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Evaluating Urban Flooding and Economic Losses in 332 Chinese Cities under Future Climate Scenarios

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Abstract

With climate change and urbanization, urban flooding has intensified, causing significant socio-economic damages. Existing studies lack evaluation of flooding risks from a national scale or multi-city comparative perspective. This study aims to assess the urban flooding risks of 332 cities in China under the Shared Socioeconomic Pathway-Representative Concentration Pathway (SSP-RCP) SSP2-RCP4.5 and SSP5-RCP8.5 for the years 2020, 2040, 2060, and 2080, and to explore the spatial clustering effects and risk driving factors. The results show that over 80% of cities are projected to experience considerable increases in flooding volume and economic losses compared to 2020, with higher growth rates in North, Northeast and Southern China. Factors such as urban land compactness and gross domestic product have important impacts on flooding risks. This study offers scientific references for formulating targeted urban flooding management policies and planning.

Highlights

- Future urban flooding risks for 332 cities in China are evaluated.
- Over 80% of cities will face increased flooding and economic losses in the future.
- Regional flooding risk differences and their driving factors are identified.

Introduction

Climate change and urbanization processes have led to frequent pluvial flooding. Cities, as the main venues for human social activities and concentration of valuable properties, are highly susceptible to severe economic losses due to urban flooding (Rainey et al., 2021). While many studies have assessed future urban flooding risks, most focus on local or single-city case studies due to the difficulty in obtaining data on flooding locations, lacking assessments on a national scale (Li et al., 2022). Furthermore, there is a lack of in-depth analysis of the risk drivers and spatial heterogeneity (Balaian et al., 2024). Against this backdrop, this study aims to (1) evaluate the flooding volume and economic losses of 332 cities in China under the Shared Socioeconomic Pathway-Representative Concentration Pathway (SSP-RCP) SSP2-RCP4.5 and SSP5-RCP8.5 scenarios for the years 2020, 2040, 2060 and 2080; (2) reveal regional differences in flooding risks; and (3) analyse the risk driving factors, providing insights for the targeted urban pluvial flooding management.

Methodology

Flooding modelling and loss assessment

The urban flooding simulation model used in this study considers surface runoff, network conveyance, node overflow, and overland flow processes. The first two processes are simulated using the Storm Water Management Model (SWMM; Rossman, 2007). Node overflow is used as the input for the

Cellular Automata Dual-Drainage Simulation (CADDIES) model to simulate overland flow (Guidolin et al., 2016). The model is validated by comparing simulated water depths with real-world data, including social media reports from Weibo, a Chinese platform similar to Twitter, with 260 million daily active users (Li and Dong, 2024), as well as monitoring data from city traffic management bureaus and Water Authorities. The results demonstrate high alignment across all sources. Subsequently, flooding economic losses are assessed using water depth-damage curves. Water depths at each time step are mapped to corresponding damage values using linear interpolation.

Analysis of spatial autocorrelations and driving factors

To analyse the spatial autocorrelation of urban flooding risks and economic losses, this study employs the Local Indicators of Spatial Association (LISA) clustering method (Anselin, 1995). This study further explores the drivers of flooding risks, including Gross Domestic Product (GDP), population, centrality (CENT), compactness (COMP) and fragmentation (FRAG). GDP and POP are sourced from publicly available future urban GDP and population projections (Jiang et al., 2022). CENT measures the centralization of population, with higher values indicating a more concentrated population. COMP evaluates the compactness of urban land, with higher values representing a more tightly packed urban form. FRAG indicator assesses the fragmentation of urban land, with higher values indicating more scattered urban patches (Chen et al., 2023). Meanwhile, this study uses Geographic Weighted Random Forest (GWRF) method to assess the relationship between the proportion of change in annual flooding volume (PCAFV) and the proportion of change in annual economic losses (PCAEL) relative to the current year, and the aforementioned driving factors. For each factor, the importance is assessed by calculating the Gini index gain at each split in every tree of GWRF models. Moreover, this study uses the SHapley Additive exPlanations (SHAP) method to determine whether the factor has a positive or negative influence on PCAFV and PCAEL.

Case study

This study focuses on 332 cities specifically their urban built-up area in China, with assessment years including 2020 (current), 2040, 2060, and 2080, under SSP2-RCP4.5 and SSP5-RCP8.5. The city-level data required for the study includes rainfall, digital elevation model (DEM), land use, population, roads, rivers and buildings. For rainfall, the current year uses precipitation data from national ground weather stations in China, while future years rely on data from the Sixth Coupled Model Intercomparison Project (CMIP6) processed by Xu et al. (2021), dynamically downscaled using the Weather Research and Forecasting (WRF) model, with a 9 km spatial and 15-minute temporal resolution. DEM, land use, population, road, river and building data are used as input for the Sustainable Urban Wastewater System Generator (SUWStor) stormwater system version to design future urban stormwater systems in 332 cities (Zhang et al., 2023).

Results and discussion

In 2020, China’s total urban flooding volume was 3.3 billion cubic meters, with economic losses of 4.7 billion CNY. Under SSP2-RCP4.5, 81% of cities are projected to see increased flooding volume, with national average PCAFV of 22%, 27%, and 40% for 2040, 2060, and 2080, respectively. Additionally, 82% of cities will face higher economic losses, with national average PCAEL of 31%, 38%, and 40%. Under SSP5-RCP8.5, 83% of cities will experience increased flooding, with PCAFV of 32%, 42%, and 45%, and 97% of cities will see significant economic loss increases, with PCAEL of 36%, 42%, and 50%.

Figure 1a presents the spatial distribution of absolute values of flooding volume and economic losses in 2020. Cities in eastern and central China exhibit the highest flooding risks, with significantly higher flooding volume than other regions. These areas are characterized by low-lying terrain, high urbanization rate and rainfall intensity, making them particularly vulnerable to urban flooding. Economic losses are concentrated in the eastern and southern regions, closely tied to dense properties. As shown in Figure 1b, both PCAFV and PCAEL show an increasing trend over time, with northern, northeastern and southern China experiencing higher growth rates. This trend is most pronounced under SSP5-RCP8.5, where extreme rainfall events, coupled with rapid urbanization, result in more than 50% increases in PCAFV and PCAEL for many cities by 2080. In contrast, southwestern and eastern China exhibit smaller increases. LISA clustering analysis reveals clear spatial patterns for PCAFV and PCAEL (Figure 1c). HH and LH clusters are mainly found in northern and northeastern China, such as Tangshan and Harbin. These cities face higher PCAFV and PCAEL, particularly as aging infrastructure and inadequate flooding control increase their vulnerability to flooding and economic losses. On the other hand, LL and HL clusters are found in southwestern and eastern China, including cities like Luzhou and Wuxi. In southwestern cities, the mountainous terrain limits flooding spread, while in eastern cities, flooding control infrastructure is more effective, both of which help reduce flooding risks.

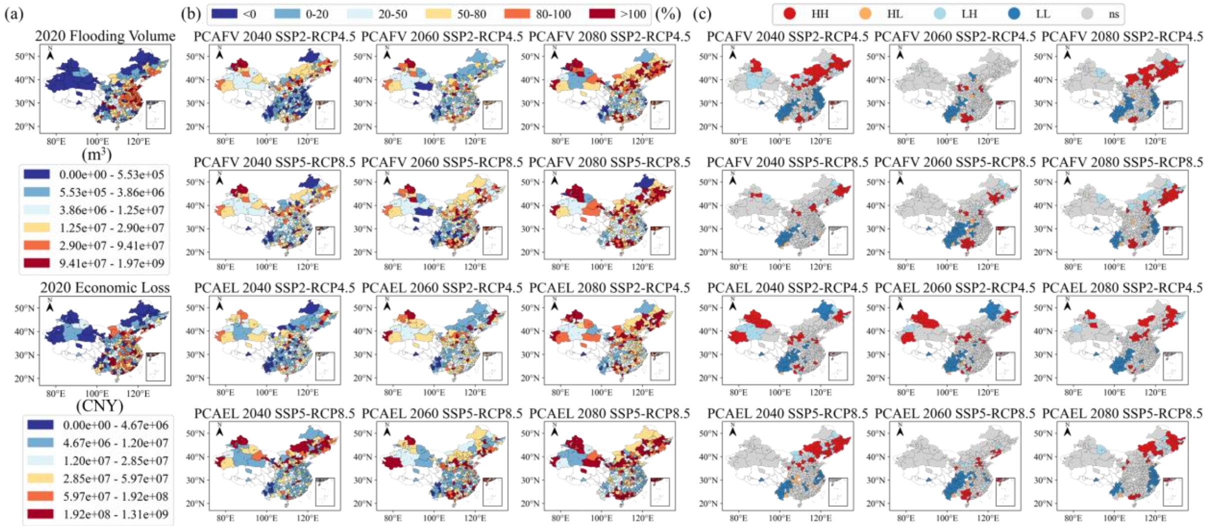

Figure 1. Spatial distribution of flooding volume and economic losses: (a) absolute values (unit: m³ for flooding volume and CNY for economic losses), (b) PCAFV and PCAEL (%), and (c) LISA clusters of PCAFV and PCAEL.

GWRF models were established using PCAFV and PCAEL as dependent variables and CENT, COMP, FRAG, GDP, and POP as independent variables for different years and SSP-RCP scenarios. The regression results all show R-squared values greater than 0.9 and RMSE below 0.07. Feature importance and SHAP values shown in Figure 2 indicate that COMP is the most influential factor, as compact cities with dense urban land exacerbate flooding and economic losses. CENT also positively impacts both PCAFV and PCAEL, as higher population centrality often correlates with greater development intensity. In contrast, GDP and POP have a negative effect, as cities with higher socio-economic development level can invest more in flooding prevention. FRAG, which reflects various land uses like green spaces and water bodies, helps reduce flooding risks and economic losses.

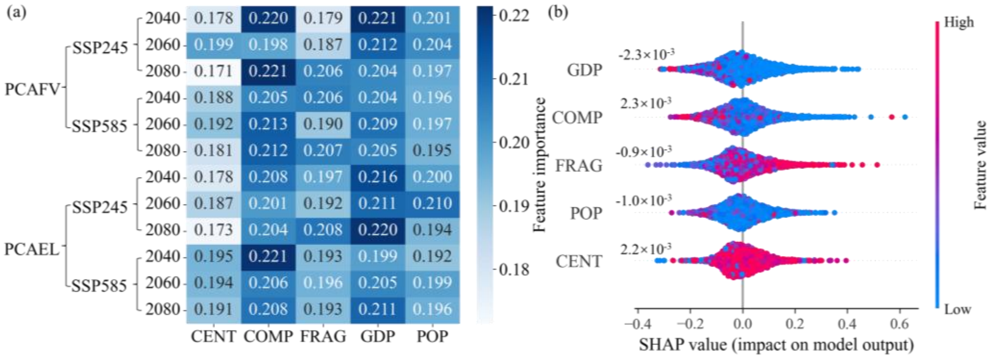

Figure 2. Feature Importance and SHAP Values in GWRF Models: (a) feature Importance and (b) SHAP values.

Based on the local importance of various features, cities were classified into three clusters using K-Means clustering (Figure 3). Cluster 1 cities, located in northwest and southwest China, are primarily influenced by GDP, POP, and CENT, with economic growth and population increase helping improve stormwater infrastructure and reduce flooding risks while centralized population posing threat to the rise of PCAFV and PCAEL. Cluster 2 cities, in Northeast and North China, are driven by FRAG and COMP, with low urbanization and decentralized land use currently. Future urban development will impact PCAFV and PCAEL significantly by altering the spatial distribution of green spaces, water bodies and impervious surfaces and changing the runoff risk arising from it. Cluster 3 cities, in central, southern, and eastern China, experience a balanced influence of CENT, COMP, FRAG, GDP, and POP, requiring multi-dimensional considerations in urban development.

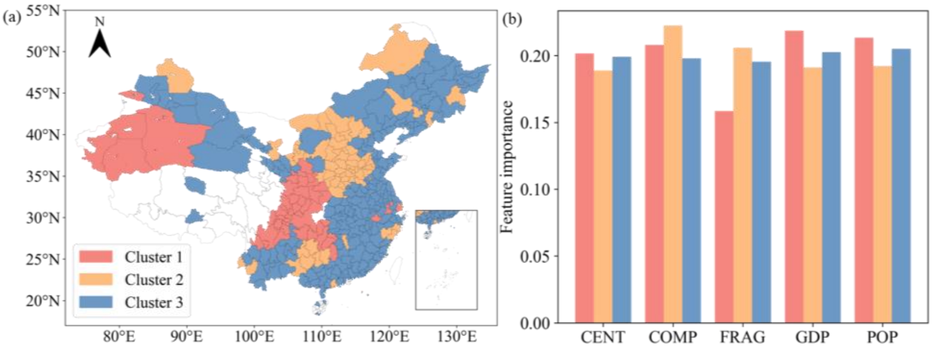

Figure 3. Clustering of cities based on feature importance: (a) spatial distribution and (b) feature importances of different clusters.

Conclusions and future work

This study provides a comprehensive assessment of urban flooding risks and economic losses across 332 cities in China in 2020, 2040, 2060 and 2080 under SSP2-RCP4.5 and SSP5-RCP8.5. The total flooding volume and economic losses in Chinese cities are projected to rise significantly in the future and displaying clear regional differences and spatial autocorrelation patterns. CENT, COMP, FRAG, GDP and POP influence PCAFV and PCAEL of cities from different regions to varying extents. Future work should explore the impact of climate adaptation strategies including blue, grey and green infrastructure on effectively reducing flooding volume and economic losses. Additionally, given the uncertainty associated with future climate projections and socio-economic changes, it is important to conduct sensitivity and uncertainty analyses on rainfall data and water depth-damage relationship to assess the robustness of the findings.

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