Increasing exposure to floods in China revealed by nighttime light data and flood susceptibility mapping

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Abstract

The impacts of floods on human society are expected to increase at both global and regional scale in the context of global climate change and increasing human activity in flood-prone areas. However, spatially explicit and dynamic assessments of flood exposure in China are still very limited, which hinders the development of risk-based flood management considering dynamic changes. Therefore, this study explored the spatial-temporal variations of flood exposure in China from 1992 to 2020 through flood susceptibility mapping and using satellite-based nighttime light data. It can be revealed that a significantly high level and rapid increase of flood exposure could be observed in China, especially around some major metropolitan areas in the eastern region. The expansion of flood exposure was mainly distributed in North China and some coastal areas during 1992–2000; while mainly occurring in South China during 2000–2013, especially in middle Yangtze River basin where flood susceptibility is highest. The changes of flood exposure in China were mainly driven by the increase in the number of lit pixels during the early period, and were dominated by the increase in the intensity of lit pixels in the later period. This process continued to the latest period of 2014–2020. This implies that upgrading of existing flood management facilities and efforts for more effective measures are urgently needed in flood-prone urban areas with increasing exposure intensity. In addition, this study demonstrated the advantage of nighttime light data for disaster assessment and monitoring. With the development of more nighttime light products of higher resolution and higher detection ability and the integration with ground-based observation, it is promising to achieve more precise monitoring and analysis of flood exposure at a large scale, and support fine-grained management of flood risk.

1. Introduction

Floods are among the most disastrous natural hazards in the world, with widespread distribution, highest frequency of occurrence and severe damages to society (Hu et al. 2018, Chen et al. 2020). Moreover, the impacts of floods have been projected to increase at both global and regional scale as a result of intensifying hydrological cycle from global warming and increasing human activity in flood-prone areas (IPCC 2012, Hirabayashi et al. 2013). In this context, effective flood management and adaptation strategies are pressingly needed to mitigate the threats, which however rely on a complete understanding of flood risk and its dynamic changes (Merz et al. 2010).

Flood exposure, usually defined as the population and value of assets subject to flooding, is an important component of flood risk (IPCC 2012, Koks et al. 2015). It indicates the population and assets under threat, and the maximum potential losses from the hazards, thus providing crucial information for disaster risk reduction. However, it has not received
considerable attention compared with the studies of physical processes in hazard assessment (Smith et al. 2019). Recently, an increasing number of studies have evaluated population and urban exposure to floods and other hazards and their changes in different regions (Güneralp et al. 2015, Qiang et al. 2017, Chen et al. 2019). Globally, Jongman et al. (2012) presented an estimation of global economic exposure to river and coastal flood for the period 1970–2050, using two different methods based on population and land use, respectively. Smith et al. (2019) used high-resolution population data to map flood exposure for 18 developing countries. They suggested that estimations based on existing demographic datasets may struggle to represent fine spatial distribution of exposure. In China, Fang et al. (2020) estimated population exposure and potential damage of coastal flood over the 21st century using future scenarios. In addition, spatiotemporal changes in urban land and population in floodplains were investigated using modelled flood inundation map, gridded urban land and disaggregated population datasets, and rapid increases in flood exposure were found in association with rapid urbanization (Du et al. 2018, Fang et al. 2018b). Overall, most existing studies are based on population census (or disaggregated) data and land cover data, and use the results from large scale flood inundation modelling with nonnegligible uncertainty.

In recent decades, with the development of various nighttime optical sensors, satellite-based nighttime light (NTL) data, which offer a unique opportunity to directly observe human activity from space, have been widely employed as a proxy for human activity (Levin et al. 2020). This has allowed a host of applications such as urbanization process mapping (Liu et al. 2012, Zhu et al. 2019), population and economic activity estimation (Chen and Nordhaus 2011), light pollution and ecological impacts monitoring (Bennie et al. 2014), as well as armed conflict and disaster assessment (Li et al. 2018a, Qiang et al. 2020). Ceola et al. (2014) examined the trends of global nighttime lights in the proximity of the river network from 1992 to 2012 to indicate human exposure to floods, and tested the correlation between nightlights and flood damages. They demonstrated that the objectively measured dataset of nightlights can effectively reveal enhanced anthropogenic pressure to rivers as well as increased exposure to riverine floods. However, spatially explicit and time series assessments of flood exposure with high resolution nighttime light data in rapidly urbanizing and flood-prone regions, such as China, are still very limited.

Therefore, in this study we attempt to investigate dynamic changes of flood exposure in China using flood susceptibility mapping and nighttime light data, with particular attention on the extent and intensity of the exposure as well as their temporal changes and spatial heterogeneity. Considering that flood hazard is relatively stable compared with the variation of socio-economic conditions, we assume that flood susceptibility remains unchanged during the study period and the change of flood exposure is mainly driven by the change of population and assets in flood-prone areas. We separated the geographical area of mainland China into four climate regions and 12 major basins (figure 1). Flood susceptibility and exposure for each climate region and basin were calculated and analyzed (Taiwan was not analyzed here as there is no sufficient data). This study would provide essential information for enhanced understanding of flood risk in China as well as more targeted risk reduction measures.

![Figure 1. Four major climatic zones in China overlaid with nighttime light in 2013 (a) and distribution of major river basins as well as historical flood events (1985–2018) (b) (12 major basins: CJ, Yangtze River; ZJ, Pearl River; HH1, Yellow River; HH2, Haihe River; HH3, Huaihe River; SER, Southeast Rivers; SWR, Southwest Rivers; NTR, North Tibet Rivers; NWR, Northwest Rivers; IMR, Inner Mongolia Rivers; HLJ, Heilongjiang River; LH, Liaohe River).](image-url)
2. Data and methods

2.1. Intercalibration and adjustment of DMSP-OLS nighttime light data

The version 4 cloud-free annual composites of nighttime light from 1992 to 2013 collected by the Defense Meteorological Satellite Program Operational Line Scanner (DMSP-OLS) were used in this study. The average stable light intensity (represented by the digital number (DN) values) were adopted, and they are collected from six different satellites (F10, F12, F14, F15, F16, and F18) with a spatial resolution of 30 arc-seconds.

Due to a lack of on-board calibration, the DN values in DMSP-OLS images cannot be converted to exact radiance, and are not comparable in different years. Therefore, a procedure of intercalibration is requisite before using the data in time series analysis. Several intercalibration methods have been developed based on the invariant-region scheme, in which theoretically unchanged regions are chosen as reference samples to establish calibration models. While the invariant areas are usually manually selected or predefined using auxiliary data (Elvidge et al. 2009, Liu et al. 2012). In addition, due to the inherent deficiencies of the DMSP sensors, the NTL data has the problem of luminosity saturation in urban core region, which would bring significant underestimation for the variation of NTL intensity (Zhuo et al. 2015, Chen et al. 2021).

Here, we proposed an auto-calibration procedure without any auxiliary data and adopted the vegetation adjusted method (Xie and Weng 2017) to reduce the saturation problem. The process is described as follows (figure 2).

(a) Resample the original DMSP-OLS images to 1 × 1 km.

(b) Select invariant pixels with following steps: calculate annual mean μ and standard deviation σ for each pixel; exclude pixels with zero μ or σ; exclude outliers for which the difference between maximum/minimum and multi-year average exceeds the threshold of 15; divide the rest pixels into eight groups according to multi-year mean value to ensure an even distribution of samples; select 1000 pixels with minimum coefficient of variation (CV) for each group as final invariant pixels.

(c) Select F152001 as the reference image which is assumed to be the ‘true’ value based on two criteria: the time of the image is in the middle of the series; the mean of invariant pixels in the image is close to the average of all years (35.1 for 2001 and 34.7 for all years).

(d) Fit a quadratic polynomial function using DN value of selected invariant pixels to build the calibration model as:

\[ \text{DN}_{\text{reali}} = a \text{DN}_{i}^{2} + b \text{DN}_{i} + c \]  \hspace{1cm} (1)

where DN and DN_{reali} are the original and calibrated DN value in year i, respectively.

(e) Apply the model to calibrate all pixels from 1992 to 2013.

(f) Normalize the calibrated NTL data to the range of 0 ~ 1.

(g) Adjust the calibrated NTL data using annual NDVI data and following formulas

\[ \text{NTL}_{\text{adj}} = \left( \frac{2}{1 - k} - 1 \right) \times \text{NTL}_{\text{cali}}. \]  \hspace{1cm} (2)

\[ k = \text{NTL}_{\text{norm}} - \text{NDVI} \]  \hspace{1cm} (3)

where NTL_{adj}, NTL_{cali}, NTL_{norm} are the adjusted, calibrated and normalized NTL data, respectively.

2.2. Flood susceptibility mapping

The analytic hierarchy process (AHP) method was adopted to assess flood susceptibility in this study, which has been widely used in natural hazard susceptibility analysis (Kazakis et al. 2015). It is worth noting that flood susceptibility calculated here represents an average level of flood hazard for the recent decades. Eight factors from four dimensions contributing to the occurrence of flood are considered: (a) topographic factors including slope (SP) and elevation above the nearest drainage (EAND); (b) drainage factors including drainage network density (DD) and distance from the nearest drainage (DFND); (c) precipitation factors including annual maximum daily rainfall (AMR), annual frequency of heavy rainfall >30 mm d⁻¹ (HRF_30) and annual total precipitation of heavy rainfall >30 mm d⁻¹ (THR_30); (d) vegetation cover factor (VC) of NDVI from MODIS. The drainage network data was extracted from FAO global river network dataset derived from HydroSHEDS, and precipitation-related factors were derived from the 0.5°×0.5° gridded precipitation dataset of China (1961–2018) provided by China Meteorological Administration. The topographic factors were derived from the 90 m SRTM DEM data. The weight of each factor was determined through a combination of AHP calculation and experts’ judgement about the relative importance of different factors (table S1 (available online at stacks.iop.org/ERL/16/104044/mmedia)). The final flood susceptibility map was produced through a combination of the eight factors with their corresponding weight.
2.3. Flood exposure change analysis

To analyze changes in flood exposure, we calculated linear change rate and average annual change rate (ACCR) for the number of lit pixels (DN > 0) and average intensity of nighttime light during 1992–2013. The intensity of nighttime light in different flood-susceptible areas was used to indicate exposure intensity, which means the intensity of human activity exposed to floods. Linear change rate is calculated as the slope of the fitted linear regression function and ACCR is defined as:

\[
ACCR = \left( \frac{t_2 - t_1}{x_{t_2} - x_{t_1}} \right) \times 100\% - 1
\]

(4)

where \(x_{t_2}\) and \(x_{t_1}\) refer to nighttime light in year \(t_2\) and \(t_1\), respectively.

3. Results

3.1. Calibration of NTL data and distribution of nighttime light

Due to a lack of actual radiation, the calibrated and adjusted NTL data were verified through a comparison with original data in terms of total DN value (TDN) and total number of lit pixels (DN > 0) (TLP). It can be seen from figure 3 that both indicators in the adjusted images are more consistent than in original images. The adjusted TDN and TLP have smoother temporal variation, demonstrating that the calibration process has greatly improved the comparability of NTL data. In addition, the correlation coefficients between GDP in China and adjusted NTL data are 0.9894 and 0.8596 for TDN and TLP respectively, while they are 0.9748 and 0.7921 for uncalibrated data, further demonstrating the performance of the calibration. Moreover, the average standard deviation for DN values of all pixels is 5.64 and 30.42 for original and final adjusted NTL, respectively, indicating significant increase in the spatial variation of NTL intensity after adjustment.

Overall, consistent increasing trends can be found in both TDN and TLP. For spatial distribution, nighttime lights were mainly concentrated in East China, where the population is densely distributed and urbanization level is relatively higher. Significant expansion of nighttime lights and increase in the intensity from 1992 to 2013 can be found around some major metropolitan areas, especially for the Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, Chengdu-Chongqing and Middle Yangtze River urban agglomerations (figure 4).

3.2. Flood susceptibility mapping and analysis

Spatial distribution of eight contributing factors after normalization and the final flood susceptibility map are shown in figure 5. It is indicated that the topographic, meteorological and drainage conditions in southern and eastern China are more favorable to
produce flood, while low vegetation cover in arid northwest China would also make it easier and quicker to generate flood flow. Overall, flood susceptibility in southern and eastern China is higher than that in the west. The middle and lower Yangtze River plain and lower Pearl River plain have the highest level of flood susceptibility. In general, the flood susceptibility pattern is consistent with the distribution of historical flood events as shown in figure 1.

The susceptibility of flooding was further divided into five categories: extremely high at the top 5%; high for the upper 25%–5%; moderate from 50% to upper 25%; relatively low from lower 25% to 50%; low for the lower 25%. Most of the extremely high and high flood-susceptible areas are distributed in the climate zones of humid subtropics and tropics (over 67.1%) and humid/semi-humid temperate areas (about 32.3%). On the contrary, northwest arid area and cold Qinghai-Tibet Plateau hold a majority of low and relatively low flood-susceptible areas (73.1% in total).

The distribution of different flood-susceptible areas in different river basins is shown in figure 6.
Figure 5. Eight factors and flood susceptibility map in China. The eight factors are slope, elevation above the nearest drainage (EAND), distance from the nearest drainage (DFND), annual average maximum daily rainfall (AMR), annual average frequency of heavy rainfall $>30$ mm d$^{-1}$ (HRF$_{30}$), annual average total precipitation of heavy rainfall $>30$ mm d$^{-1}$ (THR$_{30}$), drainage network density (DD) and vegetation cover (VC). They have all been normalized and the higher value indicates higher susceptibility of flooding.

Figure 6. The distribution of different flood-susceptible areas in each of the major 12 basins (a, sorted by the proportion of area with extremely high flood susceptibility) and the area percentage of the 12 basins in different flood susceptibility categories (b). The basins are associated with the climatic zones: ZJ, SER and most of CJ—Humid Subtropics and Tropics; HLJ, LH, IMR, HH2, HH3 and most of HH1—Humid/Semi-humid Temperate Area; NWR—Arid Area; NTR, head of CJ, HH1 and SWR—Cold Plateau.

Huaihe River basin has the highest proportion of extremely high and high flood susceptibility (over 98%), followed by Pearl River basin (75.9%) and Southeast rivers (77.4%). The Yangtze River basin has a relatively even distribution of different flood susceptibilities given its vast spread across several different geographical zones. While river basins in the west have the highest proportion of relatively low and low flood susceptibility, including Southwest rivers (80.5%), Northwest rivers (77.1%) and North Tibet rivers (64.3%). For area distribution of different river basins in different flood susceptibility categories, it is revealed that 79.8% of extremely high and 43.7% of high flood-susceptible areas are distributed in Yangtze River basin and Pearl River basin. Northwest river basins account for the largest proportion of relatively low and low flood-susceptible areas (36.6% and 41.0%, respectively).
Table 1. Number of lit pixels and average intensity of the light as well as their changes during 1992–2013 in different flood-susceptible areas.

| Flood susceptibility | Number of lit pixels | Linear rate (△/decade) | Average intensity | Linear rate (△/decade) |
|----------------------|----------------------|------------------------|------------------|------------------------|
|                      | Mean                 | Percentage             | AACR             | Mean                  | AACR                  |
| Low                  | 87 100               | 3.61%                  | 12.58%           | 73 705.99             | 0.3060                |
| Relatively low       | 177 765              | 7.30%                  | 10.33%           | 127 249.99           | 0.4673                |
| Moderate             | 435 555              | 17.69%                 | 7.97%            | 228 441.06           | 0.8940                |
| High                 | 1111 487             | 56.66%                 | 4.44%            | 337 932.52           | 4.0359                |
| Extremely high       | 306 562              | 62.71%                 | 4.72%            | 104 842.24           | 7.5080                |

Figure 7. Annual variation (a) and multi-year average (b) of nighttime light data series in different flood-susceptible areas: top, number of newly lit pixel; middle, average intensity of newly lit pixels; bottom, average intensity of existing lit pixels.

3.3. Distribution and changes of flood exposure in different flood-susceptible areas

The distribution and changes of flood exposure in different flood-susceptible areas were investigated through a combination of flood susceptibility mapping and nighttime light change analysis. It can be seen from Table 1 that the regions with high and extremely high flood susceptibility have the largest number and highest proportion of lit pixels respectively. Moreover, linear change rate in lit pixel number is also highest in high flood-susceptible areas, indicating significantly high level and rapid increase of flood exposure in China. In addition, average light intensity and the linear change rate in high and extremely high flood-susceptible areas are also significantly higher than that in low susceptible areas. While ACCR in high and extremely high flood-susceptible areas are lower than that in low susceptible areas in both cases.

Temporal variation of nighttime light in different flood-susceptible areas is shown in Figure 7.
Number of newly lit pixels (DN > 0 while was 0 in previous years), intensity of newly lit pixels and intensity of existing lit pixels (DN > 0 in both current and previous years) were calculated both annually and for multi-year average. It can be observed that the number of newly lit pixels was decreasing from 1992 to 2013 in moderate, high, and extremely high flood-susceptible areas. However, an increase in the intensity of newly lit pixels could be found for all flood susceptibility categories after 2005, despite slight decrease in the early period. The intensity of existing lit pixels for moderate, high, and extremely high flood-susceptible areas showed significant increasing trend in the later period (after 2001), while decreased all the time for low flood-susceptible areas. Overall, it can be revealed that changes of flood exposure in China (using nighttime light as proxy) were mainly driven by the increase in the number of lit pixels during the early period, while were dominated by the increase in the intensity of lit pixels in the later period.

Spatial distribution of flood exposure and its change in high and extremely high flood-susceptible areas were further investigated. It can be seen from figure 8 that both average intensity and linear change rate of nighttime light were higher around some major metropolitan areas, especially in the Yangtze River Delta and Pearl River Delta. For ACCR, rapid changes were observed in the Huaihe River basin and lower Yangtze River basin. While ACCR were relatively low in the North China plain and mountainous area of upper Pearl basin and middle Yangtze basin. Extent change of flood exposure was indicated by newly lit pixels (DN > 0) for two periods (1992–2000 and 2000–2013). The expansion of flood exposure extent was mainly found in North China and some coastal areas in the southeast during 1992–2000; while changes in the extent mainly occurred in southern China during 2000–2013, especially in middle Yangtze River basin where flood susceptibility is highest.

4. Discussion

4.1. Flood exposure change during the post-DMSP period

Since DMSP satellites stopped generating NTL data after 2013, we mainly focused on the period of 1992–2013 in this study. To reveal more recent change of flood exposure, we further used the latest annual global Visible and Infrared Imaging Suite (VIIRS) nighttime light data (VNL V2) (Elvidge et al 2021), and examined the distribution of nighttime lights in different flood-susceptible areas from 2014 to 2020. The results exhibited a similar pattern with previous
analysis and showed a continuation in the process of flood exposure change during the post-DMSP period. Specifically, the number of lit pixels remained stable or slightly increased for high flood-susceptible areas; while the number of newly lit pixels showed slightly decreasing trend. Moreover, the intensity of lit and newly lit pixels increased significantly, especially for high and extremely high flood-susceptible areas (figure S1).

4.2. Potential and limitations of NTL data
It has been demonstrated that nighttime light data (NTL) can be a valuable data source for disaster assessment and monitoring as it can offer a spatially explicit and time varying representation of human activity at high resolution. Compared with traditional statistical and census data, NTL can directly reflect the real-time distribution of human activities, and solve the problem of not being able to timely capture population mobility with traditional methods. Meanwhile, compared with other real-time data like the cellular signaling data with limited coverage, NTL can better reflect human activities at large scale. Therefore, it is very suitable for the monitoring and assessment of emergencies such as natural disasters, especially in the context of the continuous emergence of new satellite platforms and higher spatial-temporal resolution data, such as VIIRS (Elvidge et al. 2017), Luoji-1 and its successor (Li et al. 2018b).

However, the application of satellite-based nighttime light data also faces some challenges, for example the blooming effect and saturation of the luminosity data (Zhang et al. 2013), and the relatively weak ability to reflect population distribution in rural regions or underdeveloped areas. In this study, we adopted the vegetation adjusted method (Xie and Weng 2017) to deal with the saturation problem and increase the variation of NTL data. Nevertheless, the relation between vegetation and NTL may not be spatially consistent and the adjusted NTL data still cannot fully capture the variation of human activity intensity (Levin et al. 2014). In this study, the relatively high intensity of NTL in the low flood susceptibility area (figure 7) may be because that most of lit pixels in this area were located in the arid West China with low vegetation cover, which would amplify light intensity after adjustment.

Therefore, further development of nighttime light detection sensor and data processing algorithms are still of significant importance, with the anticipation to provide more data products with higher resolution and higher detection ability. In addition, an integration of NTL data and some other data from both satellite-based and ground-based observation would merit more efforts in the future, which will be helpful to achieve better monitoring and analysis of flood exposure at large scale, and support the fine management of flood risk.

5. Conclusion
A complete understanding of flood exposure and its dynamic changes is vital for effective risk reduction measures. In this study, we explored spatial-temporal changes of flood exposure in China, through a combination of flood susceptibility mapping and satellite-based nighttime light analysis. It can be revealed that a high level of nighttime light exposure was mainly found in the metropolitan areas of East China, especially in the Yangtze River Delta and Pearl River Delta, where both socio-economic development level and flood susceptibility are high. Moreover, linear change rate of lit pixel number and light intensity in these regions were significantly higher than in low susceptibility areas, indicating rapid increase of flood exposure. The expansion of nighttime light was mainly found in North China and some coastal areas in the southeast during 1992–2000, while mainly occurring in southern China after 2000, especially in middle Yangtze River basin with highest flood susceptibility.

These results are consistent with the findings of some previous studies (Du et al. 2018, Fang et al. 2018b, 2021). This implies that continuous efforts for more effective flood risk management are still needed, especially considering the occurrence of more frequent extreme events under global climate change and great divergence in the standard of flood protection (Fang et al. 2018a, Wang et al. 2021). In addition, the newly proposed national initiatives of ‘Green Development of The Yangtze Economic Belt’ and ‘Yangtze River Protection’ are expected to stimulate further development and thus increase exposure to floods in the basin. However these policies will also bring new opportunities to promote the integration of social-economic development and ecological restoration, for which the nature-based solutions for flood mitigation will be more valued and a portfolio of flood risk reduction measures will be designed (Luo et al. 2019, Zheng et al. 2020).

It is also notable that the changes of flood exposure in China were mainly driven by the increase in the number of lit pixels during the early period, and were dominated by the increase in the intensity of lit pixels in the later period. This indicates that the increase in the flood exposure intensity is now more prominent in comparison with the expansion of flood exposure extent. This trend will continue in the future as the population continues to concentrate in metropolitan areas and the pressure for ecological conservation grows, which limits the exploitation of flood plains as seen in the case of recent policy for flood detention zone adjustment (Du et al. 2021). In this context, the upgrading of flood management facilities and other measures for urban flood management are urgently needed in flood-prone urban areas with increasing exposure intensity.
In this study, flood susceptibility is assumed to be a static factor and reflects the average state during the study period. However, ongoing climate change and land cover change (e.g. urbanization or reforestation) may alter the atmospheric circulation and land surface process, leading to a nonstationary change of flood susceptibility and risk. Existing studies have found an increasing trend of extreme precipitation in the middle and lower Yangtze basin, and projected significant increase in flood frequency over China in the future (Hirabayashi et al 2013, Fang et al 2018a). Therefore, we propose further study on the modeling of flood susceptibility and the impacts of climate change and land cover change in the future to enable a more precise analysis of flood exposure and its dynamic change.

Data availability statement

The data that support the findings of this study are openly available.

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