

Article

Flood Mapping and Assessment of Crop Damage Based on Multi-Source Remote Sensing: A Case Study of the “7.27” Rainstorm in Hebei Province, China

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Abstract: Flooding is among the world’s most destructive natural disasters. From 27 July to 1 August 2023, Zhuozhou City and surrounding areas in Hebei Province experienced extreme rainfall, severely impacting local food security. To swiftly map the spatial and temporal distribution of the floodwaters and assess the damage to major crops, this study proposes a water body identification method with a dual polarization band combination for synthetic-aperture radar (SAR) data to solve the differences in water body feature recognition in SAR due to different polarization modes. Based on the SAR water body extent, the flood inundation extent was mapped with GF-6 optical data. In addition, Landsat-8 data were used to generate information on significant crops in the study area, while Sentinel-2 data and the Google Earth Engine (GEE) platform were used to classify the extent of crop damage. The results indicate that the flood inundated 700.51 km², 14.10% of the study area. Approximately 40,700 hectares (ha) or 8.46% of the main crops were affected, including 33,700 ha of maize, 4300 ha of vegetables, and 2800 ha of beans. Moderate crop damage was the most widespread, affecting 37.62% of the crops, while very extreme damage was the least, affecting 5.10%. Zhuozhou City experienced the most significant impact, with 13,700 ha of crop damage, accounting for 33.70% of the total. This study provides a computational framework for rapid flood monitoring using multi-source remote sensing data, which also serves as a reference for post-disaster recovery, agricultural production, and crop risk assessment.

Keywords: floods; agricultural losses; multi-source remote sensing; GF data; Super Typhoon Doksuri



Academic Editor: Luca Brocca

Received: 9 January 2025

Revised: 19 February 2025

Accepted: 28 February 2025

Published: 4 March 2025

Citation: Wen, C.; Sun, Z.; Li, H.; Han, Y.; Gunasekera, D.; Chen, Y.; Zhang, H.; Zhao, X. Flood Mapping and Assessment of Crop Damage Based on Multi-Source Remote Sensing: A Case Study of the “7.27” Rainstorm in Hebei Province, China. *Remote Sens.* **2025**, *17*, 904. <https://doi.org/10.3390/rs17050904>

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1. Introduction

Floods are among the most destructive natural disasters worldwide, characterized by their unpredictability and sudden onset [1]. The increasing frequency and intensity of extreme natural events, such as heavy precipitation, typhoons, earthquakes, and tsunamis,

driven by global climate change, severely threaten population safety and social development [2,3]. Since the twentieth century, approximately 6 million people have perished in floods [4]. By 2050, nearly 2 billion people worldwide will be at risk of flooding [5]. China, with its extensive coastline, significant elevation differences between eastern and western regions, and pronounced monsoon climate, is highly susceptible to typhoon-induced flooding [6]. For instance, the Super Typhoon Lekima in 2019 caused severe flooding in China's interior, affecting 14 million people and resulting in direct economic losses of CNY 65.37 billion [7]. Similarly, the Severe Typhoon In-Fa in 2021 led to substantial flooding in Zhengzhou City, impacting 14.786 million people and causing a direct economic loss of CNY 120.06 billion [8]. As a major agricultural country, China possesses 7% of the world's arable land, supporting 22% of the global population's food needs [9]. However, about 10% of China's land area and 70% of its agricultural production are threatened by flooding [10]. Notably, North China, a significant grain production region, experiences severe flooding, with 11.09% of its area regularly inundated [11]. The region's topography, primarily plains, with higher elevation in the northwest, makes it particularly vulnerable to flooding due to converging rain in low-lying areas [12].

Scholars have conducted various studies on crop loss assessment for sudden rainstorm disasters in recent years. Zhang et al. (2022) [13] used multi-source remote sensing data to realize the rapid extraction of the flood extent in the "7.20" rainstorm event in Henan Province and estimated the affected area of crops based on the NDVI. Rahman et al. (2021) [14] developed a Novel Disaster Vegetation Damage Index (DVDI) based on remote sensing data to assess crop losses during significant flood events in three states of the U.S.A. Qamer et al. (2023) [15] took the 2022 Pakistan flood as an example and proposed a framework for evaluating crop losses using multi-source remote sensing data. Singha et al. (2020) [16] mapped spatiotemporal changes and flood-affected rice in Bangladesh's major flood events based on Google Earth Engine (GEE) and Sentinel-1 data. These studies have formed the technical paradigm of "flood extent identification–crop damage assessment", but the following limitations still exist: (1) Most existing studies statically identify the maximum value of the flood range and lack the dynamic evolution of floods before and after heavy rain events. (2) Research on crop disaster assessment is mainly based on area identification, and there is a lack of research that reveals the spatial heterogeneity of crop disaster risk. In response to the "7.27" rainstorm incident in Hebei Province, Quan et al. (2024) [17] used remote sensing data to analyze the changes in the Normalized Vegetation Index (NDVI) in Hebei Province before and after the heavy rain to define the affected areas of farmland and estimate the corn yield loss. Liu et al. (2024) [18] used China's multi-source remote sensing satellite data to monitor flood changes in the Dongdian flood storage and retention area of Hebei Province. Existing research on this flood event focuses on results relating to the extent of crop damage, the estimation of staple crop losses, and the monitoring of changes in the floods at small scales (e.g., flood storage and retention areas) but lacks studies on the spatial and temporal changes of floods at large scales, the spatial heterogeneity of disaster risks, and the assessment of damage to multiple crops. Given the strategic position of Hebei Province as a central agricultural province in China and the reality of frequent floods, timely flood monitoring and agricultural disaster risk assessment are crucial for subsequent flood risk management, agricultural safety, and insurance compensation [19].

Multi-source high-resolution satellite imagery enables long-term, large-scale flood monitoring, offering detailed disaster information [20,21]. Commonly used satellite imagery for flood monitoring includes optical satellite imagery and synthetic-aperture radar (SAR) imagery. Optical satellite images, such as those from Landsat, MODIS, Sentinel, and GF sensors, provide rich spectral information, allowing for the detailed visualization of flood extents, crop damage, and biomass changes [22,23]. However, optical sensors are limited by weather conditions, as clouds can obstruct ground information acquisition [24].

In contrast, SAR imagery can penetrate clouds and operate in darkness, providing continuous data collection across different wavelengths and polarizations, which is crucial for round-the-clock ground monitoring [25]. Several methods are employed for water body extraction from SAR images, including machine learning, deep learning, object-oriented methods, and thresholding techniques [26–28]. Machine learning models, such as decision trees and Support Vector Machines (SVMs), effectively recognize terrain variations, making them suitable for identifying mountain water bodies [29]. While effective in distinguishing mountain shadows and water bodies, deep learning requires substantial initial effort, limiting its use for rapid water body extraction [30]. Object-oriented methods address fine-grained information and mixed image misclassification issues, effectively suppressing mountain shadows with the assistance of the Digital Elevation Model (DEM), but they rely on high-resolution images [31]. Thresholding methods construct models by analyzing the spectral characteristic curve of the water bodies and selecting appropriate bands and thresholds for separation. Common thresholding methods include single-band and multi-band techniques [32]. Single-band thresholding methods are effective in open areas like plains but may extract hill shadows in rolling hills [33]. Multi-band methods improve extraction by using interrelationships between different bands, significantly enhancing extraction effects [34]. With the help of the DEM, selecting appropriate elevations to mask mountain shadows can reduce their impact on water body extraction [35]. In summary, optical and SAR imagery can provide the nuanced spectral differences of features and spatial and temporal ranges of water bodies before and after flood events, respectively, complementing each other in exploring flood inundation areas and crop hazard assessments [36].

Both domestically and internationally, flood assessments can be categorized into rapid assessment, early recovery assessment, and in-depth assessment [37]. For sudden floods, early recovery and in-depth assessments are often too time consuming to meet urgent needs for quick decision-making. Rapid flood hazard assessment, however, provides timely disaster information to facilitate early mitigation measures and reduce losses. The combined use of multi-source remote sensing data eliminates the labor-intensive, small-scale, time-consuming, and discontinuous field-survey-based approach [38], making rapid flood detection and crop damage assessment feasible. Accurate crop damage assessment post-floods is crucial for subsequent crop pricing, insurance compensation, yield statistics, and the formulation of disaster prevention and mitigation policies.

This study uses the “2023 Hebei Heavy Rainstorm” as a case study to identify the spatial and temporal distribution of the flood event, map the flood inundation areas, and determine the significant crop areas affected by the flood and the intensity of the damage. Using GF-3, GF-6, Landsat-8, and Sentinel-2 data and agricultural statistics, the main research work of this paper examines the following key results: analysis of the spatial and temporal changes of the water body before and after the flood event, compensation for the difference between the SAR water body extent and the actual inundation area using optical images, consideration of the revisit period of SAR images, creation of high-resolution maps of flood inundation areas, and analysis of the spatial distribution and hazard intensity of flood-affected crops. For flood-prone areas and similar cases, this information can aid relevant departments in improving policies and disaster management, providing data references and a theoretical basis for post-disaster crop recovery, agricultural production, and risk assessment.

2. Materials

2.1. Study Areas

The study areas include Zhuozhou City, Gaobeidian City, Dingxing County, Rongcheng County, Xiong County, Bazhou City, and Wen'an County. These areas are located in the central region of Hebei Province, between 115°27'~116°54'E longitude and 38°44'~39°35'N

latitude (Figure 1b). Except for Zhuozhou City in the northwest, where the average elevation exceeds 50 m above sea level, the terrain is predominantly flat, covering a total area of 4813 km² (Figure 1c). The region experiences a temperate continental monsoon climate, with an average annual precipitation ranging from 250 to 900 mm. Influenced by the subtropical high pressure in the western Pacific Ocean, the rainy season predominantly occurs from late July to early August. This seasonal rainfall coincides with the critical growing period for key crops such as summer maize and winter wheat.

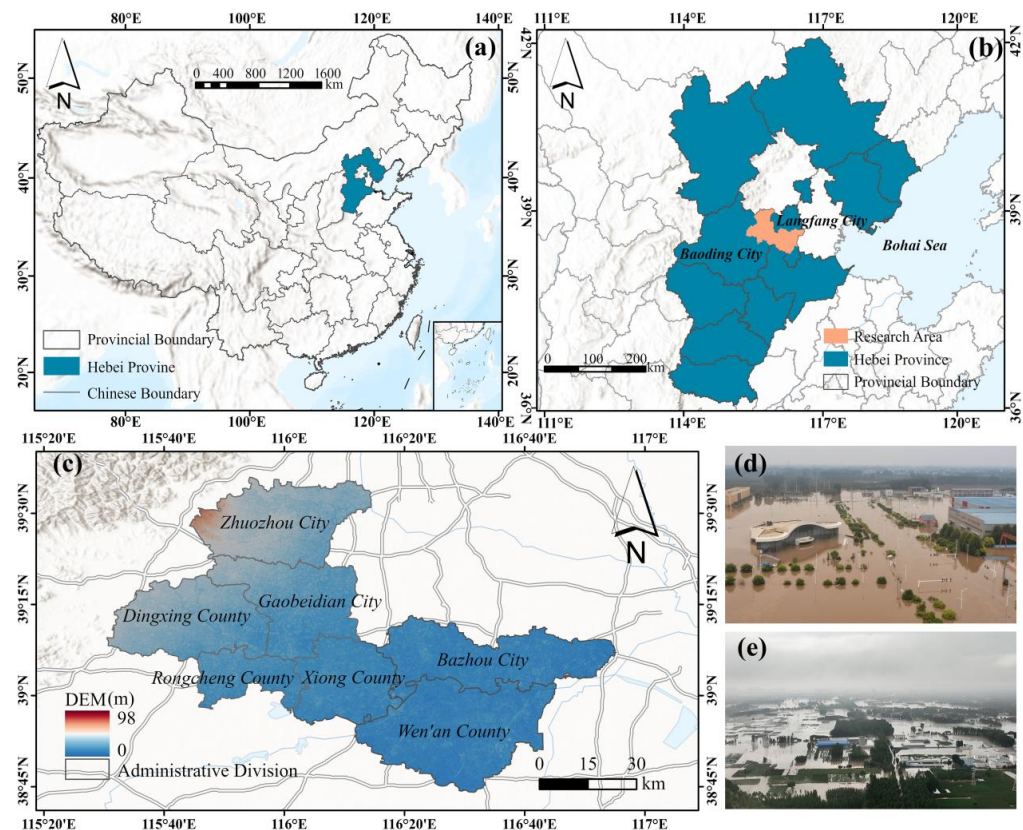


Figure 1. Overview of the study area. (a) Geographic profile of Hebei Province. (b) The study area located within Hebei Province. (c) Administrative divisions and topography of cities and counties in the study area. (d,e) Flooding situation and farmland in Zhuozhou City, from <https://news.sina.com.cn> (accessed on 1 August 2023).

On 27 July 2023, the residual warm and humid airflow from Super Typhoon Doksuri interacted with the continental subtropical high pressure, forming a high-pressure wall. The Taihang and Yanshan Mountain ranges blocked this water vapor, leading to heavy rainfall over areas including Fangshan District in Beijing and Zhuozhou City in Hebei Province. Due to the high terrain in Fangshan District, floodwaters flowed southwards into Zhuozhou City and created floods, seriously affecting the area's sustainable agricultural development and resilient urban construction.

2.2. Data and Processing

2.2.1. SAR Data

This study utilizes GF-3 SAR data for flood identification. For this study, the authors selected the GF-3 Fine Stripe 2 (FSII) mode, which provides SAR data corresponding to the time series of the affected area before and after the flood event. We used the L1A single-view complex (SLC) product, which contains information on magnitude, phase, and polarization, to distinguish pixel features between water and non-water bodies. The spatial resolution of the GF-3 SAR image is 10 m.

The L1A product requires preprocessing before flood extraction to obtain the backscatter coefficients of each pixel: (a) Multilooking processing: Distance-oriented and azimuth-oriented resolution averaging the SLC data to suppress image speckle noise. (b) Filtering processing: A Refined Lee filter smooths the image and reduces speckle noise. (c) Geometric correction: Correcting SAR geometric aberrations using the SRTM DEM and generating projection products for geocoding the images. (d) Radiometric calibration: Calculating the backscattering coefficient of the image based on the calibration constants of the SAR image metadata, the DN value of the SAR image, and related parameters using the following equation:

$$\sigma_{dB} = 10 \log_{10} \left[\frac{DN^2}{K} \sin \alpha \right] \quad (1)$$

where σ_{dB} denotes the backscattering coefficient in dB, DN denotes the pixel gray value, K denotes the absolute calibration constant, and α denotes the pixel incidence angle.

2.2.2. Optical Data

(1) GF-6 PMS

We used GF-6 optical imagery for inundation zone mapping. GF-6 imagery is provided by a panchromatic/high-resolution multispectral (PMS) camera and a medium-resolution wide-field-of-view (WFOV) multispectral camera. The higher-resolution PMS data were used to generate optical data of the study area. This study used the L1A data of the PMS camera, in which the resolution of the panchromatic image (Pan) is 2 m, and the resolution of the multispectral image (MS) is 8 m. The GF-6 data need the following processing steps: (a) Radiometric calibration: Eliminate the influence of the sensor, solar altitude angle, and imaging time on the image data, and convert the DN value to the radiance value using the following formula:

$$L = Gain \times DN + Bias \quad (2)$$

where L is the equivalent radiant luminance value at the pupil of the satellite payload channel, $Gain$ is the calibration coefficient gain, DN is the observed digital value of the image, and $Bias$ is the offset. (b) Atmospheric correction: Removing image distortion caused by atmospheric scattering and absorption of solar radiation and ground reflection (single-band panchromatic data without atmospheric correction). (c) Ortho-rectification: Correcting geometric distortions caused by topography to ensure accurate geographic coordinates. (d) Image fusion: Resampling to orthorectified high-resolution Pan and MS images to generate high-spatial-resolution multispectral images, improving the accuracy of inundation zone mapping.

(2) Landsat-8 OLI

Landsat-8 data were used to generate the seasonal crop data of the study area. Due to cloud cover and missing data in other optical images, the Landsat-8 OLI data closest to the flood event were selected. The preprocessing steps are similar to those of GF-6, except that the former can be fused directly to the image after atmospheric correction, resulting in an optical data resolution of 15 m.

2.2.3. Other Data

(1) Sentinel-2 MSI: Sentinel-2 imagery was used to produce maximum synthetic NDVI values of crops before and after the flood, aiding in crop damage classification and assessment. The Sentinel-2 imagery, produced by the European Space Agency (ESA), contains 13 spectral bands. This study used the red (band 4) and near-infrared (band 8) bands with a resolution of 10 m.

- (2) DEM data: DEM data from the Shuttle Radar Topography Mapping Mission (SRTM) with a resolution of 30 m were used to mask mountainous regions in the northwestern part of the study area, avoiding confusion between mountain shadows and water bodies.

The data's specific information is shown in Table 1, and Multi-source remote sensing data from the study area in Figure 2.

Table 1. Summary of datasets used in this study.

Data	Period	Resolution	Source	Purpose of This Study
GF-3 SAR data	11 May 2023/31 July 2023/ 1 August 2023/6 August 2023/ 7 August 2023	10 m	http://ids.ceode.ac.cn/gfds/gflogin (accessed on 7 September 2023)	Flood extent extraction
GF-6 PMS data	15 August 2023/ 19 August 2023/23 August 2023	8 m	http://ids.ceode.ac.cn/gfds/gflogin (accessed on 7 September 2023)	Inundation area identification
Landsat-8 OLI data	19 July 2023	15 m	United States Geological Survey	Crop classification
Sentinel-2 MSI data	1 July 2023–15 July 2023/ 13 August 2023–20 August 2023	10 m	Google Earth Engine	Crop disaster assessment
SRTM DEM data	2007	30 m	Google Earth Engine	To mask the hilly terrains

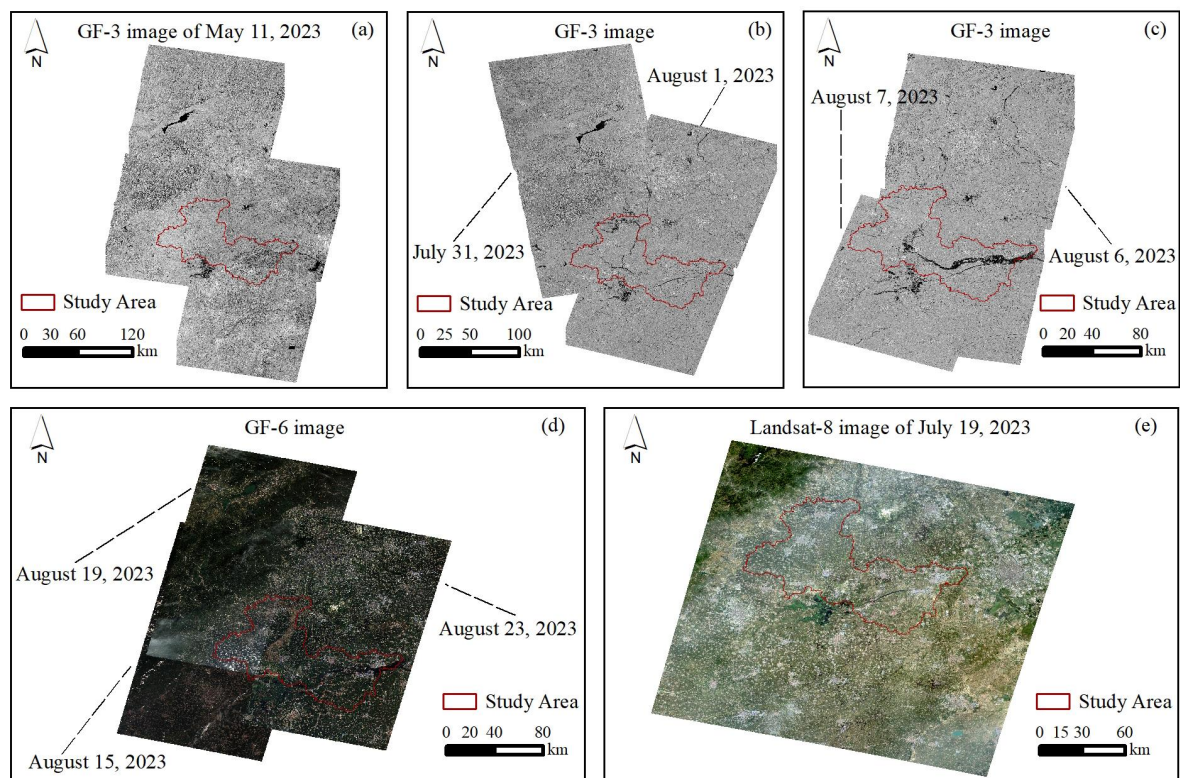


Figure 2. Multi-source remote sensing data from the study area. (a–c) are GF-3 SAR image data, (d) are GF-6 optical data, and (e) are Landsat-8 optical data.

3. Methodology

The methodology of this study consists of four main components: (1) SAR Image Analysis: The bands of dual-polarized HH and HV data of the study area were combined according to the time series pre-disaster (5.11), disaster (7.31–8.1), and post-disaster (8.6–8.7). The computed results were thresholded for segmentation to distinguish between water and non-water bodies. (Notes: References to “water body areas” in the results and discussion refer to the water body areas identified on the SAR images using this method.) (2) Multispectral Image Analysis: Object-oriented feature segmentation was performed on the time series GF-6 multispectral

images. The segmented samples were subjected to supervised classification based on an SVM to generate the optically affected area. The SAR image water body areas and the optically affected area were superimposed, excluding pre-disaster water body patches, to finally extract the flood inundation area in the study area. (3) Crop Data Generation: Using Landsat-8 images of the pre-disaster season, a random forest model generated crop data in the study area. (4) Disaster Assessment: Based on the GEE platform, Sentinel-2 MSI imagery generated the maximum synthetic NDVI values before and after the flood. The $NDVI_{disaster_level}$ index was used to classify the level of crop damage, completing the disaster assessment. The flow chart of this method is shown in Figure 3.

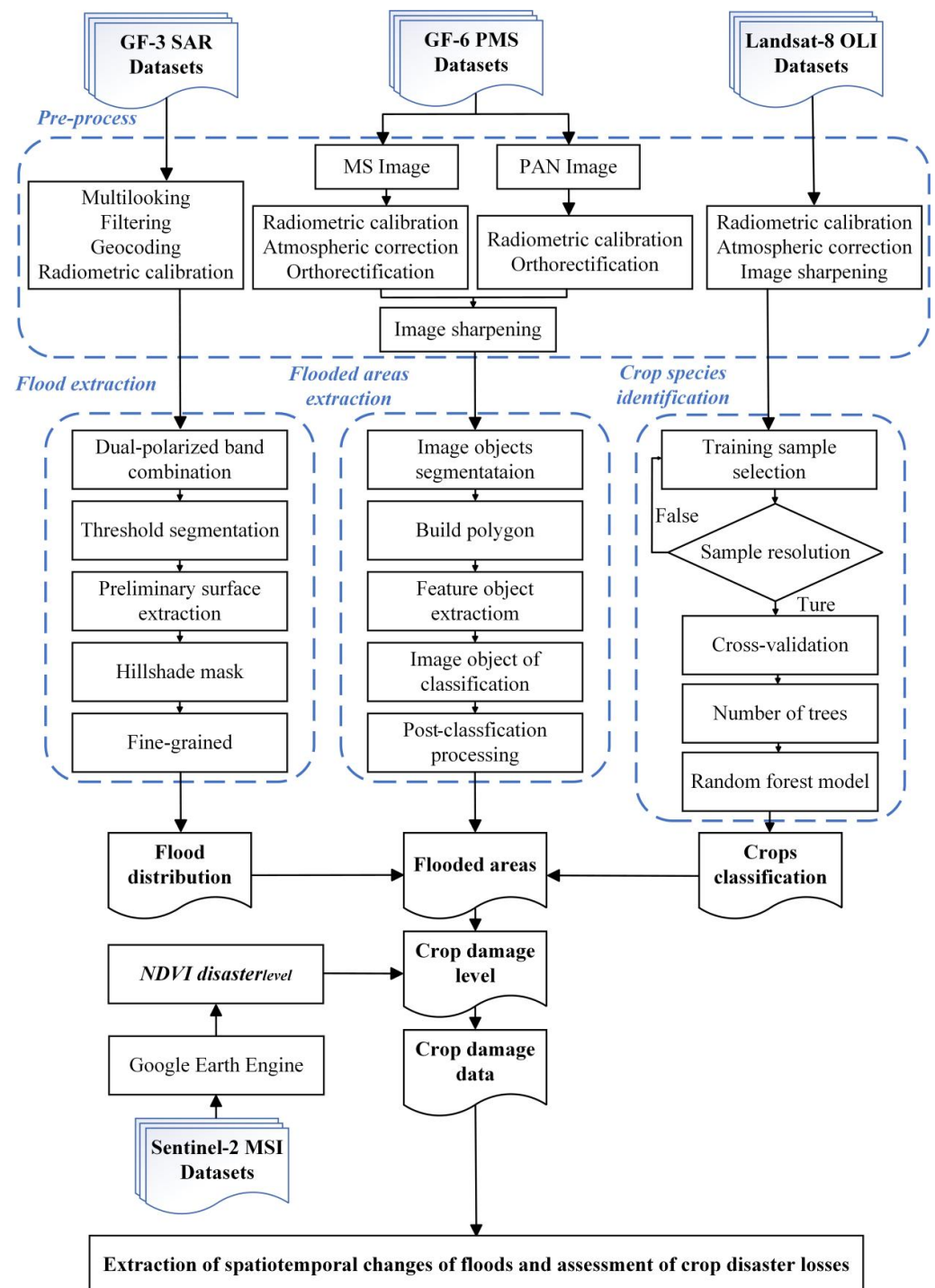


Figure 3. Flow chart of extraction and identification of spatial and temporal variations in flooding and crop damage assessment.

3.1. SAR Image Flood Recognition

3.1.1. SAR Image Band Combination

The backscattering coefficient is a crucial parameter in SAR image analysis, representing the ratio of radar-received backscattered power to incident power. For single-band SAR images, the low backscattering coefficient of water bodies is typically used for identification.

Unipolarized SAR images make the image of the water body features different due to the different sensor transmission and reception methods. Combining dual-polarized images synthesizes the water body features, enhancing differentiation from non-water bodies and improving threshold segmentation accuracy. In this study, based on the backscattering coefficient of SAR dual-polarized HH and HV images, water body recognition was performed by band combination and calculated as follows:

$$W_I = \ln(10 \times \partial_{HH} \times \partial_{HV}) - a \quad (3)$$

where W_I denotes the water body index, ∂_{HH} and ∂_{HV} denote the backscattering coefficients corresponding to the HH and HV images, and a is the water body and non-water body critical threshold. To ensure the accuracy of the flood extent, this study used SRTM DEM data to calculate the slope of the study area, masking areas with slopes greater than 5° as non-flood areas. Flooding is unlikely in areas such as hillsides [39].

3.1.2. Delineation of Critical Thresholds

The backscattering coefficients were obtained by preprocessing the single-polarized HH and HV images, which showed a distinct deep-black color due to the lower backscattering intensity of the water bodies. To amplify the characteristics of the water body, avoid subjective bias in the results due to manual threshold selection, and improve the differentiation between spectrally similar regions such as water bodies and mountain shadows [40], the critical threshold a was determined in this study using the following method: First, the W_I image is converted to a normalized pixel value matrix (range 0–1), and all pixel values are extracted as the input dataset. To enhance the robustness of clustering, the pixel values are histogram equalized to reduce noise interference. Subsequently, pre-segmentation of the image based on the Otsu algorithm is used to obtain the approximate distribution ratio of water bodies and non-water bodies, which is used to initialize the clustering center (u_1, u_2) of K-means. The number of clusters $K = 2$ is set to represent water bodies and non-water bodies, respectively. Finally, the similarity between pixels and clustering centers is measured by Euclidean distance [41], and the clustering centers are iteratively updated until convergence (maximum number of iterations equals 100) to determine the value of a , which is calculated as follows:

$$a = \frac{w_1 u_1 + w_2 u_2}{w_1 + w_2} \quad (4)$$

where w_1 and w_2 are the weights related to the clustering of water bodies and non-water bodies, and u_1 and u_2 denote the pixel values of the center of the clustering for water bodies and non-water bodies.

3.1.3. Combined Image Accuracy

The histograms of SAR data from different periods in Zhuo City were used to test the accuracy of the W_I method for water body identification (Figure 4). The SAR images in the pre-disaster period have fewer water body pixels, and the histograms show apparent single-peak features (Figure 4c). The three sets of histograms in the mid-disaster period show double peaks (Figure 4a,b,d). However, the double peaks of the histograms with HH polarization are not obvious enough, which indicates that there is confusion between

water body and non-water body pixels at the wave valley. The images with HV polarization and W_I computation show obvious double-peak features, and the distinction between water body and non-water body pixels is good. Ideally, water body and non-water body pixels can be accurately distinguished at the curve inflection points, but, in practice, more histograms have higher inflection points. Studies have shown that it is acceptable for the height of the inflection point to be no more than 40% of the crest [42], which was not exceeded in either histogram (Figure 4b,d).

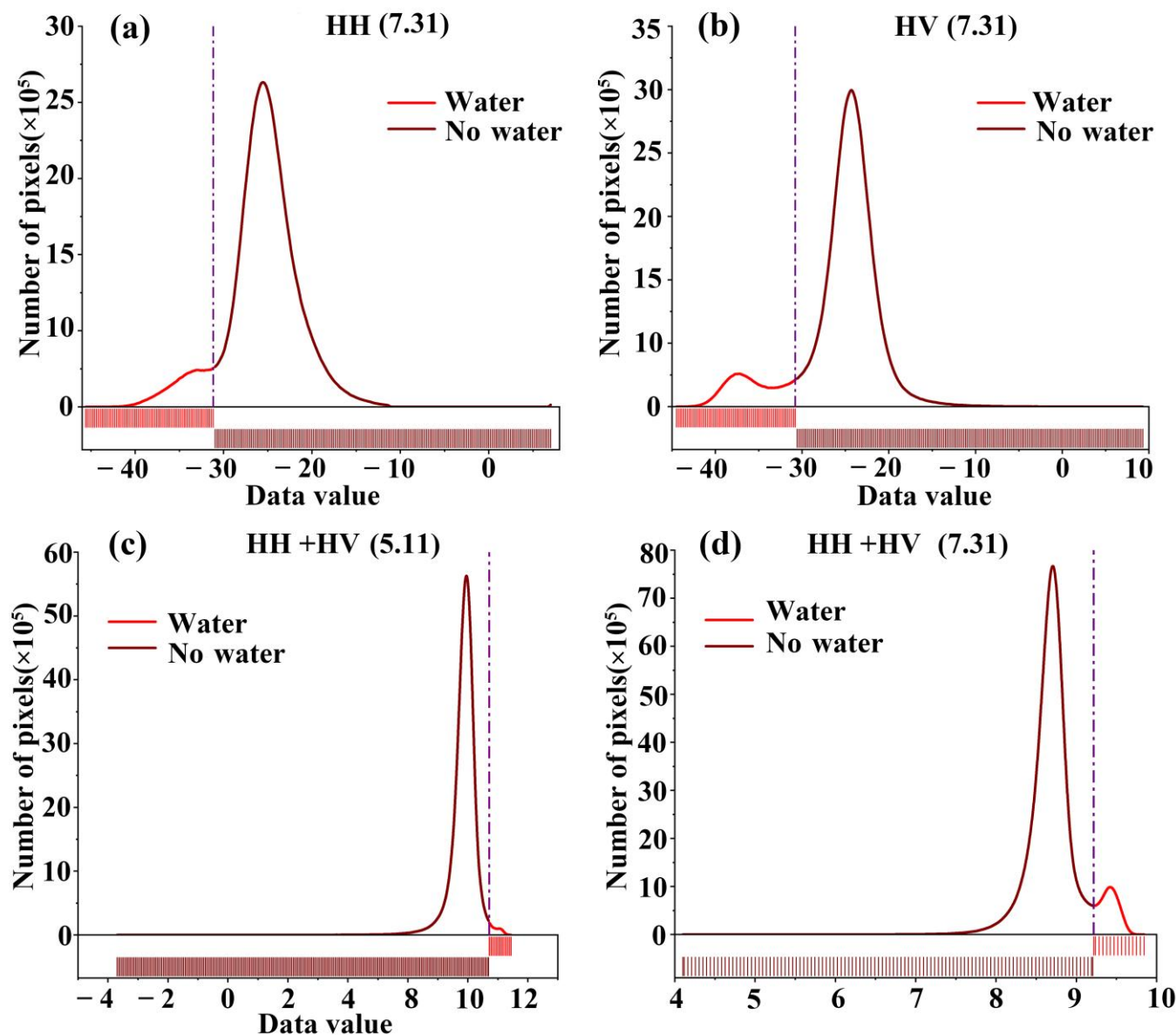


Figure 4. Histograms of backscatter coefficients of water bodies in different modes.

The point of complete differentiation of water body and non-water body pixel values in the HV histogram is in front of the inflection point, which indicates that the water body pixel values at the inflection point are small, and the separation of water body and non-water body pixels is not strong. On the other hand, the distinction between water and non-water pixels in the W_I image is exactly at the inflection point, and the value of the vertical coordinate at the inflection point is close to 0, so the water and non-water pixels are well distinguished. In addition, a visual comparison of the backscattering coefficient characteristics of SAR images in the three modes reveals that, compared to the

W_I image, the HH and HV images have different degrees of confusion at the junction of water bodies and non-water bodies (Figure 5). Therefore, the W_I meets the demand for accurate extraction of water bodies.

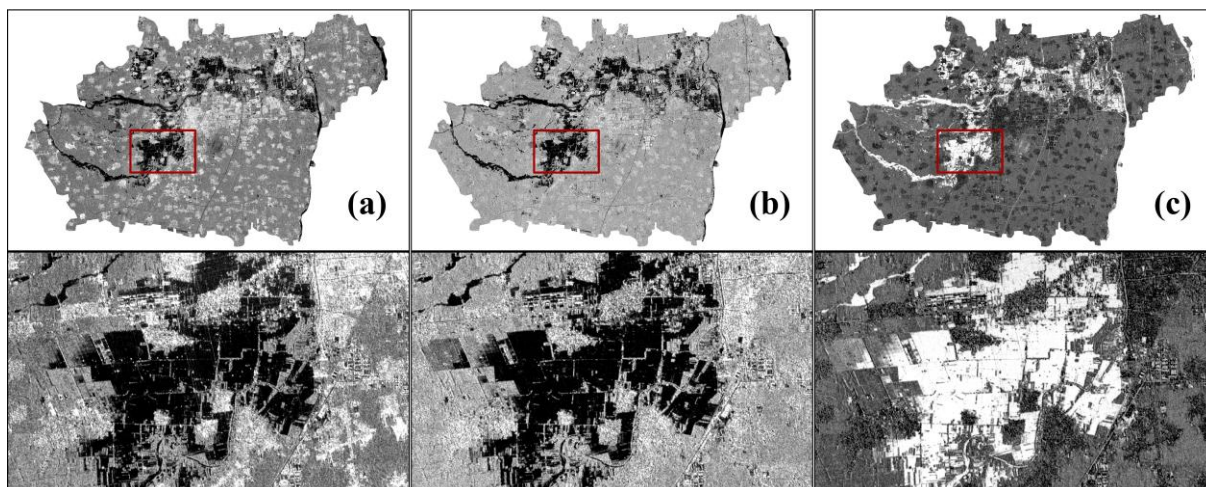


Figure 5. Characteristics of water bodies in the Zhuo City disaster with three different modal images. (a) GF-3 HH image. (b) GF-3 HV image. (c) W_I calculated image. The red box shows the magnified water results Characteristics.

3.2. Optical Image Flooding Area Mapping

Due to the satellite revisit cycle, SAR imagery during and after the disaster failed to capture the maximum value of water bodies in some study areas. The extensive farmland and other factors, such as strong winds, also affected the SAR imagery's ability to recognize water bodies accurately. Therefore, inundation area mapping based on the spectral differences before and after the flood provided by the GF-6 high-resolution optical imagery compensates for the deficiencies in SAR imagery.

3.2.1. Object-Oriented Sample Construction

High-resolution optical images offer detailed texture features of features, and the complex spatial information between pixels can affect the accuracy of traditional pixel-based classification. Object-oriented classification, based on image area objects, uses texture, shape, spectral, and spatial features to classify the image targets, improving the classification accuracy [43].

Sample objects are constructed using a multi-scale-based segmentation algorithm that synthesizes spectral and shape features of the image. The Edge algorithm is selected for threshold segmentation, detecting edges through gradient changes of pixel points, and is suitable for larger-range image segmentation [44]. In image segmentation, the lower the threshold setting, the more classified patches are, leading to the same feature being split into multiple parts, thus affecting the classification accuracy. Therefore, it is necessary to merge the images after threshold segmentation. The Full Lambda Schedule algorithm is used for threshold merging, efficiently identifying neighboring regions with large areas and robust texture features, suitable for extracting submerged areas after flooding [45].

3.2.2. Sample Classifier Selection

Significant spectral changes in seasonal crops in the study area before and after the flood, combined spectral, spatial, textural, and other attribute information, and a supervised classification method were used to train the samples [46]. The samples are categorized into flooded areas, impervious surfaces, farmland, and water bodies. Some of the post-disaster water bodies have similar spectral information to adjacent features, and this situation allows the water body image elements to be misclassified, resulting in a large extent of the

inundation zone. The optical inundation zone was masked based on the W_I calculations of the pre-disaster SAR data in Section 3.1 to eliminate the effect of misclassified pixels on the extent of the inundation. Zhuozhou City was chosen as the experimental area, and, after comparing K-Nearest Neighbor (KNN), Principal Component Analysis (PCA), and SVM classifiers, the SVM was selected for optical image classification.

3.3. Crop Classification

Crop cultivation data are critical for flood damage assessment. The government census data were unavailable during the flood event, and open-source crop-type data had low temporal resolution and an inadequate single data type. Therefore, seasonal crop planting data were produced based on optical imagery using the Landsat-8 data closest to the flood event. Based on the economic statistics from the yearbook, maize, beans, and vegetables were selected as the main crop types. We used a random forest model, a decision tree method based on Bagging, to classify crop samples [47]. Each decision tree of the random forest is constructed based on random samples and features, and the classification process mainly includes the construction of training samples and classification. The corresponding number of training samples is selected according to different crops' spatial distribution and planting area. In sample classification, the number of decision trees at each node must be adjusted to find the optimal value to avoid overfitting and underfitting phenomena. In this study, the decision tree was adjusted by cross-validation, and the number of trees was set to 500 to avoid overfitting and underfitting phenomena. To quantify the classification performance of the random forest model, the accuracy of crop classification was assessed by calculating the overall accuracy (OA), Kappa coefficient, and user accuracy (UA) for each category through the confusion matrix. The calculation formulas are as follows, respectively:

$$OA = \frac{\sum_{i=1}^n TP_i}{N} \times 100\% \quad (5)$$

where OA denotes the proportion of samples that are correctly categorized in all categories, TP_i is the number of correctly categorized samples in category i , N is the total number of samples, and n is the number of categories.

$$Kappa = \frac{OA - P_{(e)}}{1 - P_{(e)}} \quad (6)$$

where $P_{(e)}$ stands for the hypothesized probabilistic consistency of change. The *Kappa* coefficient is used to measure the consistency of the classification results with the random classification.

$$UA = \frac{TP_i}{TP_i + FP_i} \quad (7)$$

where UA denotes the proportion of true samples in the classification result of a category, and FP_i is the number of misclassified samples in category i .

3.4. Crop Damage Classification

Waterbody data, inundated area, and crop type data were synthesized to assess crop damage, as shown in Figure 2. The flood event coincided with the critical growing period of seasonal crops like maize. The difference in green biomass before and after the event was used to assess crop damage intensity. The *NDVI* was calculated using the Sentinel-2 MSI data with the following formula:

$$NDVI = \frac{\partial_{NIR} - \partial_{Red}}{\partial_{NIR} + \partial_{Red}} \quad (8)$$

where ∂_{NIR} and ∂_{Red} represent the surface reflectance in the near-infrared (NIR) and infrared (Red) bands. The maximum synthetic value images of the NDVI before and after the flood reflected crop growth conditions. $NDVI_{disaster_{Level}}$ was calculated to evaluate crop disaster intensity with the following formula:

$$NDVI_{disaster_{Level}} = NDVI_a - NDVI_b \quad (9)$$

where $NDVI_a$ represents the maximum NDVI value after the flood, and $NDVI_b$ represents the maximum NDVI value before the flood. A positive value indicates no damage, while a negative value indicates damage. The $NDVI_{disaster_{Level}}$ range is $[-1, 1]$. Disaster level is divided into six categories, with positive values being “Normal” and negative values divided at 0.14 intervals into “Very extreme damage”, “Extreme damage”, “Moderate damage”, “Slight Damage”, and “Very slight damage” [48].

4. Results

4.1. Spatiotemporal Pattern of Water Body Areas

As of 7 August 2023, the total area of flooding in the study area caused by Typhoon Doksuri was found to be 511.73 km², accounting for 10.30% of the total land area, which is 6.41% higher than the pre-disaster period. The spatial and temporal distribution of water body areas during and after the disaster was different, with some cities and counties experiencing peak floods at different times (Figure 6A–C). This study also mapped the maximum images of the water body areas in the cities and counties in the study area (Figure 6a–g). The areas of water body areas before, during, and after the disaster were 193.47 km², 270.71 km², and 457.65 km², respectively, accounting for 3.89%, 5.45%, and 9.21% of the total land area.

Most areas in the study area exhibited a significant increase in water body areas during the disaster compared to the pre-disaster period. Zhuozhou City experienced the most severe increase in flooding, with water body area content rising from 1.89% to 10.96%, a year-on-year increase of 9.07%. This significant increase can be attributed to Zhuozhou City being at the center of the residual circulation of Typhoon Doksuri during the disaster, resulting in an average rainfall of 398 mm. As shown in Figure 5c, the water body areas around the two main rivers increased dramatically. The high terrain in northwestern Zhuozhou caused heavy precipitation to flow into the central plain, leading to substantial water accumulation in the central and southwestern areas. Notably, Bazhou City and Wen'an County had larger water body areas before the disaster than during the disaster (Figure 7), with decreases of 1.28% and 3.01%, respectively, primarily because heavy rainfall occurred in these areas before the disaster. In contrast, the disaster's heavy rainfall was mainly concentrated in Zhuozhou City, which received less precipitation than in the pre-disaster period.

Except for Zhuozhou City, all other cities and counties showed a significant increase in water bodies after the disaster compared to the area before. Bazhou City and Xiong County had the most significant increase in water area, 15.71% and 5.53%, respectively, while Wen'an County had the smallest increase, 0.29%. This is due to the satellite revisit cycle. The flood map fully captures the post-flood water bodies flowing into Xiong County, Bazhou City, and Wen'an County. Although Gaobeidian City and Dingxing County had increased post-flood water bodies compared to the pre-water body areas, they did not have the most significant water bodies flowing through the region. The top three cities and counties in terms of water body areas were Bazhou City, Wen'an County, and Zhuo City, with 167.35 km², 97.96 km², and 82.38 km², respectively. Rongcheng County had the smallest water body areas, at 10.03 km² (Figure 7). The water bodies in Wencheng County before and after the disaster were comparable, but their spatial and temporal distributions differed. Before the disaster, the water bodies resulted from

local heavy rainfall and were relatively uniform in distribution. After the disaster, the water bodies were mainly concentrated on both sides of the main river channel in the north. Additionally, the areas of water bodies in Rongcheng County before and after the disaster were very close, with an increase of only 1.09 km², or 0.35%. However, this was not the area with the lowest rate of increase, which was Wen'an County, due to Wen'an's land area being three times that of Rongcheng Country.

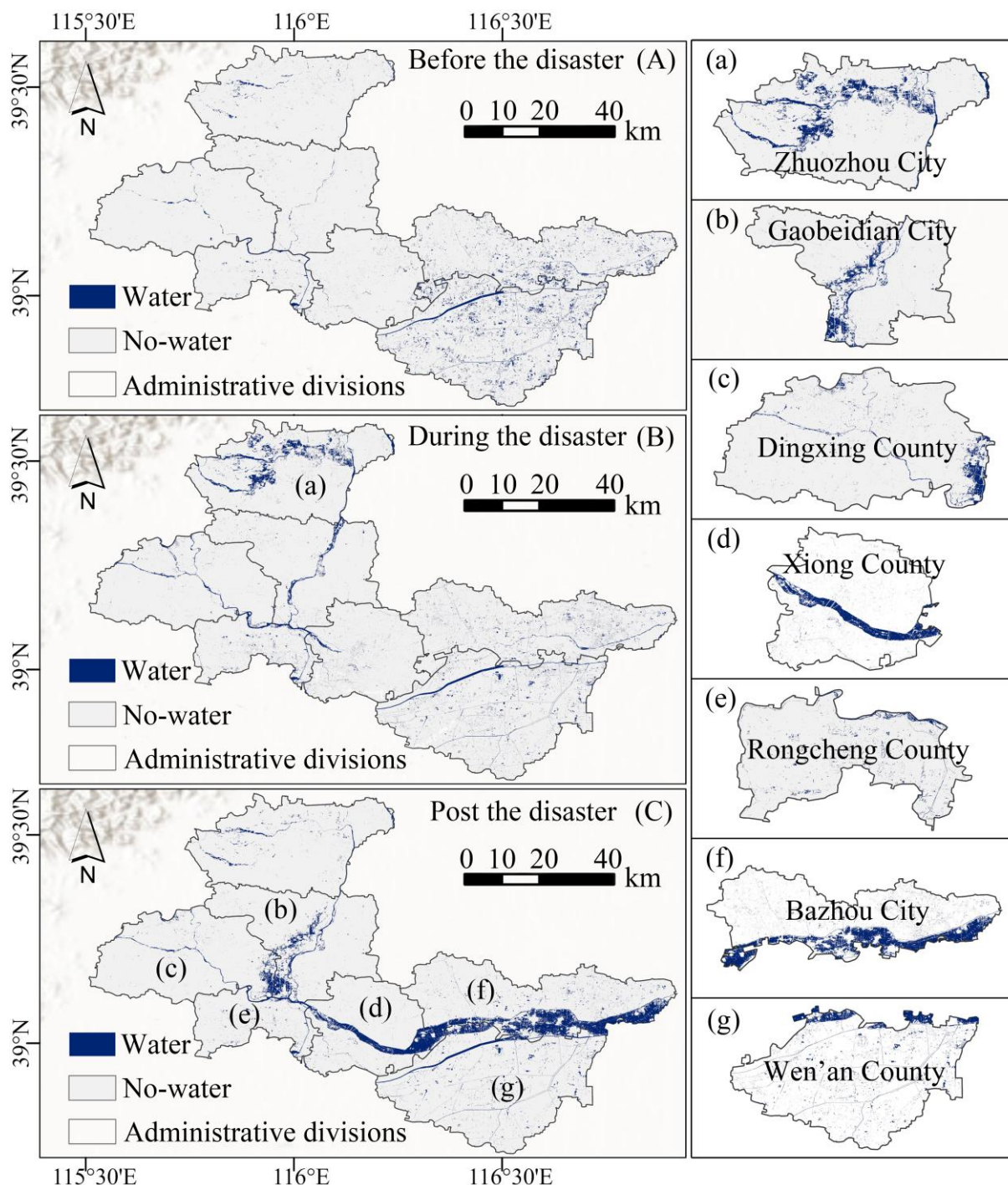


Figure 6. Maps of spatial and temporal distribution of water body areas. (A–C) represent the distribution of water body areas before, during, and after the disaster, respectively. (a–g) represent the largest water body areas in Zhuozhou City, Gaobeidian City, Dingxing County, Xiong County, Rongcheng County, Bazhou City, and Wen'an County, respectively.

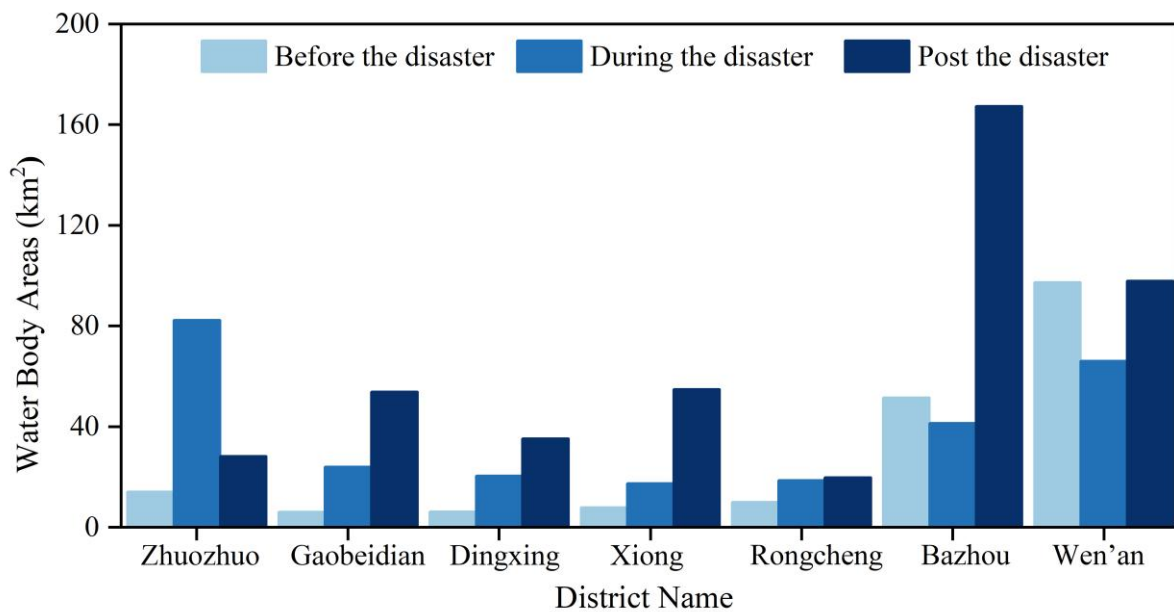


Figure 7. Histogram of water body areas at different periods in each district and county of the study area.

4.2. Flood Inundation Areas

From 31 July to 23 August 2023, the total inundation area of the study area was 700.51 km², accounting for 14.1% of the total area, which is an increase of 3.8% compared to the water body areas in Section 4.1. The accuracy of the flood inundation area classification is shown in Table 2. The overall spatial distributions of the SAR flood extent and the optical inundation extent are consistent. The SAR water body area extent also reflects the inundation tendency of the flood. Still, there are some partial differences between the two types of inundation (Figure 7). The temporal resolution of the SAR images does not include the flood peaks in Zhuozhou City and Gaobeidian City due to the revisit cycle. Some cities and counties in the study area have large areas of farmland, and the partial absorption of floodwater by the soil also accounts for the differences. Bazhou City and Wen'an County have the smallest differences between the two datasets, as the SAR imagery captured the maximum flood extent in the area after the disaster. The wider channels of the Zhongting and Zhaowangxin Rivers flowing through these areas and the more significant proportion of urban development land, where the water body areas remain on the surface for more extended periods, contribute to the more minor differences.

Table 2. Classification accuracy confusion matrix of three classifiers.

Classifier	Overall Accuracy	Kappa Coefficient
KNN	89.13%	0.85
PCA	83.74%	0.78
SVM	95.65%	0.94

From the spatial distribution of the flood inundation areas, except for the large inundation area within Zhuozhou City directly affected by heavy rainfall, it can be seen that the inundation areas of other cities and counties are distributed along both sides of the river. The three stagnant flood storage areas were the regions with the largest inundation areas. Zhuozhou City, Gaobeidian City, Dingxing County, and Rongcheng County were significantly affected by the Xiaoqing River flood diversion area and the Langouwa stagnant flood storage area, with large inundation areas on both sides of the river channel. The Dongdian storage and stagnation flood zone mainly caused the inundation area in Bazhou City and Wen'an County. Xiong County, located between the two floodplains, did not have a large inundation area compared to other

cities and counties as the Zhongting River flowing through it is an artificially dug flood control channel, deeper and wider than the North and South Rejct Rivers and the small rivers flowing through the area (Figure 8).

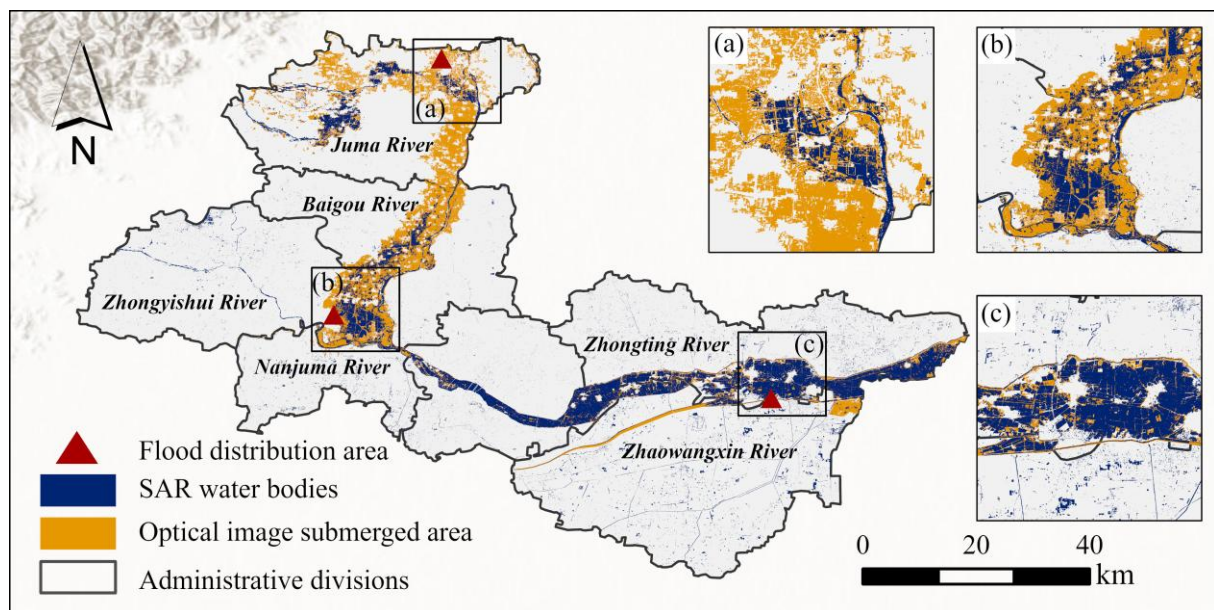


Figure 8. Synthesized map of flood inundation extent and major rivers. (a) Indicates the Xiaoqing River floodplain. (b) Langouwa flood storage and retention area. (c) The Dongdian flood storage area.

From the perspective of the inundation area of each city and county (Figure 9), Zhuozhou City had the largest inundation area of 284.31 km², accounting for 37.8% of the city's land area, followed by Gaobeidian City and Bazhou City, with inundation areas of 138.72 km² and 125.23 km², accounting for 20.57% and 15.63% of their land area, respectively. The smallest inundation area was 16.58 km² in Rongcheng County, accounting for 5.33% of the county's land area, mainly because only the northeastern part of Rongcheng County carries a small amount of the South Juma River's flooding water body. The smallest inundated area of the city's land area was Wen'an County, with 4.01%. Wen'an County has the largest land area, while most of the area of the Zhongting River, which is a flood channel, is located in Bazhou City, accounting for the smallest percentage.

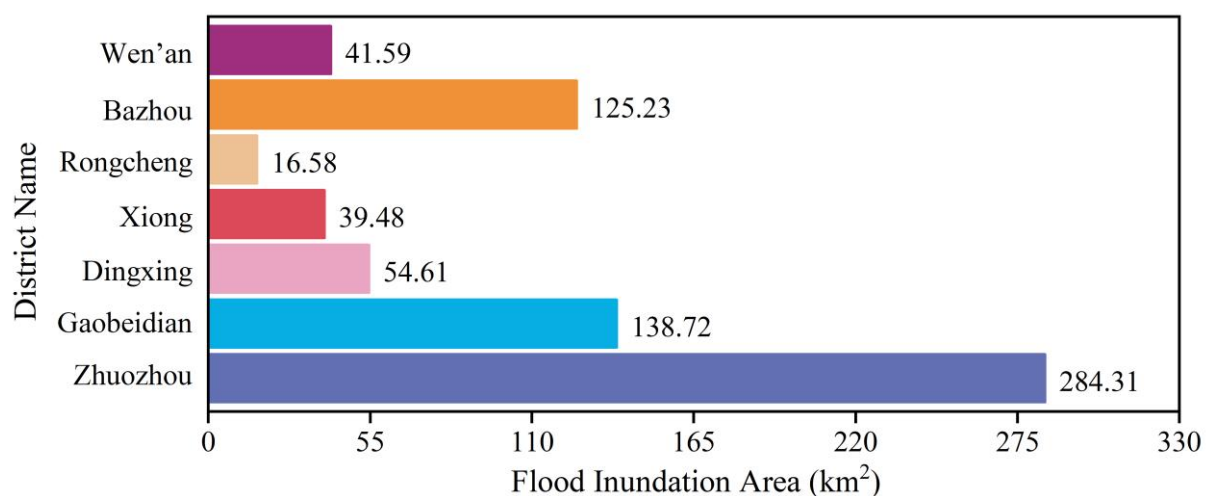


Figure 9. Flood inundation areas of each city and county.

4.3. Crop Damage Assessment

4.3.1. Crop Classification Results

Using the random forest model based on Landsat-8 imagery, 26,754-pixel points were classified, achieving an overall accuracy of 96.32% and a Kappa coefficient of 0.95. As of 19 July 2023, the area under cultivation for major crops in the study area was 26.26×10^4 ha (excluding bare land), accounting for 54.56% of the total land area (Table 3). Wen'an County had the largest crop cultivation area of 5.09×10^4 ha, accounting for 49.06% of the country's land area. In contrast, Rongcheng County had the smallest cultivated area, with 1.46×10^4 ha or 46.82% of its land area. Dingxing County had the largest share of cultivated area relative to its total area, at 69.14%, while Xiong County had the smallest proportion, at 42.09%.

Table 3. Crop classification data for the study area.

Community	Corps Cultivated Area/Hectare (ha)			
	Maize	Beans	Vegetables	Bare-Land
Zhuozhou City	25,915	6264	10,369	2581
Gaobeidian City	29,807	3247	8182	3024
Dingxing County	37,875	4565	6920	2328
Rongcheng County	10,517	1584	2461	3782
Xiong County	14,646	7038	6834	4694
Bazhou County	16,336	9808	9352	10,686
Wen'an County	35,317	8173	7388	18,351

Bare land was excluded from this crop count due to unknown land use. Bazhou City and Wen'an County had the largest bare land areas, with 1.07×10^4 ha and 1.84×10^4 ha, accounting for 13.33% and 17.70% of their respective areas. The high proportion of bare land in these areas is attributed to their location in the Xiong'an New Area of Hebei, established by China on 23 February 2017, which is undergoing extensive urban construction.

4.3.2. Damage Classification Results

The NDVI-damaged land in the study area post-flood was 1944.88 km², accounting for 40.41% of the total land area. Among the damaged categories, the largest area was very slightly damaged, totaling 1312.57 km², or 27.27%. Slightly and moderately damaged areas were close, at 4.52% and 5.19%, respectively. Areas of extreme damage accounted for 2.69%, and very extreme damage areas were the smallest at 0.72%.

The spatial distribution of NDVI-damaged and flood inundation areas was consistent, though the total NDVI-damaged area was much larger than the flood inundation areas. The difference is mainly concentrated in the very slightly damaged range due to the presence of bare soil, water bodies, and impervious surfaces before and after the flood. The NDVI differences in these areas were slight, with most values concentrated around 0, categorized as very slightly damaged (Figure 10c). Errors in image pixel value recognition are common but challenging to avoid. By overlaying and matching disaster level data with crop planting data, this study minimized the influence of pixel value misclassification to determine flood-affected crop data.

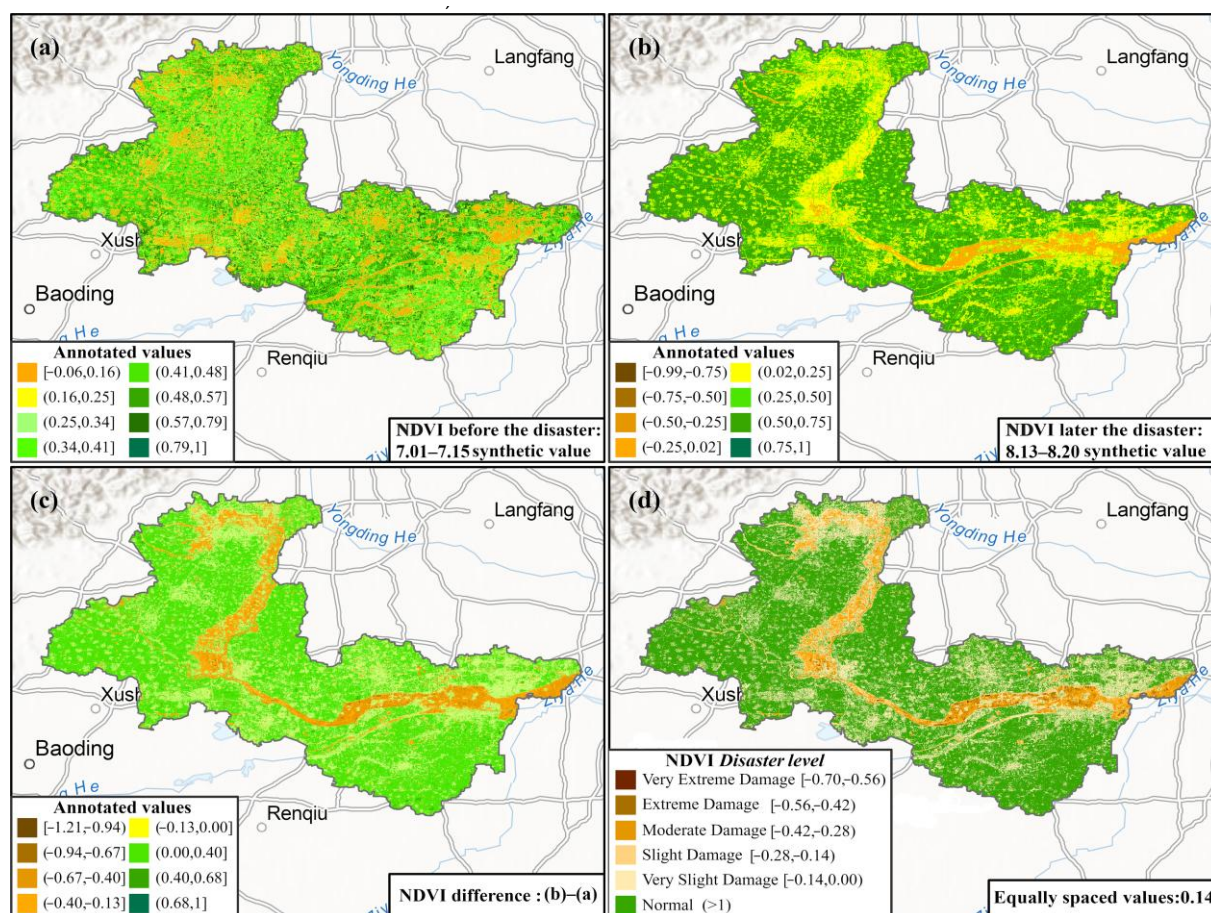


Figure 10. NDVI synthesized image and damage analysis (a) NDVI synthesized values from 1 July to 15 July before the flood. (b) NDVI synthesized values from 13 August to 20 August after the flood. (c) Maximum NDVI difference values before and after the flood. (d) NDVI disaster level results.

From the spatial distribution of the disaster level classification results, the NDVI of non-vegetation areas, such as impervious surfaces, showed negative values (Figure 10a). The green biomass near Bazhou City and Wen'an County in the maximum NDVI synthesized image before the flood was the highest, related to the crop planting time and types in each city and county. The post-flood maximum NDVI synthesized value image (Figure 10b) clearly shows the flood damage to crops, with affected areas consistent with the flood inundation distribution. Crops in unaffected areas grew well overall, and crops far from the flooded area showed excellent green growth. Figure 10d, obtained by dividing the $NDVI_{difference}$ before and after the flood by the equal intervals in Figure 10c, shows that the areas of very extreme and extreme damage are mainly concentrated near both sides of the river channel. The inundation depth and flood duration near the river channel contribute to this result, while slight damage is distributed at the far end of the river channel, consistent with the actual situation.

4.3.3. Damage Assessment Results

The area of crops affected by this flood was about 4.07×10^4 ha, representing 8.46% of the total land area of the study area. Maize was the most affected, with an area of 3.37×10^4 ha or 6.99%, mainly because maize was the dominant crop in the study area during the flood event. Vegetables were affected in an area of 0.43×10^4 ha, accounting for 0.89%. Beans were the least affected, with an area of 0.28×10^4 ha, or 0.58% (Figure 11).

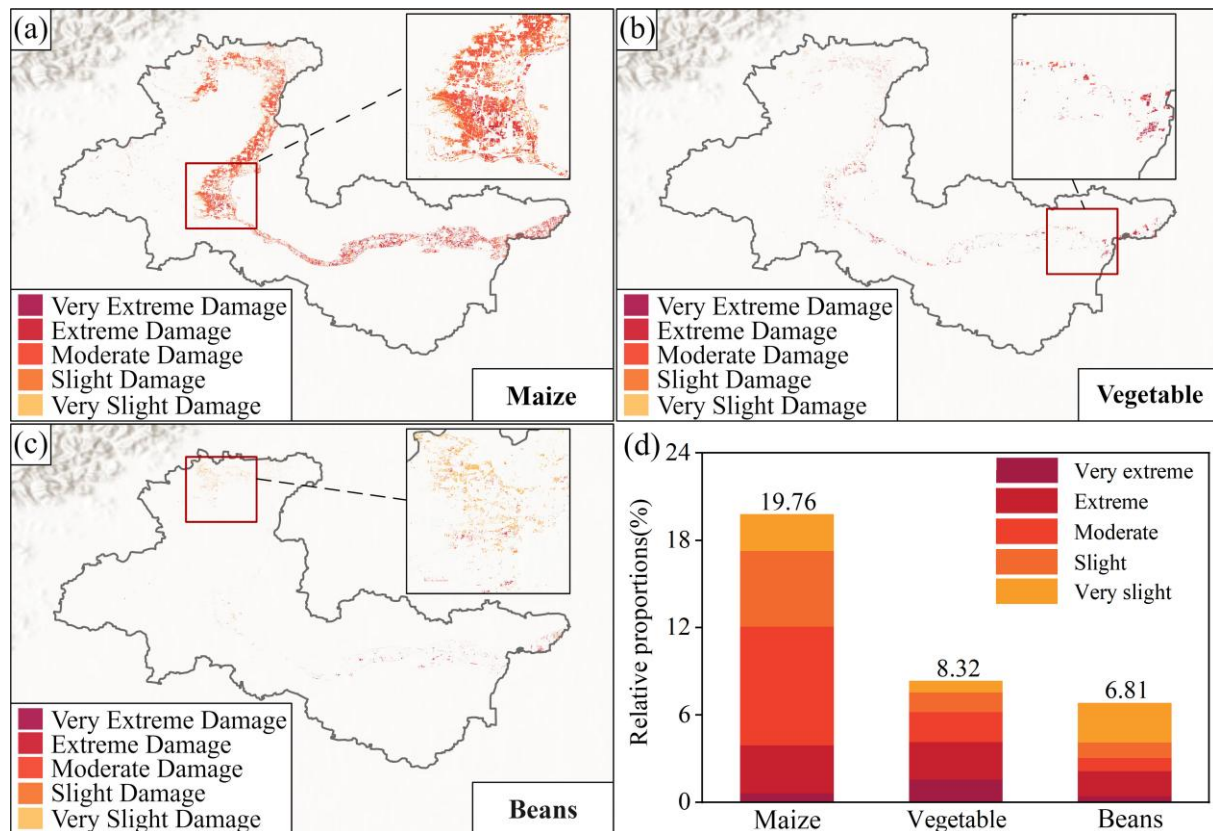


Figure 11. Spatial distribution of flood-affected crops. (a–c) represent the distribution and intensity of damage for maize, vegetables, and beans, respectively. (d) Intensity of each type of damage for the three crops as a percentage of their respective acreages. The red boxes represent enlarged affected crops.

From the distribution of crop disasters, the intensity of the three main crop disasters is consistent with the disaster level classification results, and the intensity decreased along the river on both sides (Figure 10). The disaster area of maize was the largest and most pronounced, followed by that of vegetables and beans. In the study area, beans mature slightly later than maize, and, in some areas, maize and beans are interplanted, resulting in similar spatial distributions for these crops. Compared to maize and beans, although widely planted, vegetable crops are mainly in small patches, resulting in a more scattered distribution of damage. Among the crop-affected areas in each city and county, Zhuozhou City was the most affected, with 1.37×10^4 ha, followed by Gaobeidian City, with 1.03×10^4 ha. The smallest area affected by crop damage was Rongcheng County, with an area of only 0.04×10^4 ha.

Regarding crop damage levels, moderate damage accounted for the largest share of the disaster area in all cities and counties, at 37.62%. Slight damage accounted for the second largest share, at 24.55%, while the smallest was very extreme damage, at 5.10% (Figure 12). Zhuozhou City and Gaobeidian City, at the center of the disaster, had the largest crop damage areas, corresponding to the inundated areas counted in Section 4.3. Notably, the areas of very extreme and extreme damage in Xiong County, Bazhou City, and Wen'an County were significantly higher than in other cities and counties (Figure 12e, f and d). This is because the floodwaters in these three regions mainly originated from storage and retention areas, with inundation occurring later. By the study's cut-off time, crop recovery in these regions was lower compared to areas that experienced floodwaters earlier, such as Zhuozhou City. Wen'an County and Bazhou City are adjacent, resulting in a similar histogram distribution of crop damage levels in both areas (Figure 12f,g). However, the crop damage area in Bazhou City was larger than that in Wen'an County, as most rivers flow into Bazhou City's

territory (Figure 8). Detailed crop damage data for cities and counties can be found in the Supplementary Materials.

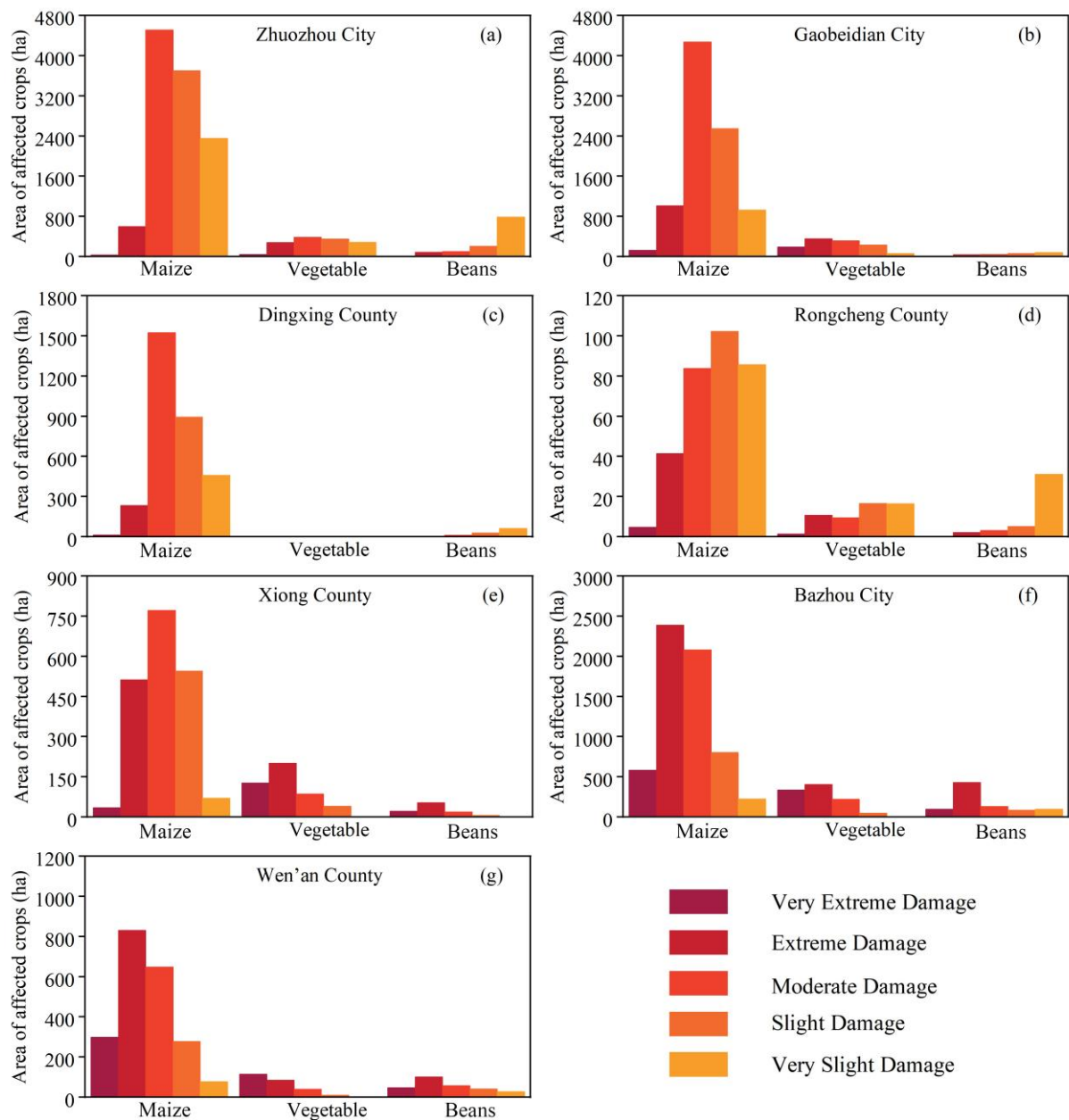


Figure 12. Quantitative crop damage assessment in cities and counties in the study area. (a–g) represent Zhuozhou City, Gaobeidian City, Dingxing County, Xiong County, Rongcheng County, Bazhou City, and Wen'an County, respectively.

5. Discussion

5.1. Challenges and Recommendations

Hebei Province is one of North China's regions frequently affected by floods, with almost all cities and counties experiencing floods of varying intensity and frequency [49]. Historically, most floods in Hebei Province occur during the rainy season, from late July to early August. Notable examples include the Haihe River flood in August 1956, the "7.16 Hebei Extraordinarily Heavy Rainstorm" in 2016, and the severe flooding caused by Typhoon In-Fa in late July 2021 [50]. Typhoons, heavy precipitation during the rainy season, and topographic features contribute to frequent floods in Hebei Province.

The main challenges for flood management in the study area during the “7.27” rainstorm event were the extensive inundation area, prolonged duration of flooding, and the slow recovery of crops after the disaster. In terms of inundation area, the regions affected by flooding are concentrated in areas directly impacted by the heavy rain (such as Zhuozhou City), along the low-lying banks of rivers (such as Gaobeidian City), and in flood storage and retention areas (such as Bazhou City and Wen’an County), and 407 km² of crops was affected, accounting for 8.64% of the total area of the study area. Regarding the duration of the flooding, it took 24 days for the water bodies in Zhuozhou City to return to the pre-disaster level, while, in other cities and counties, the flooding has not yet subsided due to flood discharge. The prolonged exposure of farmland to flooding can seriously threaten crop growth. For example, maize is the main crop grown in the study area, and it faces death after being flooded for more than 3 days. As of 23 August 2023, a total of 1.09×10^4 ha of maize in the study area had suffered very extreme damage, and the crop roots were submerged for too long and faced extinction. Regarding post-disaster recovery, the crop recovery process in the study area was slow, especially in Bazhou City and Wen’an County, where the green biomass of crops was not optimistic (Figure 10d). Flooding resulted in many crop deaths, soil erosion, and damage to the agricultural base, which prevented the farmland from quickly returning to production.

To address the challenges faced in flood management, agricultural planning should be optimized in the following ways: (1) Strengthening flood risk assessment and regional division: Crops should be divided into regions based on flood risk, and flood prevention and control measures should be prioritized and strengthened in high-risk areas. For example, graded management of flood storage and retention areas (Bazhou City and Wen’an County) and low-lying areas (Gaobeidian City) should be implemented, and the drainage ditch network and support mobile pumping stations should be encrypted. Moreover, ecological buffer zones (e.g., reed wetlands) should be built around the edges of farmland to mitigate flood impacts. (2) Optimizing crop planting structure: High-flood-risk areas can adjust the crop planting structure, e.g., through the implementation of the “maize—flood-resistant crops” crop rotation mode and a subsidy policy to guide farmers to participate. (3) Improving the post-disaster recovery mechanism and promoting the disaster early-warning system: It is recommended that the relevant departments formulate a mechanism for rapid loss determination and compensation in agriculture to shorten the financial recovery cycle of affected farmers. At the same time, remote sensing meteorological and other data can be used to develop a disaster early-warning system guide for farmers on early harvesting to minimize losses when risk thresholds are reached.

5.2. Result Validation and Uncertainty Analysis

According to the announcement of the Hebei Provincial Emergency Management Department on 1 August 2023, Zhuozhou City initially counted the flood inundation areas as comprising 225.38 km². The maximum flood inundation areas in Zhuozhou City extracted in this study (as of 23 August) comprised 284.31 km², and this difference was mainly caused by monitoring cycles and data source type. As for the crop classification results, this study evaluated the crop classification accuracy based on 3085 validation samples. Among them, the OA reached 96.32%, the Kappa coefficient was 0.95, and the UA of various crops was, from high to low, maize (95.8%), beans (88.3%), and vegetables (86.1%), indicating that the accuracy of crop classification was high. For the crop damage area accuracy evaluation, Quan et al. (2024) [17] extracted the crop damage area in Zhuozhou City, which exceeded 1.25×10^4 ha. This study calculated that the crop disaster area in Zhuozhou City was 1.37×10^4 ha, which is consistent with the results of this study.

Although this study’s methods have some advantages in flood monitoring and crop disaster assessment, they still have some limitations. First, this study’s W_I , used for water

body detection, depends on K-means clustering when performing threshold segmentation, which tends to blur the boundary areas (such as farmland and shallow water intersection areas). In the future, deep learning models (such as U-Net) can be introduced to combine high-resolution topographic data to refine the water boundary problem between farmland and shallow water boundary areas. Second, GF-3 HV polarization is highly sensitive to wind and wave disturbances, which may lead to the misjudgment of shallow water accumulation in open farmland. In response to this problem, future research is planned to fuse the texture characteristics of multi-time-phase SAR data and optical data to improve the robustness of shallow water accumulation area identification. Finally, in this study, the crop disaster assessment was evaluated using the maximum NDVI difference value, with the difference threshold set at 0.14 based on previous studies. If some waterlogging-resistant crops have been planted in North China, the results of this study may weaken the “Very extreme damage” determination (such as the actual absolute yield area being higher than the statistical value). In future research, the degree of waterlogging tolerance of the crops in the study area will be considered an important consideration, and a dynamic disaster level classification standard will be constructed that is adaptable to crop type and growth period to avoid underestimation in crop disaster evaluation.

6. Conclusions

In this study, the authors analyzed the “7.29” flood event in Hebei Province using SAR and optical images to map the flooded area. A random forest model was used to generate data on the primary crops in the study area, and the classification of agricultural disaster levels was conducted using the GEE platform. The assessment of crop disaster levels was then completed. The main conclusions are as follows: (1) The total flooded area in the study region was approximately 700.51 km², accounting for 14.1% of the total area. The largest inundated area was Zhuozhou City, with 284.31 km², while Rongcheng County had the smallest inundated area at 16.577 km². The primary flood-prone areas were concentrated in the Xiaoqing River, Langou Depression, and Dongdian Stagnant Flood Storage Area. (2) The affected area of the main crops in the study area was about 4.07×10^4 ha. Maize was the most impacted crop, with an affected area of 3.37×10^4 ha, representing 19.76% of the total maize planting area. (3) Zhuozhou City and Gaobeidian City had the largest affected crop areas, with 1.37×10^4 ha and 1.03×10^4 ha, respectively. (4) The flood event resulted in moderate damage to 27.62% of the crops in the study area, which was the largest proportion among the disaster classes. The smallest percentage of crops, 5.10%, suffered from very extreme damage. These insights can inform future flood management strategies and agricultural planning to mitigate the effects of such natural disasters.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17050904/s1>, Table S1: Maize damage area assessment data by city and county; Table S2: Vegetable damage area assessment data by city and county; Table S3: Beans damage area assessment data by city and county.

Author Contributions: Conceptualization, methodology, and writing—original draft, C.W.; supervision and funding acquisition, Z.S.; investigation and formal analysis, H.L.; data curation, Y.H.; writing—review and editing, D.G. and X.Z.; resources, Y.C.; visualization and validation, H.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Program of China (project no. 2022YFC3800700), National Natural Science Foundation of China (grant numbers 42171291 and 42361144884), the Innovative Research Program of the International Research Center of Big Data for Sustainable Development Goals (grant no. CBAS2022IRP04), and the Joint HKU-CAS Laboratory for iEarth (313GJHZ2022074MI, E4F3050300).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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