Comparison of impact and water vapor characteristics between two types of floods in Eastern China

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Abstract

Floods are one of the most devastating natural hazards, resulting in social and economic losses. As a flood-prone area, East China (EC) suffers floods mainly related to monsoons and tropical cyclones (TC). However, how the floods induced by heavy rain (HR) and TC impact on human life, and what their differences are, is not yet clear. In this paper, we assess the spatiotemporal characteristics of two types of floods in South China (SC), the middle and low reaches of the Yangtze River (YHR), and North China (NC) for 1985–2020, and investigate the impacts on human mortality and displacement. Furthermore, we use the improved areal source-receptor attribution method to quantify the water vapor contribution from each moisture source. Results show that HR-induced floods occur more frequently than TC-induced floods in three study areas for 1985–2020. The spatial pattern of the severity of floods exhibits an increasing gradient from North to South. The trends of annual mean mortality and displacement rates were significantly decreasing over time. The most important moisture sources for HR-induced floods in three study regions are all from EC. Contributions account for 26.6%, 45.0% and 54.5% in SC, YHR and NC, respectively. However, the most important moisture source for TC-induced floods in SC and YHR is from the Western Pacific Ocean. Contributions account for 21.9% and 44.3% in SC and YHR, respectively. The above result within the Lagrangian framework is well confirmed by the Eulerian framework.

1. Introduction

Floods are one of the most devastating natural hazards at the global scale, especially in coastal regions, which often cause social and economic losses (CRED 2019). The vulnerability to floods will increase in the future due to factors including population growth, urbanization, increasing coastal settlement, and global warming (Neumann et al 2015). East China (EC) is located in the East Asian monsoon area, and is frequently affected by tropical cyclones (TCs). Moreover, it has an extremely dense population density and a high economic share nationally. Thus, floods in EC have previously threatened the livelihood of millions of people, and caused unimaginable damage to property.

Previous studies have assessed flood risk and impacts on human lives and properties at various scales (up to global scales) (Mirza 2011, Marengo et al 2013, Arnell and Lloyd-Hughes 2014, Haraguchi and Lall 2015, Thuy and Anh 2015, Arnell and Gosling 2016). However, few studies have classified the impacts of floods induced by heavy rain (HR) and TCs. How the floods induced by HR and TC have impacted on human life over the whole of EC during the historical period and what the differences between the two are still unclear. Meanwhile, to reduce the damage to the public in the future, the forecasting capabilities of these two types of floods should be improved. In fact, these two types of floods are generated through different mechanisms, most directly manifested in divergent conditions of water vapor.
The simple Eulerian approach has often been used to analyze moisture transport pathways, but it is unable to assess water vapor origins from remote regions, and generally ignores any moisture changes during transport. Therefore, the more advanced method based on Lagrangian models has been widely applied to trace the pathways of moisture transport and changes of physical quantities along the pathways (Stohl and James 2004, 2005, Dominguez et al. 2006, Dirmeyer et al. 2009, Chen et al. 2013, 2018).

Some studies using Lagrangian models have detected the origins of moisture of multiple-year climatology rainfall over EC (Drumond et al. 2011a, Sun and Wang 2014, 2015, Shi et al. 2020). In this study, we further try to apply the method to two types of flood events in EC during the historical period 1985–2020.

The outline of this paper is as follows. Section 2 describes the data and methods. Section 3 investigates the spatiotemporal characteristics of floods in South China (SC), the middle and low reaches of the Yangtze River (YHR), and North China (NC) for 1985–2020, which were induced by HR and TC. Further, impacts of floods in humans in terms of death, mortality, displacement rate, and so on, are assessed. Section 4 presents the water vapor pathways and sources of HR-induced and TC-induced floods in SC, YHR, and NC. The proportion of trajectories and the contribution of water vapor to floods are quantified. We furthermore use the moisture flux within the Eulerian framework to verify our results. Section 5 draws a general conclusion.

2. Data and methods

2.1. Datasets

The Global Active Archive of Large Flood Events (GLFEs) from the Dartmouth Flood Observatory provides some relevant information on floods, including country, longitude, latitude, beginning time, ending time, death, displacement, area, cause, and severity (Brakenridge 2019). The information presented in this Archive is derived from news, governmental, instrumental, and remote sensing sources. The archive is ‘active’ because current events are added immediately.

We selected three regions in EC including (SC; 17° N–26° N, 106° E–120° E), the middle and low reaches of the (YHR; 28° N–34° N, 110° E–123° E), and (NC; 35° N–43° N, 110° E–120° E) as study areas (figure 1(a)). They all have populations of more than 200 million and are economic core regions of China, located in the East Asian monsoon area. Thus, we investigate three groups of floods in SC, YHR, and NC: floods by all causes, HR, and TC. HR comprises monsoonal and torrential rain. The period is for 1985–2020. The flood data we used can be found in the Supplementary material (available online at stacks.iop.org/ERL/17/024039/mmedia).

The gridded population count from the Global Population Count Grid Time Series Estimates version 1 (GPCv1) for 1970–2000 and Gridded Population of the World version 4 (GPWv4) for 2000–2020 were used. GPCv1 produced the dataset in 1970, 1980, 1990, and 2000. GPWv4 provided the dataset for 2000, 2005, 2010, 2015, and 2020. To match the analyzed time period of flood events for 1985–2020, we selected the gridded population data from GPCv1 (1980, 1990, and 2000), and from GPWv4 (2005, 2010, 2015, and 2020).

The reanalysis dataset from the National Centers for Environmental Prediction-National Center for Atmospheric Research reanalysis was used. They are available since 1948 at a six-hourly temporal resolution and 2.5 × 2.5° spatial resolution with 17 pressure-levels.

2.2. Methods

2.2.1. HYSPLIT water vapor tracking simulation

The National Oceanic and Atmospheric Administration Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Draxler and Hess 1998, NOAA ARL 2011) was used for trajectories and tracks of air parcels. The back-trajectory algorithm was applied for the position and time for each flood occurred in three study areas. We use six initial levels at 100, 500, 1500, 3000, 5000, and 9000 m, which were approximately at the near surface layer, with 925 hPa, 850 hPa, 700 hPa, 500 hPa, and 300 hPa. All parcels were integrated backward in time, until ten days. The outputs were recorded every six hour with variables indicating the position (latitude, longitude and altitude) and meteorological variables (temperature, specific humidity and geopotential height) (Jiang et al. 2017, Shi et al. 2020). It is noted that Shi et al. (2022) showed that the atmospheric water vapor above 500 hPa is relatively small, which accounting for less than 5%. It is thus sufficient to take 300 hPa as the highest level. Also, the choice of ten days as a reference for back trajectories is motivated by the fact that most literatures give a time scale about ten days as the residence time of water vapor in the atmosphere (Stohl and James 2005, Sodemann et al. 2008, Drumond et al. 2011b).

2.2.2. The improved areal source–receptor attribution method

In order to fully understand the moisture contribution from each moisture source, we use the improved areal source–receptor attribution method for each flood event. This method can assess the contribution of a specific water vapor source region to the precipitation in a target region. When the air parcel is located between the source and target regions, a normal operation is used to calculate water vapor changes in function of evaporation (precipitation) that increases (decreases) water vapor. When the air parcel is located within the source and target regions, a special
Figure 1. Severity of floods (dot) and population density (shaded; person km$^{-2}$ in unit) in SC, YHR, and NC for 1985–2020 (a), and monthly floods number, which were induced by all causes (solid line), heavy rain (dash-dotted line), and tropical cyclones (dotted line) (b). Three rectangles from South to North denote SC, YHR, and NC, respectively. The blue and red dots represent floods inducing by heavy rainfall and tropical cyclones, respectively.

We define the contribution of water vapor from each unit area as the Contribution Density Function (CDF). Its calculation is as follows:

$$CDF(m) = \frac{\sum_{n=1}^{w} R_n(m)}{R_{total}}$$

where $w$ is the number of trajectories departing from the grid $m$. For each trajectory $n$ departing from the grid $m$, the quantity $R_n(m)$ representing the moisture gained from the unit surface area $m$ which is then released in the target region. $R_{total}$ is thus the precipitation falling down in the target region (Sun and Wang 2014, 2015, Chu et al 2017).

2.2.3. Flood protection standard
To more reasonably assess the flood impact on human life loss and displacement, the flood loss changes over time and space must be normalized. We calculated two impact indices (mortality and displacement rate) using the normalization method presented by Chen et al (2020)

$$\text{Mortality} = \log \left(1 + \frac{\text{Number of dead}}{\text{Potential influenced population per million persons}}\right)$$

$$\text{Displacement rate} = \log \left(1 + \frac{\text{Number of displaced}}{\text{Potential influenced population per million persons}}\right).$$

3. Results
3.1. Spatiotemporal characteristics and impact of floods
To quantify the damages of flood, the severity was divided into three classes: 1, 1.5, and 2. They represent large flood events (with return periods between 10 and 20 years), very large flood events (with return periods between 20 and 100 years), and extreme flood events (with return periods larger than 100 years), respectively. Figure 1(a) shows that HR-induced floods had higher occurrence frequencies than TC-induced floods for 1985–2020. SC frequently suffered high-severity and TC-induced floods. NC only suffered HR-induced floods. The monthly flood numbers show significant seasonal variation (figure 1(b)). Floods in SC, YHR, and NC peak in turn during June and August, and TC-induced floods reached their peak later than HR-induced floods.

We further provide the death number, displaced population, and area affected by two types of floods
Figure 2. Death number (a), displaced population (b), and area ((c); km$^2$ in unit) affected by HR-induced floods and TC-induced floods in SC, YHR, and NC for 1985–2020.

Similar to the spatial pattern of the severity of floods, impact deaths and areas of floods both exhibit an increasing gradient from North to South, and HR-induced floods caused more deaths and affected more areas than TC-induced floods. On average, impact deaths (areas) of floods were between 100 (100 000) and 999 (one million) persons (km$^2$) in SC. There was an extremely high death number (over 1000) on the southeastern coast. In terms of the displaced population, YHR suffered the most significant threat. On average, the displaced population in YHR was more than 100 000.

Time series and trends of mean annual mortality and displacement rates of floods in SC, YHR, and NC for 1985–2020 are given in figure 3. The results show that the trends of annual mean impact indices were significantly decreasing over time, especially mortality in SC and YHR, as well as displacement rate in YHR. On average, the displaced population in YHR was more than 100 000.

3.2. Difference in moisture transport pathways and water vapor sources of two types of floods

From the previous analysis, we can see the obvious difference between two types of floods. In this section, we systematically analyze the difference from the perspective of moisture transport pathways and water vapor source. Furthermore, we use the Eulerian method to verify the characteristic of the moisture transport of two types of floods. The moisture transport pathways or moisture sources are just a composite of conditions comprised in each type of flood event.

3.2.1. Floods in SC

We first analyzed the moisture transport pathways obtained as the mean trajectory which is the average of all back-trajectories departing from pre-defined geographic sectors. Figure 4(a) shows the main water

in NC ($p < 0.001$; figure 3(f)) were also shown. We regard that the significant decrease of mortality and displacement rate are related with improvements in the forecast capabilities of floods, developments in the infrastructure construction and efficient application in measures against floods.
Figure 3. Time series of annual mean mortality (a)–(c) and displacement rate (d)–(f) in SC (a), (d), YHR (b), (e), and NC (c), (f) for 1985–2020. The grey, black, and orange lines denote the annual trend of HR-induced floods, TC-induced floods, and ALL-induced floods, respectively. *, **, *** represent the trends that pass the 90%, 99%, and 99.9% significant student’s t test, respectively.

Figure 4. Moisture transport pathways (a), (b) and moisture sources (c), (d) of HR-induced (a), (c) and TC-induced (b), (d) floods in SC. (a), (b) Five transport channels based on average trajectories were identified, from East China (EC), the west Pacific Ocean (PO), the South China Sea (SCS), the Indian Ocean (IO), and the Eurasian westerly (EA), respectively. The colors and thickness on the pathways indicate the average specific humidity of air parcels along the trajectories, and the percentage of trajectories, respectively. (c), (d) Water vapor CDF showing the contribution of moisture source regions to the precipitation in SC (10⁻³ in unit).
vapor transport pathways of HR-induced floods in SC. We find that the most important water vapor transport channel was from the Indian Ocean (IO), which accounted for 45.5% of all trajectories. The parcels coming from the IO moved across the Bay of Bengal and the Indochina Peninsula, and finally entered SC at its southwest boundaries. The secondary moisture transport channel is from the west Pacific Ocean (PO), accounting for 25.9% of all trajectories. The average pathways started from about 140° E, 20° N, and then moved eastward into SC at the southern boundary. These two channels were the two important moisture transport channels for HR-induced floods, with the sum of the trajectories number of these two channels being more than 70%. The number of moisture transport trajectories for the other three channels were all less than 10%. In brief, the IO channel is the most important moisture transport channel for HR-induced floods. This result is consistent with previous works of Chu et al. (2017), Chen and Luo (2018), and Shi et al. (2020).

However, the transport pathways cannot provide accurate moisture source characteristics. Based on the improved areal source–receptor attribution method, figure 4(c) shows the spatial distribution of moisture CDF for HR-induced floods. Large contribution density values were mainly located near the coasts of Southeast China and the northern part of the SCS, with an average contribution density of about $1 \times 10^{-3}$. In turn, the CDF in the southern part of the SCS was about $2 \times 10^{-4}$. The secondary moisture source is from the IO, especially in the Bay of Bengal. The CDF in the Bay of Bengal was also larger than $1 \times 10^{-4}$. On the contrary, the CDF in the PO was relatively small. A CDF of $1 \times 10^{-4}$ only extended to 130° E, and that of $1 \times 10^{-5}$ extended to 160° E.

For TC-induced floods in SC, the most important moisture channel was still the IO channel, and the secondary important moisture channel was also the PO (figure 4(b)). However, compared with HR-induced floods, the PO channel significantly increased and the IO channel decreased. The portion of trajectories in the PO channel reached 37.0%, and compared with HR-induced floods, the corresponding pathway was a bit northeastward shifted. The average pathways started from about 150° E and then moved westward at the eastern boundary. The other three channels were still weak, with the portion of trajectories being less than 8%.

As for the moisture contribution of TC-induced floods, the maximum of the CDF was located in SC and the northern part of the SCS. Besides, the CDF in the southern part of the SCS was mainly larger than $2 \times 10^{-4}$. However, compared with HR-induced floods, the main difference of the moisture contribution was in the IO and the PO. In the IO region, the CDF significantly decreased, especially in the Bay of Bengal. Only in a small part of the Bay of Bengal, the CDF was larger than $1 \times 10^{-4}$. The CDF of $1 \times 10^{-4}$ in the PO extended to 140° E, and that of $1 \times 10^{-5}$ extended to 170° E, which were about 10 longitudes to the east.

In summary, the main moisture transport channel for two types of floods were both the IO channel, and the most important moisture source was from SC and the northern part of the SCS. TC-induced floods achieved more water vapor trajectories and moisture contribution from the PO, compared with HR-induced floods. This is because the TC was mainly produced in the PO.

3.2.2. Floods in Yangtze-Huaihe River Basin
Similar to the moisture transport characteristics of HR-induced floods in SC, the IO channel was still the most important one for HR-induced floods in YHR and the portion of trajectories reached 41.3% (figure 5(a)). The PO (24.8%) was the secondary transport channel. The contributions of the SCS channel (12.0%) and EA channel (11.0%) were also increasing.

However, different from the spatial distribution of moisture CDF of HR-induced floods in SC, the maximum of the CDF was in EC for HR-induced floods in YHR, and the value was greater than $1 \times 10^{-3}$ (figure 5(c)). The moisture contribution from the SCS and IO significantly decreased mainly due northward of the target region.

For TC-induced floods in YHR, the PO channel became the strongest moisture channel, and the number of the trajectories was 48.0% of all the trajectories (figure 5(b)). This means that nearly half of the trajectories came from the PO. In addition, the trajectories number of the IO channel accounted for only 25.1%.

The spatial distribution of CDF also underwent great changes. As shown in figure 5(d), the large values of CDF were located in the PO, and the values of CDF reached $1 \times 10^{-3}$. The CDF in the PO significantly increased, with a CDF of $1 \times 10^{-4}$ extending to 150° E and one of $1 \times 10^{-5}$ extending to 180° E. However, the CDF in the IO region and SCS region was quite small, and only in some small regions the CDF was greater than $1 \times 10^{-5}$. In a word, the PO was the most important moisture source for TC-induced floods in YHR.

Obviously, the IO channel was the most important moisture channel, and the large values of CDF were located in the EC region for HR-induced floods in YHR. However, the PO channel was the most important moisture channel and moisture source for TC-induced floods in YHR.

3.2.3. Floods in NC
All 15 floods in NC were caused by HR; figure 6 therefore only provides the moisture transport pathways and the spatial distribution of CDF for HR-induced floods in NC. Results show that the most
Figure 5. As in figure 4, but for floods in YHR.

Figure 6. As in figure 4, but for floods in NC.
Figure 7. Bar charts showing the proportion of trajectories (blue bars; %) and moisture contributions (red bars; %) leading to HR-induced and TC-induced floods in SC, YHR, and NC. The background map shows the division of geographic sectors including East China, South China Sea, Indian Ocean, west Pacific Ocean, and Eurasia.

Important moisture transport pathway was the EA, with the proportion of 36.1% (figure 6(a)). It should be noted that, although the number of trajectories at mid-latitude EA was the largest, the specific humidity of this channel was small. This led the vertically-integrated water vapor transport in this channel to be relatively small. In addition, the IO channel and PO channel were two other important moisture channels, with proportions of 20.0% and 17.2%, respectively. The specific humidity in both these two channels was higher than 10 g kg$^{-1}$. Thus, they led to precipitation for HR-induced floods in NC.

The spatial distribution of CDF for HR-induced floods in NC indicates that the maximum value occurred in the EC region with a contribution density exceeding $2 \times 10^{-3}$. Compared with the two former target regions, the CDF in NC significantly decreased in the south and increased in the north.

On the whole, the main moisture transport channels for HR-induced floods in NC were the EA channel, IO channel, and PO channel, but the most important moisture source was from EC.

3.2.4. Moisture contribution from different source regions
In this section, we want to compare the moisture contributions of two types of floods from each moisture source. To be consistent with the above moisture transport channel, we used the same five moisture source regions: EA, EC, PO, IO and SCS (Shi et al 2020).
Figure 7 shows the proportion of trajectories (blue bars in %) and moisture contribution (red bars in %) from five moisture source regions for two types of floods in three study regions. Results show that the moisture contribution from EC was rather high for the floods, especially for HR-induced floods with CDF always being higher than 25%. It means that the local water recycling plays an important role in the generation of HR-induced floods, especially in NC with CDF reaching 54.5%. However, for TC-induced floods, the CDF from EC was less than 20%. It can be noted that EC was not the most important moisture source for TC-induced floods, but also provided a lot of water vapor for precipitation.

PO was another important moisture source for the flood, and it was the most important moisture source region for TC-induced floods. The regional contributions from the PO for TC-induced floods were all larger than 20%, especially in YHR, reaching 44.3%. This is because all the TCs affecting YHR were produced in the PO and then brought the water vapor from the PO.

The moisture contribution from SCS was greatly affected by the target area, but less affected by the type of flood. The CDF from SCS for floods in SC, YHR,
and NC were more than 20%, around 10%, and only 3.7%, respectively. This was related with the distance between SCS and the target region.

As mentioned before, the IO channel was the important moisture transport channel for floods in SC and YHR, but the CDF from the IO was relatively small. Specifically, the CDF from the IO for floods in SC, YHR, and NC were about 15%, less than 10%, and less than 5%, respectively. Shi et al. (2020) explained that the pathway of the IO channel goes through the Indian Peninsula and the Indochina Peninsula which are important moisture sink regions to rainfall in target region. Moisture is thus lost along the trajectories, which induces a low contribution from the IO to precipitation in EC.

For EA, moisture contribution rates were all lower than the proportions of accounted trajectories; the moisture contribution values were all less than 4%. This was related with the low specific humidity of air parcels from EA.

In summary, the most important moisture source for HR-induced floods in three study regions were all from EC. The more northerly the study area, the greater the contribution of local water vapor. However, the most important moisture source for TC-induced floods in SC and YHR were both from PO, because most TCs originated from PO.

3.2.5. Verification within the eulerian framework

The HYSPLIT Lagrangian model was used to find the greatest difference in moisture transport characteristics between two types of floods. Here, we further use the moisture flux within the Eulerian framework to verify our results and give a discussion.

Figure 8 provides the moisture flux for two types of floods in SC and YHR. Left panels represent the vertically integrated atmospheric water vapor transport of the flood in SC. The difference shows the westerly anomaly and positive values in moisture flux were located in IO and south part of SCS. On the contrary, the easterly anomaly and negative values in moisture flux were located in northwestern part of the PO between 20° N and 35° N (figure 8(e)). It means for TC-induced floods in SC, the stronger southeast monsoon from PO with the weaker southwest monsoon from SCS affected SC. The result that PO played a role in TC-induced floods in SC is consistent with that obtained within the Lagrangian framework.

As for YHR, the PO moisture transport for TC-induced floods was also stronger than that for HR-induced floods (figure 8(f)). In addition, we found that the southwest monsoon for TC-induced floods in YHR is southeastward than that in SC and could not directly affect YHR. It further combined with the stronger southeast monsoon from PO and then arrived YHR (figures 8(c) and (d)). Thus, we confirmed that the PO provided more moisture for TC-induced floods in YHR than that in SC within the Eulerian framework.

4. Conclusions

We have applied the GLFE flood data to assess the spatiotemporal characteristics of HR-induced and TC-induced floods in SC, YHR, and NC for 1985–2020, and investigated impacts on human mortality and displacement. Further, we used the improved areal source–receptor attribution method to quantify the water vapor contribution from each moisture source for the two types of flood events. Thus, we can clearly see a picture of the differences between the two types of floods in SC, YHR, and NC from the perspective of water vapor transport pathways and contributions. Finally, we used the moisture flux within the Eulerian framework to verify our results and give a simple explanation.

(a) HR-induced floods had higher occurrence frequencies than TC-induced floods over the whole of EC for 1985–2020. The spatial pattern of the severity of floods exhibited an increasing gradient from North to South. In addition, monthly flood numbers showed significant seasonal variations. Floods in SC, YHR, and NC peak in turn during June and August; TC-induced floods reached their peak later than HR-induced floods.

(b) Trends of mean annual mortality and displacement rates were significantly decreasing for 1985–2020, especially mortality in SC and YHR, and displacement rates in YHR. Specifically, significant decreasing trends of annual mean mortality of HR-induced floods in SC, TC-induced floods in SC, and HR-induced floods in YHR (p < 0.01) were observed. The decreasing trends of the mean annual displacement rates of HR-induced floods in YHR (p < 0.01) and HR-induced floods in NC (p < 0.001) were also shown.

(c) For the floods in SC, the IO channel plays the most important role, but the key moisture source was from SC and the northern part of the SCS. TC-induced floods achieved more water vapor trajectories and moisture contribution from the PO, compared with HR-induced floods. This is because TCs were mainly produced in the PO. For the floods in YHR, the PO became the most important moisture channel and contribution region for TC-induced floods. For the floods in NC, the main moisture transport channels were the EA channel, PO channel, and IO channel, but the most important moisture source was from EC.

In short, the most important moisture sources for HR-induced floods in three study regions are all from EC. However, the most important moisture source
for TC-induced floods in SC and YHR is from the Western PO. The above result within the Lagrangian framework is well confirmed by the Eulerian method.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: http://floodobservatory.colorado.edu/Archives/index.html.

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