Using GRACE mascon to Analyse the Behaviour of Terrestrial Water Storage Anomaly in 11 months Lead Time of Floods

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ABSTRACT

Extreme weather events are increasing in both frequency and intensity due to climate change. Among those impactful events, floods are often the deadliest natural disaster that kills people and damages economies. River runoff is commonly used as proxy for flood study; however, it is hard to apply when a flood does not occur in river basin. Here, I investigate the use of remote sensing technique to study hydro-metrological approach to flood. The Gravity Recovery and Climate Experiment (GRACE) mission collects gravity data and converted into GRACE mascon by Goddard Space Flight Center (GSFC). I used this data to analyse the behaviour of Terrestrial Water storage Anomaly (TWSA) in 11 months before the 15 deadliest flash flood events around the globe from 2004 to 2021. I grouped flood events by origin, magnitude, and duration of flood. I took the correlation coefficient (R-value) of TWSA for every pair of 15 events and averaged them to estimate correlation as a group. R-value for all 15 events was 0.0304, showing no correlation within groups. I repeated the same process for all subgroups and found one subgroup with positive correlation. While most of the subgroups showed no correlation, monsoonal rain showed 0.5880. This is significantly different from R-value of all 15 events ($p<0.01$). Thus, TWSA of monsoonal rain triggered flood events had the statistically significant pattern of TWSA behaviour in 11 months lead time of event occurrence. Although there might be a seasonal factor affecting the result, this study showed the possibility of generalizing TWSA behaviour for flood events.

KEYWORDS

Gravity Recovery and Climate Experiment (GRACE), flooding, Terrestrial Water Storage Anomaly, time series analysis, hydro-meteorology

INTRODUCTION

Over the last decades, extreme weather events are increasing both in frequency and severity, making it an urgent topic to be studied and discussed (Lubchenco and Karl 2012). Communities around the globe have been influenced and damaged by extreme temperatures, wildfires, droughts, and floods, which are in many cases suspected to be attributed to climate change (Dole et al. 2011, Samaniego et al. 2018, Zscheischler et al. 2018). Extreme events can have devastating effects, societally, economically, and ecologically (Min et al. 2011). For example, Hurricane Harvey in United States in 2017, accompanied by unexpected, and widespread floods, caused $125 billion damage and at least 88 fatalities (Houston Health Department 2017). Extreme events can affect mortality rates of a human population, as well as create insecurity and anxiety about the future (Deschênes and Moretti 2009, Konisky et al. 2016). Thus, understanding the characteristics of such events is critical to mitigating, predicting, and reducing the effects of events in the future.

Specifically, floods cause tremendous damage on ecosystems and human society (Bouwer 2019). Floods is the one of the most common natural disasters worldwide, and one of the disasters causing the most fatality (Driessen et al. 2016, 2018, FitzGerald et al. n.d., Tariq and van de Giesen n.d.). The floods can happen anywhere, including rural and urban settings. Despite there are hazardous areas shown by governments and other organisations, the unexpectedly huge floods occurred and caused damages to the society. Governments often produce flood hazard maps that attempt to predict areas that are at risk for flooding. However, most of these hazard maps are created according to predicted precipitation and elevation of the area instead of hydrometeorological aspects of the flood events. Hydrometeorological aspects such as Terrestrial Water Storage Anomaly (TWSA), deviation of all forms of water stored on and under the surface of Earth from its standard, may add another factor to those assessments. More research could be done, and it may provide deeper understanding of the mechanism of floods and help society to prepare for and respond to increasing flood events.

Many studies of floods are done from perspectives of precipitation and runoffs. (Min et al. 2011, Pall et al. 2011, Rogger et al. 2012, Davenport et al. 2021). However, Types of flood events can be determined by both precipitation and runoffs, and hydrometeorology (Nied et al. 2014). TWSA is also a critical factor in causing floods. Remote sensing of hydrological variables is emerging as a viable source of the terrestrial water cycle (Tang et al. 2009). Satellite remote sensing allows us to observe all aspects of the land surface, and these data inherently include the effects of human disturbances (Gao et al. 2010). Among the space borne sensors that provide data for water storage, data from the Gravity Recovery and Climate Experiment (GRACE) mission and its successor GRACE follow on, hereafter referred as GRACE, are unique in that the changes in TWS can be directly measured (Molodtsova et al. 2016); therefore, GRACE is suitable for studying global trend in TWSA. While river runoff data are limited to local use, GRACE data can be applied to any part of the globe. To differentiate GRACE and utilise its strong point, I focus on flash flood events, which are hard to predict by runoffs and often away from river basin.

My main research question is to investigate whether there is a statistically significant pattern of TWSA behaviour of TWSA in 11 months lead time of global flash flood events. To answer this question, I ask if 1) types of precipitation event triggered floods affect the behaviour of TWSA; 2) magnitude of floods affect behaviour of TWSA; 3) duration of floods affect TWSA. My hypothesis is to have linear increase before flood events in general. Also, I suppose that the rate of increase and time the increase start would be different for each factors influencing TWSA.

METHODS

GRACE Data Processing

The Gravity Recovery and Climate Experiment (GRACE) mission and its follow-on mission are programs by NASA. It was first launched in March of 2002 (Greicius 2013a). GRACE and its successor GRACE follow-on are here after referred to as GRACE. GRACE accurately maps variations in Earth's gravity field. According to NASA’s article, GRACE consists of two identical spacecraft that fly about 220 kilometers apart in a polar orbit 500 kilometers above Earth. GRACE maps Earth's gravity field by making accurate measurements of the distance between the two satellites, using GPS and a microwave ranging system (Greicius 2013b). Among many products from GRACE, I will use data called “NASA GSFC global mascon solution” in this study, and I refer to this as GRACE mason. This product is provided by Goddard Space Flight Center

(GSFC), NASA's center critical for carrying out NASA's missions of space exploration and scientific discovery. The data processing is already done by GSFC to remove any data disruption done by earthquakes and other geological events (Loomis et al. 2019). However, there might be some small gaps of data due to events such as new satellite launch. A study showed an approach that could be effective for future forecasting and data gap correction (Long et al. 2014). However, I did not employ it in this study because I was not looking for long duration data. The special and temporal resolution of GRACE is 1 arc and monthly, and the size of each mascon is about 12000 square kilometers with monthly resolution (Loomis et al. 2019). Despite of its coarse resolution, GRACE data is effective for this study since it allows us to study Terrestrial Water Storage Anomaly (TWSA) of the whole globe.

EM-DAT Data Processing

The Emergency Events Database (EM-DAT) is the international disaster database maintained by the Centre for Research on the Epidemiology of Disasters, CRED, at the School of Public Health of the Université catholique de Louvain located in Brussels, Belgium (CRED. 2021). EM-DAT has data about natural disasters since 1900. It includes natural, technological, and complex disasters. For my study, I will use Natural disaster data since 2004 and I will filter through this database to identify major flood events worldwide. It is useful for this study because the data is global scale. Also, each major flood event includes data on location, start date, end date, area, casualties, economical impact, and so forth.

Flood Events of Interest

There were 3158 flood events recorded in EM-DAT from 2004 to 2021. I selected 15 events of interest for my study. Some flood events have incomplete data. Among all the available events, I only used flood events that are flash floods and have data in total death, disaster magnitude, latitude, longitude, start/end year, month, and day. I selected top 15 events that caused the most death to analyse for general behaviour of TWSA in 11 months lead time of flood events occurrence.

Table 1. Summary of selected flood events. Data was downloaded form EM-DAT and only required data are extracted.

#	Events	Origin	Dis Mag Value	Dis Mag Scale	start	stop	Duration
1	India, June 2008	Monsoonal rain	350600	Km2	11-Jun	21-Jul	40
2	Ethiopia, May 2006	Heavy Rain	4225	Km2	5-Aug	8-Aug	3
3	Afghanistan, Apr 2014	Torrential rain	83722	Km2	24-Apr	2-May	8
4	North Korea, July 2006	Monsoonal rain	55620	Km2	12-Jul	20-Jul	8
5	Indonesia, June 2006	Heavy rains	3100	Km2	19-Jun	23-Jun	4
6	India, Aug. 2010	Heavy rains	145000	Km2	6-Aug	8-Aug	2
7	Chile, Mar. 2015	N/A	154773	Km2	25-Mar	8-Apr	14
8	Afghanistan, Nov. 2006	Heavy rains	5000	Km2	16-Nov	20-Nov	4
9	India, June 2007	Monsoonal rain and tropical cyclone	449300	Km2	22-Jun	4-Jul	12
10	Thailand, May 2006	Monsoonal rain	78280	Km2	22-May	11-Jun	20
11	The Philippines, Dec. 2010	Continuous rains due to tail-end of a cold front	10773	Km2	24-Dec	25-Jan	32
12	Burundi, Feb. 2014	Heavy rains	3237	Km2	19-Feb	10-Mar	19
13	Algeria, Oct. 2008	Heavy rains	34760	Km2	1-Oct	17-Oct	16
14	Pakistan, Apr. 2016	Heavy rains	111748	Km2	2-Apr	8-Apr	6
15	Yemen, Oct. 2008	Tropical storm (level 3)	133200	Km2	23-Oct	24-Oct	1

Analysis

I used MATLAB for all my analysis (*MATLAB* R2021b Update1 (9.11.0.1811744). 2021). First, I removed monthly seasonality to create seasonally stationary data. Removing the seasonal components from the time series would remove the reoccurring pattern from dataset and give cleaner signals of change. Each data processing was done for each GRACE mascon. Then, I extracted appropriate mascon for each flood events according to their latitude, longitude, and day of event occurrence, and plotted them from 11 months lead time of the events to 2 months after events. To find the general behaviour of TWSA shared by all 15 events, I conducted correlation coefficient analysis for every possible pair of floods. R-value only showed correlation of a pair of floods; hence I took mean of them to estimate the correlation as a group. Furthermore, I grouped 15 events by origin, magnitude, and duration to see if there are stronger correlation within smaller subgroups.

Grouping flood events of interest by their origin

Origin is the rainfall event that triggered each flood and was provided in EM-DAT data. According to the frequency within 15 events of interest, I made three subgroups: monsoonal rain, heavy rain, and others. Others included tropical storm, for example.

Grouping flood events of interest by their disaster magnitude

Disaster magnitude is the area that are affected by flood events and was provided in EM-DAT data in unit of square kilometers. I made three subgroups according to spatial resolution of GRACE and GRACE mascon. First subgroup was x =<6000 km2. 6000 km2 is about a half of one mascon size. I supposed that it might be too small for GRACE to detect change in TWSA if an event was smaller than 50% of mascon size. Second subgroup was 6000km2 < x =< 132000km2. 132000km2 is about a half of spatial resolution of GRACE since 22 mascons (264000km2) approximately defines the spatial resolution according to Loomis et. al. in 2019. Third subgroup was x > 132000km2 which is larger than 50% of GRACE resolution.

Grouping flood events of interest by their duration

Duration is the time that the area affected was under inundation. I calculated it using start day and end day provided in EM-DAT data. For duration, I made three subgroups according to temporal resolution of GRACE and frequency of events. First subgroup was x =< 1 week. One week is 25% of GRACE temporal resolution, however, since the frequency of less than two weeks were high, I decided to separate events less than two weeks in to two subgroups. Second subgroup is 1 week < x =< 2 weeks. Two weeks was 50% of GRACE resolution. Second subgroup is separated from the first subgroup because of its frequency. Third subgroup is 2 weeks < x. I expected that events more than 50% should be enough for TWSA to be recorded.

For every subgroup, I repeated correlation coefficient analysis to see if there were stronger correlation within smaller groups, and I plotted them in boxplot. To show the difference from all 15 events, I conducted t-test between the mean R-value of all 15 events and each subgroup to show significancy in difference.

RESULTS

Analysis

I found that there is one subgroup that has a statistically significant pattern of TWSA behaviour, although I did not find any general behaviour in 15 events of interest. Of 15 events, the R-value varied from 0.8695 to -0.8534, and its mean was 0.0304 (Figure 1).

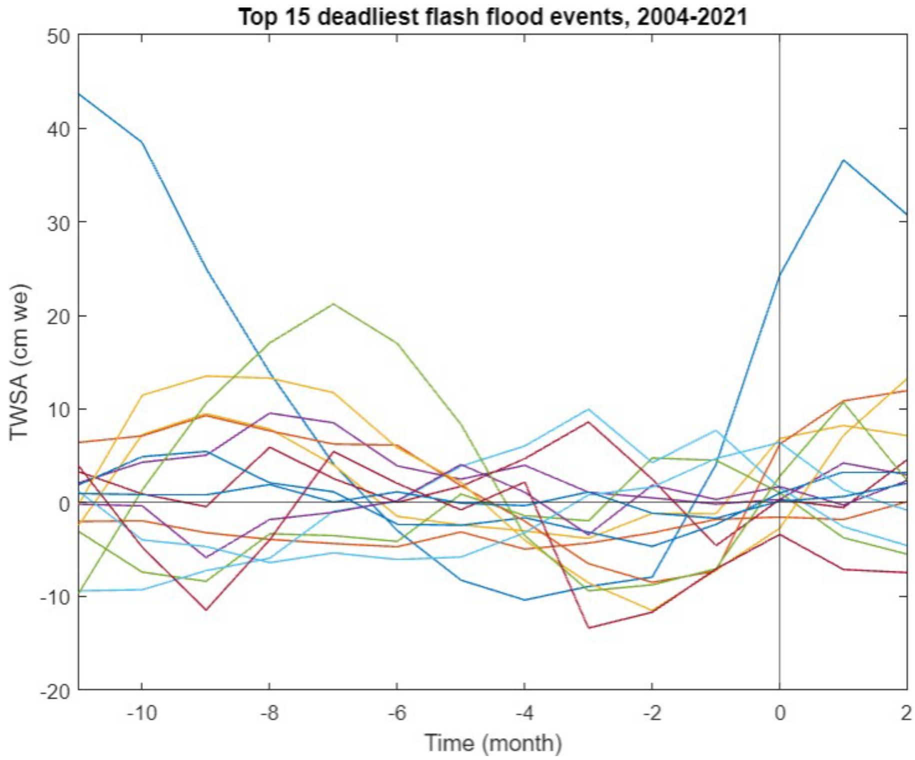

Figure 1. TWSA of the top 15 deadliest flash flood events from 2004 to 2021 are shown in one figure. Each colour represents each 15 flood events. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

Grouping flood events of interest by their origin

I grouped 15 flood events by their origin rainfall events: monsoonal rain, heavy rain, and others (Figure 2,3,4). For monsoonal rain, R-value varied from 0.8695 to 0.1087 and its mean was 0.5880. For heavy rain, the R-value varied from 0.7092 to -0.8534 and its mean was -0.0626. For others, R-value varied from 0.6215 to -0.7142 and its mean was -0.0503. All the R-value in monsoonal rain group showed positive correlation, and its mean is large, while heavy rain and others varied from negatives to positives, and the means were small. The p-value for each subgroup compared to the average of group of all events was 0.0089, 0.4398, 0.4944, respectively (Figure 5). Hence, only monsoonal rain subgroup showed the statistical significance ($p<0.05$).

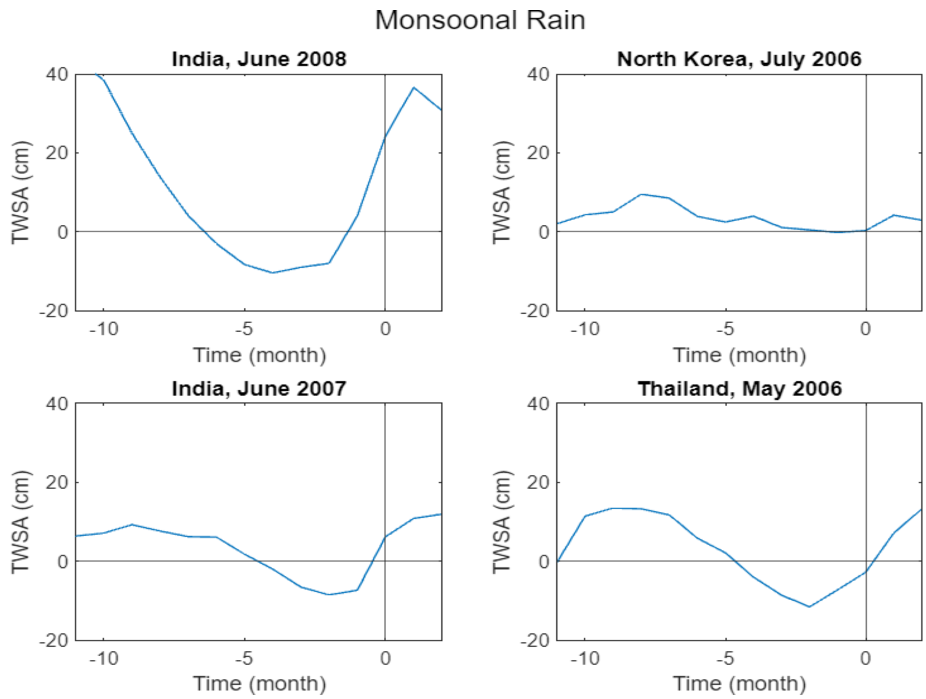

Figure 2. TWSA in 11 months lead time of events triggered by monsoonal rain. the x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

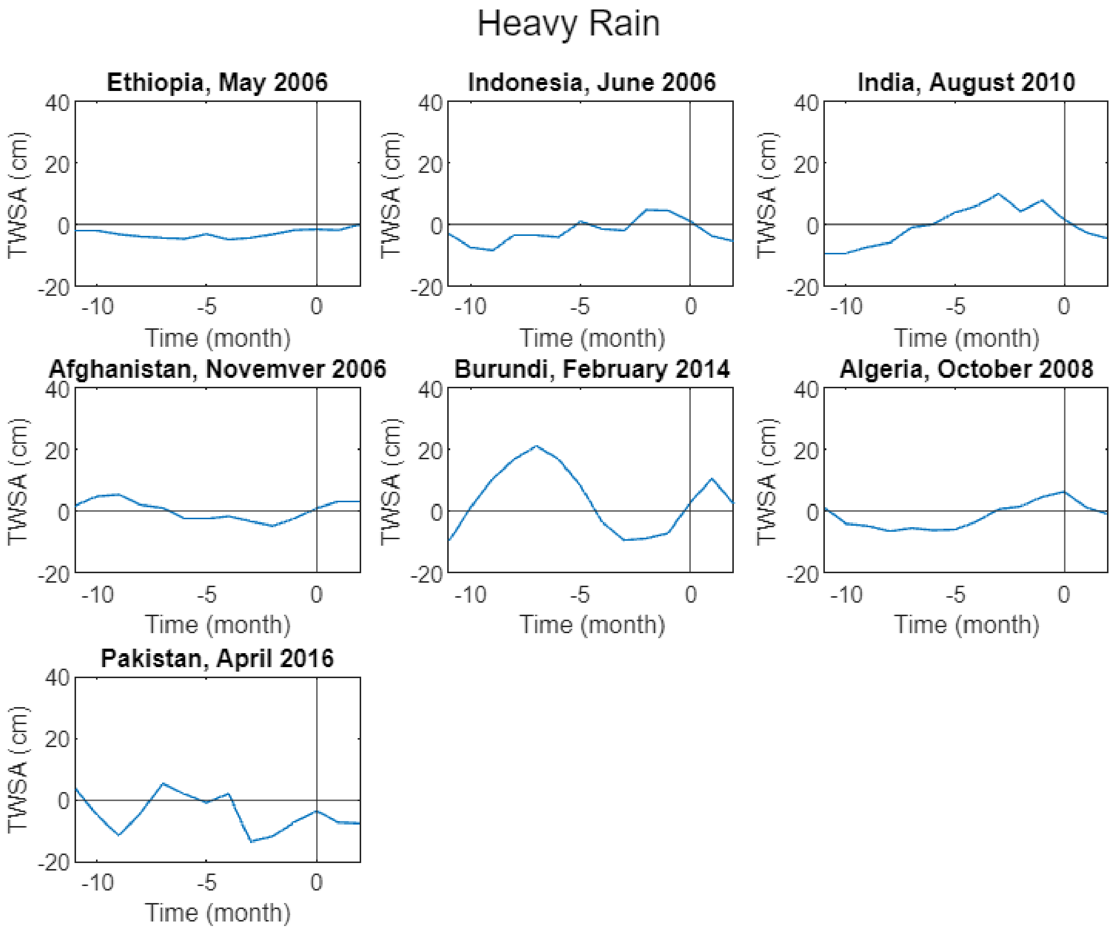

Figure 3. TWSA in 11 months lead time of events triggered by heavy rain. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

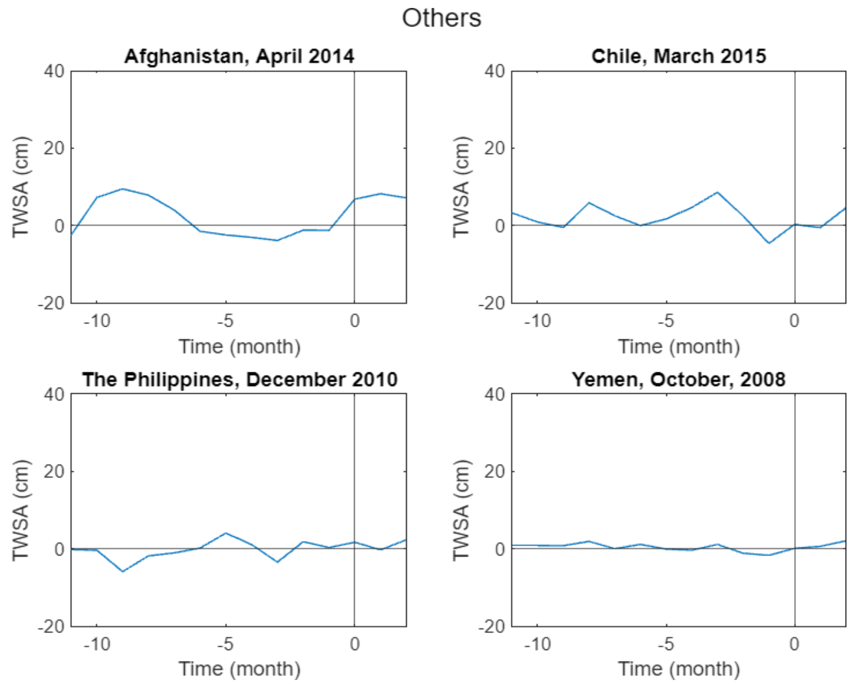

Figure 4. TWSA in 11 months lead time of events triggered by other rainfalls. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

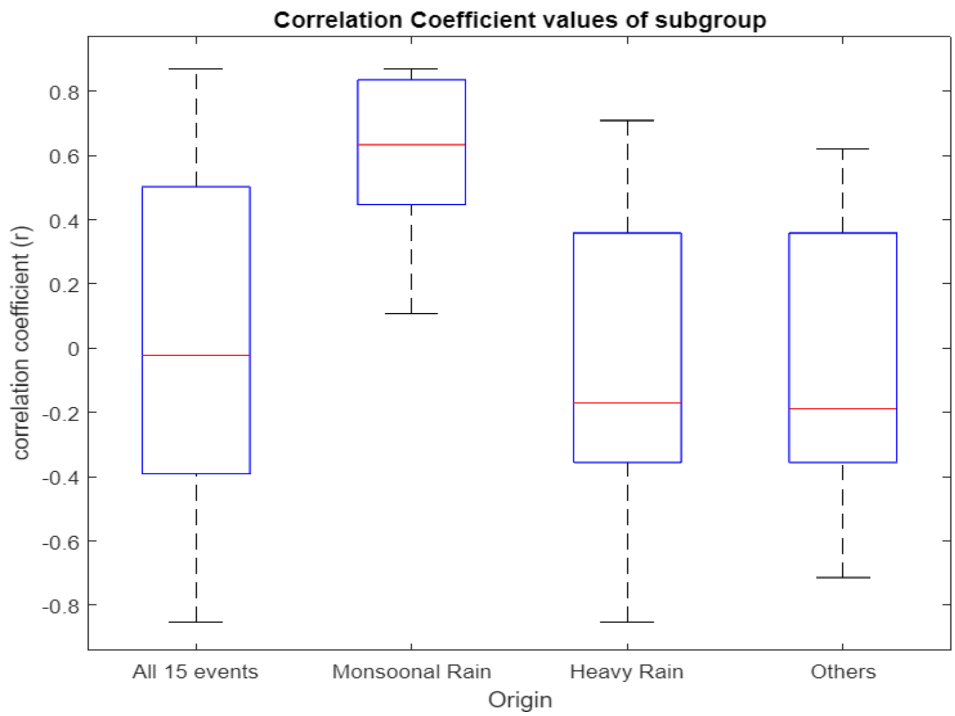

Figure 5. Distribution of R-value for all 15 events and origin subgroups. Correlation coefficient of all 15 flash flood events group and other subgroups are plotted as boxplot. Median, 25 percentile, 75 percentile, minimum, and maximum are indicated by red line, bottom blue line, top blue line, bottom black line, and top black line, respectively.

Grouping flood events of interest by their disaster magnitude

I grouped 15 flood events by their disaster magnitude in square kilometres: x =<6000 km2, 6000km2 < x =< 132000km2, and x > 132000km2 (Figure 6,7,8). For x =<6000 km2, the R-value varied from 0.3548 to -0.7855 and its mean was -0.1262. For 6000km2 < x =< 132000km2, the R-value varied from 0.8358 to -0.7897 and its mean was -0.0033. For x > 132000km2, the R-value varied from 0.6684 to -0.8420 and its mean was -0.0229. All the R-value of all subgroups varied from negatives to positives, and the means were small. None of subgroups showed high correlations (Figure 9). The p-value for each subgroup compared to the average of group of all events was 0.4623, 0.8107, 0.7544, respectively. Hence, there were not statistically significance pattern of TWSA behaviour in flood events grouped by disaster magnitude.

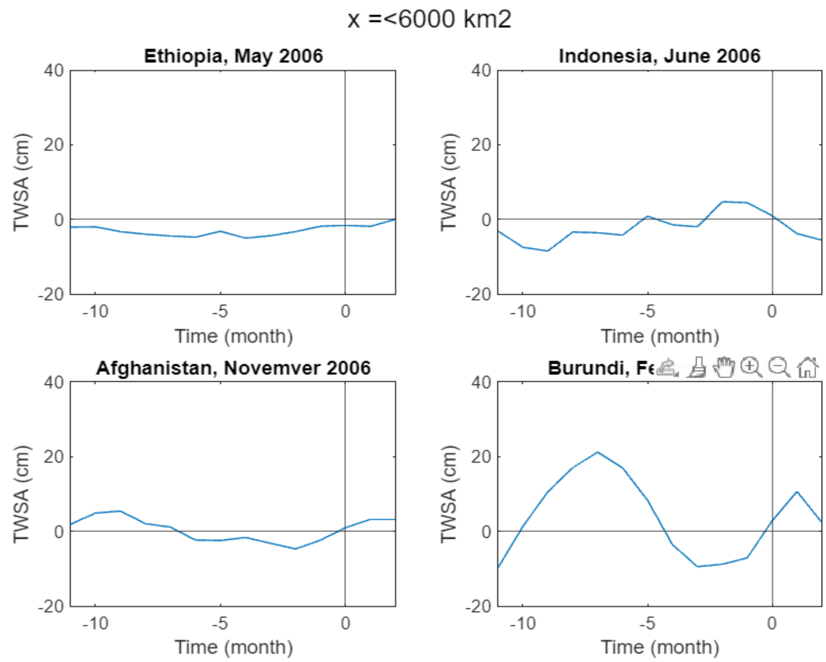

Figure 6. TWSA in 11 months lead time of events smaller than 6000 km2. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

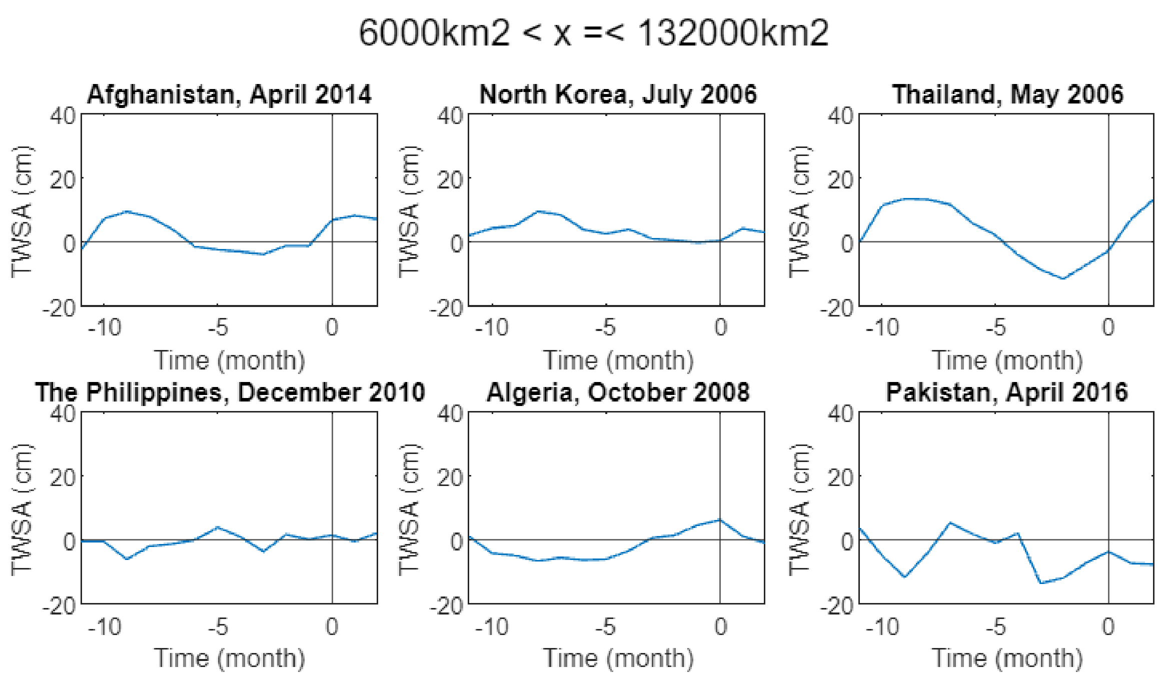

Figure 7. TWSA in 11 months lead time of events larger than 6000 km2 and smaller than 132000 km2. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis

shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

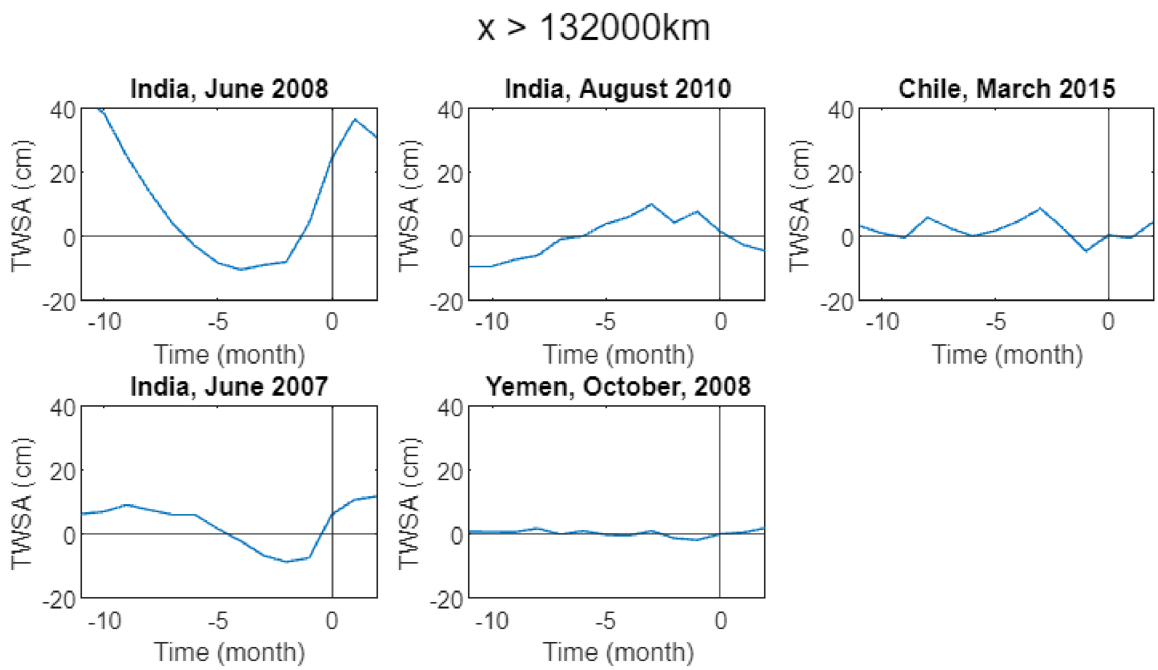

Figure 8. TWSA in 11 months lead time of events larger than 132000 km2. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

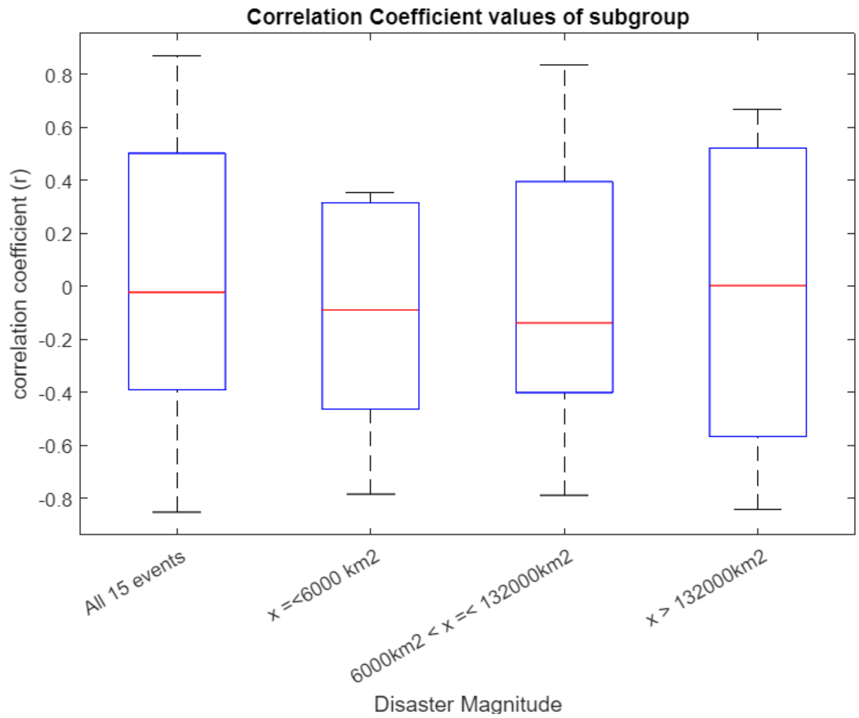

Figure 9. Correlation coefficient of 15 flood events group and other subgroups are plotted as boxplot. Median, 25 percentile, 75 percentile, minimum, and maximum are indicated by red line, bottom blue line, top blue line, bottom black line, and top black line, respectively.

Grouping flood events of interest by their duration

I grouped 15 flood events by their duration: x =< 1 week, 1 week < x =< 2 weeks, 2 weeks < x (Figure 10,11,12). For x =< 1 week, the R-value varied from 0.7092 to -0.8534 and its mean was -0.1425. For 1 week < x =< 2 weeks, the R-value varied from 0.6802 to -0.2028 and its mean was 0.3021. For 2 weeks < x, the R-value varied from 0.8099 to -0.7369 and its mean was -0.0741. All the R-value of all subgroups varied from negatives to positives, and the means were small. None of subgroups showed high correlations (Figure 13). The p-value for each subgroup compared to the average of group of all events was 0.2155, 0.1994, 0.5377, respectively. Hence, there were not any statistically significant patten of TWSA behaviour in flood events grouped by duration.

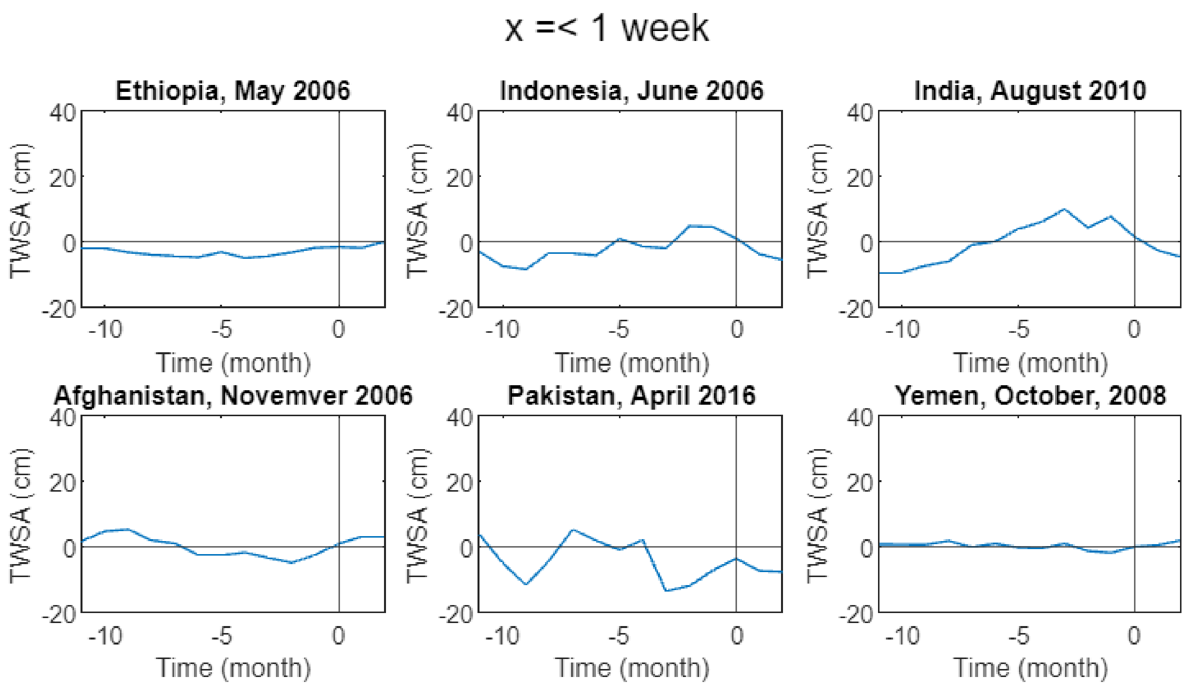

Figure 9. TWSA in 11 months lead time of events shorter than one week. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

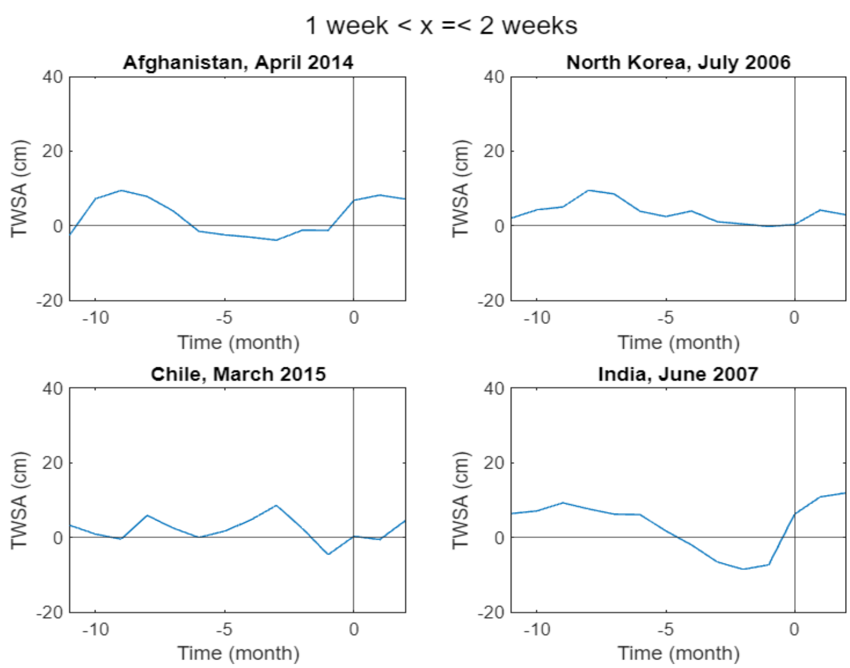

Figure 10. TWSA in 11 months lead time of events shorter than two weeks. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

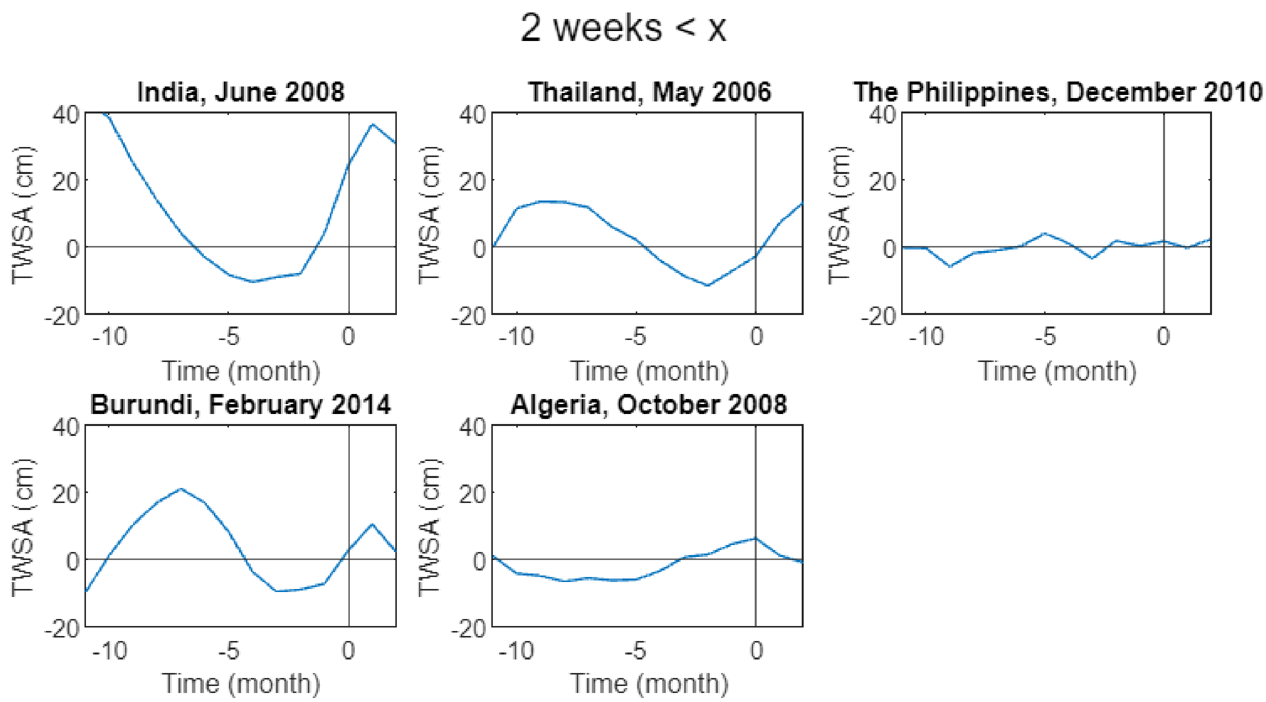

Figure 11. TWSA in 11 months lead time of events larger than 6000 km2 and smaller than 132000 km2. The x-axis shows time series of 11 months lead time of the event occurrence to 2 months after the occurrence, and the y-axis shows TWSA in cm water equivalent. Time of event occurrence is indicated with black vertical line, and 0 TWSA is indicated with black horizontal line.

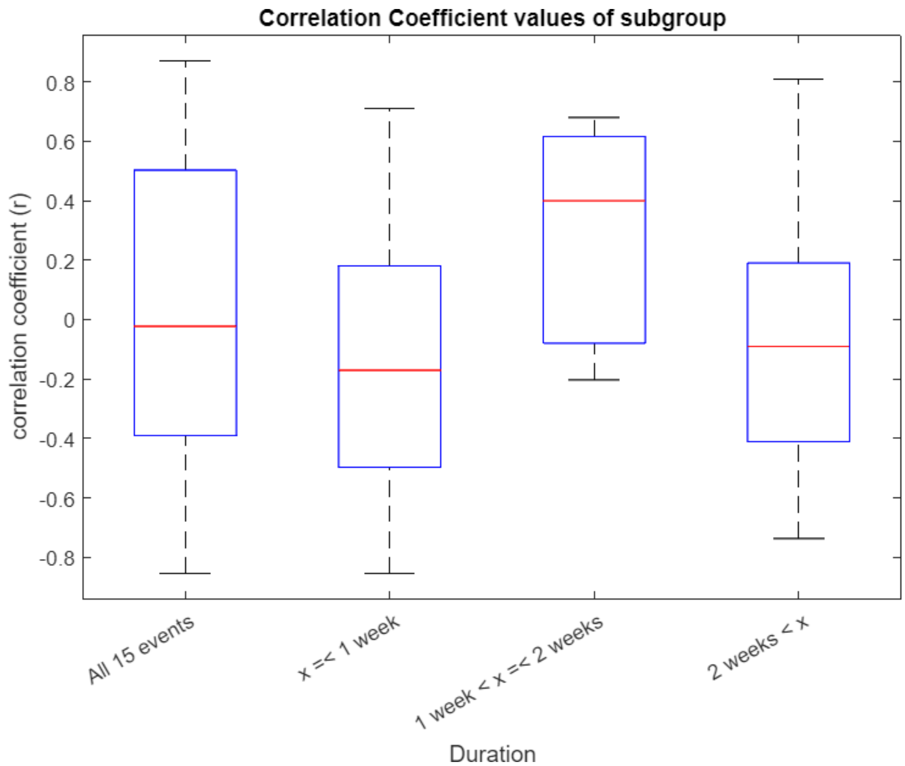

Figure 12. Correlation coefficient of 15 flood events group and other subgroups are plotted as boxplot. Median, 25 percentile, 75 percentile, minimum, and maximum are indicated by red line, bottom blue line, top blue line, bottom black line, and top black line.

DISCUSSION

I found that TWSA behaviour of 11 months lead time cannot be defined as simple trend such as linear increase. TWSA behaved like waves, with multiple increase and decrease. I expected that flood events would share TWSA behaviour in their lead time, but I did not find a statistically significant pattern of TWSA behaviour among all 15 flood events as there were no correlation among them. This implicated that TWSA cannot be used for general proxy of flooding like river runoffs. However, I found that there was a correlation within the monsoonal rain subgroup. While there was no correlation among all 15 events, monsoonal rain subgroup showed the significantly higher correlation than all 15 events with 99% confidence. I expected that I would be able to generalise subgroups of flash floods by this statistically significant pattern of TWSA behaviour, although I could not generalise flash floods.

Analysis

A significant pattern of TWSA behaviour found in a subgroup of origin

I found the statistically significant pattern of TWSA behaviour within monsoonal rain subgroup. It showed significantly higher correlation compared to all 15 flood events. However, I cannot conclude that the behaviour is solely because of monsoonal rain. This might be because of characteristics of monsoonal rain and factors causing monsoonal rain. Monsoon is seasonal shift in atmospheric circulation which results in change in precipitation pattern (NOAA 2022). Monsoon is caused by the temperature difference between land and ocean and can result in either dry or wet weather. Monsoonal rain occurs when ocean is colder than land, which is usually spring or summer. The four flood events that were grouped in monsoonal rain happened in India twice, North Korea, and Thailand, and from May to July. Since they are all in north hemisphere, May, June, and July were around summer. Thus, the statistically significant pattern of TWSA behaviour I found could be due to seasonal changes, despite it is true that they were triggered by monsoonal rain.

A significant pattern of TWSA behaviour found in a subgroup of disaster magnitude

I did not find any statistically significant pattern of TWSA behaviour within subgroups of disaster magnitude. My hypothesis was that flood events larger than a half of the spatial resolution of GRACE would have correlation, and smaller subgroups would not. Hence, I expected x > 132000km2 subgroup to have high correlation supporting a statistically significant pattern of TWSA behaviour that implicates the possibility of direct use of TWSA data for flood analysis. However, since I could not find any correlation within it, disaster magnitude is not likely affecting the relationship between TWSA and flood events. Despite the result I got, some studies have stated that GRACE is effective for analysing large scale flood (Chen et al. 2010, Reager et al. 2014, Molodtsova et al. 2016). The possible reason that disaster magnitude did not affect the TWSA in this study was the number of mascons I use per flood events. To keep it consistent and to avoid using mascons that are not affected by flood events, I used one mascon per flood event according to the latitude and longitude provided. Although the flood size satisfied the spatial resolution of GRACE, which is about 22 mascons, I only took data from one mascon from the centre of flood events (Loomis et al. 2019). I might get different results if I change number of mascons I use, respect to the magnitude of flood events.

A significant pattern of TWSA behaviour found in a subgroup of duration

I did not find any statistically significant pattern of TWSA behaviour within subgroups of duration. My hypothesis was that flood events longer than 2 weeks, which is a half of GRACE temporal resolution, would have high correlation. If flood events were shorter than the spatial resolution of GRACE, it is possible that TWSA due to flood would not be recorded. Hence, I expected x > 2 subgroup to have high correlation supporting a statistically significant pattern of TWSA behaviour that implicates low accuracy of TWSA data for flood analysis. However, since I could not find any correlation within it, duration is not likely affecting the relationship between TWSA and flood events. Despite the result I got, a study have stated that TWSA is effective for long-term flood analysis (Molodtsova et al. 2016). However, Molodtsova et al. used Brazil's long-term flood for their case study. Since it is very long-term flooding, it is possible that flood events of interest in this study was not long enough.

A statistically significant pattern of TWSA behaviour?

I did not find the statistically significant pattern of TWSA behaviour that allows me to generalise flash floods globally. However, I found the one in a subgroup of monsoonal rain. It implicates that TWSA behaviour of floods triggered by monsoonal rain could be generalised, or it could be generalised over seasons. Disaster magnitude and duration of flood events did not show statistically significant effect on TWSA behaviour, contrast to my hypothesis. The result implicates that special and temporal resolution did not matter to flood analysis by TWSA, but there was still a space for improvement in subgroup setting.

Limitation

My study sample was the deadliest 15 flood events while there were about 600 events available that satisfies the requirements, so I cannot claim that the behaviour I found in this study can be apply to any other monsoonal rain triggered flood events. Also, my study intended to find the general behaviour of TWSA that could be applied to certain group of floods events while other studies are often focus on one specific flood or one specific region to study floods (Chen et al. 2010, Rogger et al. 2012, Deep and Vimal 2020). Because of generalization I tried to make, the results I got small sample size remains as small implication rather than conclusion. Another limitation is GRACE spatial and temporal resolution. Since GRACE TWSA data has large resolution both in spatial and temporal, change of TWSA in short term, for example, a week before flood events, would not be recorded by GRACE mission, allowing river runoffs to be a better proxy.

Future direction

First of all, I would suggest using larger sample size. This study was about generalization TWSA behaviour in 11 months lead time of flood events. Thus, I suppose using larger sample size would support conclusion stronger. Next, I would suggest having subgroups of combinations. I only grouped them by trigger, spatial, or temporal factor, however, it would be better to have them combined. For example, a new suggested subgroup would be, large-scale and long-duration flood events. Also, this study showed that there was a statistically significant pattern of TWSA behaviour within monsoonal rain subgroup, and it would be due to rainfall pattern or season. Therefore, grouping by season would be another possible factor for subgroups. Lastly, this study only used one mascon for each flood events of interest regardless of their disaster magnitude. However, it would be better to change the number of mascons I use for each flood events, considering the area affected.

Conclusion

My results implicates that there might be a statistically significant pattern of TWSA behaviour that can be generalized over a big group of flood events. This is a great possibility in use of TWSA data regarding to floods. Since GRACE mission covers the whole globe, implementation issue by local government would not be a problem. While river runoffs and precipitation data are in situ data, GRACE TWSA data is the one set of data that can be used without complicated calibration due to instrument differences. Floods is the natural disaster that gives damage to society the most; it kills people and it damages economy (Driessen et al. 2018). As flood events are increasing due to urbanization and higher frequency and intensity of extreme precipitation, this is the field needing urgent attention (Zhang et al. 2018). Although this study is not enough to conclude existence of general behaviour of TWSA before floods, it still supports making metrological approach to flood events (Nied et al. 2014). The relationship between TWSA and floods remains an open research field and should be investigated more.

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REFERENCES

Bouwer, L. M. 2019. Observed and Projected Impacts from Extreme Weather Events: Implications for Loss and Damage. Pages 63–82 *in* R. Mechler, L. M. Bouwer, T. Schinko, S. Surminski, and J. Linnerooth-Bayer, editors. Loss and Damage from Climate Change: Concepts, Methods and Policy Options. Springer International Publishing, Cham.

Chen, J. L., C. R. Wilson, and B. D. Tapley. 2010. The 2009 exceptional Amazon flood and interannual terrestrial water storage change observed by GRACE. Water Resources Research 46:W12526.

CRED, Ucl., Brussels, Belgium. (n.d.). EM-DAT. https://public.emdat.be/.

Davenport, F. V., M. Burke, and N. S. Diffenbaugh. 2021, January 26. Contribution of historical precipitation change to US flood damages | PNAS. https://www.pnas.org/content/118/4/e2017524118.

Deep, S., and M. Vimal. 2020. Strong Influence of Changes in Terrestrial Water Storage on Flood Potential in India - Shah - 2021 - Journal of Geophysical Research: Atmospheres - Wiley Online Library. Journal of Geophysical Research: Atmospheres Vol.126.

Deschênes, O., and E. Moretti. 2009. Extreme Weather Events, Mortality, and Migration. The Review of Economics and Statistics 91:659–681.

Dole, R., M. Hoerling, J. Perlwitz, J. Eischeid, P. Pegion, T. Zhang, X.-W. Quan, T. Xu, and D. Murray. 2011. Was there a basis for anticipating the 2010 Russian heat wave? Geophysical Research Letters 38.

Driessen, P., D. Hegger, M. Bakker, H. van Rijswick, and Z. Kundzewicz. 2016. Toward more resilient flood risk governance. Ecology and Society 21.

Driessen, P. P. J., this link will open in a new window Link to external site, D. L. T. Hegger, this link will open in a new window Link to external site, Z. W. Kundzewicz, H. F. M. W. van Rijswick, A. Crabbé, C. Larrue, P. Matczak, this link will open in a new window Link to external site, M. Pettersson, S. Priest, C. Suykens, G. T. Raadgever, and M. Wiering. 2018. Governance Strategies for Improving Flood Resilience in the Face of Climate Change. Water 10:1595.

FitzGerald, G., W. W. Du, A. Jamal, M. Clark, and X.-Y. Hou. (n.d.). Flood fatalities in contemporary Australia (1997–2008) - FitzGerald - 2010 - Emergency Medicine Australasia - Wiley Online Library. https://onlinelibrary.wiley.com/doi/full/10.1111/j.1742-6723.2010.01284.x.

Gao, H., Q. Tang, C. R. Ferguson, E. F. Wood, and D. P. Lettenmaier. 2010. Estimating the water budget of major US river basins via remote sensing. International Journal of Remote Sensing 31:3955– 3978.

Greicius, T. 2013a, June 6. Mission Overview. Brian Dunbar.

http://www.nasa.gov/mission_pages/Grace/overview/index.html.

Greicius, T. 2013b, June 6. Spacecraft. Brian Dunbar. http://www.nasa.gov/mission_pages/Grace/spacecraft/index.html.

Houston Health Department. 2017, August 28. Hurricane Harvey 2017 Houston Health Department Response Report. Houston Health Department.

Konisky, D. M., L. Hughes, and C. H. Kaylor. 2016. Extreme weather events and climate change concern. Climatic Change 134:533–547.

Long, D., Y. Shen, A. Sun, Y. Hong, L. Longuevergne, Y. Yang, B. Li, and L. Chen. 2014. Drought and flood monitoring for a large karst plateau in Southwest China using extended GRACE data. Remote Sensing of Environment 155:145–160.

Loomis, B. D., S. B. Luthcke, and T. J. Sabaka. 2019. Regularization and error characterization of GRACE mascons. Journal of Geodesy 93:1381–1398.

Lubchenco, J., and T. R. Karl. 2012. Predicting and managing extreme weather events. Physics Today 65:31–37.

MATLAB. (n.d.). . The MathWorks, Inc., Natick, Massachusetts, United States.

Min, S.-K., X. Zhang, F. W. Zwiers, and G. C. Hegerl. 2011. Human contribution to more-intense precipitation extremes. Nature 470:378–381.

Molodtsova, T., S. Molodtsov, A. Kirilenko, X. Zhang, and J. VanLooy. 2016. Evaluating flood potential with GRACE in the United States. Natural Hazards and Earth System Sciences 16:1011–1018.

Nied, M., T. Pardowitz, K. Nissen, U. Ulbrich, Y. Hundecha, and B. Merz. 2014. On the relationship between hydro-meteorological patterns and flood types. Journal of Hydrology 519:3249–3262.

NOAA. 2022. What Is a Monsoon? | NOAA SciJinks – All About Weather. https://scijinks.gov/what-is-a- monsoon/.

Pall, P., T. Aina, D. A. Stone, P. A. Stott, T. Nozawa, A. G. J. Hilberts, D. Lohmann, and M. R. Allen. 2011. Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470:382–385.

Reager, J. T., B. F. Thomas, and J. S. Famiglietti. 2014. River basin flood potential inferred using GRACE gravity observations at several months lead time. Nature Geoscience 7:588–592.

Rogger, M., B. Kohl, H. Pirkl, A. Viglione, J. Komma, R. Kirnbauer, R. Merz, and G. Blöschl. 2012, June 7. Runoff models and flood frequency statistics for design flood estimation in Austria â€“ Do they tell a consistent story? | Elsevier Enhanced Reader. https://reader.elsevier.com/reader/sd/pii/S0022169412004714?token=207025AD3EB2A6D4C2

B09B4F24309B6317C571F8F72B208E649EBCEEEA7E28FB24D4BE4D5534FE6BA4A12FE9F67F0838&originRegion=us-east-1&originCreation=20211207085042.

Samaniego, L., S. Thober, R. Kumar, N. Wanders, O. Rakovec, M. Pan, M. Zink, J. Sheffield, E. F. Wood, and A. Marx. 2018. Anthropogenic warming exacerbates European soil moisture droughts. Nature Climate Change 8:421-+.

Tang, Q., H. Gao, H. Lu, and D. P. Lettenmaier. 2009. Remote sensing: hydrology. Progress in Physical Geography: Earth and Environment 33:490–509.

Tariq, M. A. U. R., and N. van de Giesen. (n.d.). Floods and flood management in Pakistan | Elsevier Enhanced Reader. https://reader.elsevier.com/reader/sd/pii/S1474706511002348?token=00EBBCC8AE59EEA8A6DD5AD6843D30A2E75B22EA206EE881D6DA3FACF7101CDBF83AFC85198F74E224140922480063F6&originRegion=us-east-1&originCreation=20211207083212.

Zhang, W., G. Villarini, G. A. Vecchi, and J. A. Smith. 2018. Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. Nature 563:384-+.

Zscheischler, J., S. Westra, B. J. J. M. van den Hurk, S. I. Seneviratne, P. J. Ward, A. Pitman, A. AghaKouchak, D. N. Bresch, M. Leonard, T. Wahl, and X. Zhang. 2018. Future climate risk from compound events. Nature Climate Change 8:469–477.