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Liked, Not Shared: Social Media Engagement During the 2018 Kerala Floods

Pallavi Rachel George[a] and Adrija Majumdar[b]

Abstract

Social media has emerged as a critical space for communication during natural hazards. Despite growing usage, research on the content of such communications is limited, particularly in highly vulnerable emerging economies, such as India. In this study, we take the case of the 2018 Kerala floods and analyze Twitter ('X') content to examine how information is processed and disseminated during a once-in-a-century flooding event. We map over 100,000 tweets to four phases of the flooding event, based on precipitation intensity between 1st June 2018 to 31st August 2018. We utilize Latent Dirichlet Allocation (LDA), a topic modelling technique, and identify three main themes: collective trauma, rescue-and-relief, and donations. We estimate negative binomial regression models to study user engagement with these themes, conceptualizing 'retweeting' as active and 'favoriting' (i.e., liking) as passive engagement. The study finds a marked difference between the two engagement behaviors, with rescue-and-relief tweets being actively retweeted during the flood peak (not before or after) and liked during the flood peak and recovery phases. Collective trauma-related tweets are more likely to be liked during the flood peak, but we do not see a corresponding increase in retweets at any point. Donations-related tweets are retweeted during the flood peak, but otherwise neither retweeted nor liked as much as the other themes. Importantly, during the flood onset phase, tweets with thematically undifferentiated content were more likely to be retweeted and favorited, compared to the theme-specific tweets, indicating an evolution from general content to information-specific content as the disaster progressed. Overall, the study points to the distinct and deliberate ways that social media content was consumed and shared during the 2018 Kerala floods, particularly highlighting variations in information processing across different phases of the disaster as it unfolded.

Keywords: Floods; Social media analytics; Twitter; Disaster response; User engagement

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[a] Public Systems Group, Indian Institute of Management Ahmedabad
[b] Information Systems, Indian Institute of Management Ahmedabad

Introduction

Social media plays a pivotal role in the generation and sharing of disaster-related information (Panagiotopoulos et al., 2016; Su et al., 2025). Platforms such as Twitter (now 'X'), Facebook, and Instagram are increasingly used by government agencies, community organizations, and citizens for information dissemination and coordination (Arvandi et al., 2025). This has spurred academic and practitioner interest in understanding how social media is utilized during disasters (Alathur et al., 2021; Alexander, 2014; Erokhin & Komendantova, 2024; Fang et al., 2019; Gaspar et al., 2019; Karimiziarani et al., 2023; Li et al., 2020; Moghadas et al., 2023; Muniz-Rodriguez et al., 2023; Ogie et al., 2022; Stieglitz & Dang-Xuan, 2013; Su et al., 2025; Zobeidi et al., 2024).

Studies have predominantly explored social media usage during disasters in North American contexts (Garske et al., 2021; Karimiziarani & Moradkhani, 2023; Muniz-Rodriguez et al., 2023; K. Wang et al., 2021, 2023). India has a large and growing population of social media users, estimated at 500 million unique users (Vengattil, 2026). It is also one of the most climate-vulnerable countries in the world (Eckstein et al., 2021). However, studies on social media usage in India are few (Karmegam & Mappillairaju, 2020; Young et al., 2022). We address this gap by studying the 2018 floods in Kerala, India, the fifth biggest flooding event in the world between 2015 and 2019 which claimed close to 500 lives and caused total economic losses of at least Rs. 31,000 crores (Krishnakumar, 2019).

In addition, most studies treat disasters as a single event for analysis, rather than exploring them temporally, despite hazards like floods and cyclones often stretching into multiple days or weeks, with temporal and spatial variations in intensity. Few studies have examined how social media usage evolves in response to the dynamics of a disaster, such as precipitation or storm intensity (Fang et al., 2019; W. Wang et al., 2024; Zander et al., 2023). Based on these studies, we develop a precipitation intensity-based temporal classification of the Kerala floods. Moreover, studies usually undertake sentiment analysis and/or topic modelling as methods of analysis (Garske et al., 2021; Katamaneni et al., 2021; Mendon et al., 2021; Weismayer et al., 2021). We additionally explore active and passive engagement with themes across the phases of the floods, which provides insights on information diffusion patterns. The study is guided by two research questions:

RQ1: What are the main themes discussed on Twitter ('X') during the 2018 Kerala floods?

RQ2: How did user engagement with the main themes evolve during the 2018 Kerala floods?

We use 139,462 tweets between 1st June 2018 and 31st August 2018 on the Kerala floods, employing Latent Dirichlet Allocation (LDA)-based topic modelling and negative binomial regression analysis for the study. Section 2 provides a brief background on existing studies on social media use during disasters. Section 3 describes the 2018 Kerala floods and categorizes the disaster phases. Section 4 details the data collection and methodology, followed by results in Section 5. Section 6 discusses the findings and Section 7 concludes.

2. Social Media during Disasters

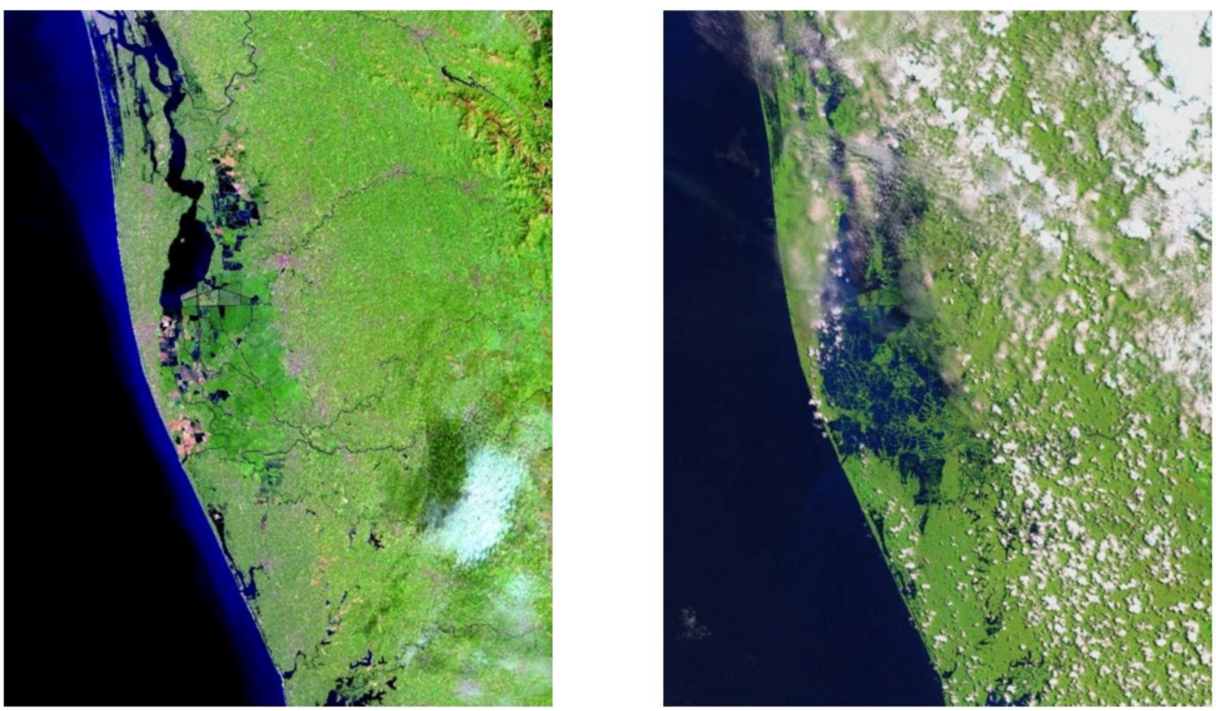
Social media analytics have grown in importance for disaster risk reduction, facilitating our understanding of "how populations react to and recover from disasters, what their immediate needs are, and how they perceive various risk reduction measures" (Erokhin & Komendantova, 2024, p. 1). Early studies have highlighted the importance of social media platforms in fostering collective action to support Haiti after the 2010 earthquake (Keim & Noji, 2011) and in responding to Hurricane Sandy (Ambinder & Jennings, 2013). More recent explorations have identified the prominence of themes such as post-disaster reconstruction, physical wellbeing, grief, donations, evacuation, and prayers of support across various flooding events, cyclones, earthquakes, and pandemics (Glasgow et al., 2016; Karimiziarani et al., 2023; Karimiziarani & Moradkhani, 2023; Muniz-Rodriguez et al., 2023; Ogie et al., 2022; Zander et al., 2023).

Despite studies from India being limited overall, there are some interesting studies on the 2018 Kerala floods. A recent study compares social media data to independent crowdsourced databases to examine the validity of social media for ground-truthing (Young et al., 2022). Studies have also used the 2018 Kerala floods as a case to demonstrate different social media analytical techniques, such as topic modelling and sentiment analysis (Mendon et al., 2021; Sayeedunnisa et al., 2019). Our research builds on these studies by examining the temporal evolution of themes and user engagement across different phases of the Kerala floods. To explore user engagement, we categorize 'Retweet' function as indicative of active engagement and 'Favorite' function as passive engagement (Dolan et al., 2016).

3. The 2018 Kerala Floods

Kerala is the first state on India's mainland to receive the southwest monsoons, usually starting in the first week of June. It is flanked by the Arabian Sea on the west and bordered by the Western Ghats on the east. The 2018 floods in Kerala are considered as a 'once in a century' flooding event, with flooding of such intensity last experienced in 1924 (Kallungal, 2024). **Fig. 1** shows the before and after images of submerged areas in Kerala, as captured by NASA's Earth Observatory. Close to 500 people died during the flood, with extensive damage to agriculture, infrastructure, and Kerala's highly biodiverse environment (RGIDS, 2018). The mobilization of people in Kerala as well as those Keralites living overseas to collectively overcome the floods was considered unprecedented in the state's history. India's official entry for the international feature film category of the 96th Academy Awards in 2024 was a movie about Kerala's 2018 floods, titled '2018: Everyone is a Hero' (Livemint, 2023).

Fig. 1. Images of submerged lands in Kerala before and after the 2018 floods



February 6, 2018 | August 22, 2018

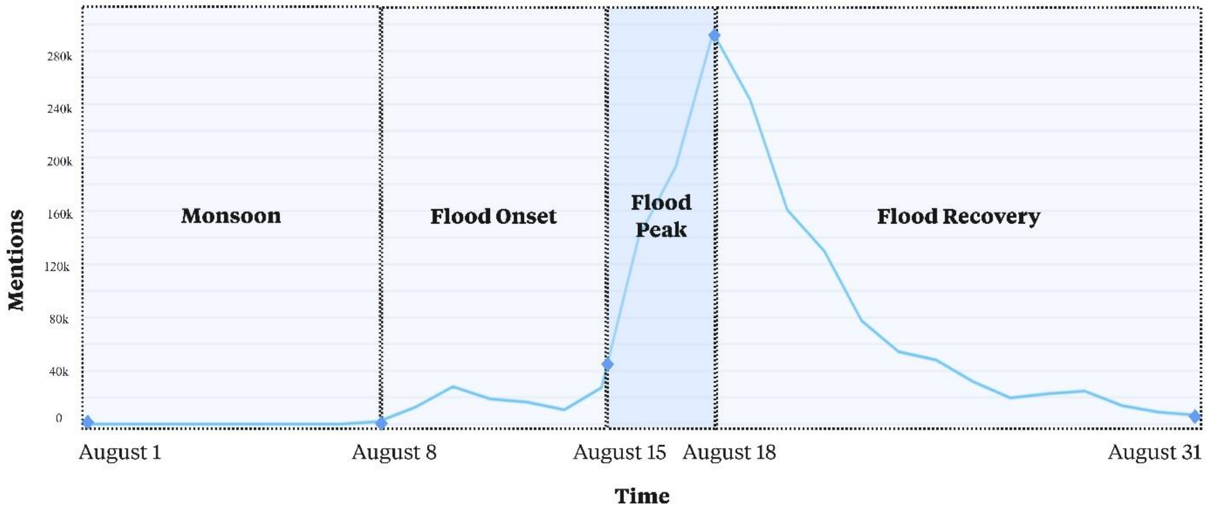
Source: Earth Observatory, NASA

3.1 Phases of the 2018 Kerala Floods

Previous studies have shown that in the case of flooding events, social media activities are consistent with precipitation intensity as the disaster progresses (Fang et al., 2019; Zander et al., 2023). Kerala experienced abnormally high rainfall from 1 June 2018 to 19 August 2018. This resulted in severe flooding in 13 out of 14 districts in the state. As per the India Meteorological Department (IMD), Kerala received 2346.6 mm of rainfall from 1 June 2018 to 19 August 2018, in contrast to an expected 1649.5 mm of rainfall. The rainfall over Kerala during the months of June and July, and between the 1st and 19th of August was 15%, 18% and 164% above normal, respectively (Hydrology (S) Directorate, 2018; State Relief Commissioner, 2018). A storm over the whole state of Kerala spread between August 15th and August 17th, 2018. It was so severe that 35 dams were opened, with all five gates of the Idukki dam opened for the first time in almost 3 decades. The heavy rains induced landslides in the hilly regions and flooding in the low-lying regions. Kochi airport, India's fourth busiest airport, was shut due to flooding of its runway.

Based on the severity of rainfall, we categorize the flooding into four phases. Phase one (**Monsoon**) runs from 1st June to 7th August 2018. These were days of initial rainfall corresponding to the regular monsoon months in India. Here, the rainfall was between 15 to 18 percent above normal. The tweets in this stage were mainly about Kerala rains rather than mentions of floods. Phase two (**flood onset**) can be seen from 8th August 2018 to 14th August 2018. During this phase, flooding begins to occur in various parts of the state, prompting the government to issue precautionary warnings. Phase three (**flood peak**) comprised of three days between 15th August 2018 and 17th August 2018, with largescale destruction in the state. Incidents of entire towns and villages getting submerged, bridges collapsing, and people stranded on rooftops begin to emerge. We also see coordinated rescue efforts by citizens, particularly the role of fishermen who used their fishing boats to complement the rescue efforts of the National Disaster Response Force (NDRF) teams. Phase four (**flood recovery**) ran from 18th August 2018 to 31st August 2018 when the alerts were lifted, and recovery plans were initiated by the government. In this stage, we get information about compensation and details of damages. **Fig. 2** provides the day-wise breakdown of the number of tweets between 1st June and 31st August 2018, indicating a peaking of tweets between August 15th and August 17th, 2018, the days of most intense flooding.

Fig. 2. Phases of Kerala Floods 2018 and Tweets



4. Data Collection and Methodology

For this paper, the following inclusion and exclusion criteria were deployed in collecting the tweets: public Twitter updates only, in English, and tweets that used at least one of the following hashtags:- #KeralaFloods, #DoForKerala, #IndiaForKerala, #KeralaDonationChallenge #KeralaFloodRelief, #Standwithkerala, #SOSkerala, #KeralaFloods2018, and #Keralarains. The hashtags were selected following the inclusion criteria used by Mendon et al. (2021). The tweets were collected from 1st June 2018 to 31st August 2018. Apart from the messages, information about the creation time of the tweet, the number of retweets and favorites of the tweet, the use of media in the tweet, and the number of followers of the creator were collected. In total, we collected 139,462 tweets from Sprinklr Insights, a data partner of Twitter (‘X’).

4.1 Topic Modelling

Natural Language Processing techniques are useful in studying large data but remain largely underutilized in social sciences (Bally & Sebi, 2025; Gruenhagen & Cox, 2025). To address the first research question (RQ1) we employed Latent Dirichlet Allocation (LDA)-based topic modelling. LDA is one of the most widely used probabilistic generative models for uncovering latent thematic structures in large collections of text. Proposed by Blei et al. (2003), LDA assumes that each document in a corpus is a mixture of a small number of underlying topics, and each topic is characterized by a distribution over words. Tweets were preprocessed through standard textcleaning procedures (removal of URLs, non-alphanumeric characters, tokenization, stop-word removal, and lemmatization). Using NLTK packages from Python, we discovered three non-overlapping topics. Two researchers qualitatively examined the top words associated with each topic. The patterns recognized in the word list of the themes were named as **Collective Trauma**, **Rescue and Relief**, and **Donations**.

Collective trauma refers to tragedy that is represented in the collective memory of the group, going beyond the facts of the event, and entering into the memory of those directly affected and other members of the community or society (Hirschberger, 2018). In the context of the Kerala floods, the sharing of information regarding the destruction, such as people who have lost their lives, homes, and property, and collective appeals for help and prayers, all indicate the collective management and memorialization of a tragedy.

Rescue and Relief tweets comprise collective action through the organization of resources such as food, essentials and clean water. It also involves the organization of community members into teams, volunteers, the army, and, in the case of the Kerala floods, the role of fishermen who used their boats to carry out rescue. This topic also includes details of relief camps, operating phone numbers, district helplines, and frequent updates to ensure the correct information is provided.

The third category, donations, comprises tweets seeking financial support, information about how to donate, and information about who has donated (including celebrities and foreign countries). Tweets about donations also include requests to cancel Onam celebrations (the state festival of Kerala) and contribute those funds as donations. **Table 2** provides the topics and the top words for each of these topics as generated from LDA analysis. **Table 3** illustrates sample tweets categorized in each topic.

We coded a tweet to a particular topic if the tweet had the highest probability of occurring in that topic, compared to the other two topics. Approximately 16,000 tweets were loaded equally across all the topics, implying that they had an equal share of words from all three topics. We treat these as a separate fourth category in the regression analysis.

Table 2. Main Themes

Collective Trauma	Rescue and Relief	Donations
help	rescue	uae
need	operation	crore
victim	army	govt
support	team	aid
affected	update	foreign
helping	fisherman	onam
share	hero	money
life	work	donated

Table 3. Sample Tweets for the Themes

Collective Trauma	Rescue and Relief	Donation
While many of us comfortably enjoy the rains sipping on hot tea, there are many, rich and poor, who are affected, very badly. Here's such an example from a cousin's place in Kottayam. #rains #keralarains	Maybe we should have more lifeboats and life-jackets for even volunteers to reach out with emergency material. All our houses in low lying areas and sea coast should have at least 1 room at the first floor level in case of emergencies. #KeralaRains #SecureCoastalAreas	Hi guys, if you are looking to help the people stranded in the #KeralaFloods or contribute in anyway. Here's a chance for ppl in #Chennai to help. Spread the word, Contribute, Volunteer. #CareForKerala #KeralaSOS
Hope all the victims of #KeralaFloods will recover soon..... #godsaveyourowncountry #kerala	Pls share it and join hands and we can arrange whatever needful too #keralafloods Pls contact kayamkulam fire station- 0479 244 2101 Kayamkulam police station -0479 244 5929	The State Bank of India (SBI) has donated Rs 2 crore to Chief Minister's Distress Relief Fund (CMDRF) and announced waiver of fees and charges on services offered by the bank in Kerala. #KeralaFloods
I join the nation in praying for the Rain affected districts of Kerala. Stay strong Kerala. #KeralaRains.	#KeralaFlood #KeralaFloods2018 around 30 people caught on terrace and needs immediate support from Kaladi-Kanjoor rescue team, . Location near Thuravumkara-Maelethetta, back side of Airport Runway- ¦	Please donate your weekend spending to Kerala CM Distress Relief Fund. Your small contribution may save several lives and provide them the basic needs. I have done my part, now it's your turn #KeralaFloods #DoForKerala
#keralarains Looks like some massive rains in #Kerala Stay safe brothers and sisters !	Govt has asked for 20 boats. 50+ boats from Vizhinjam is ready for rescue operations. More fishermen from Pozhiyoor and near villages agreed to send their boats. Vizhinjam fishermen will join rescue operations soon. #KeralaFloods We shall overcome!	Request #Malayalis #kerala ites across the world to cancel all Onam celebrations & contribute those amounts, however small it is to the rehabilitation & support to the people who have lost everything in #keralarains . #KeralaFloods .

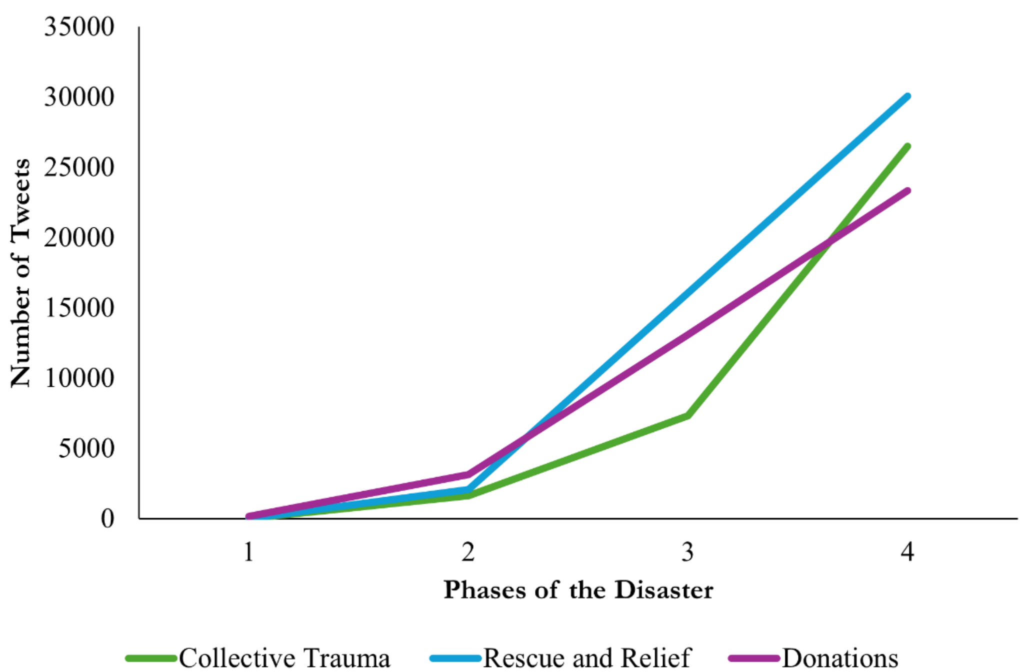
4.2 Active and Passive User Engagement

Consistent with the literature, we consider retweeting behavior as an active form of engagement and marking a tweet as favorite as a passive form of engagement (Brodie et al., 2013; Dolan et al., 2016; Shahbaznezhad et al., 2021). We estimate a negative binomial regression model to study the association between retweets and favorites (both dependent count variables), and the three topics (collective trauma, rescue and relief, and donations). Based on previous studies, we include media attachment, word count, tweet length and the log of followers as control variables (Stieglitz and Dang-Xuan, 2013).

5. Results

Fig. 3 displays the distribution of the number of tweets per topic across the phases. Examining the distribution of topics across the phases, we find that all three topics were similarly placed in the second phase (flood onset) of the disaster. However, rescue and relief related tweets increase sharply from then onwards. While phase three was dominated by 'rescue and relief' tweets and donation tweets, in phase four, we find that 'rescue and relief' and collective trauma tweets were more dominant.

Fig. 3. Distribution of Topics



Active engagement through retweeting can be seen as a stronger attempt at ensuring the message of the tweet reaches other members in each user's respective networks. On the other hand, liking a tweet is still a positive but passive form of engagement, where a user intends to show support for the message, without particularly wanting it to be shared within their networks.

Table 4 presents the results for retweets (active engagement) and **Table 5** for favorites (passive engagement). In **Table 4**, we find that in phase two (flood onset), tweets with a dominance of any one topic – collective trauma, rescue and relief, and donations – were less likely to be retweeted compared to tweets have equal distribution of the topics (the baseline category in the regression analysis). However, in the third phase (flood peak), tweets about rescue and relief ($\beta = 0.214$, $p<0.01$) and donations ($\beta = 0.117$, $p<0.01$) were more likely to be retweeted. In the fourth phase (flood recovery), we observe that tweets that were equally distributed among the three topics were more likely to be retweeted compared to the individual topic categories. Consistent with the literature, we find that tweets from creators with more followers and tweets with a media attachment were more likely to be retweeted (Shi et al., 2014; Soboleva et al., 2017; Yadav et al., 2024).

Table 4. Active User Engagement

	Dependent Variable: Retweets			
	Phase One	Phase Two (Flood Onset)	Phase Three (Flood Peak)	Phase Four (Flood Recovery)
Constant	-0.695	-0.382***	-1.247***	-1.209***
Collective Trauma	0.315	-0.451***	-0.005	-0.158***
Rescue and Relief	0.595	-0.535***	0.214***	-0.037**
Donations	0.379	-1.149***	0.117***	-0.190***
Media	0.929***	1.413***	0.617***	0.251***
Word Count	0.043**	0.092***	0.046***	0.023***
Tweet Length	-0.008**	-0.011***	-0.002***	-0.0003
Followers (log)	0.096***	0.258***	0.234***	0.211***
Observations	201	7,575	43,904	87,782
Log Likelihood	-401.162	-19,719.95	-99,002.09	-1,62,265.90
theta	1.562***	0.577***	0.795***	1.262***
Akaike Inf. Crit.	818.324	39,455.90	1,98,020.20	3,24,547.90
Note: **p<0.05; ***p<0.01				

Similarly, in **Table 5**, we find equally distributed tweets to be more liked (favorites) than tweets dominating in any other topic category in phase two (flood onset). However, in phase three (flood peak), tweets related to collective trauma (β = 0.182, p<0.01) and rescue and relief (β = 0.200, p<0.01) were more likely to be favorited. Tweets about rescue and relief continue to be favorited more in the fourth phase (flood recovery) as well (β=0.181, p<0.1).

Table 5. Passive User Engagement

	Dependent Variable: Favorites			
	Phase One	Phase Two (Flood Onset)	Phase Three (Flood Peak)	Phase Four (Flood Recovery)
Constant	-0.144	0.755***	-0.788***	-0.905***
Collective Trauma	0.231	-0.195***	0.182***	0.028
Rescue and Relief	0.789	-0.554***	0.200***	0.181***
Donations	0.27	-0.862***	0.002	-0.038
Media	0.890***	1.674***	0.711***	0.360***
Word Count	0.048**	0.106***	0.056***	0.033***
Tweet Length	-0.008***	-0.015***	-0.004***	-0.001***
Followers (log)	0.127***	0.228***	0.288***	0.312***
Observations	201	7,575	43,904	87,782
Log Likelihood	-516.186	-25,102.18	-1,26,646.60	-2,54,894.50
theta	1.368***	0.484***	0.693***	0.631***
Akaike Inf. Crit.	1,048.37	50,220.37	2,53,309.30	5,09,805.10
Note: **p<0.05; ***p<0.01				

6. Discussion

In this paper, we examine the main themes discussed on social media during the 2018 floods, and examine user engagement with them across different phases of flooding. Three topics were identified and studied in detail: collective trauma, rescue and relief, and donations. Broadly, the topics indicate the importance of emotional processing, operational coordination, and resource mobilization as three fundamental objectives of utilizing social media during natural hazards.

Phase Two (flood onset) is where initial information is being received about the disaster. Therefore, tweets having equal distribution of all three topics – collective trauma, rescue and relief, and donations – are more likely to be retweeted and favorited compared to tweets dominating any one topic. But in phase Three (flood peak), rescue and relief tweets and donation-related tweets are more likely to be retweeted than tweets having equal distribution of the three topics. This indicates that more specific content begins to gain prominence compared to more general tweets. In this phase, tweets about collective trauma and rescue and relief are more likely to be favorited than tweets having equal distribution of all three topics. Therefore, the users actively engage with rescue and relief and donation tweets, while passively engaging with collective trauma and rescue and relief tweets. Rescue and relief, thus is particularly significant in this stage, with users engaging both actively and passively with it. In phase Four (flood recovery), as in phase Two (flood onset), tweets with equal distribution of all three topics are more likely to be retweeted, but rescue and relief tweets are more likely to be favorited than tweets with equal distribution of all three topics.

Overall, the findings suggest that rescue and relief tweets are actively retweeted during the peak of the floods, precisely when coordination is urgent, not before or after. However, they are still liked, indicating continued acknowledgement or gratitude, without perceiving a need for amplification. Similarly, donation-related tweets are actively retweeted only during the peak flooding days. Importantly, collective trauma tweets are liked during flood peak days, but they are less likely to be retweeted across all the phases.

6.1 Limitations

We have restricted our study to tweets in English, and Malayalam is the local language of Kerala. While there were tweets in Malayalam as well, methodological limitations prevented their use. Future research can develop innovative methodological solutions to analyze tweets in Malayalam and other languages. In addition, we used only the Twitter platform. Future studies can examine how disasters are discussed on other platforms, depending on the availability of data. Studies can explore how the same disaster is discussed differently on different platforms, which could offer insights into whether there is a strategic engagement with platforms during disasters. Further, we studied a single flooding event in this research, since it was a once-in-a-century flood that had a significant impact on the community. Further studies can explore other flooding events to test the generalizability of our findings. Specifically, we urge scholars to engage with social media use in emerging economies and low-income countries during disasters, so that more context-specific research can be produced, along with ensuring that findings of the research are practically relevant to the highly climate-vulnerable communities in these locations. We also acknowledge that, despite the growing use of social media platforms, there exist various limitations with using social media data, such as self-selection bias, misinformation content, and technical challenges that analytical models face in interpreting language nuances (Erokhin & Komendantova, 2024).

7. Conclusion

Social media has come to play a crucial role during natural hazards, often enabling critical information to be shared, as well as a space for affected communities to organize and process their emotions (Alexander, 2014; Arvandi et al., 2025; Su et al., 2025). Social media platforms are "critical conduits for capturing a wide array of voices from affected communities and provide a real-time pulse on societal impacts during crises" (Erokhin & Komendantova, 2024, p. 8).

In this article, we study social media discourse during the 2018 Kerala floods in India, identifying three main themes: collective trauma, rescue and relief, and donations, which broadly map the functional utility of social media for emotion processing, operational coordination, and resource mobilization during disasters, respectively. Operational coordination (rescue and relief) and resource mobilization (donations) were most actively retweeted during the peak days of flooding (August 15th to August 18th, 2018), while emotion processing (collective trauma) tweets were liked. This indicates a conscious attempt by users to share operational coordination-related information with their personal networks, in recognition of the importance of spreading that information, while showing solidarity with the collective trauma (emotion processing) tweets. Our study sheds light on how information is processed during a once-in-a-century flooding event, providing insights relevant to practitioners and academics of disaster risk reduction.

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