Monitoring Surface Water Inundation of Poyang Lake and Dongting Lake in China Using Sentinel-1 SAR Images

Zirui Wang 1,2, Fei Xie 3, Feng Ling 4,∗ and Yun Du 4

1 Faculty of Resources and Environmental Science, Hubei University, Wuhan 430062, China; 201931108010029@stu.hubu.edu.cn
2 Chucai Honors College, Hubei University, Wuhan 430062, China
3 Hubei Institute of Land Surveying and Mapping, Wuhan 430034, China; feixiewh@gmail.com
4 Key Laboratory for Environment and Disaster Monitoring and Evaluation of Hubei, Innovation Academy for Precision Measurement Science and Technology, Chinese Academy of Sciences, Wuhan 430077, China; duyun@whigg.ac.cn
∗ Correspondence: lingf@whigg.ac.cn; Tel.: +86-27-68881901

Abstract: High-temporal-resolution inundation maps play an important role in surface water monitoring, especially in lake sites where water bodies change tremendously. Synthetic Aperture Radar (SAR) that guarantees a full time-series in monitoring surface water due to its cloud-penetrating capability is preferred in practice. To date, the methods of extracting and analyzing inundation maps of lake sites have been widely discussed, but the method of extracting surface water maps refined by inundation frequency map and the distinction of inundation frequency map from different datasets have not been fully explored. In this study, we leveraged the Google Earth Engine platform to compare and evaluate the effects of a method combining a histogram-based algorithm with a temporal-filtering algorithm in order to obtain high-quality surface water maps. Both algorithms were conducted on Sentinel-1 images over Poyang Lake and Dongting Lake, the two largest lakes in China, respectively. High spatiotemporal time-series analyses of both lakes were implemented between 2017 and 2021, while the inundation frequency maps extracted from Sentinel-1 data were compared with those extracted from Landsat images. It was found that Sentinel-1 can monitor water inundation with a substantially higher accuracy, although minor differences were found between the two sites, with the overall accuracy for Poyang Lake (95.38–98.69%) being higher than that of Dongting Lake (95.05–97.5%). The minimum and maximum water areas for five years were 1232.96 km² and 3828.36 km² in Poyang Lake, and 624.7 km² and 2189.17 km² in Dongting Lake. Poyang Lake was frequently inundated with 553.03 km² of permanent water and 3361.39 km² of seasonal water while Dongting Lake was less frequently inundated with 320.09 km² of permanent water and 2224.53 km² of seasonal water. The inundation frequency maps from different data sources had R² values higher than 0.8, but there were still significant differences between them. The overall inundation frequency values of the Sentinel-1 inundation frequency maps were lower than those of the Landsat inundation frequency maps due to the severe contamination from cloud cover in Landsat imagery, which should be paid attention in practical application.

Keywords: Sentinel-1; surface water mapping; Edge Otsu classification; temporal filtering; Poyang Lake; Dongting Lake; inundation frequency map; GEE

1. Introduction

Lakes account for about 3% of the Earth’s land surface, taking up 4.2 million km² in area [1,2]. These lakes are important components of the terrestrial hydrosphere, playing an essential role in water supply, flood control, the water cycle, and regional climate change [3–8]. In the context of climate change and human activity, surface water bodies have been severely affected with regard to lake acreage, resulting in a noticeable water area variation that affects human survival and social development [9–11]. Therefore, timely and accurate monitoring of
the characteristics of surface water could satisfy a need for flood control, drought relief, and agricultural production [12–14].

Satellite remote sensing provides an effective way to monitor timely water change across a large area. To date, many surface water mapping studies have been based on optical sensors. The datasets that have a coarse resolution such as Moderate Resolution Imaging Spectroradiometer (MODIS) [15–18] and medium resolution such as Landsat [19,20] and Sentinel-2 [21,22] have been widely covered in previous research. The mapping methods implemented on optical imagery include decision tree approaches [23], spectral information and threshold [24–29], and deep learning [30–32]. Although the well-defined optical imagery can extract surface water bodies with a high accuracy [33,34], the cloud cover problem always limits the requirement of a full and regular time-series. Especially in monsoonal regions, monthly cloud-free optical remote sensing images are difficult to generate, severely affecting the following time-series analysis [35–37]. Moreover, the peak surface water extent often coincides with flood events, which always have serious contamination problems, resulting in a date gap [38,39]. Therefore, an effective identification method without cloud influence is essential in water dynamics monitoring.

Synthetic Aperture Radar (SAR) has been utilized as a promising tool as its sensors are cloud-proof and illumination-independent [40], addressing the cloud contamination problem in optical images well. The Copernicus Sentinel-1 satellite was launched by the European Space Agency (ESA) in 2014, with consistent and free data available to the public, which solved the problem of the high expense of using high-resolution SAR data such as TerraSAR-X (X-band), COSMO-SkyMed (X-band), and RADARSAT-2 (C-band) [41,42] at a large scale. Its cloud-penetrating ability and consistent SAR images enable research into the continuous and regular monitoring of features of and changes to surface water bodies [43]. The processing and identification methods utilized for SAR images are similar to the optical images, covering decision tree approaches [44], threshold [45,46], and deep learning [47–49]. Although the benefits of cloud-penetrating ability and consistent monitoring can be concluded in SAR imagery, the influence of geographic environment and speckle noise should be taken into consideration as well [50].

In order to obtain high-quality surface water products in the context of practical applications, an automatic approach is needed to avoid manual and subjective imagery interpretation. The threshold-based algorithm is popular, but the accuracy of classification of the surface water products should be carefully evaluated and further improved. SAR instruments have a strong ability to penetrate clouds; however, transportation facilities such as ships will cause extremely bright spots under SAR imagery [51], which will lead to severe errors of omission. To dates, little work has focused on removing the errors caused by these objects. Therefore, we combine the threshold-based algorithm with an approach involving eliminating the misclassification of transportation to obtain products with better quality.

Poyang Lake and Dongting Lake are the largest and second-largest lakes in China, both located in monsoonal regions and connected to Yangtze River, playing important roles in maintaining ecology balance and regulating runoff of the Yangtze River [52]. For these two lakes, prior studies have been performed focusing on monitoring surface water area variation using various data, and inundation frequency (IF) maps have been generated to discuss the change of the water [53–56]; however, there are still some limitations that should be studied further. First, for Sentinel-1 images, the water mapping algorithms need to be improved. Second, the distinction between IF maps generated from different data sources have not been extensively studied.

This study is dedicated to extracting water bodies on a high spatiotemporal scale with a considerably high accuracy of classification, enabling us to obtain a substantial number of surface water maps with high quality. The goals of this study are to (1) propose a fast and novel surface water mapping approach that combines a threshold-based algorithm with a temporal filtering that removes the misclassification caused by ships and assess the performance of the algorithm in two sites; (2) analyze the water dynamics directly in the
form of water area and in the form of inundation frequency maps over both lake sites; and (3) compare the inundation frequency maps of Sentinel-1 images with those extracted from Landsat images.

2. Materials and Methods
2.1. Study Area

For this study, we focused our analysis on the central region of China. More specifically, we selected Poyang Lake and Dongting Lake as our study areas with the purpose of comparing and analyzing the results of water body extraction (Figure 1).

Figure 1. Study area of Poyang Lake and Dongting Lake located in Jiangxi and Hunan, respectively. The blue region indicates the water body and river system.

Poyang Lake (approximately 28°22′ to 29°45′N and 115°47′ to 116°45′E) is located in the province of Jiangxi. With an average area of approximately 3210 km² and a mean volume of approximately 25.2 km³ [57], Poyang Lake is China’s largest freshwater lake. Poyang Lake is divided by Songmen Mountain into a narrow and deep northern outlet and a wide and shallow southern part. The outlet connects with the Yangtze River, resulting in annual runoff of 143.6 billion m³ [58]. In the period of the dry season, the water discharges along the northern outlet to the Yangtze River, while in the period of the wet season, the Yangtze River reverses flows to Poyang Lake because of the higher water level [59].

Dongting Lake (approximately 28°30′ to 30°20′N and 110°40′ to 113°10′E) is located in Hunan Province. With a mean surface water area of 1148 km², Dongting Lake is China’s second largest freshwater lake. Several rivers are connected to the primary body of water, three of which are also connected to the Yangtze River (Songzi River, Hudu River, and Ouchi River), and the water flows into the Yangtze River at the northeastern exit near Chenglingji [60]. The lake is also supplied by other major rivers, namely, the Xiangjiang River, Zishui River, Yuanjiang River, and Lishui River [61]. Located in an area with a subtropical monsoon climate, the lake has a distinct dry season from October to March when water flows from the lake in the rivers, and a distinct wet season from April and September, when flood water is stored [60].
2.2. Materials

2.2.1. Sentinel-1 Data

The Sentinel-1 mission contains Sentinel-1A and -1B satellites, which were launched in April 2014 and April 2016, respectively, and are equipped with C-band radar. C-band radar has cloud-penetrating capability, which means that Sentinel-1 data can provide continuous images for analysis, especially effective during the wet season, which this study covers. In this study, a total of 240 dual-polarization Sentinel-1 level-1 Ground Range Detected (GRD) products spanning the period from 1 January 2017 to 26 December 2021 were used. This Sentinel-1 C-band dataset provides vertical transmitting with vertical transmitting, vertical receiving (VV) and vertical transmitting, horizontal receiving (VH) polarization modes. Only VV polarization data were used in this study, as a previous study indicated that VV polarization performed best in surface water mapping [62,63]. The Level-1 GRD products were preprocessed on the Google Earth Engine (GEE) platform. For the preprocessing, we used the Lee-Sigma speckle filter [64] to eliminate the granular noise before surface water mapping. Table 1 shows the specific information of the Sentinel-1 GRD images used in this study, which were acquired in the span of half a month.

| Region        | Bands | Res. (m) | Scenes 2017 | 2018 | 2019 | 2020 | 2021 |
|---------------|-------|----------|-------------|------|------|------|------|
| Poyang Lake   | VV    | 10       | 48          | 48   | 48   | 48   | 48   |
| Dongting Lake | VV    | 10       | 96          | 96   | 92   | 80   | 80   |

2.2.2. JRC Monthly Water History Data

The dataset was built by Pekel et al. [2] in 2016, which contains maps of the spatial and temporal distribution of water extent for a long period (1984–2020). The surface water maps were generated by scenes from a Landsat series satellite specifically from 16 March 1984 to 31 December 2020. Each pixel was individually classified into water/nonwater using an expert system and the results were collated into a monthly history for the entire time period for change detection. This dataset enables users to obtain surface water extent in the form of water maps or inundation frequency maps. For this study, we merged 48 maps between 2017 and 2020 to generate Landsat inundation frequency maps.

2.2.3. Validation Data

The Sentinel-2A satellite was launched on 23 June 2015, providing 5 days of repeat frequency data at the equator and 2–3 days at the mid latitude [65,66]. The Sentinel-2 dataset has a distinguished quality with a high spatial resolution of 10 m and multispectral sensors with 13 bands. The false color composition containing visual bands and near-infrared band decreases the difficulty of the visual interpretation by noticeably identifying the water from the vegetation areas, which will lead to a set of high-quality sample points [52,67]. We collected validation data from GEE with a cloud proportion lower than 5%. Furthermore, the selected scenes corresponded to the Sentinel-1 SAR acquisition for the close data and the same region. To verify the classification accuracy of the water inundation from Sentinel-1, we classified each scene into water/nonwater by giving sample points from visual interpretation.

The Database for Hydrological Time Series of Inland Waters (DAHITI) was built in 2013 to provide a continuous water level time series of inland water [68]. The water level data in DAHITI were acquired by means of satellite altimetry or a hypsometric curve describing the relationship between water levels and surface areas, and the former was selected as the additional validation data for this study.
2.3. Methods

The workflow is shown in Figure 2 and can be divided into four fractions: preprocessing, water extent delineation, accuracy design, and water dynamics analysis. The preprocessing step mainly focused on Sentinel-1 SAR imagery corrections, involving format transformation and smoothing. Subsequently, an optimized Otsu’s method (Edge Otsu’s method) and a temporal-filtering algorithm were used to obtain surface water maps. Thirdly, the accuracy of extracted water body images was assessed, and finally, the analysis and comparison of Poyang Lake and Dongting Lake changes were conducted. Figure 2 depicts the workflow.

2.3.1. Data Preprocessing

The Sentinel-1 SAR imagery was preprocessed on the GEE platform. A radiometric conversion from a linear scale to a dB scale was conducted using the expressions of \( \sigma_{0dB} = 10 \times \log_{10}(\sigma_0) \) \[69\]; and the Lee-Sigma speckle filter was applied to \( \sigma_0 \) bands to reduce the granular noise characteristic of SAR data \[64\]. The mean values of the same location were used to represent the semimonthly water body extent.

2.3.2. Edge Otsu’s Algorithm

The water body maps were automatically extracted by an unsupervised algorithm. Otsu’s method is a histogram-based thresholding approach that calculates the interclass variance between two classes, a foreground and background class, which provides a threshold for each scene under unique circumstances \[70\]. To obtain better water pixels, an optimized Otsu’s method was utilized in this study. Edge Otsu’s method was first purposed by Donchyts et al. \[71\], which is a combination of the Canny edge detection algorithm and Otsu’s method, proven to perform better than Otsu’s method or other optimized Otsu’s methods under the same circumstance \[50\].

The workflow of the Edge Otsu water mapping algorithm is shown in Figure 3. Following the experimental routine, we firstly selected the threshold to binarize the image. Then, a Canny edge detector was conducted on the images to highlight the edges of
water bodies, specifically the edges of Poyang Lake and Dongting Lake in this study. Subsequently, the edges of water bodies were buffered to collect samples that constructed the histogram. Finally, Otsu’s method was conducted on the histogram sampled from buffered edges to calculate histogram-based threshold implemented on the entire image.

![Figure 3](image)

**Figure 3.** Specific method of the Edge Otsu algorithm followed by preprocessing, default threshold binarization, detecting edges, buffering, and Otsu threshold binarization.

We noted that the initial threshold that binarized the SAR image had a strong influence on the final accuracy of classification. Markert et al. utilized $-16$ dB as a default initial threshold with a considerably high accuracy [50], and Guo et al. obtained the best threshold to binarize the SAR imagery over the Yangtze River basin through the experiments, which was $-21$ dB specifically [72]. Both of the initial thresholds and their effects are discussed in this study. Moreover, the morphological dilation (buffer) of the edges of the water bodies was utilized to perform better sampling. The selection of the buffer size would directly affect the quality of the histogram, in which case poor selection would cause skewed distribution of buffer small water bodies. In this study, we selected a buffer size of 3000 m in a large-scale study according to the study by Markert et al. [50].

2.3.3. Temporal-Filtering Algorithm

Ship transportation can be frequently witnessed in both Poyang Lake and Dongting Lake. However, as Figure 4a indicates, in the case of water extraction from SAR imagery, the ships might severely contaminate the data sources and affect the final surface water maps. The ships in SAR imagery present the characteristic of a star-shaped, high-brightness area with slightly darker edges [51]. An unsupervised histogram-based thresholding algorithm could not classify ships into the water class due to the significant distinction of the physical properties of these two objectives in SAR imagery. Consequently, a simple binarizing approach could not detect severe misclassification caused by ship contamination extracted from SAR imagery (Figure 4b).

Here, we propose an approach to postprocessing to solve the issue mentioned above. First, we merged all of the images extracted by the Edge Otsu algorithm to generate inundation frequency maps over the study areas. Then, water maps were extracted again by the algorithm combining the Edge Otsu algorithm and the temporal-filtering algorithm based on both dB values and IF values.
where the values were higher than those considered as sand, cities, vegetated areas, and ships.

The temporal-filtering algorithm was driven by two vital parameters, namely, dB and IF values, respectively, which we founded during the experiments. Based on observation and physical properties, we chose the threshold of $-16$ dB to binarize the SAR imagery, in which case the values were higher than those considered as sand, cities, vegetated areas, and ships.

However, we considered the threshold selection for the IF map to be tricky. During the experiments, we found that selecting a threshold too high would lead to poor processing effects, while selecting a threshold too low would lead to obvious misclassification, both of which would reduce the classification accuracy. When the water area was very small, the area covered by ship spots should be nonwater, which has little influence on the final result. Therefore, according to the rule that the smaller the water area is, the smaller the area covered by ship spots will be, we believed that a rule could be formulated to select the threshold given the situation of each image. Here, we propose a threshold selection method based on the water area. The IF maps were equally divided into 10 classes and labeled. Specifically, we labeled the area of water extent in class 90–100% $S_{\text{IF},1}$, class 80–90% $S_{\text{IF},2}$, and so on. The area of each class was determined by the following expression:

$$S_{\text{class},n} = \sum_{i=1}^{n} S_{\text{IF},i} \quad (n \leq 10)$$

where $S_{\text{class}}$ is utilized as a criterion to select the final binarizing IF value. Specifically, the IF threshold is determined by both the area of each surface water map ($S_{\text{water}}$) and water area criterion ($S_{\text{class}}$) as follows:

- If $S_{\text{water}} < S_{\text{class},1}$, assign threshold 1;
- If $S_{\text{class},i} < S_{\text{water}} < S_{\text{class},i+1}$, assign threshold $IF_i$ according to expression of $IF_i = 1 - 0.1 \times i$;
- If $S_{\text{water}} > S_{\text{class},10}$, assign threshold 0.

The masks extracted by two thresholds were subsequently intersected to obtain the ship-covered water area (Figure 4e). The intersect mask extracted by two indicators guaranteed a lower possibility of misclassifying sand and vegetated area into the ship-covered area. In addition, a special case should be taken into consideration. Due to the special material and vertical structure, the cities and center parts of the ships were extremely bright in SAR imagery with dB values higher than 0, while the IF values of the cities remained at 0 except for the extreme flooding situation. So, we used 0 dB to obtain the high-value parts of the ship and a 0 IF value to exclude the cities.

![Figure 4](image-url)
2.3.4. Evaluation Design

To demonstrate the classification accuracy from Sentinel-1 SAR, we chose four images over Poyang Lake and four images over Dongting Lake (eight in total) whose dates corresponded to the validation datasets. Sentinel-2 images with 10 m-resolution were utilized for visual interpretation of the sample points in water/nonwater classifications on the GEE platform. We utilized a confusion matrix to calculate accuracy metrics, which consisted of a cross-control sample count of the classification map and reference data [52,73,74]. The matrix was composed of four categories, namely, True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). In this study, four metrics were calculated to measure the accuracy: overall accuracy (OA), producer’s accuracy (PA), user’s accuracy (UA), and F$_1$-Score (F$_1$) [52]. The metrics are calculated using the following expressions:

$$\text{OA} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{PA} = \frac{TP}{TP + FN}$$

$$\text{UA} = \frac{TP}{TP + FP}$$

$$F_1 = \frac{2TP}{2TP + FP + FN}$$

We selected PA and UA metrics, which provide measures on recall (error of omission) and precision (error of commission) rates for the method. The F$_1$ values indicate the classification quality, which belongs to $[0, 1]$. The higher the value, the better the classification.

Furthermore, the correlation between the surface water area extracted by Sentinel-1 SAR images and water level was evaluated with the determinate coefficient R$_2^2$.

2.3.5. Analysis of Water Dynamics

Poyang Lake and Dongting Lake are very important to the ecological environment and water resources of China. Hence, monitoring the water dynamics of both lakes has an essential value. To do so, the fundamental methods include monitoring area changes using the indicator’s area, which evidently shows the dynamics over five years. In this section, we conducted inundation frequency analysis, which could effectively show the spatiotemporal dynamics change of surface water area zonally and sequentially [75]. We merged all of the images spanning five years to obtain the general characteristic of water dynamics of Poyang Lake and Dongting Lake.

In addition, the comparison work of inundation frequency maps derived from Sentinel-1 images and Landsat images as conducted for the period of 2017 to 2020. Due to the difference of spatial and time resolution, we assumed that the distinction of IF maps from these two different data sources would be noticeable. The Pearson index and scatter diagram were used during the comparing session.

3. Results

The Edge Otsu algorithm and temporal-filtering algorithm were both applied to the Sentinel-1 SAR dataset, across all of the dates and scenes where validation datasets coincided. The classification maps were validated by 10,000 sample points within the study area manually interpreted from Sentinel-2 images. The detailed information and verification results are displayed in Table 2. It can be seen that the general classification accuracy of Poyang Lake was high with overall accuracy ranging from 95.36% to 98.69%. The producer’s accuracy and user’s accuracy were analogous with an accuracy range of 91.35–98.53% and 90.75–97.71%, respectively. The high values in both PA and UA for each consequence shows that the results were supported by both accurate interpretation and proper estimation of water extent. The F$_1$-Score was consistently high with an average
accuracy of 0.95, which proves the effectiveness of the water extent classification, having an acceptable accuracy.

### Table 2. The statistical evaluation of input points samples calculated from confusion matrix.

| Date              | Reference Site | Date              | Reference Site | Site       | OA/%  | PA/%  | UA/%  | F1   |
|-------------------|----------------|-------------------|----------------|------------|-------|-------|-------|------|
| 17 September 2017 | 17 September 2017 | Poyang Lake       | 95.36          | 91.35      | 90.75 | 0.91  |
| 19 July 2018      | 19 July 2018    | Poyang Lake       | 97.20          | 92.97      | 97.37 | 0.95  |
| 2 August 2020     | 1 August 2020   | Poyang Lake       | 98.69          | 98.53      | 97.67 | 0.98  |
| 23 July 2021      | 22 July 2021    | Poyang Lake       | 98.41          | 97.10      | 97.71 | 0.97  |
| 17 July 2017      | 17 July 2017    | Dongting Lake     | 96.01          | 82.72      | 99.68 | 0.90  |
| 17 August 2019    | 16 August 2019  | Dongting Lake     | 95.05          | 80.84      | 98.75 | 0.85  |
| 20 August 2020    | 18 August 2020  | Dongting Lake     | 97.00          | 88.73      | 98.91 | 0.93  |
| 1 August 2021     | 1 August 2021   | Dongting Lake     | 97.50          | 86.59      | 98.46 | 0.92  |

Compared with the Poyang Lake verification results, the results of Dongting Lake were slightly lower, with the overall accuracy ranging from 95.05% to 97.5%. The user’s accuracy of Dongting Lake was higher than that of Poyang Lake, with a considerably higher accuracy range of 99.71% to 99.68%, while the producer’s accuracy was comparably lower, with a range of 80.84% to 88.73%. The lower overall accuracy could be explained by the complex geographic environment and the large residential site area especially located in South Dongting, which worsened the effect of the Edge Otsu algorithm by creating more noise.

Figure 5 depicts the correlation between water area and water level in Poyang Lake (Figure 5a) and Dongting Lake (Figure 5b) in the form of scatter diagrams. The results presented a strong relationship between water level and water area extracted from SAR images over two study sites with considerably high R^2 values of 0.840 and 0.822. Overall, the results suggest that the water area calculated in this study was acceptable.

![Figure 5](image)

**Figure 5.** The correlations between water level data and water area extracted from Sentinel-1 SAR images of Poyang Lake (a) and Dongting Lake (b). The redline indicates fitting curve.

Figure 6 shows the surface water area of Poyang Lake and Dongting Lake calculated from SAR images and JRC monthly water history data. It can be seen that the distinction of the data volume was huge, with continuous and adequate acquisition of Sentinel-1 data and discontinuous acquisition of Landsat data. The cloud cover caused severe contamination of optical images while the SAR images were unaffected, which offered a full time series of water area. Additionally, it can be seen that the overall water area extracted from the Landsat images was higher than that from Sentinel-1 images due to the distinction of the extracting methods.
Figure 6 shows the surface water area of Poyang Lake and Dongting Lake calculated from SAR images and JRC monthly water history data. It can be seen that the distinction of the data volume was huge, with continuous and adequate acquisition of Sentinel-1 data and discontinuous acquisition of Landsat data. The cloud cover caused severe contamination of optical images while the SAR images were unaffected, which offered a full time series of water area. Additionally, it can be seen that the overall water area extracted from the Landsat images was higher than that from Sentinel-1 images due to the distinction of the extracting methods.

Figure 6. Water inundation area time series from Sentinel-1 SAR data and JRC data of (a) Poyang Lake and (c) Dongting Lake, and the box plot of monthly water area from Sentinel-1 SAR data of (b) Poyang Lake and (d) Dongting Lake.

Figure 6a shows the surface water area of Poyang Lake from SAR imagery during the study period. Throughout the study period, the area of water body varied between 1232.96 km$^2$ and 3828.36 km$^2$. In general, the annual average water body area increased in the study period, ranging from 2355.41 km$^2$ in 2017 to 2396.55 km$^2$ in 2021, reaching a peak at 2482.16 km$^2$ in 2020, which presented a steady trend. In the period of 2017–2021, the water body area displayed a seasonal behavior with the lowest value in winter, reaching an annual maximum in early summer and declining again during the fall. As Figure 6 indicates, a severe flood took place in 2020. The water area values of Poyang Lake in June to August 2020 were 2859.68 km$^2$, 3762.32 km$^2$, and 3719.55 km$^2$, respectively, and the water level values of these months were 18.8 m, 19.95 m, and 18.12 m, respectively. The results indicate that the affected area of this flood in the Poyang Lake site was more than 900 km$^2$, and the water level in July 2020 exceeded the warning water level of 19 m. To further analyze the seasonal behavior, we present the monthly water variation of Poyang Lake using a box plot (Figure 6b). The results suggest that the water body area increased in spring and early summer (January to July), with a noticeable decline following in fall and winter (August to December). A steep increase could be seen in late spring, which led to a noticeable peak in March or April in every year. This behavior coincided with the spring floods of the year [76]. However, the annual peak value could always be witnessed in the rainy season (July to August), whereas the year 2021 differed from the other years, when the peak value appeared in May.

Figure 6c shows the water body area of Dongting Lake from SAR imagery during the study period. The annual average water body area changed from 1201.92 km$^2$ in
2017 to 1109.25 km\(^2\) in 2021, reaching a peak at 1329.16 km\(^2\) in 2020. Surface water area presented significant seasonal variation as well. The lake had an average water body area of 1424.4 km\(^2\) in the rainy season, and an area of 939.16 km\(^2\) in the dry season. Compared to a previous work, which indicated that the water body area of Dongting lake increased from 440 km\(^2\) in 2005 to 1900 km\(^2\) in 2009 [77], both the minimum and maximum values increased, ranging from 624.7 km\(^2\) to 2189.17 km\(^2\) in the study period, which showed a difference value greater than 200 km\(^2\). The peak values could always be witnessed in July except for 2021, during which the peak value appeared in September. The water area values of Dongting Lake in July and August (the Sentinel-1 SAR images in June 2020 over Dongting Lake was not complete) were 2189.87 km\(^2\) and 2119.56 km\(^2\), respectively, and the water level values of that were 31.08 m and 28.43 m, respectively. The results of this study cannot indicate whether a flood took place in Dongting Lake, but the official record of the peak water level was 34.47 m, which exceeded the warning water level of 32.5 m. Figure 6d depicts the monthly water variation of Dongting Lake using a box plot. We found that the water area fluctuation of Dongting Lake coincided with that of Poyang Lake, which soared from January to July and declined from August to December. Significant water area variation occurred in September and October when water started to retreat from the lake into the rivers.

We merged all surface water maps to obtain the inundation frequency maps, which show the spatiotemporal dynamics over the study areas in the period of 2017 to 2021 in Figure 7. The area of permanent water in Poyang Lake was 553.03 km\(^2\), taking up 12.37% of the whole lake body area, mainly distributed in the branch lakes and the edges of the main lake body in the south and east region, while the seasonal water area of Poyang Lake was 3361.39 km\(^2\). The significant distinction between permanent water and seasonal water of Poyang Lake illustrated the fact that Poyang Lake was deeply affected by the monsoon climate and Yangtze River flows, which meant that Poyang Lake had a high risk of flooding due to climate factors. The area of permanent water in Dongting Lake was 320.59 km\(^2\), taking up 11.2% of the whole lake body area, mainly distributed in East Dongting Lake, South Dongting Lake, and Datong Lake, while the seasonal water area of Dongting Lake was 2224.53 km\(^2\). Dongting Lake was affected by the monsoon driven environment. However, compared with Poyang Lake, the ratio of permanent or stable surface water of Dongting Lake was evidently lower, which was caused by the factors of precipitation, evaporation, run off, and infiltration [75]. In addition, the average elevation of the lake was considered as another main factor that caused this distinction as that of the Poyang Lake was 21 m while that of Dongting Lake was 33.5 m.

The seasonal water was reclassified into five classes for both of the study areas (Table 3). As for Poyang Lake, the 80–100% class accounted for the largest proportion (25.20%) of the inundation extent, with an area of 846.98 km\(^2\), while the class 20–40% accounted for the smallest proportion (17.25%), with an area of 579.75 km\(^2\). As for Dongting Lake, the 0–20% class accounted for the largest proportion (42.47%), with an area of 944 km\(^2\), and nearly took up the half of the whole lake area, while the 60–80% accounted for the smallest proportion (7.39%), with an area of 164.35 km\(^2\). The inundation frequency results suggested that both of the lakes have noticeable seasonal characteristics. Comparing the two lakes, Poyang Lake was more likely to be inundated than Dongting Lake on the spatial and time scales.

The distribution of seasonal water had strong regional characteristics. We roughly divided Poyang Lake along the latitudinal direction into the north tunnel (29°20’ to 29°45’N), main lake body (28°45’ to 29°20’N), and south branch lakes (28°22’ to 28°45’N) to illustrate the inundation ratio in different areas (Figure 8). In the north tunnel area of Poyang Lake, the 80–100% class and 60–80% class accounted for a high proportion (33.81% and 35.27%), while the 20–40% class accounted for the lowest proportion (4.13%). It can be seen that this area was frequently inundated, with a high proportion of the IF value over 60%. In the main lake body, the 80–100% class accounted for the largest proportion (32.46%) and four high proportions were occupied by the 60–80%, 40–60%, 20–40%, and 0–20% classes, with proportions of 15.72%, 17.38%, 17.05%, and 17.39%, respectively. In the south branch
lakes, the 80–100% class took up an extremely high proportion (55.34%) and the 0–20% class accounted for the second highest proportion (21.97%). The high proportion of the 80–100% class and 0–20% class suggested that the region is slightly affected by the external factors and the water remains calm.

Figure 7. Inundation frequency map over (a) the Poyang Lake region and (b) the Dongting Lake region from 2017 to 2021.

Table 3. Inundation frequency classes with corresponding proportion and area.

| IF Value | Poyang Lake | Dongting Lake |
|----------|-------------|---------------|
|          | Ratio/%     | Area/km²      | Ratio/%     | Area/km²      |
| 0–20%    | 19.82%      | 666.35        | 42.47%      | 944.77        |
| 20–40%   | 17.25%      | 579.75        | 15.64%      | 347.99        |
| 40–60%   | 18.86%      | 634.03        | 15.72%      | 349.67        |
| 60–80%   | 18.87%      | 634.28        | 7.39%       | 164.35        |
| 80–100%  | 25.20%      | 846.98        | 18.78%      | 417.75        |

Dongting Lake was divided into the west, south, and east part in this study (Figure 8). In West Dongting Lake, the 0–20% class accounted for the largest proportion (54.01%), the 80–100% class accounted for the second largest proportion, and the 40–60% class accounted for the lowest proportion (2.82%). The seasonal water distribution in south Dongting Lake was similar to that in West Dongting Lake, with the largest proportion in the 0–20% class (54.85%) and second largest proportion occupied by the 80–100% class (20.26%). Compared with the West and South Dongting Lake, the proportions occupied by the 20–40% class and 40–60% class were noticeably higher (20.39% and 25.11%), which indicated that East Dongting Lake was more stable than other parts.
over 60%. In the main lake body, the 80–100% class accounted for the largest proportion (32.46%) and four high proportions were occupied by the 60–80%, 40–60%, 20–40%, and 0–20% classes, with proportions of 15.72%, 17.38%, 17.05%, and 17.39%, respectively. In the south branch lakes, the 80–100% class took up an extremely high proportion (55.34%) and the 0–20% class accounted for the second highest proportion (21.97%). The high proportion of the 80–100% class and 0–20% class suggested that the region is slightly affected by the external factors and the water remains calm.

Figure 8. Inundation frequency distribution in Poyang Lake and Dongting Lake.

4. Discussion

For this study, the use of high-resolution and cloud-free SAR images showed high potential of flood mapping particularly in a monsoon-driven environment. Adopting threshold-based and history temporal-filtering algorithms in this study improved the effect of water detection especially in ship-covered areas.

4.1. Surface Water Mapping Algorithms

During the experiments, we noted that unsupervised classification was severely affected by the commission and omission from the misclassification from the edges of the lake. However, the problem was subsequently solved, leading to a high verification accuracy. Figure 9 highlights a case from South Dongting on 18 July 2020 with corresponding original SAR imagery and optical imagery for comparison. The SAR images in Figure 9a show the target spot that the temporal-filtering algorithm aimed to correct, and the optical images in Figure 9b prove that the unusual bright spot was caused by the ships. The images in the middle show the effect of the Edge Otsu algorithm with different initial thresholds, indicating that an Edge Otsu threshold of $-21$ dB caused large amounts of noise and misclassifications, which were mainly distributed on the edge of the lands, ship-covered spots, and small ponds. Figure 9c indicates that $-16$ dB Edge Otsu algorithm had an excellent performance in water extraction in these two cases except for the classification of ship-covered spots, while the $-21$ dB algorithm expanded the misclassified area, causing even lower accuracy (Figure 9d).

The sequential temporal-filtering algorithm presented a great effect in error correction. As presented in Figure 9e, the ship-covered spots were successfully detected and reclassified by the algorithm. The temporal-filtering algorithm was a combination of the IF mask and SAR mask, and determined water/nonwater by both the IF value and SAR value of each pixel. While successfully filtering the ship-covered spots, the algorithm might cause noticeable misclassification. During the experiments, we noted that the distribution of IF values was crucial to the effects of filtering and causing errors of misclassification, and permanent water pixels had extremely low dB values, which would be filtered by the SAR mask. Therefore, the pixels presenting IF values ranging from 60% to 80% may be the main factor for the misclassification effect. As discussed in Section 3, the IF values between 60%
and 80% accounted for 18.87% in Poyang Lake and accounted for 7.39% in Dongting Lake. In the dry season, pixels presenting 60–80% inundated might be mistakenly classified as water by the temporal-filtering algorithm, indicating that the algorithm was more suitable for Dongting Lake due to the IF map distribution.

Figure 9. Parts of surface water mapping over South Dongting on 18 July 2020 and Poyang Lake for 17 September 2017 using the Edge Otsu and temporal-filtering algorithm with (a) Sentinel-1 imagery over part of the South Dongting Lake region, (b) Sentinel-2 imagery over part of the South Dongting Lake region, (c) Edge Otsu processed image from (a) with the initial thresholds of −16 dB, (d) Edge Otsu processed image from (a) with the initial thresholds of −21 dB, and (e) temporal-filtering processed image from (c).

4.2. The Inundation Frequency Maps

To further demonstrate the effect of the dataset used to calculate the IF maps, we excluded the SAR data for the dates when optical data were severely contaminated by cloud cover and then calculated the IF values from the remaining dataset. The scatter diagrams are shown in Figure 11 to present the results. A positive correlation can be seen between the IF maps from SAR and optical images. The $R^2$ of Dongting Lake was 0.8756, which was higher than that of Poyang Lake (0.8218). After excluding all the SAR images whose dates corresponded to those of the optical images, the value of $R^2$ increased from 0.8218 to 0.8726 over Poyang Lake and 0.8756 to 0.8975 over Dongting Lake.
According to the results above, we assumed that there is a strong correlation between the IF maps generated from Sentinel-1 SAR images and Landsat optical images, and the correlation over the Dongting Lake region was stronger than that over the Poyang Lake region.

Figure 10. Difference between inundation frequency maps extracted from SAR imagery and optical imagery. (D-value short for Difference Value.).

To further demonstrate the effect of the dataset used to calculate the IF maps, we excluded the SAR data for the dates when optical data were severely contaminated by cloud cover and then calculated the IF values from the remaining dataset. The scatter diagrams are shown in Figure 11 to present the results. A positive correlation can be seen between the IF maps from SAR and optical images. The $R^2$ of Dongting Lake was 0.8756, which was higher than that of Poyang Lake (0.8218). After excluding all the SAR images whose dates corresponded to those of the optical images, the value of $R^2$ increased from 0.8218 to 0.8726 over Poyang Lake and 0.8756 to 0.8975 over Dongting Lake.

Despite the high correlation between the two types of IF maps, distinct differences could be found. This was particularly noticeable around the permanent water regions at both lake sites, showing a specific tendency for Landsat IF values being higher around these regions than Sentinel-1 IF values. After removing the SAR images corresponding to the invalidated JRC data, the $R^2$ increased, suggesting a more similar expression of the inundation of the two datasets. We believe that the main reason for the above result was that the absence of long-term summer optical images led to detection errors of seasonal water, which eventually led to the low IF values of seasonal water area in the IF maps. However, the absent images during summer must be taken into consideration when calculating the IF map. So, we believe that IF maps from SAR images are more applicable.

Figure 11. The correlation between the Landsat IF map and Sentinel-1 IF map of Poyang Lake (a) and Dongting Lake (b). The correlation results between the IF maps of Poyang Lake (c) and Dongting Lake (d) after removing the Sentinel-1 SAR images whose dates corresponded to the severely contaminated Landsat optical images.
Despite the high correlation between the two types of IF maps, distinct differences could be found. This was particularly noticeable around the permanent water regions at both lake sites, showing a specific tendency for Landsat IF values being higher around these regions than Sentinel-1 IF values. After removing the SAR images corresponding to the invalidated JRC data, the $R^2$ increased, suggesting a more similar expression of the inundation of the two datasets. We believe that the main reason for the above result was that the absence of long-term summer optical images led to detection errors of seasonal water, which eventually led to the low IF values of seasonal water area in the IF maps. However, the absent images during summer must be taken into consideration when calculating the IF map. So, we believe that IF maps from SAR images are more applicable.

4.3. Limitation and Caveats

For this study, there are some caveats to note. First, time-consuming, histogram-based thresholding algorithms cannot perfectly meet the requirements of near-real-time water monitoring due to complex manual operations, which can be replaced by less time-consuming, nonparametric, histogram-based thresholding algorithms [78]. The effects of all algorithms in this study are deeply influenced by the manual selection of the thresholds. For example, the effect of the Edge Otsu algorithm is affected by the initial binarization threshold and that of temporal-filtering threshold is affected by the threshold for IF maps and SAR imagery. Second, the usage of the algorithms can be refined. For example, a better filtering approach can be conducted to obtain better results, more choices of thresholds and parameters can be put into the Edge Otsu algorithm and temporal-filtering algorithm for discussion, and a more flexible and statistical threshold can be applied to the temporal-filtering algorithm with higher classification accuracy. Thirdly, the study was limited by the geographic location and data selection. Due to the monsoon climate, few validation data were used in this study as the cloud-cover proportion was extremely high. Lastly, as previous studies suggested, Sentinel-1 C-band data cannot penetrate the canopy structure to observe the underlying water [63], and so, L-band data are preferred.

4.4. Future Work

Additional work can build upon this study. Firstly, further analytical work can be performed on multiple spatial scales. For example, the effects of the algorithm and the pros/cons of the inundation frequency maps from SAR imagery can be discussed over the Yangtze River basin or even bigger region. Secondly, the temporal-filtering algorithm will be further discussed. We expect a global or local threshold for this algorithm to be automatically calculated based on statistical results from the histogram of each image. Thirdly, the pattern of the temporal filtering from frequency maps in this study can be further extended and applied on different study areas such as vegetation extraction and cloud removal using different datasets such as Landsat series and Sentinel-2 data. The filtering method can be conversely utilized as filling method in cases where the images are missing or severely contaminated, which has been explored in former work [79,80]. Lastly, all the methods can be integrated into an automatic surface water mapping software in order to supply near-real-time and high-quality water inundation products for monitoring.

5. Conclusions

This study combined an Edge Otsu algorithm with a temporal-filtering algorithm for retrieving the dynamic surface water extent of Poyang Lake and Dongting Lake from Sentinel-1 SAR VV band data. The objectives were to propose a novel approach for obtaining surface water products with a considerably high accuracy, analyze the water variation of Poyang Lake and Dongting Lake, and compare the inundation frequency maps from different datasets. The results indicated that the approach performed well in Poyang Lake region and Dongting Lake region, with an evaluation accuracy of 95–99% and 95–98%, respectively. The algorithms with different thresholds had different influences on the final surface water maps. The initial threshold to binarize the SAR imagery in the Edge Otsu
algorithm was essential to the accurate classification of the edges of the objects. Thresholds of $-16$ dB and $-21$ dB were tested and discussed in this study, and the higher one had better performance in classifying the water, while the lower one caused great amounts of noise. The effect of the temporal-filtering algorithm was discussed as well, which was found to be effective in filtering noises caused by ships. We merged all of the surface water products processed by the temporal-filtering algorithm to construct the inundation frequency map over two study sites. As the IF results suggested, Poyang Lake tended to remain calm and steady, while Dongting Lake was more likely to be affected by the climate, Yangtze River flow, and human activities. Finally, the relationship between the IF maps from SAR and optical images was discussed. The results indicate a strong correlation between them, with high $R^2$ values of 0.8218 and 0.8756. After we excluded the Sentinel-1 SAR images whose dates corresponded to those of the severely contaminated Landsat optical images, the $R^2$ values increased to 0.8726 and 0.8975, respectively. Therefore, we considered the difference between the IF maps from two datasets to be mainly caused by the varying degrees of contamination of the cloud cover.

**Author Contributions:** F.L., F.X. and Y.D. conceived the main idea. Z.W. conducted the experiments. The manuscript was written by Z.W. and improved by F.L., F.X. and Y.D. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Innovation Group Project of Hubei Natural Science Foundation under Grant 2019CFA019 and Hubei Provincial Key Research and Development Program (No. 2020BCA074).

**Data Availability Statement:** The Sentinel-1/2 data and JRC monthly water history data were obtained from Google Earth Engine platform (https://earthengine.google.com/, accessed on 11 March 2022). The water level data were obtained from Database for Hydrological Time Series of Inland Waters (DAHITI) website (https://dahiti.dgfi.tum.de/en/products/water-level-altimetry/, accessed on 11 March 2022).

**Conflicts of Interest:** The authors declare no conflict of interest.

**References**

1. Downing, J.A.; Prairie, Y.T.; Cole, J.J.; Duarte, C.M.; Tranvik, L.J.; Striegl, R.G.; McDowell, W.H.; Kortelainen, P.; Caraco, N.F.; Melack, J.M.; et al. The global abundance and size distribution of lakes, ponds, and impoundments. *Limnol. Oceanogr.* 2006, 51, 2388–2397. [CrossRef]
2. Pekel, J.F.; Cottam, A.; Gorelick, N.; Belward, A.S. High-resolution mapping of global surface water and its long-term changes. *Nature* 2016, 540, 418–422. [CrossRef] [PubMed]
3. Barrow, C.J. *Water Resources and Agricultural Development in the Tropics*; Routledge: Abingdon, UK, 2016.
4. Duan, Z.; Bastiaanssen, W.G.M. Estimating water volume variations in lakes and reservoirs from four operational satellite altimetry databases and satellite imagery data. *Remote Sens. Environ.* 2016, 134, 403–416. [CrossRef]
5. Messager, M.L.; Ettinger, A.K.; Murphy-Williams, M.; Levin, P.S. Fine-scale assessment of inequities in inland flood vulnerability. *Appl. Geogr.* 2021, 133, 102492. [CrossRef]
6. Song, J.H.; Kang, M.S.; Song, I.; Jun, S.M. Water balance in irrigation reservoirs considering flood control and irrigation efficiency variation. *J. Irrig. Drain. Eng.* 2016, 142, 04016003. [CrossRef]
7. Vervoorter, C.; Kutser, T.; Seekell, D.A.; Tranvik, L.J. A global inventory of lakes Regime Assessment Method for Lakes based on high-resolution satellite imagery. *Geophys. Res. Lett.* 2014, 41, 6396–6402. [CrossRef]
8. Yang, K.; Smith, L.C. Internally drained catchments dominate supraglacial hydrology of the southwest Greenland Ice Sheet. *Geophys. Res. Earth Surf.* 2016, 121, 1891–1910. [CrossRef]
9. Cheng, Y.; Niemeyer, R.J.; Mao, Y.; Yearsley, J.R.; Nijssen, B. Climate change impacts on river temperature in the southeastern United States: A case study of the Tennessee River basin. In *AGU Fall Meeting Abstracts*; American Geophysical Union: Washington, DC, USA, 2016.
10. Chiang, T.Y.; Perng, Y.H.; Liou, L.E. Impact and adaptation strategies in response to climate change on Taiwan’s water resources. *Appl. Mech. Mater.* 2017, 858, 335–341.
11. Klein, I.; Gessner, U.; Dietz, A.J.; Kuenzer, C. Global WaterPack–A 250 m resolution dataset revealing the daily dynamics of global inland water bodies. *Remote Sens. Environ.* 2017, 198, 345–362. [CrossRef]
12. Luo, S.; Song, C.; Liu, K.; Ke, L.; Ma, R. An Effective Low-Cost Remote Sensing Approach to Reconstruct the Long-Term and Dense Time Series of Area and Storage Variations for Large Lakes. *Sensors* 2019, 19, 4247. [CrossRef]
13. Tong, X.; Pan, H.; Xie, H.; Xu, X.; Li, F.; Chen, L.; Luo, X.; Liu, S.; Chen, P.; Jin, Y. Estimating water volume variations in Lake Victoria over the past 22 years using multi-mission altimetry and remotely sensed images. *Remote Sens. Environ.* 2016, 187, 400–413. [CrossRef]

14. Wu, Q.; Lane, C.R.; Wang, L.; Vanderhoof, M.; Christensen, J.R.; Liu, H. Efficient Delineation of Nested Depression Hierarchy in Digital Elevation Models for Hydrological Analysis Using Level-Set Method. *Water Resour. Assoc.* 2018, 55, 354–368. [CrossRef] [PubMed]

15. Ahamed, A.; Bolten, J.D. A MODIS-based automated flood monitoring system for southeast asia. *Int. J. Appl. Earth Obs. Geoinf.* 2017, 61, 104–117. [CrossRef]

16. Yilmaz, K.K.; Adler, R.F.; Tian, Y.; Hong, Y.; Pierce, H.F. Evaluation of a satellite-based global flood monitoring system. *Int. J. Remote Sens.* 2010, 31, 3763–3782. [CrossRef]

17. Feyisa, G.L.; Meilby, H.; Fensholt, R.; Proud, S.R. Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery. *Remote Sens.* 2014, 6, 2305–2316. [CrossRef]

18. Feng, M.; Sexton, J.O.; Channan, S.; Townshend, J.R. A global, high-resolution (30-m) inland water body dataset for 2000: First results of a topographic–spectral classification algorithm. *Int. J. Digit. Earth* 2016, 9, 113–133. [CrossRef]

19. Markert, K.N.; Chishtrie, F.; Anderson, E.R.; Saah, D.; Griffin, R.E. On the merging of optical and SAR satellite imagery for surface water mapping applications. *Remote Sens. Phys.* 2018, 9, 275–277. [CrossRef]

20. Li, X.; Liao, A.; Chen, L.; Chen, J.; He, C.; Cao, X.; Chen, J.; Peng, S.; Sun, F.; Gong, P. High-resolution remote sensing mapping of global land water. *Sci. China Earth Sci.* 2014, 57, 2305–2316. [CrossRef]

21. Shi, L.; Ling, F.; Foody, G.M.; Chen, C.; Fang, S.; Li, X.; Zhang, Y.; Du, Y. Permanent disappearance and seasonal fluctuation of urban lake area in Wuhan, China monitored with long time series remotely sensed images from 1987 to 2016. *Int. J. Remote Sens.* 2019, 40, 8484–8505. [CrossRef]

22. Liu, X.; Li, F.; Cai, X.; Ge, Y.; Li, X.; Yin, Z.; Shang, C.; Jia, X.; Du, Y. Mapping water bodies under cloud cover using remotely sensed optical images and a spatiotemporal dependence model. *Int. J. Appl. Earth Obs. Geoinf.* 2021, 103, 102470. [CrossRef]

23. Jones, J.W. Efficient wetland surface water detection and monitoring via landsat: Comparison with in situ data from the everglades. *Remote Sens.* 2015, 7, 672–681. [CrossRef]

24. Xu, H. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Remote Sens.* 2010, 5631–5649. [CrossRef]

25. Li, X.; Ling, F.; Foody, G.M.; Boyd, D.S.; Jiang, L.; Zhang, Y.; Zhou, P.; Wang, Y.; Chen, R.; et al. Measuring river wetted width depth estimation network. *Remote Sens.* 2016, 596. [CrossRef]

26. Yin, Z.; Ling, F.; Li, X.; Cai, X.; Chi, H.; Li, X.; Wang, Q.; Du, Y. Monitoring surface water area variations of reservoirs using daily MODIS images by exploring sub-pixel information. *ISPRS J. Photogramm. Remote Sens.* 2020, 168, 141–152. [CrossRef]

27. Jones, J.W. Improved automated detection of subpixel-scale inundation—Revised dynamic surface water extent (dswe) partial water mapping. *Remote Sens. Lett.* 2014, 5, 794–817. [CrossRef]

28. Li, X.; Ling, F.; Foody, G.M.; Boyd, D.; Ge, Y.; Li, X.; Du, Y. Monitoring surface water area variations of reservoirs using daily MODIS images by exploring sub-pixel information. *ISPRS J. Photogramm. Remote Sens.* 2020, 168, 141–152. [CrossRef]

29. Du, Z.; Li, W.; Zhou, D.; Tian, L.; Ling, F.; Wang, H.; Gui, Y.; Sun, B. Analysis of Landsat-8 OLI imagery for land surface water mapping. *Remote Sens. Lett.* 2014, 5, 672–681. [CrossRef]

30. Ji, L.; Geng, X.; Sun, K.; Zhao, Y.; Gong, P. Target detection method for water mapping using Landsat 8 OLI/TIRS imagery. *Water* 2015, 7, 794–817. [CrossRef]

31. Yang, X.; Zhao, S.; Qin, X.; Zhao, N.; Liang, L. Mapping of urban surface water bodies from Sentinel-2 MSI imagery at 10 m resolution via NDWI-based image sharpening. *Remote Sens.* 2017, 9, 596. [CrossRef]

32. Du, Y.; Zhang, Y.; Ling, F.; Wang, Q.; Li, W.; Li, X. Water Bodies’ Mapping from Sentinel-2 Imagery with Modified Normalized Difference Water Index at 10-m Spatial Resolution Produced by Sharpening the SWIR Band. *Remote Sens.* 2016, 8, 354. [CrossRef]

33. Feng, M.; Sexton, J.O.; Channan, S.; Townshend, J.R. A global, high-resolution (30-m) inland water body dataset for 2000: First results of a topographic–spectral classification algorithm. *Int. J. Digit. Earth* 2016, 9, 113–133. [CrossRef]

34. Liao, A.; Chen, L.; Chen, J.; He, C.; Cao, X.; Chen, J.; Peng, S.; Sun, F.; Gong, P. High-resolution remote sensing mapping of global land water. *Sci. China Earth Sci.* 2014, 57, 2305–2316. [CrossRef]

35. Markert, K.N.; Chishtrie, F.; Anderson, E.R.; Saah, D.; Griffin, R.E. On the merging of optical and SAR satellite imagery for surface water mapping applications. *Remote Sens. Phys.* 2018, 9, 275–277. [CrossRef]

36. Shi, L.; Ling, F.; Foody, G.M.; Chen, C.; Fang, S.; Li, X.; Zhang, Y.; Du, Y. Permanent disappearance and seasonal fluctuation of urban lake area in Wuhan, China monitored with long time series remotely sensed images from 1987 to 2016. *Int. J. Remote Sens.* 2019, 40, 8484–8505. [CrossRef]

37. Li, X.; Liao, A.; Chen, L.; Chen, J.; He, C.; Cao, X.; Chen, J.; Peng, S.; Sun, F.; Gong, P. High-resolution remote sensing mapping of global land water. *Sci. China Earth Sci.* 2014, 57, 2305–2316. [CrossRef]

38. Li, X.; Ling, F.; Cai, X.; Ge, Y.; Li, X.; Yin, Z.; Shang, C.; Jia, X.; Du, Y. Mapping water bodies under cloud cover using remotely sensed optical images and a spatiotemporal dependence model. *Int. J. Appl. Earth Obs. Geoinf.* 2021, 103, 102470. [CrossRef]

39. Oddo, P.C.; Bolten, J.D. The Value of Near Real-Time Earth Observations for Improved Flood Disaster Response. *Front. Environ. Sci.* 2019, 7, 127. [CrossRef]
40. Long, S.; Fatoyinbo, T.E.; Policelli, F. Flood extent mapping for Namibia using change detection and thresholding with SAR. Environ. Res. Lett. 2014, 9, 035002. [CrossRef]

41. Gstaiger, V.; Huth, J.; Gebhardt, S.; Wehrmann, T.; Kuenzer, C. Multi-sensoral and automated derivation of inundated areas using TerraSAR-X and ENVISAT ASAR data. Int. J. Remote Sens. 2012, 33, 7291–7304. [CrossRef]

42. Pulvirenti, L.; Pierdicca, N.; Chini, M.; Guerriero, L. An algorithm for operational flood mapping from synthetic aperture radar (SAR) data using fuzzy logic. Nat. Hazards Earth Syst. Sci. 2011, 11, 529–540. [CrossRef]

43. Sanyal, J.; Lu, X. Application of remote sensing in flood management with special reference to monsoon Asia: A review. Nat. Hazards 2004, 33, 283–301. [CrossRef]

44. Olthof, I.; Tolszczuk-Leclerc, S. Comparing Landsat and RADARSAT for current and historical dynamic flood mapping. Remote Sens. 2018, 10, 780. [CrossRef]

45. Schumann, G.; Di Baldassarre, G.; Bates, P.D. The utility of spaceborne radar to render flood inundation maps based on multialgorithm ensembles. IEEE Trans. Geosci. Remote Sens. 2009, 47, 2801–2807. [CrossRef]

46. Chini, M.; Hostache, R.; Giustarini, L.; Matgen, P. A hierarchical split-based approach for parametric thresholding of SAR images: Flood inundation as a test case. IEEE Trans. Geosci. Remote Sens. 2017, 55, 6975–6988. [CrossRef]

47. Westerhoff, R.S.; Kleusken, M.P.H.; Winsemius, H.C.; Huizinga, H.J.; Brakenridge, G.R.; Bishop, C. Automated global water mapping based on wide-swath orbital synthetic-aperture radar. Hydrol. Earth Syst. Sci. 2013, 17, 651–663. [CrossRef]

48. Benoudjit, A.; Guida, R. A novel fully automated mapping of the flood extent on SAR images using a supervised classifier. Remote Sens. 2019, 11, 779. [CrossRef]

49. Shen, X.; Anagnostou, E.N.; Allen, G.H.; Brakenridge, G.R.; Kettner, A.J. Near-real-time non-obstructed flood inundation mapping using synthetic aperture radar. Remote Sens. Environ. 2019, 221, 302–315. [CrossRef]

50. Markert, K.N.; Markert, A.M.; Mayer, T.; Nauman, C.; Haag, A.; Poortinga, A.; Bhandari, B.; Thwal, N.S.; Kunlamai, T.; Chishtie, F.; et al. Comparing Sentinel-1 Surface Water Mapping Algorithms and Radiometric Terrain Correction Processing in Southeast Asia Utilizing Google Earth Engine. Remote Sens. 2020, 12, 2469. [CrossRef]

51. Chen, X.; Wu, T.; Ruan, X. Updated Progress in Polarisometric SAR Techniques on Vessel Detection. Remote Sens. Technol. Appl. 2009, 6, 841–848.

52. Song, L.; Song, C.; Luo, S.; Chen, T.; Liu, K.; Li, Y.; Jing, H.; Xu, J. Refining and densifying the water inundation area and storage estimates of Poyang Lake by integrating Sentinel-1/2 and bathymetry data. Int. J. Appl. Earth Obs. Geoinf. 2021, 105, 102601. [CrossRef]

53. Ding, X.; Li, X. Monitoring of the water-area variations of Lake Dongting in China with ENVISAT ASAR images. Int. J. Appl. Earth Obs. Geoinf. 2011, 13, 894–901. [CrossRef]

54. Hu, Y.; Huang, J.; Du, Y.; Han, P.; Huang, W. Monitoring spatial and temporal dynamics of flood regimes and their relation to wetland landscape patterns in Dongting Lake from MODIS time-series imagery. Remote Sens. 2015, 7, 7494–7520. [CrossRef]

55. Li, J.; Wang, C.; Xu, L.; Wu, F.; Zhang, H.; Zhang, B. Multitemporal Water Extraction of Dongting Lake and Poyang Lake Based on an Automatic Water Extraction and Dynamic Monitoring Framework. Remote Sens. 2021, 13, 865. [CrossRef]

56. Tian, H.; Li, W.; Wu, M.; Huang, N.; Li, G.; Li, X.; Niu, Z. Dynamic Monitoring of the Largest Freshwater Lake in China Using a New Water Index Derived from High Spatiotemporal Resolution Sentinel-1A Data. Remote Sens. 2017, 9, 521. [CrossRef]

57. ILEC (International Lake Environment Committee Foundation). World Lake Database; ILEC: Kusatsu, Japan, 1999.

58. Feng, L.; Hu, C.; Chen, X.; Li, R.; Tian, L.; Murch, B. MODIS observations of the bottom topography and its inter-annual variability for Lake Kinneret, Israel. Environ. Monit. Assess. 2011, 1581. [CrossRef]

59. Shankman, D.; Keim, B.D.; Song, J. Flood frequency in China’s Poyang Lake region: Trends and teleconnections. Int. J. Climatol. 2006, 26, 1255–1266. [CrossRef]

60. Zhang, J.; Xu, K.; Yang, Y.; Qi, L.; Hayashi, S.; Watanabe, M. Measuring water storage fluctuations in Lake Dongting, China, by Topex/ Poseidon satellite altimetry. Environ. Monit. Assess. 2006, 115, 23–37. [CrossRef]

61. Yuan, Y.; Zeng, G.M.; Liang, J.; Huang, L.; Hua, S.S.; Li, F.; Zhu, Y.; Wu, H.P.; Liu, J.Y.; He, X.X.; et al. Variation of water level in Lake Dongting over a 50-year period: Implications for the impacts of anthropogenic and climatic factors. J. Hydrol. 2015, 525, 450–456. [CrossRef]

62. Twele, A.; Cao, W.; Plank, S.; Martinis, S. Sentinel-1-based flood mapping: A fully automated processing chain. Int. J. Remote Sens. 2016, 37, 2990–3004. [CrossRef]

63. Uddin, K.; Matin, M.A.; Meyer, F.J. Operational Flood Mapping Using Multi-Temporal Sentinel-1 SAR Images: A Case Study from Bangladesh. Remote Sens. 2019, 11, 1581. [CrossRef]

64. Lee, I.; Wen, J.; Ainsworth, T.L.; Chen, K.; Chen, A. Improved Sigma Filter for Speckle Filtering of SAR Imagery. IEEE Trans. Geosci. Remote Sens. 2009, 47, 202–213. [CrossRef]

65. Salameh, E.; Frappart, F.; Turk, I.; Laignel, B. Intertidal topography mapping using the waterline method from Sentinel-1 & -2 images: The examples of Arcachon and Veyrs Bays in France. ISPRS J. Photogramm. Remote Sens. 2020, 163, 98–120. [CrossRef]

66. Yang, K.; Smith, L.C.; Sole, A.; Livingstone, S.J.; Cheng, X.; Chen, Z.Q.; Li, M.C. Supraglacial rivers on the northwest Greenland Ice Sheet, Devon Ice Cap, and Barnes Ice Cap mapped using Sentinel-2 imagery. Int. J. Appl. Earth Obs. Geoinf. 2019, 78, 1–13. [CrossRef]

67. Schlaffer, S.; Chini, M.; Dorigo, W.; Plank, S. Monitoring surface water dynamics in the Prairie Pothole Region of North Dakota using dual-polarised Sentinel-1 synthetic aperture radar (SAR) time series. Hydrol. Earth Syst. Sci. 2021, 26, 841–860. [CrossRef]
68. Schwatke, C.; Dettmering, D.; Bosch, W.; Seitz, F. DAHITI—An innovative approach for estimating water level time series over inland waters using multi-mission satellite altimetry. *Hydrol. Earth Syst. Sci.* **2015**, *19*, 4345–4364. [CrossRef]

69. Li, K.; Shao, Y.; Zhang, F. Rice information extraction using multi-polarization airborne synthetic aperture radar data. *J. Zhejiang Univ. (Agric. Life Sci.)* **2011**, *37*, 181–186.

70. Otsu, N. A threshold selection method from gray-level histograms. *IEEE Trans. Syst. Man Cybern.* **1979**, *9*, 62–66. [CrossRef]

71. Donchyts, G.; Schellekens, J.; Winsemius, H.; Eisemann, E.; Van de Giesen, N. A 30 m resolution surface water mask including estimation of positional and thematic differences using landsat 8, srtm and openstreetmap: A case study in the Murray-Darling Basin, Australia. *Remote Sens.* **2016**, *8*, 386. [CrossRef]

72. Guo, S.C.; Du, P.J.; Meng, Y.P.; Wang, X.; Tang, P.F.; Lin, C.; Xia, J.S. Dynamic monitoring on flooding situation in the Middle and Lower Reaches of the Yangtze River Region using Sentinel-1A time series. *Natl. Remote Sens. Bull.* **2021**, *25*, 2127–2141.

73. Steinhausen, M.J.; Wagner, P.D.; Narasimhan, B.; Waske, B. Combining Sentinel-1 and Sentinel-2 data for improved land use and land cover mapping of monsoon regions. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *73*, 595–604. [CrossRef]

74. Yang, X.; Qin, Q.; Yé sou, H.; Ledauphin, T.; Koehl, M.; Grussenmeyer, M.; Zhu, Z. Monthly estimation of the surface water extent in France at a 10-m resolution using Sentinel-2 data. *Remote Sens. Environ.* **2020**, *244*, 111803. [CrossRef]

75. Xing, L.; Tang, X.; Wang, H.; Fan, W.; Wang, G. Monitoring monthly surface water dynamics of Dongting Lake using Sentinel-1 data at 10 m. *PeerJ*. **2018**, *6*, e4992. [CrossRef]

76. Zeng, L.; Schmitt, M.; Li, L.; Zhu, X. Analysing changes of the Poyang Lake water area using Sentinel-1 synthetic aperture radar imagery. *Int. J. Remote Sens.* **2017**, *38*, 7041–7069. [CrossRef]

77. Huang, S.; Li, J.; Xu, M. Water surface variations monitoring and flood hazard analysis in Dongting Lake area using long-term Terra/MODIS data time series. *Nat. Hazards* **2012**, *62*, 93–100. [CrossRef]

78. Cao, H.; Zhang, H.; Wang, C.; Zhang, B. Operational Flood Detection Using Sentinel-1 SAR Data over Large Areas. *Water* **2019**, *11*, 786. [CrossRef]

79. Mullen, C.; Penny, G.; Müller, M.F. A simple cloud-filling approach for remote sensing water cover assessments. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 2373–2386.

80. Zhao, G.; Gao, H. Automatic correction of contaminated images for assessment of reservoir surface area dynamics. *Geophys. Res. Lett.* **2018**, *45*, 6092–6099. [CrossRef]