DYNAMIC MONITORING OF THE CHAO LAKE DURING THE FLOOD SEASON BASED ON GAOFEN-3 SAR IMAGERY

Xi Zhang [1, *], Jinyan Sun [1], Dandan Dong [1]

[1] Anhui and Huaihe River Institute of Hydraulic Research, No.55 Hongfeng Road, Hefei 230088, China - (719483984, 1109591110, 1393230470)@qq.com

KEY WORDS: Chao Lake, Dynamic monitoring, Gaofen-3 SAR imagery, flood season, Water area, Water level.

ABSTRACT:

Ecological environment of lakes is vital to the people's livelihood. The flood disaster of lakes not only causes direct economic loss, but also breaks down the social order. Chao Lake, located in the middle and lower reaches of the Yangtze River, is one of the five major freshwater lakes in China with the area of 780 square kilometers. The dynamic monitoring of floods in the Chao Lake plays a crucial role in preventing flood disasters in the Anhui. This paper used CNNs to detect the flooded area of the Chao Lake from the Gaofen-3 SAR imagery from July and September 2020, July 2021, and August 2022. Then, the water area and water level were calculated to conduct a further quantitative analysis. The experiments demonstrate that SAR images play a crucial role in rapidly extracting water body information and monitoring the evolution of flooding.

1. INTRODUCTION

The monitoring of lake water area and level is of significant The monitoring of lake water area and level is of significant importance for disaster warning, environmental protection, water resource planning, as well as meteorological and climatological research. By monitoring the water area and level of lakes, potential flood risks can be detected early, allowing for timely measures to be taken for warning and protection. Lake water area and level monitoring aids in determining the water resource status and the health of the aquatic ecosystem of lakes. It also helps in assessing the balance between water supply and demand, promoting rational water resource management, and maintaining the ecological balance of lakes. Lake water level monitoring helps planners understand the availability and changes in water resources, enabling them to develop reasonable water resource planning and management strategies. Additionally, by monitoring lake water area and level, in-depth research on the interaction between lakes and the climate system can be conducted, providing crucial data for meteorological and climatological predictions and models. Overall, the monitoring of lake water levels plays a vital role in disaster warning, environmental protection, water resource planning, and meteorological and climatological research. It allows for early detection of potential flood risks, facilitates the assessment of water resource availability, promotes rational water resource management, and contributes to the understanding of the interaction between lakes and the climate system.

Traditional monitoring of lakes is based on the field survey. It boasts relative accuracy, but suffers from the drawbacks of being costly, limited by terrain, and having low observation frequency. However, remote sensing satellite imagery has the advantages of large instantaneous coverage, periodic repetition, and frequent updates of data. It has been widely applied in the water resources protection and disaster prevention and mitigation. Furthermore, Gaofen-3, a Synthetic Aperture Radar (SAR) satellite with 1-meter spatial resolution, is immune to variations in lighting and weather conditions, enabling it to operate continuously round the clock (Dastour et al., 2022; Ferrentino et al., 2020). To some degree, it can penetrate through clouds surface vegetation, loose sand layer, and snow and ice. As a result, it helps to compensate for the lack of optical imagery. Apart from this, the plum-rain season of 2020 is the longest recorded rainy period in history since 1961, with an average precipitation of 949 millimeters. This is almost triple the amount of precipitation received over the same period in recent years. This paper used CNN to detect the flooded area of the Chao Lake from the Gaofen-3 SAR imagery between July and September of 2020. Then, the water area and water level were calculated to conduct a further quantitative analysis.

2. MATERIAL AND METHOD

2.1 Study Area

The experimental area is situated in Chao Lake, located in the central part of Anhui Province. Chao Lake is the largest freshwater lake within the urban area of the provincial capital city in China. It is surrounded by rivers that flow into the lake in a radial pattern, with a total of seven first-class tributaries. The entire lake area is connected by a sole waterway known as the Yuxi River. During the flood season, the Yuxi River is controlled through the Yuxi lock to prevent urban flooding and the backflow of the Yangtze River. This presents significant challenges for flood control. In July 2020, due to heavy and persistent rainfall during the rainy season, the water levels of Chao Lake and its surrounding areas continued to rise. The water level at Chao Lake Zhongmiao station reached its highest recorded level. As a result, nine neighboring polders experienced successive breaches. In this context, Gaofen-3 data

* Corresponding author

played a crucial role in providing data support for studying the evolution of the flooding situation (Huang et al., 2020).

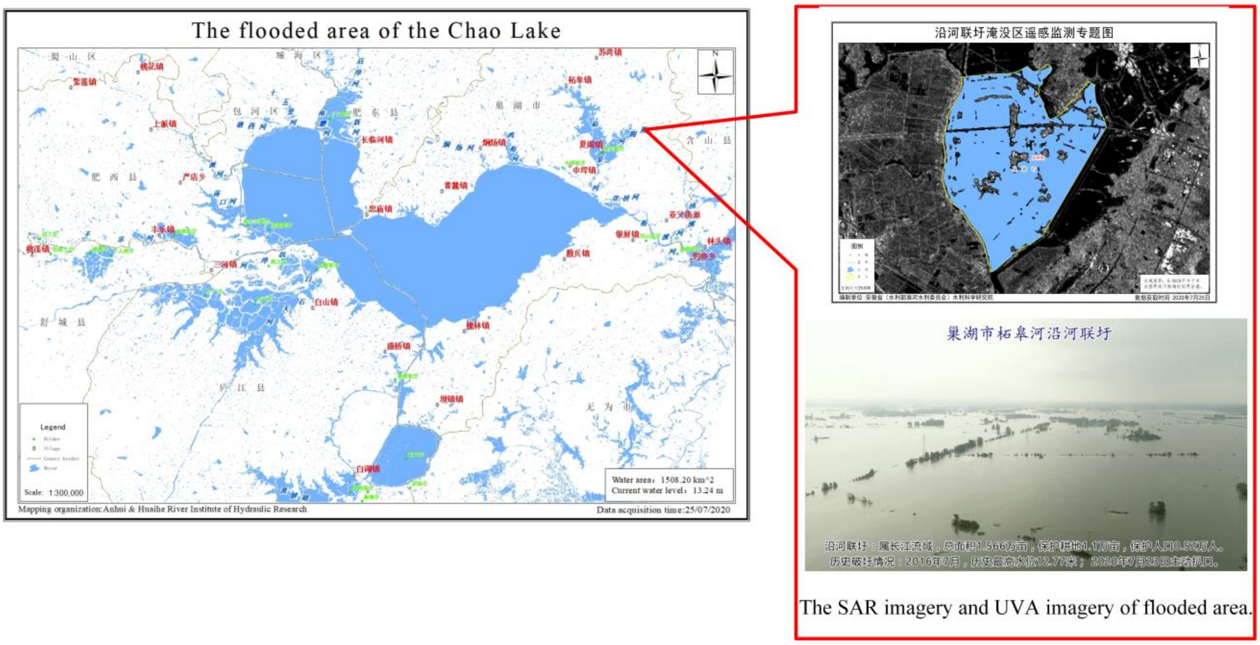


Figure 1. The thematic map, SAR imagery, and UVA imagery of the flooded area of the Chao Lake.

3. EXPERIMENT

This paper used the Convolutional Neural Network (CNN) based extraction algorithm for flooding evolution of multi-temporal GF-3 SAR image, which uses convolutional neural network for water body extraction and reduces the effect of noise on SAR image (Gu et al., 2019). Firstly, the multi-temporal multi-source remote sensing image data of Gaofen-3 covering the study area since entering the flood season, which contains 10-meter fine-stripe FSII mode and 5-meter fine-stripe FSI mode data, were selected for image preprocessing, respectively. And the water body area of multi-temporal Gaofen-3 was extracted separately using the backscatter coefficient significance detection of the preprocessed SAR images using convolution kernel with the same. For the post-processing of the water body area extraction and iteratively comparing the changes of the inundation area in the study area and recording the water level information of the key hydrological stations in the area. It provides a reference direction for automated realization of water-related time such as monitoring of spatial and temporal evolution of flooding in Gaofen-3 data. The flow chart is shown in Figure 2.

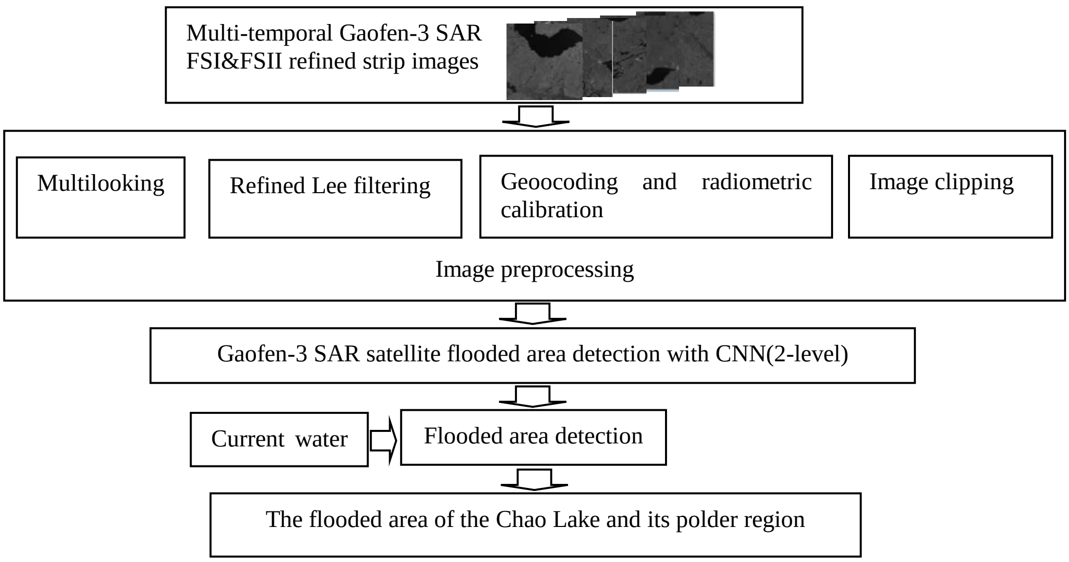


Figure 2. The workflow of the dynamic monitoring of the flooded area of the Chao Lake and its polder region.

3.1 Image preprocessing

The Gaofen SAR images were preprocessed using the SarScape module of the ENVI software, including Multilooking, Refined Lee Filtering, Geoocoding and Radiometric Calibration, Image clipping, etc. For each set of SAR images, phase alignment will be performed to obtain the pixel-to-pixel mapping after preprocessing. Image clipping, and so on. After preprocessing each group of SAR images separately, phase alignment is performed to obtain the pixel-to-pixel mapping. Before classification, phase alignment of both images is required to remove most of the systematic phase differences. All these steps are performed on the VV and VH polarizations by geometrically correcting and finally outputting the geoTIFF image.

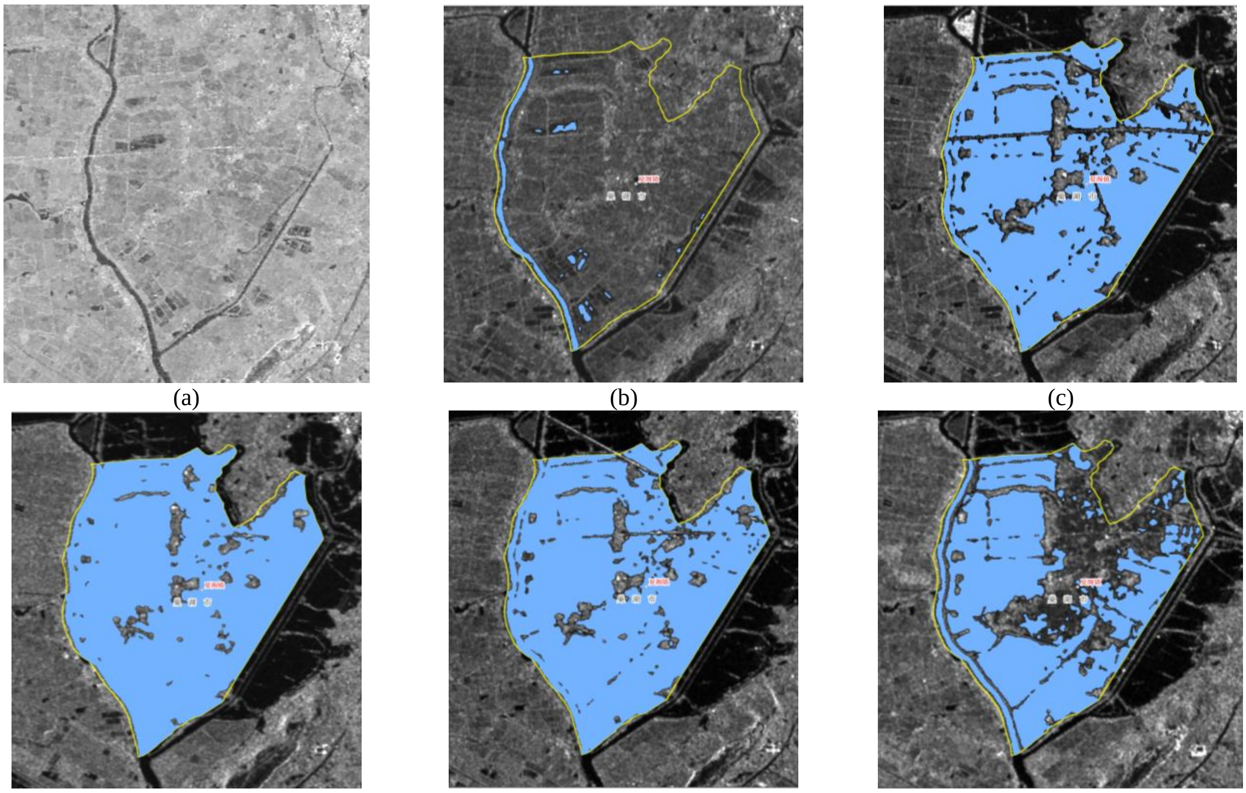
3.2 Water body area extraction based on convolutional neural network

In this experiment, the CNN architecture consists of two convolutional layers, two pooling layers, one fully connected layer, and one classification layer (Shang et al., 2017; Wu et al., 2019). The region of interest in the image is selected as the feature samples, and each convolutional layer has 20 feature maps. The input image block size is set at 27×27.

The first convolutional layer employs a 4×4×20 convolution kernel, resulting in a feature map size of 24×24×20 after processing. The pooling ratio for this layer is 2×2, reducing the feature map size to 12×12×20.

The second convolutional layer uses a 5×5×20 convolution kernel, producing an output feature map size of 8×8×20. Similarly, a pooling ratio of 2×2 is applied, resulting in a final feature map size of 4×4×20.

Following the second convolutional layer, a fully connected layer with a feature vector size of 320×1 is employed. The CNN is trained with a learning rate of 0.05 and 100 iterations. To ensure accurate extraction of the water body area, the same convolutional kernel is used to compute both the training set and test set of the CNN for each set of SAR images.



(a) (b) (c) (d) (e) (f)

Figure 3. The **w**ater area of polder region of the Chao Lake for different dates. (a) The water area of polder region on July 30th, 2021 is 0.63km^2. (b) The water area of polder region on July 17th, 2020 is 0.58km^2. (c) The water area of polder region on July 24th, 2020 is 8.56km^2. (d) The water area of polder region on July 28th, 2020 is 9.70km^2. (e) The water area of polder region on August 7th, 2020 is 9.16km^2. (f) The water area of polder region on September 14th, 2020 is 6.13km^2.

4. EXPERIMENT RESULTS

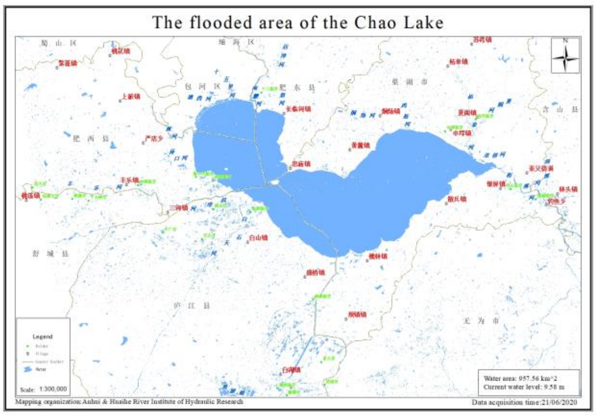
A total of 15 sets of Gaofen-3 SAR imagery data, consisting of 27 views, were utilized for monitoring in this area. These sets include 25 views of 10-meter fine-stripe FSII mode data and 2 views of 5-meter fine-stripe FSI mode data. Among them, 22 views were captured during the 2020 flood season, 3 views in 2021, and 2 views in 2022. The experimental results indicate that all 15 sets of images cover the entire extent of Chao Lake.
Since entering the rainy season in 2020, Anhui province has experienced 10 rounds of large-scale and persistent heavy rainfall. The duration of the rainy season was 60 days, with an average precipitation of 856 millimeters, which is 2.1 times the normal level for the same period. The intensity of rainfall in many areas reached extreme levels. The duration of the rainy

season, the number of heavy rainfall days, the total precipitation, the coverage area, and the intensity of the rainy season were all the highest on record since complete meteorological data has been recorded. In the Chao Lake Basin, the average precipitation during the rainy season (June 10th to July 31st) was 949 millimeters, nearly three times the normal level for the same period (326 millimeters), making it the highest on record since 1961.

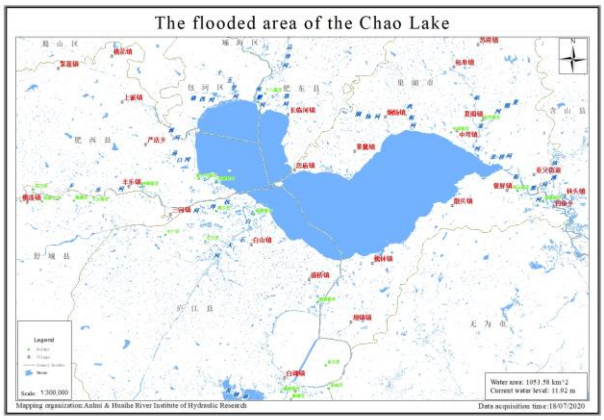
Table 1 displays the water body area of the lake corresponding to different time phases' water levels. Four sets of images completely cover both the lake area and the surrounding key polder areas. The changes in flood inundation within the monitored lake area and the surrounding polder areas can be observed in Figure 4. Table 1 and figure 4 describe changes of the water area and level of the Chao Lake in both qualitative and quantitative ways.

	Date	The water area of the Chao Lake (km^2)	The water level of the Chao Lake (m)	Remaks
1	21/6/2020	771.53	9.58	The flood season in 2020
2	9/7/2020	775.92	10.80	
3	18/7/2020	780.58	11.92	
4	25/7/2020	793.26	13.24	
5	28/7/2020	793.90	13.13	
6	30/7/2020	792.79	13.07	
7	5/8/2020	791.88	12.68	
8	7/8/2020	784.95	12.52	
9	9/8/2020	787.57	12.37	
10	11/8/2020	787.05	12.26	
11	26/8/2020	784.01	11.90	
12	17/8/2020	787.61	11.83	
13	14/9/2020	780.15	10.34	
14	30/7/2021	770.07	8.80	Normal years
15	5/8/2022	769.55	8.77	

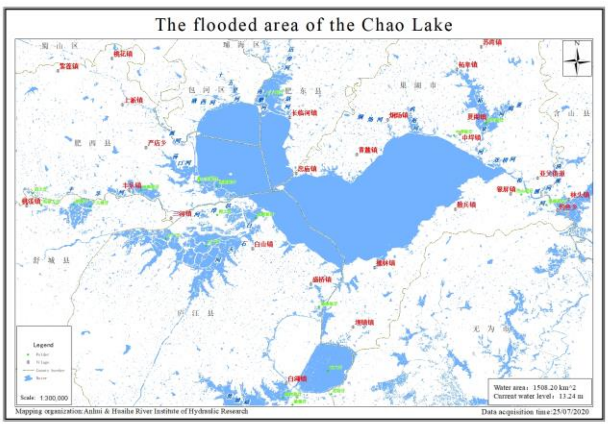
Table 1. The water area and water level of the Chao Lake during the summer of 2020-2022.



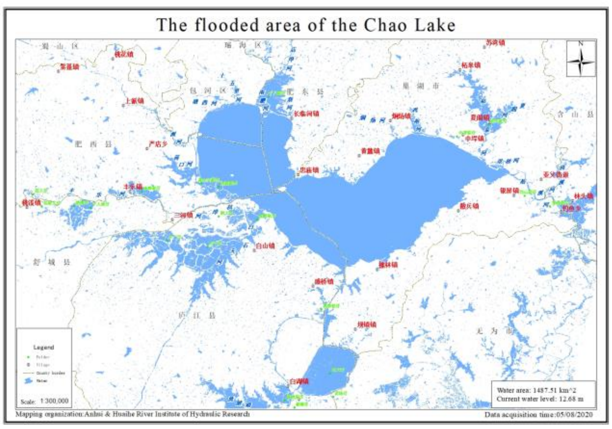
(a)



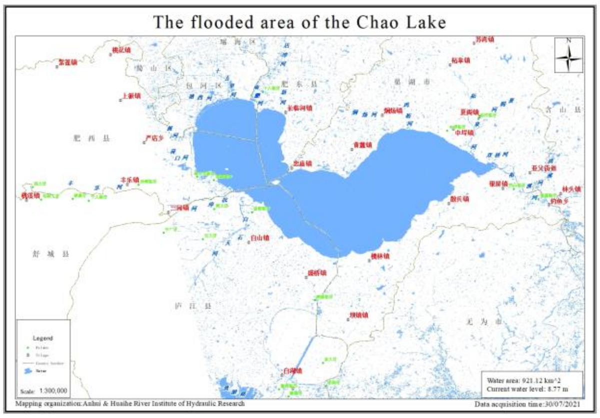
(b)



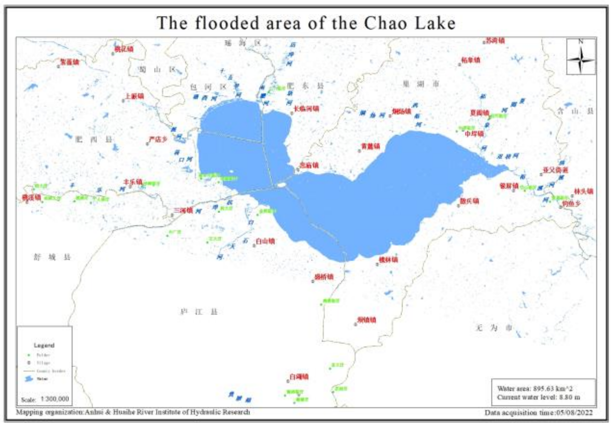
(c)



(d)



(e)



(f)

Figure 4. The flooded area of the Chao Lake for different dates, including: (a) June 21st, 2020, (b) July 18th, 2020, (c) July 25th, 2020, (d) August 5th, 2020, (e) July 30th, 2021, and (f) August 5th, 2022.

As we can see from figure 5 and figure 6, the water area of the Chao Lake increases from 746.84 square kilometers on July 1st, 2020 to 1508.2 square kilometers on July 25th, 2020. Additionally, during this period, the water level of the Chao Lake also increases from 10.61 meters to 13.24 meters. Then the water area decreases to 1106.31 square kilometers on September 14th and the water level decreases to 10.34 meters. The plum-rain season of 2020 lasts from June 10th to July 31st, and it is consistent with the variation trend of the water area and water level of the Chao Lake. During the period, the lake has been hit by torrential rainstorms.

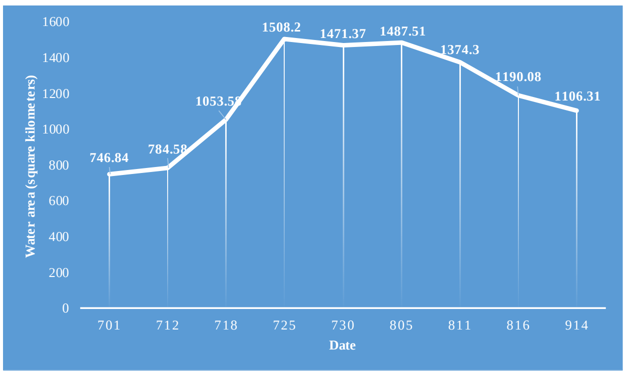


Figure 5. The water area of the Chao Lake during the flood season in 2020.

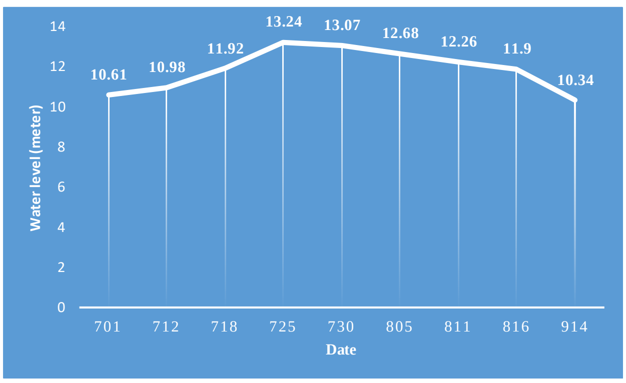


Figure 6. The water level of the Chao Lake during the flood season in 2020.

5. CONCLUSIONS

In this paper, we investigate a method for extracting water body information based on multi-temporal phase convolutional neural network SAR images. Specifically, we utilize the GF-3 fine stripe 2 imaging mode (FSII) SAR images captured during the 2020 flood season to extract changes in flooded water bodies within the Chao Lake and its surrounding area. Furthermore, we compare these results with SAR images from the GF-3 fine stripe FSI and FSII imaging modes taken during the summer of 2021 and 2022 to determine the water body area during non-flood periods. By combining this information with the corresponding water level data, we are able to monitor changes in inundation areas of the lake and the surrounding polder areas.

This method demonstrates promising applications for rapidly extracting water body information from SAR images and monitoring the evolution of flooding. In the future, we aim to establish a flood prediction model by integrating meteorological data, water conditions, and findings from disaster field research. Additionally, we plan to conduct further research on regional flood generation and explore methods for disaster prevention and mitigation.

ACKNOWLEDGEMENTS

The work presented in this paper is supported by the Science and Technology Project of Anhui & Huaihe River Institute of Hydraulic Research (No. KJGG202201), the Youth Science and Technology Program of Anhui Province Key Laboratory of Water Conservancy and Water Resource (No. KY202001), the Foundation of the Key Research and Development Program in Anhui Province (No. 202104b11020046).

REFERENCES

Dastour, H., Ghaderpour, E., Hassan, Q.K., 2022. A Combined Approach for Monitoring Monthly Surface Water/Ice Dynamics of Lesser Slave Lake Via Earth Observation Data. *IEEE Journal of Selected Topics in Applied Earth Observations and*

Remote Sensing, 15(6402-6417), doi.org/10.1109/JSTARS.2022.3196611.

Ferrentino, E., Nunziata, F., Buono, A., Urciuoli, A., Migliaccio, M., 2020. Multipolarization Time Series of Sentinel-1 SAR Imagery to Analyze Variations of Reservoirs' Water Body. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13(840-846), doi.org/10.1109/JSTARS.2019.2961563.

Gu, X.Z., Zeng, Q.W., Shen, H., Chen, E.X., Zhao, L., Yu, F., Tu, K., 2019. Study on water information extraction using domestic GF-3 image. *Journal of Remote Sensing*, 23(3): 555–566. doi.org/ 0.11834/jrs.20198171.

Huang, Z.J., Wang, C.L., Zhang, X., Zhu, P.,2021. Application of space-air-ground integrated remote sensing technology in flood monitoring in Anhui Province in 2020. *China Flood & Drought Management*, 31 (4): 6-9. doi.org/ 10.16867/j.issn.1673-9264.2021078.

Shang, R.H., Yuan, Y., Jiao, L.C., Hou, B., Ghalamzan, E. A. M., Stolkin, R., 2017. A fast algorithm for SAR image segmentation based on key pixels. *IEEE journal of selected topics in applied earth observations and remote sensing*, 10(12): 5657-5673. doi.org/ 10.1109/jstars.2017.2743338.

Wu, C., Yang, X., Wang, J., 2019. Flood Detection in Sar Images Based on Multi-Depth Flood Detection Convolutional Neural Network. 2019 6th Asia-Pacific Conference on Synthetic Aperture Radar (APSAR), Xiamen, China, pp. 1-6, doi.org/ 10.1109/APSAR46974.2019.9048485.