

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

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Supporting information

SI: Topic modeling

S1 Fig shows the number of tweets in time mentioning news articles whose content presents (a) hurricane-related topics and (b) climate change-related topics. The dotted lines represent the dates of the impacts of the 18 hurricanes under exam.

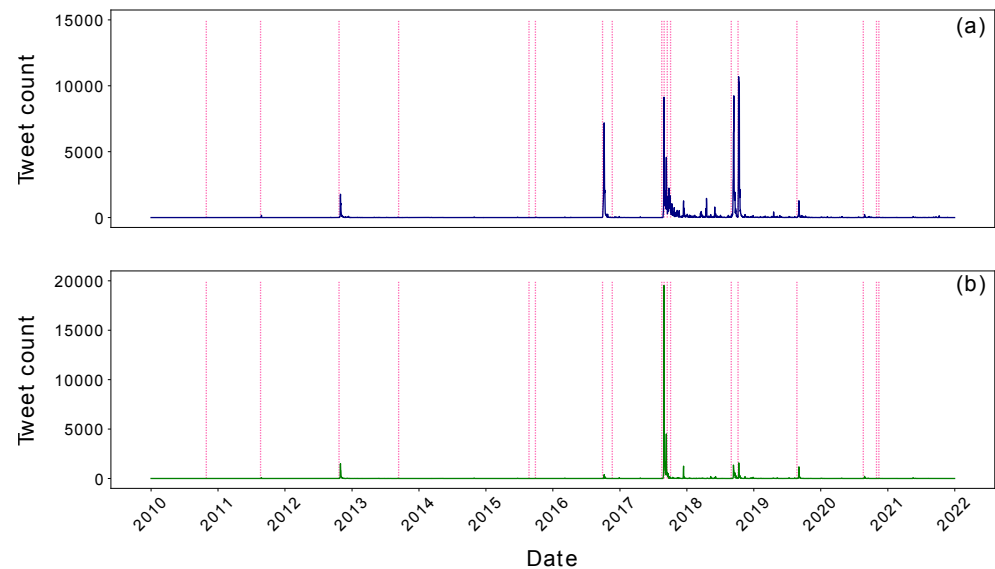


Fig S1. Count of original tweets mentioning (a) hurricane-themed news articles and (b) climate change-themed news articles in time. The dotted lines represent the dates of the impacts of the 18 hurricanes under exam.

The peaks of the counting of tweets mentioning news articles about hurricanes shared on the Twitter platform co-occur with the hurricane's impacts. The climate change-related tweets are still connected to hurricane impacts - even if the tweets count is inferior to the one sharing hurricane content -, especially in the occasion of the impact of the close impacts of four hurricanes in November 2017.

S2 Fig shows the number of reliable news outlets and unreliable news outlets in our *hurricane news* in time, alongside the general average Newsguard score in time.

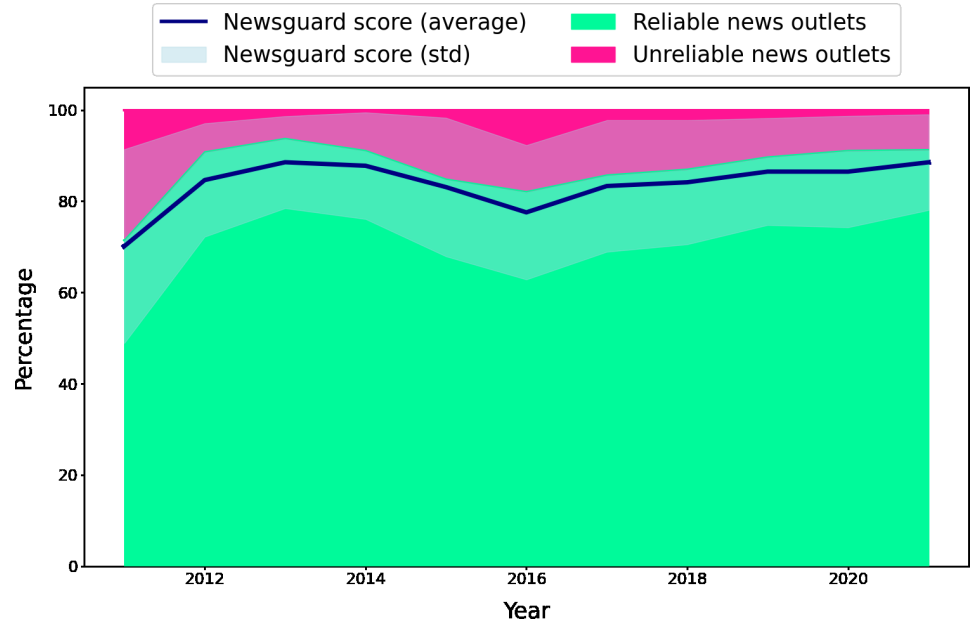


Fig S2. Percentage of reliable and unreliable news outlets individuated by Newsguard in time, alongside the average Newsguard score in time for our database of news outlets *hurricane news*.

We can observe that the fractions of reliable and unreliable news remained stable in time, such as the general average Newsguard score.

SI: Statistical analysis

In order to understand if there is an increase in public attention towards climate change in specific periods not affected by hurricanes, we also consider the various time intervals between one hurricane and another. To do this, we define a second baseline - the distribution of the number of tweets on 15 dates specifically selected to be non-overlapping with the dates of the impact of 18 hurricanes in our database. We select 15 dates to ensure that we have a sufficient number of non-hurricane periods to compare against our hurricane periods. We specifically choose dates within the 2010-2021 timeframe to ensure that they were relevant to our study. To avoid any overlap with the dates of the hurricanes in our dataset, we exclude a three-month period before and after each hurricane date. By selecting dates in this manner, we are able to obtain the maximum number of non-hurricane periods for comparison. This allowed us to obtain a comprehensive understanding of public attention towards climate change both during and outside of hurricane periods. These dates were selected to have a baseline that is not related to hurricanes at all. We will refer to this baseline as the *extra hurricanes* baseline. It is important to note that all counts in this baseline are

normalized by the average tweet count from the 30 days prior to the selected date. We show here the results of the comparison of the percentage change with respect to the *extra hurricanes* baseline.

S3 Fig 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 tweets posted in the area affected by the hurricane (pink curve) and the ones posted elsewhere (blue curve). The green curve represents the percentage change of tweets for the *extra hurricanes* baseline, with respect to the average of the number of tweets the month before the dates used in this baseline, specifically chosen to be outside the range of dates relative to hurricanes impacts.

The curves are the average for every two weeks after the hurricane across all the hurricanes, the shadow area around them represents the relative standard deviation.

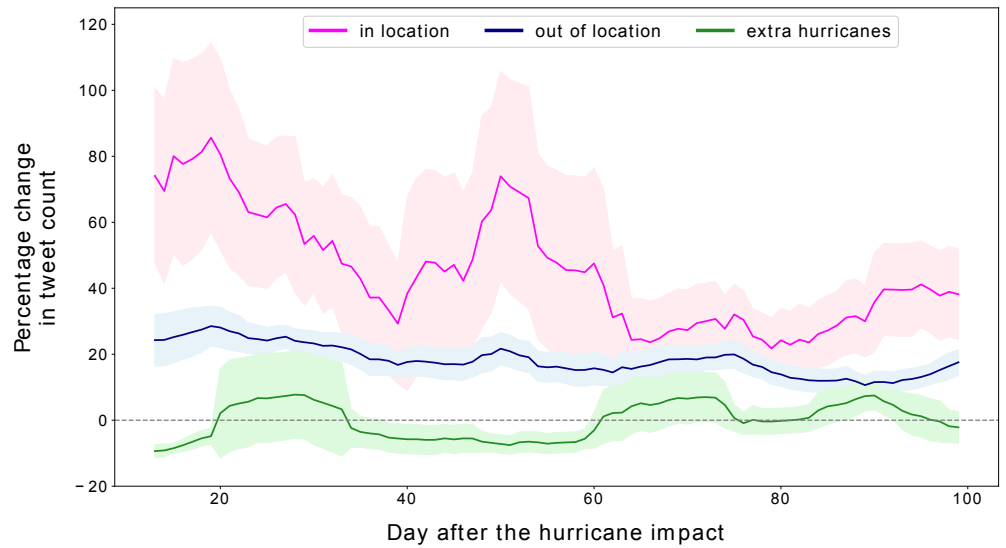


Fig S3. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane. We compare the *in location* and the *out of location* curve with respect to the *extra hurricanes* baseline (green). The shadow areas around the curves are the standard deviations of the mean among all the hurricanes.

The biggest percentage increase corresponds to the *in location* curve. In second place comes the *out of location* curve. We can state that the attention to the climate change debate is subject to a great increase in the areas where the hurricane hit, right after the impact, bigger than the one observed for the percentage change observed elsewhere. In general, though, the percentage change of the number of tweets about climate change right after a hurricane is significantly greater than with respect to random dates or after dates temporally distant from the impact- as we can observe from the comparison with the two baselines in S3 Fig.

The major differences between the tweet count *in location* and *out of location* are with respect to the tweet count *extra hurricanes*. It means that the hurricanes have a significant impact on the climate change debate on Twitter, provoking a big percentage increase with respect to the month before the impact - while from before to after the dates were specifically chosen to not overlap the hurricane impact dates this increase is not significant at all (as confirmed by results shown in S3 Fig).

As a general comment, we can say that the response to the impact of the hurricanes on Twitter is an increase in public attention towards the issue of climate change,

specifically in the places where the hurricanes hit.

S1 Table shows the p-values derived from the comparison of the four curves shown in Fig 2 and S3 Fig.

Comparison of distributions	T statistic	p-value
in location vs out of location	3.96	3.83e−4
in location vs extra hurricanes	6.79	6.61e−7
in location vs random	5.10	3.44e−7
out of location vs extra hurricanes	7.11	2.73e−5
out of location vs random	2.96	3.90e−3
random vs extra hurricanes	4.00	3.50e−4

Table S1. Result of Students’ T statistical test from the comparison of all the distributions shown in Fig 2 and S3 Fig. All the values under the 5% threshold allow us to reject the H_0 - hypothesis that states that the first distribution has a smaller mean than the second.

S1 Table shows that in the weeks near the impact, the increase in the tweet count *in location* is significantly higher than the one *out of location*. Moreover, the tweet count *in location* is significantly higher than the two baselines we provide - *random* and *extra hurricanes*. This result confirms what we find in Fig 2 and S3 Fig.

We present here the result for the robustness check for the analysis of the percentage increase discussed in Section **Hurricanes increase online discussion around climate change**. We take into account here only the 6 most impacting hurricanes in terms of economic damages, that are, in descending order, Maria, Irma, Sandy, Michael, Laura, and Matthew - see Table 1.

We analyse the percentage change for these hurricanes which caused the most costly damages, to ascertain its consistency with the result we find for all the hurricanes. S4 Fig and S5 Fig show the percentage change of *in location* and *out of location* tweets with the *random* and the *extra hurricanes* baseline respectively.

We can see that the *in location* and the *out of location* percentage change is always higher with respect of the baselines, as shown also in Fig 2 and in S3 Fig.

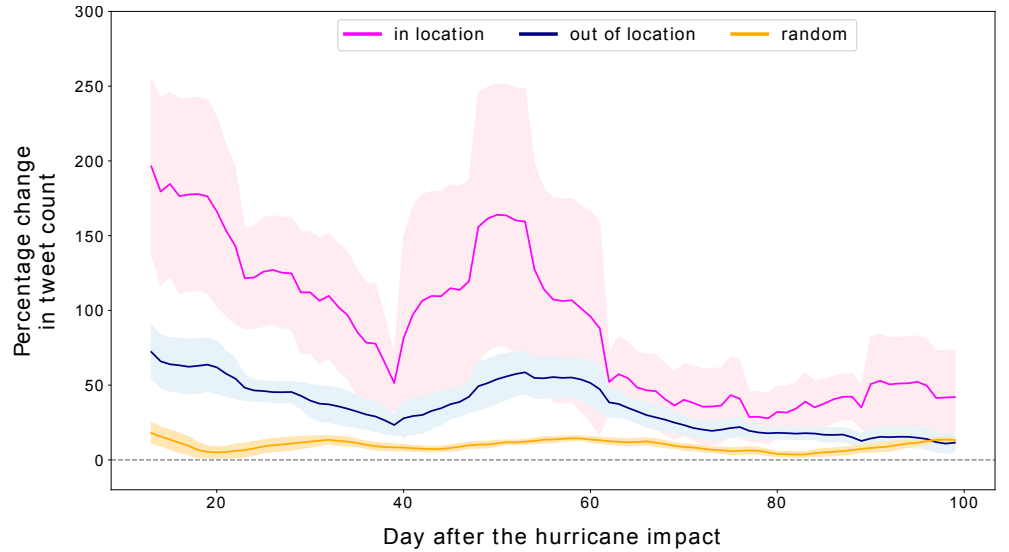


Fig S4. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane. We take into exam the 6 most disastrous hurricanes in terms of economic damages. We compare the *in location* and the *out of location* curve with respect to the the *extra hurricanes* baseline (green). The shadow areas around the curves are the standard deviations of the mean among all the hurricanes.

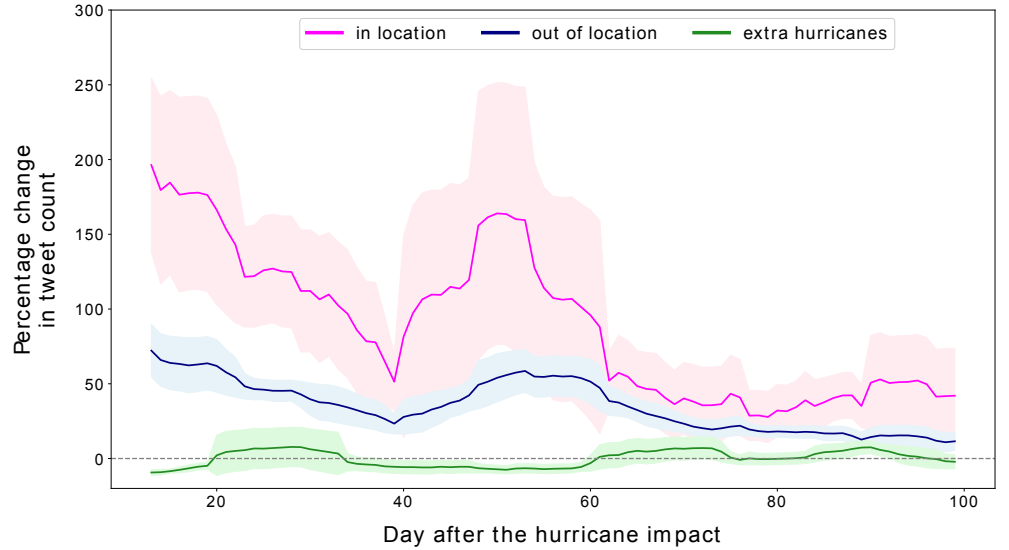


Fig S5. Percentage change in the number of tweets after the hurricane, with respect to the average of the number of tweets in the 30 days before the hurricane. We take under exam on the 6 most disastrous hurricanes in terms of economic damages. We compare the *in location* and the *out of location* curve with respect to the the *extra hurricanes* baseline (green). The shadow areas around the curves are the standard deviations of the mean among all the hurricanes.