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# How does extreme weather impact the climate change discourse? Insights from the Twitter discussion on hurricanes

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## Abstract

The public understanding of climate change plays a critical role in translating climate science into climate action. In the public discourse, climate impacts are often discussed in the context of extreme weather events. Here, we analyse 65 million Twitter posts and 240 thousand news media articles related to 18 major hurricanes from 2010 to 2022 to clarify how hurricanes impact the public discussion around climate change. First, we analyse news content and show that climate change is the most prominent non hurricane-specific topic discussed by the news media in relation to hurricanes. Second, we perform a comparative analysis between reliable and questionable news media outlets, finding that unreliable outlets frequently refer to climate-related conspiracies and preferentially use the term "global warming" over "climate change". Finally, using geolocated data, we show that accounts in regions affected by hurricanes discuss climate change at a significantly higher rate than accounts in unaffected areas, with references to climate change increasing by, on average, 80% after impact, and up to 200% for the largest hurricanes. Our findings demonstrate how hurricanes have a key impact on the public awareness of climate change.

## Introduction

Discussions around climate change are pervasive across environmental policy [1–3], political debate [4], and public opinion [5]. Nonetheless, given the significant polarization around climate-change beliefs [6], more must be done to fully understand the factors which shape individual perspectives on this crucial issue. This challenge becomes all the more important in scenarios where attributing causality to climate change is complex, for instance in the case of hurricanes, where the role of climate change remains a contested matter [7, 8].

Understanding climate perceptions is important since there is evidence that people's attitude towards climate change is influenced by extreme weather. Previous studies have noted that both small and large variations in local weather temperature patterns can impact an individual's perception and discussion of climate change [9–11]. For example, evidence shows that individuals are more likely to express a positive sentiment towards climate change when temperatures exceed historic expectations, relative to when temperatures are below historic averages [12]. This shows how the evaluation of temperature changes can be influenced by factors such as memory limitations, and cognitive biases [13]. Commonly referred to as the "boiling frog" effect, this phenomenon suggests that an individual's perception of weather is primarily shaped by recent experiences rather than longer historical period. [14].

In this paper, we ask how the impact of a hurricane on a local area affects public attention towards climate change. Our analysis combines social media data from Twitter with a dataset of news media articles concerning hurricanes. Social media is known to play a pivotal role in facilitating climate discussions [6, 15–18], potentially contributing to growing polarization of views related to climate change [6], with users confined to climate-sceptic or pro-climate action echo-chambers [19]. These echo chambers attract politicians and users with opposed views, and often reference different news media outlets [20].

Twitter data, in particular, has proven useful for studying the public perception of climate change [21], specifically in relation to long-term changes in individuals' perceptions of climate-related hazards [22], and when exploring the connection between non-state climate action, public opinion formation, and climate governance [23]. The platform also provides access to location data which is useful for better understanding the differential impact of events, in this case hurricanes, at a regional level.

In terms of disaster management and response, policy makers consider the use of climate information crucial for effective decision making [24, 25]. Previous work suggests that Twitter data may contribute to this effort by providing valuable additional data in real time, as shown by studies on Hurricane Harvey [26], Hurricane Sandy [27], and the 2015 South Carolina flood [28]. By employing a data-driven approach, disaster managers and responders may effectively mitigate the consequences of such events and enhance residents' preparedness as the disaster unfolds.

There are of course limitations to Twitter analysis—users are not wholly representative of the general population—but the platform has a disproportionate influence on the views of politicians and journalists [29–33], making it a critical tool for studying how to mobilise climate action and respond to disasters.

These approaches complement traditional methods studying the news media who are known to play a critical role in the public understanding of, and attention towards, climate change [34, 35]. Research has shown how news media coverage of climate change has evolved over the years [16], particularly when discussing climate science or policy, with the personalization and dramatisation of climate news blamed for a lack of accurate and informative media coverage [36]. This is particularly problematic when discussing individual events where attribution to climate change is difficult, or where evidence for the role of climate change in driving, for instance, hurricanes is disputed [7, 8].

When we discuss hurricanes, it is known that people's opinions on climate change can change if they are directly affected by one [37]. However, how their views change depends on the social and political context of the individuals and communities involved [38]. Some studies have shown that politicians frequently do not accept the role that climate change plays in extreme weather or that little can be done to prevent such events. However, the public often blames governments for not doing enough to prevent or handle these situations [39]. Other factors known to affect climate perceptions include the recent COVID-19 pandemic: a study examining the social media discourse on climate change mitigation during the pandemic found an increase in climate action related tweets over time [40].

In this paper, we broaden the existing literature that considered only one, or a few, hurricanes by analyzing the 18 largest hurricanes since 2010 whose names have been retired. We choose this focus on hurricanes for two reasons. First, hurricanes are uniquely named and categorised, which allows for easy tracking and identification in Twitter content, unlike other extreme climate events where accurate labelling of data is harder. Second, because the attribution of hurricanes to climate change is disputed [7, 8], understanding how the public associate the two is of extra importance.

In the remainder of this paper, we first outline our three datasets: two Twitter datasets, totalling approximately 65 million tweets on climate change and on 18 of the most severe North Atlantic hurricanes from 2010 to 2022, and a dataset of news summaries which are referred to in the tweets about hurricanes. We provide a description of each dataset, and use a topic modelling approach to understand the themes discussed by the news media around hurricanes and climate change. In particular, we consider how content differs in its language depending on whether the news source is reliable or questionable. Finally, we reveal the local impact of hurricanes on the discussion of climate change using geo-located tweets, but reveal that there is a rapid decay in public attention in subsequent weeks. We end the paper by discussing our results and their implications for climate communication policies.

## Materials and methods

### Data

In this Section, we introduce three datasets related to hurricanes and climate change. The first dataset, collected using the official Twitter API, consists of all tweets containing a substring referring to any of the 18 hurricanes studied. For example, for Hurricane Sandy we collect all tweets with the substring "hurricane sandy" (case insensitive). We refer to this dataset as the *hurricane tweets* throughout the paper. In total, this dataset includes over 36 million original tweets (i.e. excluding retweets) posted by more than 6 million users between January 1, 2010 and December 31, 2021 whose names were retired, see Table 1. To avoid conflation between different events, we only study those hurricanes whose names have been retired. This ensures that keyword searches refer to a single unique hurricane and that the hurricanes studied are of enough impact to warrant analysis. We do not analyse content prior to 2010 due to a lack of meaningful tweet volume.

The dataset of hurricane tweets is primarily used to collect news articles of relevance to the hurricane discourse by identifying all the URLs in tweets which refer to known news domains. This results in over 240 thousand news articles which are discussed in the context of the 18 hurricanes studied. These news articles are used to perform the news media analysis and topic modelling described in Section Topic modelling.

Finally, our third dataset consists of all original tweets which include the substring "climate change", posted to Twitter from January 1, 2010 to December 31 2021. This dataset, referred to throughout the paper as the *climate change tweets*, totals over 29 million original tweets posted by over 4 million users. Approximately 2% of these tweets include geolocation data at the state level. This dataset is used to assess how the online climate discourse changes in the aftermath of a hurricane, both in the regions affected and in unaffected regions, see Section Hurricanes increase online discussion around climate change. It is important to note that we use this dataset which does not require explicit references to hurricanes in order to fairly assess whether the absolute volume of climate related content is changing relative to the pre-hurricane period.

All Twitter data was collected and processed between January 2022 and May 2022, before Twitter's change in management and rebranding as "X". Data remains accessible to

**Table 1. Number of tweets *in location* and *out of location* aggregated over one month before and after the impact of each hurricane.** The Damage column lists the cost of damages caused by each hurricane in US Dollars [52].

| Hurricane | In location (before) | In location (after) | Out of location (before) | Out of location (after) | Damage (billion USD) | Month |
|---|---|---|---|---|---|---|
| Tomas | 0 | 0 | 65174 | 71163 | 0.3 | Oct-Nov,'10 |
| Irene | 55 | 88 | 53210 | 77436 | 14.2 | Aug,'11 |
| Sandy | 109 | 507 | 89519 | 213982 | 68.7 | Oct,'12 |
| Ingrid | 18 | 30 | 122234 | 177436 | 1.5 | Sept,'13 |
| Erika | 184 | 205 | 281762 | 340991 | 0.5 | Aug,'15 |
| Joaquin | 54 | 78 | 346666 | 335414 | 0.2 | Sept-Oct,'15 |
| Matthew | 334 | 474 | 235957 | 265128 | 15.1 | Sept-Oct,'16 |
| Otto | 13 | 6 | 301822 | 318113 | 0.2 | Nov,'16 |
| Harvey | 483 | 1107 | 221326 | 344326 | 125.0 | Aug-Sept,'17 |
| Irma | 531 | 1086 | 237229 | 350830 | 77.2 | Aug-Sept,'17 |
| Maria | 170 | 71 | 333506 | 212094 | 91.4 | Sept,'17 |
| Nate | 25 | 19 | 307093 | 205139 | 0.8 | Oct,'17 |
| Florence | 54 | 65 | 187104 | 192252 | 24.0 | Aug-Sept,'18 |
| Michael | 310 | 624 | 180396 | 348129 | 25.1 | Oct,'18 |
| Dorian | 697 | 986 | 341384 | 473079 | 5.1 | Aug-Sept,'19 |
| Laura | 144 | 442 | 149860 | 282564 | 23.3 | Aug,'20 |
| Eta | 413 | 275 | 235765 | 219886 | 8.3 | Oct-Nov,'20 |
| Iota | 16 | 16 | 229882 | 211220 | 1.4 | Nov,'20 |

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researchers using the free Twitter API in accordance with Twitter's terms of service (see Data Availability). Data is provided as Tweet IDs, the same format used by existing Twitter studies, see for example [6].

## Topic modelling

To analyze the 240 thousand news articles referred to in the hurricane tweets we use a topic modelling approach. The topic modelling tool BERTopic [41] extracts latent topics from a group of documents. It is well suited for analysing Twitter data where tweets are documents from whose texts the model can derive coherent themes, due to its ability to generate a vector representation of sentences while preserving their semantic structure [42, 43]. BERTopic's contextual understanding (which n-gram models lack due to their focus on fixed-length word sequences), robustness to noise and variability, handling of polysemous words, hierarchical structure, and scalability make it a powerful tool for analyzing and extracting topics from tweets [41]. BERTopic creates document embeddings using pre-trained transformer-based language models. It then produces topic representations by clustering embeddings using a class-based TF-IDF procedure [44]. This tool has proved to be effective in classifying topics from Twitter posts [6, 45], including in relation to climate change [6].

Note that text cleaning before applying BERTopic is not explicitly required because BERT models are pre-trained on large corpora and have already learned to handle various types of textual data, including noise, special characters, and different writing styles. However, to avoid unwanted classifications we remove mentions, urls, and emojis in the text before passing the tweet as an input to BERTopic.

For each news article, we use NewsGuard, a media reliability assessor, to classify a news source as reliable or unreliable. NewsGuard editors analyze news outlets based on nine journalistic criteria [46]. These criteria are used to assign a reliability score to each news outlet between 0 and 100. Outlets with a score lower than 60 are considered unreliable. Reliability scores from NewsGuard are known to be broadly in line with scores from other media reliability providers [47].

Finally, to compare the language used by reliable and unreliable news sources when discussing hurricanes we used the Shiftiterator package [48]. This package creates word shift graphs that highlight which words contribute to understanding the differences between two texts. The comparison method is based on word frequency counts, and the proportion shift of each word is calculated by evaluating the probabilities that the word appears in each text.

Note, that our study does not consider the topics of the tweets themselves since their length and format complicate accurate and representative topic modelling, preventing a direct comparison between tweet and news media content. The required modifications to the topic modelling approach are out of current study's scope but may be considered for future work.

## Geolocated tweet analysis

To assess how discussions around climate change are affected by hurricane impacts, we use geolocation data provided in the Twitter metadata to count the number of tweets inside and outside the impact area of each hurricane in the period of a one month before the impact date and three months after it.

The geolocation data is provided by Twitter at the state level in the US as part of the tweet metadata. We find that approximately 2% of the tweets analyzed are geolocated in our dataset. Similar data, both self-reported and GPS located, has been used previously to understand the spatial dynamics of discussions, events, and trends occurring on the platform [49–51].

We define a tweet *in location* if it is geolocated in the state affected by a specific hurricane; we define it *out of location* otherwise. The areas of impact of each hurricane have been determined using [52–54]. As a result, we obtain for each day two distributions of the number of tweets for each hurricane for both the *in location* and the *out of location* regions. The two *in location* and *out of location* counts are normalised using the relative average number of tweets in the 30 days before the hurricane. Table 1 reports the counts for *in location* and *out of location* for all the hurricanes aggregated over one month before and one month after the impact respectively.

We analyse this data to assess how attention towards climate change varies before and after a hurricane impacts, in and outside the regions impacted. To compute statistics, we normalise counts for each hurricane and each day as

$$\hat{x}^{loc} = \frac{x^{loc}_{after} - c^{loc}_{norm}}{c^{loc}_{norm}} \tag{1}$$

where we indicate as $\hat{x}$ the fractional change in the tweet count after the impact ($x_{after}$) with respect to $c_{norm}$, the count normalisation on one month before the impact defined as

$$c^{loc}_{norm} = \frac{\sum_{day=1}^{30} x^{loc}_{before}(day)}{30}; \tag{2}$$

where $x_{before}$ represents the tweet count before the impact. The superscript *loc* indicates whether the count is for *in location* or *out location* tweets.

This estimator assesses the fractional change in the tweet count following a hurricane's impact. The methodology builds on principles of changepoint analysis [55] and characterizes the point in a time series where significant changes take place. By doing so, we uncover shifts in the underlying discussion of climate change when a hurricane impacts.

To fairly assess changes in online attention to climate change, we compare the aggregated tweet count to two different baselines. The first baseline, referred to as the "random baseline", is the count of the number of climate change tweets on 100 randomly selected dates within the time interval from January 1st 2010 to December 31st 2021. This baseline provides a general understanding of the climate change debate worldwide over the last 12 years. Results are robust using an alternative *extra hurricane* baseline: we select 15 non-hurricane dates to establish a baseline for tweet counts about climate change, by excluding a three-month period before and after each hurricane to avoid overlaps, see S1 Text. All counts using both baselines are normalised by the average tweet count from the 30 days prior to the selected date. For a statistical comparison of the changes in tweet count, we use the Students' *T* test [56].

## Results and discussion

### Hurricane-related news articles

We now analyse the news articles referenced in the hurricane tweets to better understand the topics discussed during, and in the aftermath, of a hurricane impact. To associate each article to a topic we train BERTopic on the hurricane news database, see Section Topic modelling. Fig 1A shows the top ten topics most covered by news articles in our dataset.

Fig 1A shows that climate change is the leading topic which is not specific to an individual hurricane. Hurricane specific news typically provides information on the regions impacted by the hurricane and the degree of damage caused. In the climate related news identified, we find

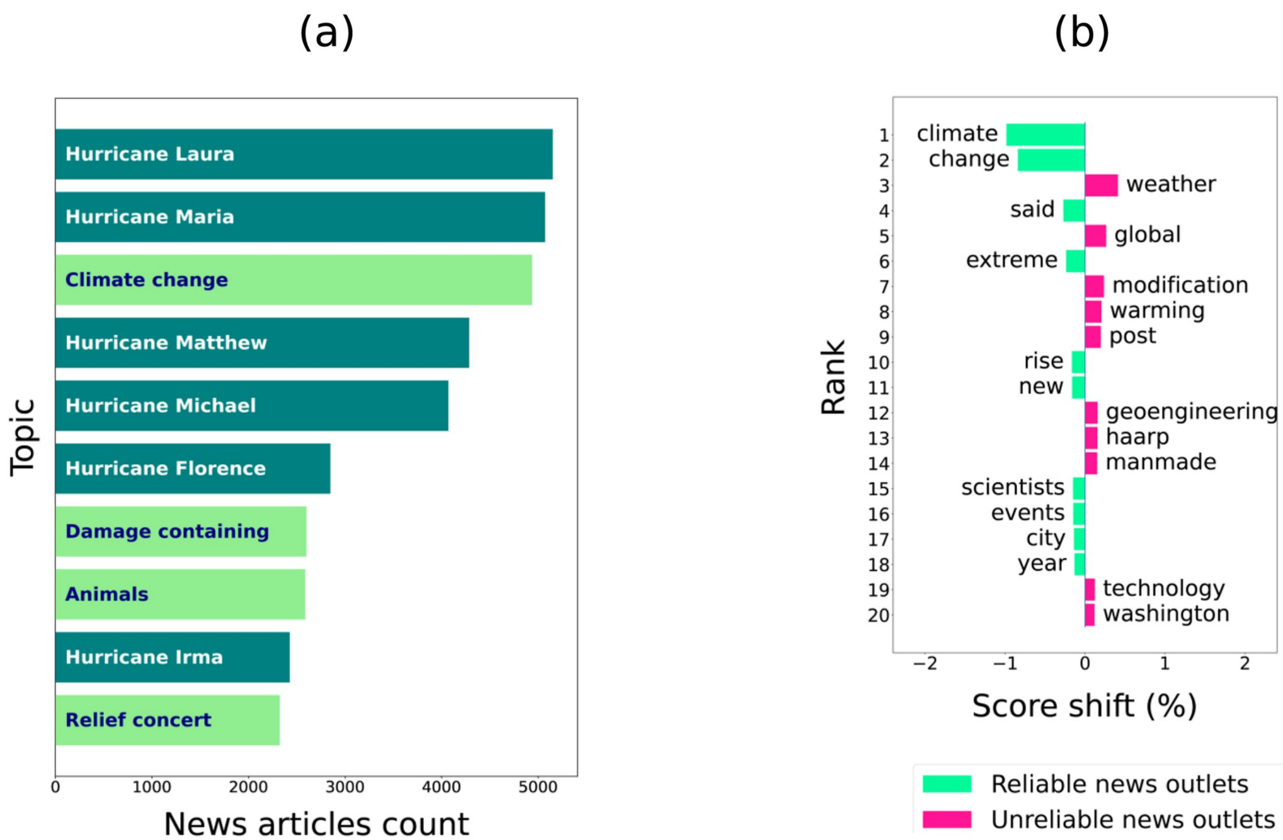


**Fig 1. Leading topics in hurricane related news articles, and key news terminology by reliability of the news sources.** Climate change coverage is among the most covered topics in news articles about hurricanes. (a) The most prominent topics in the news dataset. Dark green bars correspond to hurricane specific topics, light green topics are not specific to an individual hurricane. (b) The terminology used by reliable (green) and unreliable (magenta) media outlets in the news articles which fall under the "climate change" topic. Words are ranked in descending order by the relative frequency within the two sets. The score shift indicates whether the term is disproportionately used by reliable (left) or unreliable (right) news outlets.

https://doi.org/10.1371/journal.pclm.0000277.g001 that around 15% of news stories are from unreliable sources. Over time, the average NewsGuard score of the media outlets represented in this dataset is approximately stable, with little evidence that reliable or unreliable news sources are becoming more prominent, see S2 Fig.

We now analyse the relative importance of the terminology used by reliable and unreliable news sources by quantifying which words contribute to a pairwise difference between two texts. Fig 1B shows that reliable news sources disproportionately refer to "climate change", whereas unreliable news sources prefer terms such as "global warming" and "weather". This finding aligns with previous research that has associated the term "global warming" with hoax frames and less scientifically accurate content [12, 57]. Other studies have also found that climate sceptic content is prominent in the US, particularly in Republican states relative to Democrat states, and relative to the UK, Canada, and Australia [58].

In unreliable news articles (magenta), we find references to terms that are often used by conspiracy theorists (such as "modification", "geoengineering" or "haarp") to suggest that governments, or other powerful entities, are manipulating the climate for their own benefit [59]. These words sit in contrast to the terms used by reliable news sources such as "scientists", "report" or "study". The term "haarp" is of particular interest, referring to High-Frequency Active Auroral Research Program, the US civil and military installation located in Alaska, discussed principally following Hurricane Sandy [60].

Such conspiracy theories are important since they can influence public attitudes towards geoengineering [61]. These conspiracy theories have the potential to undermine trust in scientific experts and institutions, making it more difficult to build support for climate action.

## Hurricanes increase online discussion around climate change

We now assess how the discussion around climate change changes in regions impacted by a hurricane, relative to unaffected regions. We do this using the geolocated climate change tweets which, we note, do not necessarily refer to specific hurricanes.

We compare the distribution of geolocated tweets within the affected areas (the *in location*) and outside (the *out of location*) by normalising the tweet counts, see Section Geolocated tweet analysis. The change in the tweet count is compared to two random baselines, see Section Geolocated tweet analysis. Statistical analysis comparing the in-location and out-of-location change in tweet count to the baselines is provided in S1 Table.

Fig 2 shows the percentage change in the number of tweets after the hurricane impacts, with respect to the average of the number of tweets in the 30 days before, for the *in location*, *out of location*, and random baseline. For each curve, the shaded area corresponds to the standard deviation of the percentage change in the aggregated average tweet count across all hurricanes.

The biggest positive increase in tweet count is for the *in location* curve, an increase that peaks at around 80% in the first three weeks following impact, before decaying to 40% at the end of the three month follow-up period. We note that if we only analyse the largest hurricanes (measured in terms of USD damage) then *in location* tweets related to climate change can increase by up to 200%, see S4 and S5 Figs. This finding is supported by previous research [62], in which the authors concluded that the attention received by a storm is highly correlated with storm wind scale categories.

The *out of location* curve also increases following a hurricane's impact, with a stable increase in the following three months of around 20%. In general, the percentage change in the number of tweets about climate change right after a hurricane is significant; the *random* baseline in Fig 2, fluctuates but remains below 20% throughout. We stress that the *random* baseline may include dates that coincide with both the impact of hurricanes and other events

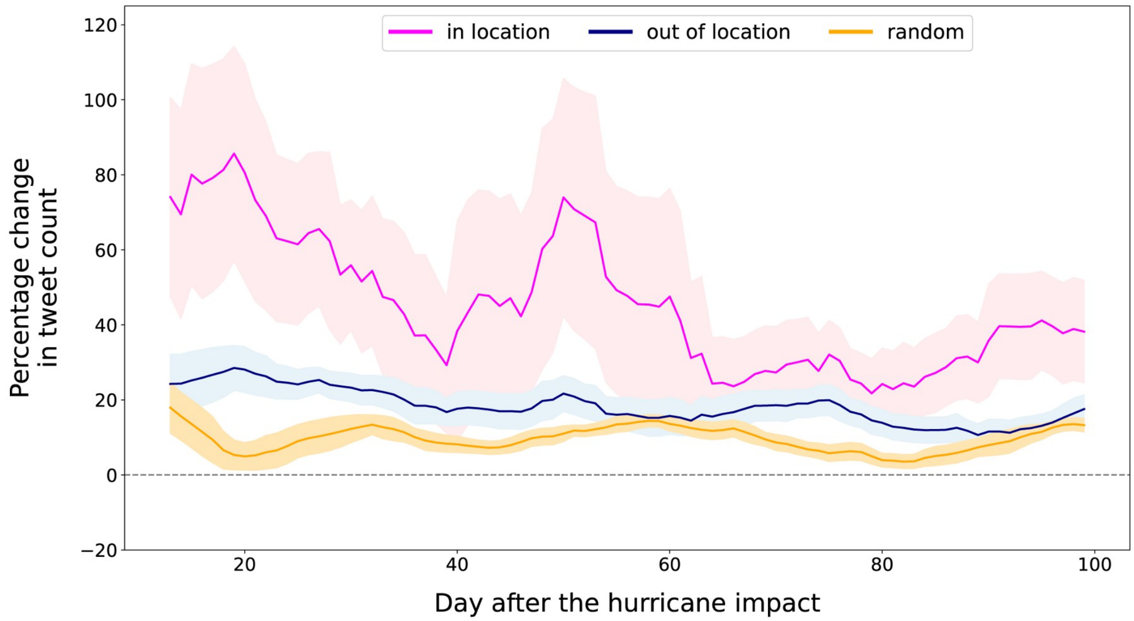


**Fig 2. The impact of hurricanes on Twitter attention towards climate change in affected and unaffected regions, relative to a random baseline.** We show the percentage change in the number of tweets after a hurricane impacts, with respect to the average number of tweets in the 30 days before the hurricane. We compare the *in location* (pink line) and the *out of location* curve (blue line) with respect to the *random* baseline (orange line). The shaded region around each curve is the standard deviations of the mean across all hurricanes.

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related to climate change. As a result, any variations in the baseline data may be attributed to these factors. However, our analysis reveals that these variations are small.

We note that for the number of *in location* tweets there is a reduction after a period of around 2 months. Indeed, the values for the three categories (*in location*, *out of location* and *random*) are comparable. The comparisons of the above distributions using the Students' T-test are shown in S1 Table. Based on the statistical test conducted, the results show that the *in location* distribution is significantly larger than the *out of location*, *random*, and *extra hurricane* baselines (see S1 Text). The *out of location* curve is also found to be significantly larger than both baselines.

## Conclusions

In this paper, we have explored the impact of hurricanes on the public attention towards climate change over the past 12 years. With respect to the previous literature on hurricane impacts and social media [38], we have studied a wider range of hurricanes, placing a particular emphasis on the spatial and temporal effects of a hurricane's impact. We have also considered the impact of news media reliability in relation to how they cover climate change following a hurricane.

Our analysis shows that hurricanes trigger a surge in the online discussion around climate change, as indicated by the increased use of climate change related terms in tweets and news articles following a hurricane. In regions directly affected by a hurricane, the number of climate change related tweets increase by 80% after impact, and up to 200% for the largest hurricanes. Note, however, that such an increase is limited both temporally and geographically, with a rapid decay in the public attention towards climate change after approximately two months. Our findings imply that the heightened public concern and focus towards climate change might be transient in nature, highlighting the necessity for ongoing endeavors to ensure continuous public engagement with the issue beyond the immediate aftermath of a hurricane disaster.

With regards to hurricane news coverage, the choice of terminology can signal the reliability of a news source and how it chooses to frame discussions around climate change [6, 57, 58]. In accordance with the findings of our study, it has been observed that trustworthy news outlets are more inclined to use the phrase "climate change" in their publications, whereas less credible sources have a tendency to favour the term "global warming" [57, 58]. Furthermore, references in unreliable news media sources to "HAARP"—a conspiracy theory asserting the US government's manipulation of weather through a radio transmitter—underscores how Twitter can be used to disseminate climate-related conspiracy theories and misinformation [61].

Media outlets with a climate sceptic agenda often prefer language which emphasises uncertainties in the science; such language comes under the broader set of themes often referred to as the "discourses of delay" [63]. Identifying such claims and studying their spread is becoming increasingly important given that recent evidence has shown that particular discourses related to political hypocrisy and inaction may offer a gateway into climate sceptic communities on social media for regular users [6].

There are limitations to our study which present opportunities for future work. First, our social media analysis is limited to Twitter. Previous work suggests that Twitter dominates other social media platforms in the online discussion around climate change [6], however, future work should consider how climate change is communicated on other platforms. Second, we have restricted our analysis to hurricanes when a discussion of other extreme weather events (e.g., droughts, floods, heatwaves) would be equally warranted. However, accurately retrieving data for such events which, unlike hurricanes, are not uniquely named is difficult. Third, our analysis only considers English language tweets referring to tropical storms in North America. Future work should consider storms in other parts of the world and should analyse non-English language content, and the role of social bots which a previous study showed contribute to approximately 16% of all tweets related to climate change [64]. Finally, our datasets are keyword-based which miss part of the relevant discussion around climate change and hurricanes. This is a common limitation in most Twitter-based communication studies, but extending analysis to a broader set of terms could be beneficial for furthering our analysis.

It is important to stress that Twitter users are not fully representative of the general public in terms of their demographics, interests, and behaviors. Many individuals effected by hurricane disasters will not be captured by the dataset, including, for example, those with limited internet access or occupied with the recovery effort in the aftermath of the disaster. Future work should attempt to account for these individuals using a wider range of data sources. However, the demographics captured by Twitter are still valuable, particularly given that Twitter perceptions have a strong impact on the perceptions of journalists and politicians [29–33].

The results of our study have policy implications for effectively curbing the spread of climate misinformation. The transient spike in climate change awareness that occurs in the aftermath of a hurricane suggests that efforts to counteract climate misinformation should be implemented proactively. Interventions activated only in the weeks following a hurricane may not garner the same level of attention as those executed immediately after a hurricane's impact [14]. This research also highlights that tackling climate misinformation on social media requires a detailed understanding of how climate content is consumed, not just how it is produced, and stresses that consumption behaviours can vary drastically between regions. These insights may prove valuable to policy makers during and in the immediate aftermath of a hurricane disaster, allowing for optimised communication strategies which maximise community engagement with disaster preparedness and response, and minimise the risk that individuals underestimate (due to misinformation or otherwise) the impact and damage of a disaster.

In summary, this research offers insights into how hurricanes influence the public's attention towards climate change and emphasizes the need for measures to maintain engagement in the months following a hurricane disaster.

## Supporting information

**S1 Text. The text contains two sections about topic modelling and statistical analysis.**
(PDF)

**S1 Fig. Count of original tweets mentioning (a) hurricane-themed news articles and (b) climate change-themed news articles in time.**
(PDF)

**S2 Fig. Percentage of reliable and unreliable news outlets individuated by Newsguard in time, alongside the average Newsguard score in time for our database of news outlets hurricane news.**
(PDF)

**S3 Fig. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane.**
(PDF)

**S4 Fig. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane.** We take into exam the 6 most disastrous hurricanes in terms of economic damages.
(PDF)

**S5 Fig. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane.** We take under exam on the 6 most disastrous hurricanes in terms of economic damages.
(PDF)

**S1 Table. Result of Students' T statistical test from the comparison of all the distributions shown in Fig 2 and S3 Fig.**
(PDF)

## Author Contributions

**Conceptualization:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi, Fabiana Zollo, Walter Quattrociocchi, Andrea Baronchelli.

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**Investigation:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi.

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**Resources:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi.

**Software:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi.

**Supervision:** Fabiana Zollo, Walter Quattrociocchi, Andrea Baronchelli.

**Validation:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi.

**Visualization:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi.

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**Writing – review & editing:** Maddalena Torricelli, Max Falkenberg, Alessandro Galeazzi, Fabiana Zollo, Walter Quattrociocchi, Andrea Baronchelli.

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