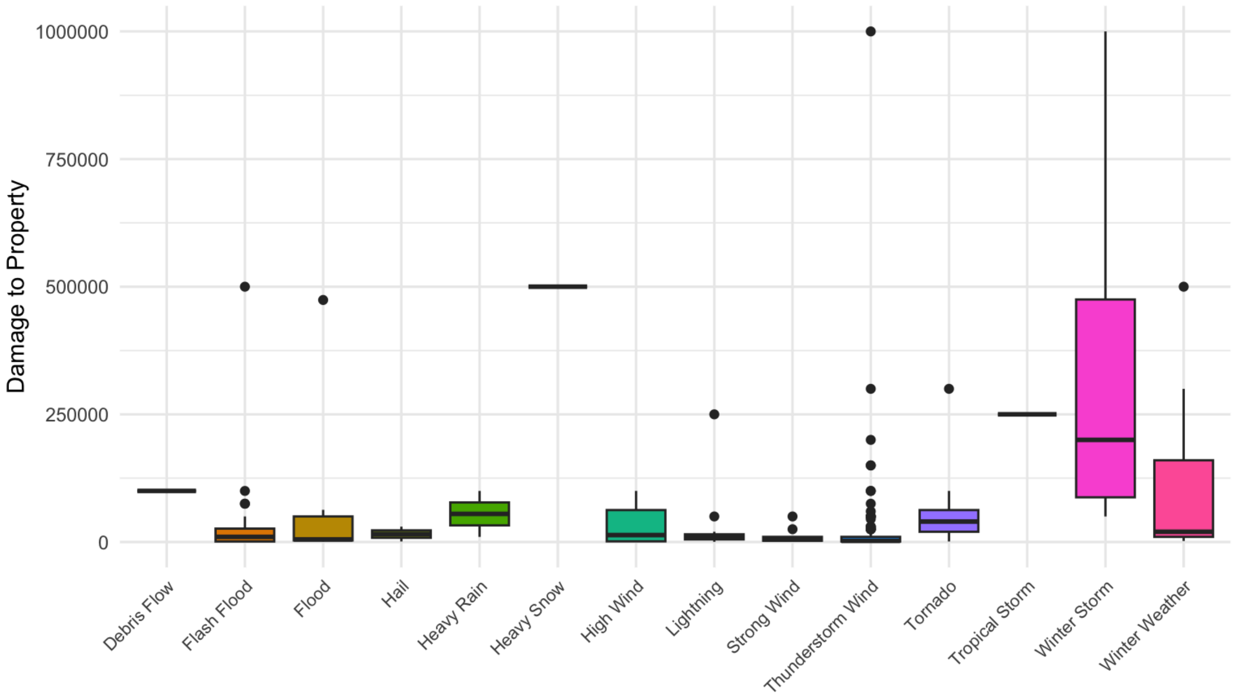
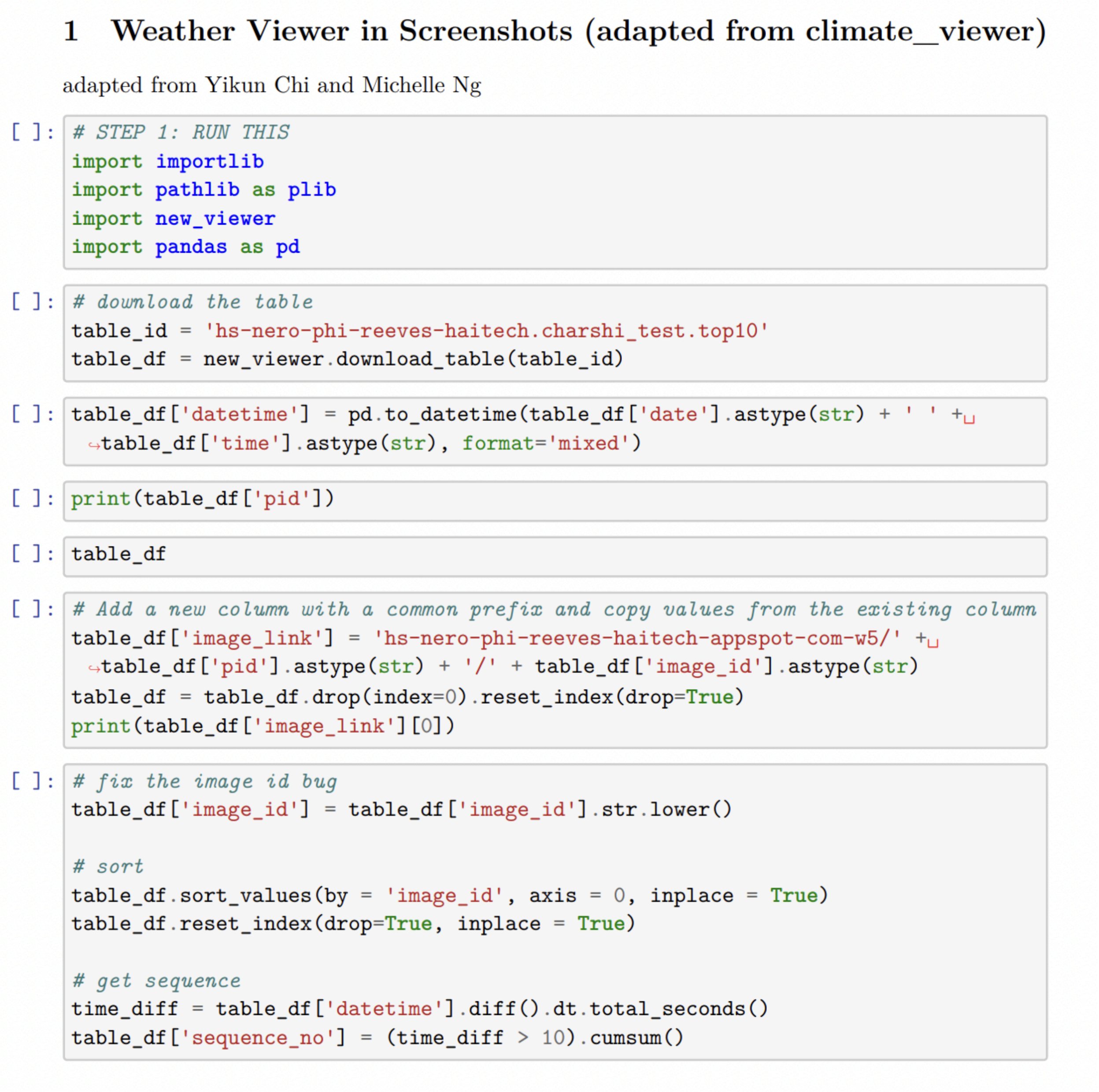


Figure 4: barplots of damage to property, with significant outliers removed, in the combined NOAA/HSP data

Appendix B



1 Weather Viewer in Screenshots (adapted from climate_viewer)

adapted from Yikun Chi and Michelle Ng

```
[ ]: # STEP 1: RUN THIS
     import importlib
     import pathlib as plib
     import new_viewer
     import pandas as pd
```

```
[ ]: # download the table
     table_id = 'hs-nero-phi-reeves-haitech.charshi_test.top10'
     table_df = new_viewer.download_table(table_id)
```

```
[ ]: table_df['datetime'] = pd.to_datetime(table_df['date'].astype(str) + ' ' +␣
       ↪table_df['time'].astype(str), format='mixed')
```

```
[ ]: print(table_df['pid'])
```

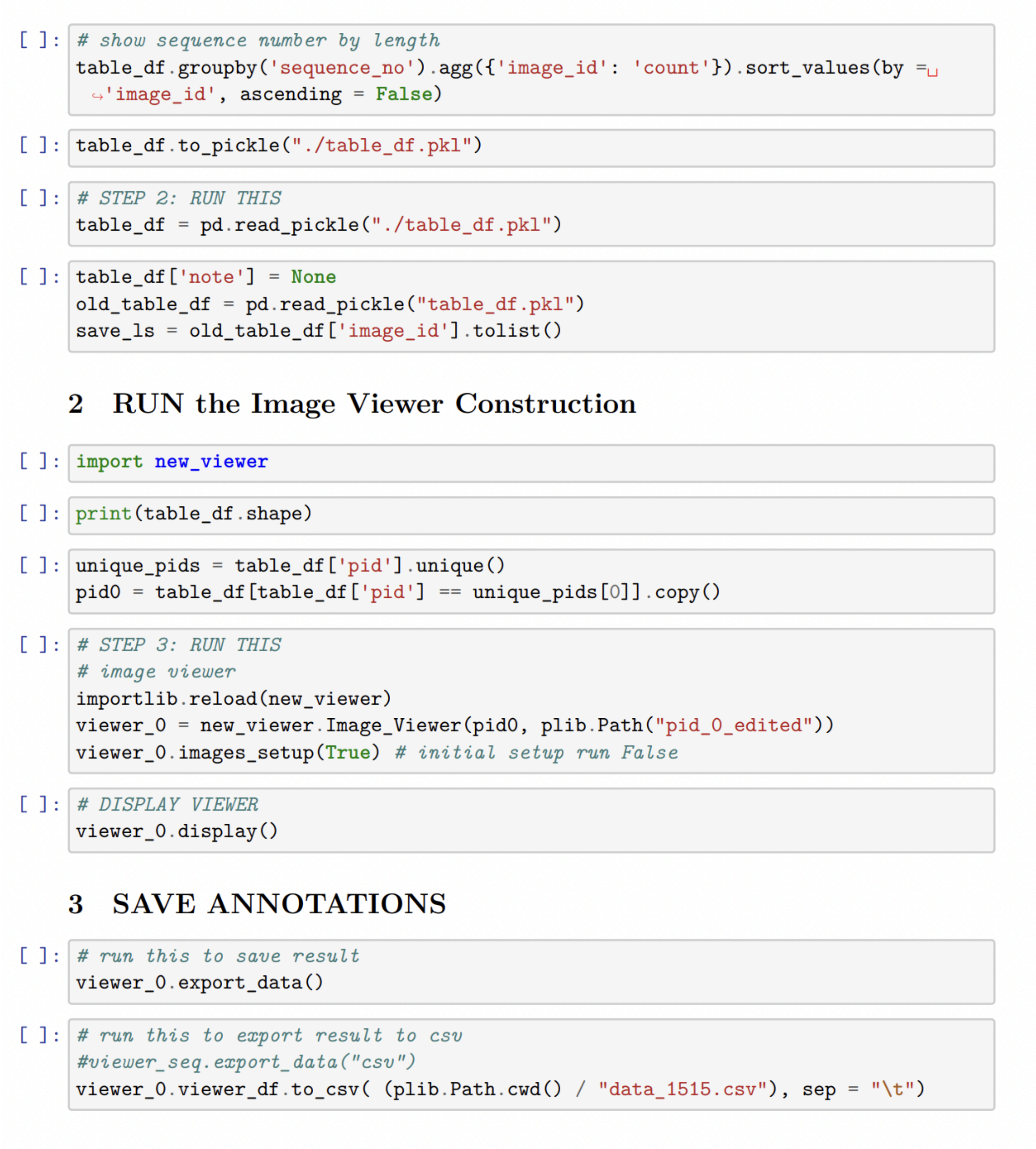
```
[ ]: table_df
```

```
[ ]: # Add a new column with a common prefix and copy values from the existing column
     table_df['image_link'] = 'hs-nero-phi-reeves-haitech-appspot-com-w5/' +␣
       ↪table_df['pid'].astype(str) + '/' + table_df['image_id'].astype(str)
     table_df = table_df.drop(index=0).reset_index(drop=True)
     print(table_df['image_link'][0])
```

```
[ ]: # fix the image id bug
     table_df['image_id'] = table_df['image_id'].str.lower()

     # sort
     table_df.sort_values(by = 'image_id', axis = 0, inplace = True)
     table_df.reset_index(drop=True, inplace = True)

     # get sequence
     time_diff = table_df['datetime'].diff().dt.total_seconds()
     table_df['sequence_no'] = (time_diff > 10).cumsum()
```



```
[ ]: # show sequence number by length
     table_df.groupby('sequence_no').agg({'image_id': 'count'}).sort_values(by =␣
      ↪'image_id', ascending = False)
```

```
[ ]: table_df.to_pickle("./table_df.pkl")
```

```
[ ]: # STEP 2: RUN THIS
     table_df = pd.read_pickle("./table_df.pkl")
```

```
[ ]: table_df['note'] = None
     old_table_df = pd.read_pickle("table_df.pkl")
     save_ls = old_table_df['image_id'].tolist()
```

2 RUN the Image Viewer Construction

```
[ ]: import new_viewer
```

```
[ ]: print(table_df.shape)
```

```
[ ]: unique_pids = table_df['pid'].unique()
     pid0 = table_df[table_df['pid'] == unique_pids[0]].copy()
```

```
[ ]: # STEP 3: RUN THIS
     # image viewer
     importlib.reload(new_viewer)
     viewer_0 = new_viewer.Image_Viewer(pid0, plib.Path("pid_0_edited"))
     viewer_0.images_setup(True) # initial setup run False
```

```
[ ]: # DISPLAY VIEWER
     viewer_0.display()
```

3 SAVE ANNOTATIONS

```
[ ]: # run this to save result
     viewer_0.export_data()
```

```
[ ]: # run this to export result to csv
     #viewer_seq.export_data("csv")
     viewer_0.viewer_df.to_csv( (plib.Path.cwd() / "data_1515.csv"), sep = "\t")
```

This python code was used to annotate and manually tag screenshots for the ten participants.

Appendix C

Event	Pid	Hazard	State	Date	Link to article
1	1	Winter Weather	TX	2021-02-11	The Great Texas Freeze: February 11-20, 2021

2	2	Cold/Wind Chill	OH	2021-02-01	Medical Examiner: 5 killed by winter weather in Cuyahoga County in last week
3	3	Winter Weather	IN	2021-01-30	Snowfall of January 30-31, 2021
4	1	Tornado	TX	2020-11-24	Confirmed Tornado Touchdown in Arlington Texas Tuesday Night, November 24, 2020
5	4	Flash Flood	AZ	2020-08-22	The Arizona monsoon in photos: Dust storms, lightning and flash floods
6	5	Tornado	PA	2021-09-01	EF2 tornado on Sep. 01, 2021 16:35 PM EDT
7	6	Lightning	MN	2020-08-08	Severe storms bring large hail, damaging winds, torrential rain to Twin Cities
8	7	Flash Flood	MI	2021-06-26	50 Drivers Rescued and 350 Vehicles Damaged
9	1	Hail	TX	2021-03-24	Tornado on Mar. 24, 2021 17:04 PM CDT
10	8	Strong Wind	NC	2020-10-29	Zeta causes more than 400,000 power outages across North Carolina as winds gust over 50 mph
11	9	Thunderstorm Wind	FL	2021-09-01	Severe storms rolling through South Florida flood Miami streets
12	10	Thunderstorm Wind	TX	2020-08-22	Storms do some damage as they move through Austin area

A table containing links to media articles highlighting the 12 chosen storm events.