Reviewer 2

Urban flooding is a hot issue in the world. There are still many challenges in urban flood emergency response, one of which is collecting the timely flooding information. This research demonstrates a technological workflow to get flooding information from social media and deeply mine valuable information from them. It's doubtlessly a good try, though there is still a long way to put it in practical use. Here are some specific comments and suggestions as following.

Response: We appreciate the reviewer for the suggestions. Below are our response point by point.

About the introduction section:

The introduction section seems a little logically weak and needs a better organization. For example:

(1) The content in the first paragraph seems a little far away from the research topic. I would like to introduce the topic directly from urban floods in the world, and then explain why we need to get data from social media for urban flood emergency management and what the difficulties are.

Response: Thanks for the comments. The first and second paragraph was revised to introduce the background of worldwide urban flooding disaster and the necessary of applying social media data for flood emergency management. This section has been re-organized as follows:

Cities are concentrated with population, infrastructures, as well as socio-economic activities, thus they are susceptible to flooding. World's urban population growth, increasing trends in extreme precipitation and conservative underground stormwater infrastructure all exacerbate urban flooding in frequency and severity (I.P.C.C, 2021), such as 2021 Henan flooding (Chik and Xue, 2021) and 2021 London flooding (Greater London Authority, 2022). Developing a better knowledge of the spatiotemporal patterns of how the general public responds to a weather extreme event is a critical step in reducing damage and increasing urban resilience (Loo and Leung, 2017; Zou et al., 2018; Fang et al., 2019; Wang et al., 2020). Unfortunately, during and shortly after a disaster, limited information is available about the extent and consequences of urban flooding. Traditionally, Remote sensing from satellite is a method to provide flooding snapshots. However, it has several constraints. Firstly, remote-sensing imagery, especially high-precision and processed data, is expensive and not readily available (Di Baldassarre et al., 2011). Secondly, it usually has a 48-72 hours delay of the actual flood event due to orbital and weather conditions, making the data not timely enough (Schumann et al., 2009; Havas et al., 2017). Thirdly, post-processing is essential for remote assessments, such as removing the back-ground noise and vegetation effect, which is time-consuming (Grimaldi et al., 2016; Assumpção et al., 2018; Wang et al., 2016). As all social groups can join in the real-time search, sharing, and self-publishing of material relevant to urban flooding, the freeness, timeliness and availability are clearly advantaging of social media data compared to traditional flood data sources (Guan and Chen, 2014; Havas et al., 2017). Social media data can serve as a source of information for flooding relief as well as a significant data source for urban flooding risk assessments (Wang et al., 2016).

For the difficulties to collect and apply social media data, it was introduced in detail in the rest part of the Introduction (3-6 paragraphs). There are two main difficulties. First, filtering and identifying valuable urban flooding data from the huge-volume and informal social media messages posted continuously are challenging. Second, utilization of social media data is generally restricted due to the inherent issues of social media data, such as the lack of validation, and the biased demographic composition of users. The integration of social media data with other traditional data, like radar precipitation, public facilities data, and census data, is expected to provide additional information and raw scientific conclusions.

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(2) At the beginning of the second paragraph, it would be better to state the urban flood situation in a worldwide view, not only from China, because urban flooding is a worldwide hot issue. China can be used as one of examples.

Response: Thanks for your advice. The second paragraph has been revised to describe the worldwide urban flooding situation as background.

(3) The traditional observation methods are mentioned as "costly, delay and time-consuming" methods in Line 57. But discussion about the traditional observation methods seems insufficient. It would be better to give more discussion on what kinds of traditional observation methods there are and how costly, delay and time-consuming they are before Line 57.

Response: The traditional observation method mentioned here is remote-sensing imagery. It has several constraints. Firstly, remote-sensing imagery, especially high-precision and processed data, is expensive and not readily available (Di Baldassarre et al., 2011). Secondly, it usually has a 48-72 hours delay of the actual flood event due to orbital and weather conditions, making the data not timely enough (Schumann et al., 2009; Havas et al., 2017). Thirdly, post-processing is essential for remote assessments, such as removing the back-ground noise and vegetation effect, which is time-consuming (Grimaldi et al., 2016; Assumpção et al., 2018; Wang et al., 2016). Therefore, the method is *"costly, delay and time-consuming"*. More detailed discussion of the tradition method has been added in the first paragraph.

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(4) Line 45 seems to indicate that the existing researches use the unified format data. If there are unified format data, why do we need to use the unformatted data from Weibo and Tiktok? Please give more explanations about it. It would be better to give more details about the existing researches on utilizing the social media data for flood emergency management. What have they done and what are their limits?

Response: Thanks for the suggestion. The unified format data here refers to categorizing flooding data from open source platforms. There are some dedicated platforms actively collecting and proliferating flooding information with time, location, account, the coordinate system. For example, PetaJakarta, an open source flood map of Jakarta, Indonesia to share real-time flood information based on Twitter; Twitter Alerts, a platform allows public report disaster situations with unified format. Due to the formalised massages, these data can be collected and applied easily. Unfortunately, these data are limited due to low participants and the platform cannot be directly transferred to the areas where we expect to collect data. Therefore, we develop an effective approach in this study, aiming to effectively identify and filter valuable data from colloquial and informal messages, and an application to a Chinese city based on social media of Weibo and Tiktok is performed.

More details about the researches and their limits were added in the third paragraph in the revised manuscript.

Based on social media data or a combination of social media data and traditional data (mainly remote sensing imagery), some researchers have conducted study on the analysis and prediction of the impacted area during flood events and flood risk management. Yu et al. (2016) apply public reported data operating by government as validation data of an extreme storm event in Shanghai and capture the broad patterns of inundated areas at the city-scale. Baranowski et al. (2020) analyze atmospheric phenomena responsible for floods on Sumatra based on governmental reports and crowd-sourcing data based on Twitter messages from 2014 to 2018. Besides, some open source platforms, actively collecting and proliferating storm-flooding information with time, location, account, the coordinate information, have been applied to generate urban flooding maps and engage in urban flooding response, such as "PetaJakarta", "Twitter and Flickr", "Tweak the Tweet", "Twitter Alerts", "GeoFeedia" (Thumerer et al., 2000; Eilander et al., 2016; Jongman et al., 2015; Sun et al., 2016). However, a majority of the existing studies focus on urban flooding adopting officially initiated crowdsourcing data, which are usually in a unified format. Unfortunately, these data are limited due to low participants and similar system to integrate storm-inundated related information are not organized based on other popular social media. These platforms remain critical for sharing disaster information, and there is a wealth of effective flooding data waiting to be harvested, particularly for Chinese cities. It is worthwhile to consider how to use these unstructured data effectively.

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(5) From Line 57, two research questions are listed. There might be one more question: how are the data from social media validated before they are used? Or what are the uncertainties when they are used? Please give a little more statement about it.

Response: Thanks for the comments. The uncertainty of social media data is mainly considered from two aspects. For the reliability of volunteers, the detailed local flooding information is a criterion to identify; simply indicating that a specific location is submerged without providing photos, videos, or detailed descriptions, such as submerged ankle, is not considered as flood-points data. And a buffer area is applied to reduce the uncertainty of the coordinate. The workflow of data pre-processing also reduce the uncertainty from semantics. Although these methods cannot guarantee the quality of all the social media data, they can still provide an additional data reference for flood management and simulation in data-scarce cities.

About Table 2:

(1) Table 2 seems a little confusing. Usually the first row is the header which defines the content of each column, and each column has contents matching with the header. In this table, row 5 seems like a new header, and row 7 doesn't seem to match either headers. It would be better to reorganize this table.

Response: Thanks for the comments. The table 2 has changed as follows for clearer expression.

	Hourly analysis				Daily analysis
Time lag (h)	Integration	Storm 1	Storm 1 filtering	Storm 2	Integration
0	0.0835	0.0444	0.2493	0.1454	
2	0.0784	0.0994	0.3028	0.0861	
4	0.2041	0.3213	0.5472	0.128	
5	0.2621	**0.3646**	**0.5889**	0.215	
6	0.2553	0.2753	0.4636	0.268	**0.6287**
8	0.2373	0.2472	0.3589	0.3169	
10	0.3445	0.3040	0.4039	0.3601	
12	0.4084	0.2772	0.3864	0.4713	
14	0.4416	0.2428	0.2559	0.5653	
16	**0.5126**	0.2701	0.1771	**0.6862**	

(2) More explanation about time flag in Table 2 would be better. Does it mean: the Pearson correlation coefficient between the hourly precipitation and the hourly tweet number with a certain time lag? If it

does, please specifically clarify the hours of precipitation and hours of tweets analyzed during calculating their Pearson correlation coefficient.

Response: Yes, the time lag is mean to calculate Pearson correlation coefficient for hourly series considering certain time lag between precipitation and tweet number. Specifically, for 0h time lag setting on integration hourly analysis, Pearson correlation coefficient is calculated between the precipitation and the tweet number from 00:00 10th to 24:00 18th. For 2h time lag setting on integration hourly analysis, Pearson correlation coefficient is calculated between precipitation from 00:00 10th to 22:00 18th and tweet number from 02:00 on 10th to 24:00 on 18th. The rest follows the same rule. The specific clarification was added in description of table 2.

(3) Line 212 describes Storm 1 filtering as by excluding relevant discussions. Please give more explanations on how relevant discussions are identified in a huge number of tweets.

Response: Relevant discussions under this context refer to the hot topics that deviate from the rainstorm events. Identification of the hot topics relies on screening through the social media messages. During the studied event, "Dama" playing mahjong was the main relevant discussions, which include two types. The first one is reposted tweets based on the forwarding of the original Weibo video of this hot news (http://t.cn/A6UCsJ7B). They are easy to identify and all the tweets with the video address are filtered. The second one is origin tweets without forward of the Weibo video. These data are determined by the keywords "Dama" and "play mahjong".

About Table 4.

It might be more figurative to transpose this table by placing the check-in data and flood-point data for one district in one row in order to give a better comparison.

Response: Thanks for the advice. We have revised the table as follows.

District	Check-in data No.	Flood-points data No.	Check-in data %	Flood-points data %
Xinjin	24	3	0.69	1.29
Shuangliu	656	33	18.94	14.22
Longquanyi	289	13	8.35	5.6
Central urban	1772	112	51.17	48.28
Wenjiang	152	6	4.39	2.59
Chongzhou	22	1	0.64	0.43
Qingbaijiang	32	1	0.92	0.43
Pidu	219	16	6.32	6.9
Xindu	161	13	4.65	5.6
Dujiangyan	32	2	0.92	0.86
Pujiang	10	2	0.29	0.86
Qionglai	5	2	0.14	0.86
Jianyang	16	1	0.46	0.43
Dayi	7	2	0.2	0.86
Jintang	37	25	1.07	10.78
Pengzhou	29	0	0.84	0

About Section 4

Some contents in Section 4 seem a week relation with the results of this research. For example:

(1) In Section 4.1 the author seems to discuss the value or the role of social media for various stakeholders. It's a fact, but not a result of this research. It might be better to use this content to develop the necessity of this research in the introduction section.

Response: Thanks for the comments. We agree that part of the section 4.1 is a fact of the value for various stakeholders. However, we have also performed discussion and extension of results section from the lens of social media data based on the previous spatiotemporal analysis. For example, severe inundation areas can be spotted quickly by temporal evolution analysis of related topics, which can help to better coordinate/ deploy the rescue resources to the public's needs promptly. And as focusing on VIP accounts greatly improving flood-points identify efficiency, these accounts can get higher credibility weights in flood risk management system incorporating social media. Besides, some suggestions and prospects are given to all parties based on the previous analysis. Therefore, the section 4.1 was streamlined. Considering the comments below for section 4.3, we will merge 4.1 and 4.3 into the last section of the Discussion.

4.2 Recommendations and duties of stakeholders from the lens of social media data

Social media platforms are a reliable and usable resource throughout the flood lifespan. According to the spatiotemporal study above, recommendations and duties of stakeholders from the lens of social media data are analysed from three aspects: flooding-affected people, rescue agencies and the government. For flooding-affected people, social media can provide more opportunities to communicate with the outside to obtain a greater sense of security. People can publish first-hand flood information in near real-time to those outside the impact zone and rescue organizations, which is of great value to help timely warning and rescue. For formal rescue agencies, flood-point data filtered from the check-in data have great guiding significance during flooding. The general public reactions can be spotted quickly by temporal evolution analysis of related topics, which can help to detect severe inundation areas and better coordinate/ deploy the rescue resources to the public's needs promptly. Besides, rescue operations can be supported by the in-time detailed information from social media, such as coordinated information, the depth and area of inundation area and the status of the trapped people through pictures or videos.

For the government, that would be valuable to incorporate flood information posted on social media platforms into flood risk management processes. Effective information management and easily accessible communication practice play a key role to identify urban flooding risk and to capture public responses (Unisdr, 2009). Similar to Twitter, and Flickr, it is responsible for government to promote more standardized and formalized system to collect and proliferate storm-flooding information with a prescriptive syntax and generate urban flooding maps based on Weibo and other social media platforms. And as VIP accounts can greatly improve flood-points identify efficiency, these accounts can be provided higher credibility weights. Furthermore, social media collaboration with map services companies and meteorological departments should be facilitated to integrate real-time rainfall, transport, urban flood information and other relevant data into real-time digital maps (Loo and Wang, 2017). Besides, the emerging topics during and after the rainstorm can also serve as a reference for the direction of essential safety education by the government. For example, the hot discussions of the news in Chengdu such as Dama playing mahjong in the storm and swimming on the flooded avenue demonstrate the lack of public crisis awareness facing urban flooding.

Reference

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(2) Section 4.3 is titled as "comparison with other platforms and countries". I would like to make comparison just between researches, weakening the idea of countries. Furthermore, the content in this

section seems like the progress of other similar research. Is it possible to put it in the introduction section as existing research progress?

Response: Thanks for the suggestion. The progress of other similar research of this part is modified to weak the idea of countries and is put in the introduction section in second paragraph. The rest part that the recommendations for decision makers in Section 4.3 is revised and integrated into Section *4.2 Recommendations and duties of stakeholders from the lens of social media data*.

(3) Section 4.2 gives a good example of deeper mining of the value of social media data. It might be better to focus on this example and give more details about it in Section 4.

Response: We agree with the reviewer. For flood modeling and validation part, we will present more detailed information about the data input, the model and its setup. The quality of simulation results and social media data will be discussed to explore social media data application in data scare cities.

Others

Some other minor questions or suggestions are seen in the manuscript.

Response: Appreciate for the comments. They are revised in the manuscript with highlight.