

## Article

# Extracting Wetlands in Coastal Louisiana from the Operational VIIRS and GOES-R Flood Products

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**Abstract:** Visible Infrared Imaging Radiometer Suite (VIIRS) and Advanced Baseline Imager (GOES-R ABI) flood products have been widely used by the National Weather Service (NWS) for river flood monitoring, and by the Federal Emergency Management Agency (FEMA) for rescue and relief efforts. Some water bodies, like wetlands, are detected as water but not marked as permanent or normal water, which may result in their misclassification as floodwaters by VIIRS and GOES-R flood products. These water bodies generally do not cause significant property damage or fatalities, but they can complicate the identification of truly hazardous floods. This study utilizes the severe Louisiana flood event caused by Hurricane Ida to demonstrate how to differentiate wetlands from real-hazard flooding. Since Hurricane Ida made landfall in 2021, and there was no major flood event in 2022, VIIRS and ABI flood data from 2021 and 2022 were selected. The difference in annual total flooding days between 2021 and 2022 was calculated and combined with long-time flood frequency to distinguish non-hazard floodwaters due to wetlands identified from real-hazard floods caused by the hurricane. The results were compared with the wetlands from the change detection analysis. The confusion matrix analysis indicated an accuracy of 91.58%, precision of 89.97%, and F1-score of 76.63% for the VIIRS flood products. For the GOES-R ABI flood products, the confusion matrix analysis yielded an accuracy of 86.88%, precision of 97.49%, and F1-score of 75.21%. The accuracy and F1-score values for the GOES-R ABI flood products are slightly lower than those for the VIIRS flood products, possibly due to their lower spatial resolution, but still within a feasible range.

**Keywords:** non-hazard floodwater; wetlands; GOES-R flood product; VIIRS flood product

## 1. Introduction

Visible Infrared Imaging Radiometer Suite (VIIRS) and Advanced Baseline Imager (GOES-R ABI) flood products are widely used by the National Weather Service (NWS), the Federal Emergency Management Agency (FEMA), and the International Charter Program for flood monitoring and relief and rescue efforts. The VIIRS and GOES-R ABI flood detection algorithms separate water from land by assessing the spectral differences between water bodies and other land cover types in visible, near-infrared, and shortwave infrared channels, and then compares those results with permanent water from global water masks and water layers to identify floodwaters [1–5]. Given that wetlands are either covered by water or saturated with water, VIIRS and GOES-R ABI flood mapping recognizes them as

water. However, because they are not permanent or normal water, they may be incorrectly classified as floodwaters by VIIRS and GOES-R ABI flood products.

Wetlands are invaluable ecosystems on the Earth's surface, often referred to as the "kidneys of the Earth" due to their long-term and significant ability to filter pollutants, store water, and recharge groundwater [6]. As defined by the Environmental Protection Agency (EPA), wetlands are "areas that are inundated or saturated by surface or groundwater at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions. Wetlands generally include swamps, marshes, bogs, and similar areas" [7]. These areas are typically covered by water or saturated with water, with low water levels usually near the ground surface, and may be covered or mixed with vegetation [8]. The coast of Louisiana, located in the north-central Gulf of Mexico (GOM), contains about 40% to 45% of the wetlands in the lower United States (U.S.) [9]. The wetlands in Louisiana are among the most significant and extensive in the country, serving as natural buffers against storms and flooding. Due to tidal flushing, seasonal and interannual marsh phenology [10], the short-lived nature of small water bodies [11], and flood events [11,12], the amount and depth of water in Louisiana's coastal wetlands vary greatly. Wetland types can be defined by several factors, including water levels, fertility, natural disturbance, and salinity [13]. For example, around Lake Pontchartrain, wetlands include freshwater marsh, brackish marsh, hardwoods, and cypress swamp [14]. Louisiana's wetlands consist of diverse types, such as swamps, marshes, and bayous, each with unique characteristics and biodiversity. They are water-saturated coastal swamps, classified as a clumped emergent wetland class by Lamb et al. [15], including estuarine emergent, palustrine emergent, and phragmites australis.

Remote sensing can provide frequent and consistent data to facilitate wetland identification and has been used to map and monitor wetlands for more than 30 years [16]. Early efforts in satellite-based wetlands mapping relied on aerial photography and Landsat imagery [17–22]. With the rapid development of new satellite sensors and image analysis techniques, it is critical to choose the appropriate remote sensors and data analysis methods that are most practical for accurate wetland identification [23]. High spatial resolution (<5 m) satellite imagery, such as Quickbird, WorldView, and SPOT, has been used for mapping small-scale wetlands [24–28], but higher spatial resolutions than Landsat (30 m) cannot cover large areas and thus limit their wide applicability. Previous studies have demonstrated that vegetation indices (VIs) derived from optical sensors, such as Landsat, Sentinel-2, and MODIS, using visible (VIS) and near-infrared (NIR) reflectance are highly effective for identifying wetland vegetation [17,29–31]. VIs based on VIS and NIR reflectance are among the most useful for distinguishing different types of wetlands [31–33]. They are also effective for classifying different types of emergent wetland vegetation [31–33]. The combination of the Normalized Difference Water Index (NDWI) with VIs can efficiently map the extent of marshes [30]. Furthermore, incorporating shortwave infrared (SWIR) bands has proven effective for detecting open water and enhancing the identification of inundated wetland vegetation [18,30,34,35].

Active microwave synthetic aperture radar (SAR) systems have provided an advantage for mapping and monitoring wetlands under cloudy conditions [36–39]. In tidal wetlands, C-band SAR signals interact more strongly with canopy structures, while longer-wavelength L-band SAR signals are more sensitive to sub-canopy surface water states [40,41]. With the launch of the Sentinel-1 SAR satellites by the European Space Agency (ESA) in 2014, many regions of the coastal U.S. can be observed nearly every 12 days, C-band SAR systems have provided opportunities for the identification of vegetation structures in wetlands. The time-series data of Sentinel-1 SAR were applied to classify wetlands [33,42,43] and identify inundation patterns [43–45]. However, compared to optical sensors, which provide wide area coverages and frequent observations, SAR availability is limited due to its narrow swath width and long revisit time. To combine the advantages of SAR and optical sensors, Lamb et al. [15] proposed a fused Radar–Optical approach for mapping wetlands in the Mid-Atlantic and Gulf Coast Regions of the United

States. Optical sensors such as Landsat, Sentinel-2, and MODIS provide global coverage with minimal impact on wetland classification accuracy [34]. The VIIRS and the GOES-R ABI are optical sensors that use VIS, NIR, and SWIR reflectance, NDWI, and VIs for water detection [1–5]. To generate satellite-based flood maps, water bodies are first identified from satellite imagery. By comparing pre-flood and post-flood water classification maps, floodwater can be detected. However, in an operational environment, such comparisons are often impractical. Instead, operational flood products are generated by comparing water classification maps with permanent or normal water bodies using Reference Water Mask data [46]. This approach may misclassify certain water bodies, such as wetlands, as floodwaters because they are not considered permanent or normal water. Since wetlands are diverse ecosystems characterized by the presence of water, either seasonally or permanently, the water in wetlands may be misclassified as floodwaters by the VIIRS and the GOES-R ABI flood products and thus may interfere with the assessment of real-hazard flooding. There are also false positive problems with SAR-based flood mapping. The Sentinel-1-based flood extent product from the operational Copernicus Global Flood Mapping (GFM) system developed an Exclusion Mask to exclude the “Unclassified” areas in urban areas, flat and waterproof areas, dense vegetation, sandy surfaces, and terrain shadows [47]. The SAR-based flood mapping by Microsoft filters false positives using soil moisture, elevation (specifically slope), and land surface temperature [48].

Some researchers classify wetlands, floodplains, and water bodies as the same land use type, usually corresponding to flooded areas [49,50]. In a previous study, we explored using long-time flood frequency to extract non-hazardous floodwaters [51]. In VIIRS and GOES-R flood products, cloud and terrain shadows are marked [52,53], and snow and ice are identified. This study aims to examine the identification and extraction of wetlands in operational VIIRS and GOES-R ABI flood products, using the wetlands in Louisiana as an example.

The main objective of this study is to develop a method to extract wetlands in operational VIIRS and GOES-R ABI flood products. The hypothesis is that non-hazard floodwaters in operational optical sensor-based flood products, like permanent wetlands in this study, usually last much longer than hazard floods caused by tropical cyclones or hurricanes, heavy rainfall, and storm surges. It is expected that the methodology developed in this study can be applied to optical sensor-based flood mapping and identify the potential false positive or non-hazard floods due to wetlands, a common problem in optical sensor-based operational flood products. The methodology is described in Section 2. Section 3 presents the results of wetland extraction from VIIRS and GOES-R ABI flood products using the methods developed in this study, including comparisons with change detection analyses. Section 4 discusses these findings, and Section 5 concludes with a summary.

## 2. Materials and Methods

### 2.1. Study Area

The study site is the coastal wetlands in Louisiana (LA), which include the Bird’s Foot Delta, the Breton Sound, and the Wax Lake Delta, as shown in Figure 1.

The Mississippi River Delta spans 12,000 square kilometers of coastal wetlands, with 40% of the United States’s salt marshes located within it. It consists of numerous rivers, wetlands, and low-lying islands along the coast. At the delta’s edge, the Chandeleur Islands act as a natural barrier against ocean storms for Louisiana’s densely populated coastal areas, including New Orleans. The marshland swamps in coastal Louisiana are among the nation’s most fragile and valuable wetlands and one of the lowest-lying areas in the United States. With 3 million acres of wetlands, Louisiana accounts for about 40 percent of the wetlands in the continental United States, highlighting their ecological significance.

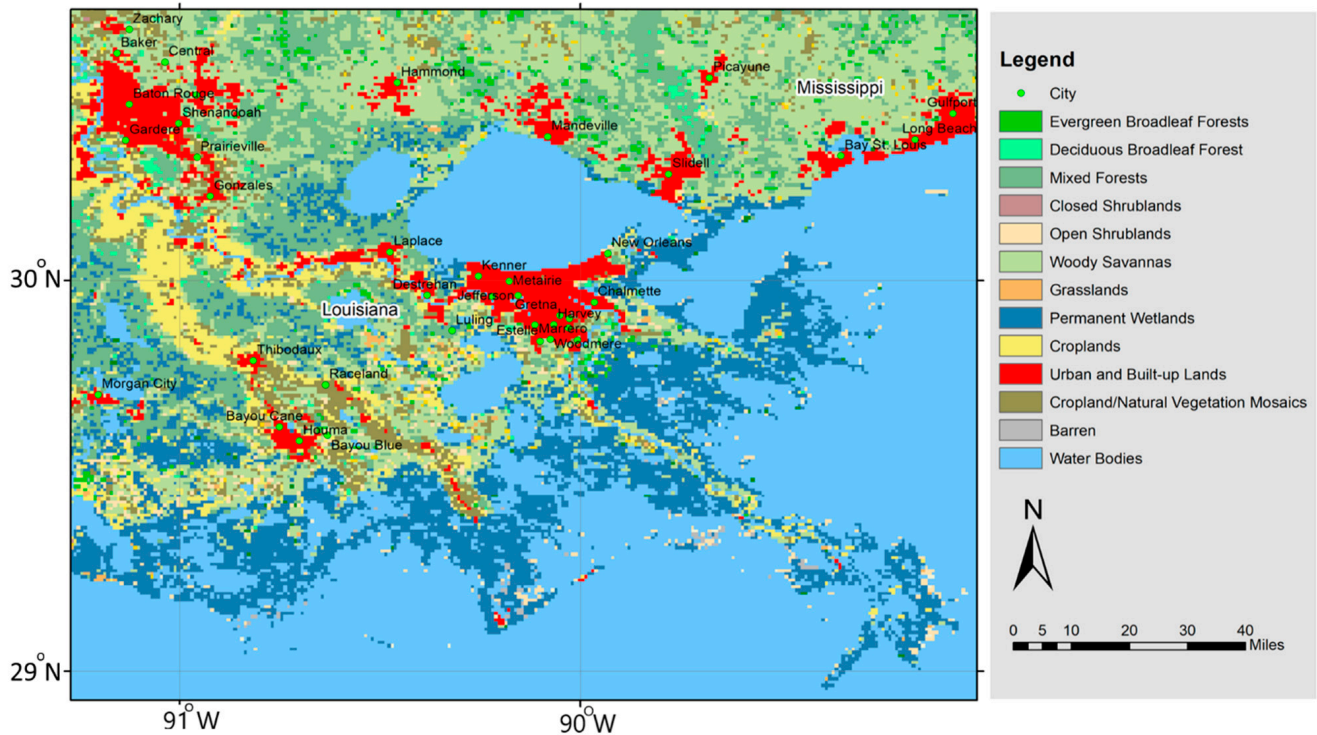


**Figure 1.** Surface type classification map of the study region (**top**) and Louisiana's top 10 wetlands and swamps covering large tracts of the state (**bottom**). (Photo: JupiterImages/Comstock/Getty Images).

## 2.2. Data Used

The datasets used in this study are as follows:

- VIIRS five-day composite flood maps, indicating floodwater fractions from 1 January 2021 to 31 December 2022. This data since October 2019 is archived at George Mason University (<https://jpssflood.gmu.edu>, accessed on 24 September 2024). The data in four formats, NetCDF, PNG, Shapefile, and TIF, can be available.
- GOES-R ABI flood maps, indicating floodwater fractions from 1/1/2021 to 12/31/2022. These data from October 2019 have been archived at George Mason University (<https://jpssflood.gmu.edu>, accessed on 24 September 2024).

- VIIRS global land cover data [54] is used in this study. The VIIRS land cover map classifies the global surface into 17 types defined by the International Geosphere-Biosphere Programme (IGBP) [55], including permanent wetlands used in this study.
- The Sentinel-1-based flood extent product from the operational Copernicus Global Flood Mapping system (<https://global-flood.emergency.copernicus.eu/glofas-forecasting/>, accessed on 24 September 2024).
- SAR-based flood mapping data provided by Microsoft [48].

### 2.3. Methods

Hurricane Ida made landfall in Louisiana as a deadly and extremely destructive Category 4 hurricane in late August 2021, leading to catastrophic flooding in the New Orleans region. Hurricane Ida ranks as the sixth-costliest Atlantic hurricane in the United States, with total damages exceeding \$75.25 billion (2021 USD). Flooding damage alone is estimated to be between \$16 to \$24 billion [56]. Unlike 2021, there was no major flood disaster in 2022. Therefore, we extracted flood data from around the Louisiana coastal region for the entire years of 2021 and 2022 and used a post-analysis method to establish a non-hazard flood mask for the wetland area. By combining this mask with the normal open water area, we extracted the real-hazard flood area from the flood map following Hurricane Ida.

#### 2.3.1. Data Pre-Processing

Since Hurricane Ida made landfall in 2021 and there was no major flood event in Louisiana during 2022, VIIRS and ABI flood data from 2021 and 2022 were selected for comparison. For the VIIRS flood products, four VIIRS Areas of Interest (AOIs), including AOI 19, AOI 20, AOI 23, and AOI 24, were needed to composite the Louisiana coastal area. Data from 2021 and 2022 for each AOI were merged into a three-dimensional array, with the z-axis representing a year's time series. Due to some missing data, comparisons were made between the two years. For dates with missing data in one year, the corresponding data for those dates were excluded from the other year. Unlike the VIIRS flood data, no multiple AOI combinations were required for the ABI data in the Louisiana coastal area. Only one ABI AOI data, AOI 02, was processed similarly for both years.

The 2020 VIIRS Global Surface Type Classification Map was used to extract wetland areas from flood maps and needed to be matched with VIIRS and ABI data. This land cover data were resampled to the same cell size as the flood data, and the same range was intercepted.

#### 2.3.2. Change Detection Analysis

Change detection analysis offers a straightforward approach to measuring changes between two classification images that represent the differences. Change detection analysis methods are often applied to identify and quantify differences between images of the same scene at different times or under different conditions. By comparing floodwaters before and after a real hazardous flood event, non-hazard floods due to standing water like wetlands can be found. The biggest difference between the time series data in 2021 and 2022 is the flooding caused by Hurricane Ida in 2021. By comparing the differences in 2021 and 2022 data, real, hazardous floods due to Hurricane Ida can be identified.

#### 2.3.3. Extracting Non-Hazard Floodwaters Due to Wetlands in VIIRS and GOES-R ABI Flood Products

In the VIIRS and ABI flood maps, some wetlands consistently appear as floodwaters, even in the absence of flood events. This study aims to distinguish non-hazard floodwaters due to wetlands from real, hazardous flooding caused by hurricane landfall in the Louisiana region. FEMA defines flooding with a threshold value of a 40% floodwater fraction, meaning that a pixel with more than 40% water coverage is considered at least partially flooded [57]. To identify non-hazard floodwaters in the VIIRS and ABI flood maps, the

corresponding pixels in wetlands, according to the surface type map, were extracted from the flood maps. The total number of flooding days with a water fraction greater than 40% were counted for each pixel as  $c(x_i)$  for 2021 and 2022. Floods can take from a few hours to a few weeks to completely dry out, depending on their extent. Observations of the VIIRS and GOES-R ABI flood products show that large flood events, like hurricane flooding, usually recede in about 15 days, whereas non-hazard floodwaters in wetlands usually persist much longer. Therefore, pixels with fewer than 15 flooding days  $c(x_i)$  were excluded from both the 2021 and 2022 data. The difference in annual total flooding days in wetland areas between 2021 and 2022 was then calculated, and the absolute value of the result for each pixel, referred to as  $\Delta c(x_i)$ , was obtained. Pixels with the difference in annual total flooding days between 2021 and 2022 data greater than or equal to zero were extracted. Non-hazard floodwaters in wetlands, which persist for a long time but show no significant difference between years, were identified as those with  $\Delta c(x_i)$  less than 15 days.

$$\text{Pixel category} = \begin{cases} \text{non-hazard wetlands} & \text{if } 0 \leq \Delta c(x_i) \leq 15 \\ \text{hazard flooding} & \text{if } \Delta c(x_i) > 15 \end{cases} \quad (1)$$

where the  $c(x_i)$  is the count of flooding days in pixel  $x_i$  with water fraction values greater than 40% in a year, and  $\Delta c(x_i)$  is the difference in total flooding days  $c(x_i)$  between 2021 and 2022.

#### 2.3.4. Long-Time Flood Probability

In the VIIRS and GOES-R ABI flood products, some water bodies, including wetlands, riverbanks, and coastlines, often display as floodwaters for months and even longer, even without actual flood events. These non-hazard floodwaters, which last much longer than real, hazardous floods, should be excluded to improve the accuracy of hazard flood detection.

This research created a  $5 \times 5$  square area centered on each normal open water pixel to represent a water buffer. Using a three-dimensional array from the full-year 2021 data, we counted occurrences of each pixel with a water fraction above 40% and calculated the total clear days by excluding cloudy conditions. The flood response frequency for each pixel is the ratio of flooding days to clear days, which include both flooding days and no-flooding days.

$$p(x_i) = \frac{\sum \text{flooding days}}{\sum (\text{flooding} + \text{no-flooding}) \text{ days}} \quad (2)$$

$$\text{Pixel category} = \text{non-hazard flooding} \text{ if } p(x_i) > 70\% \quad (3)$$

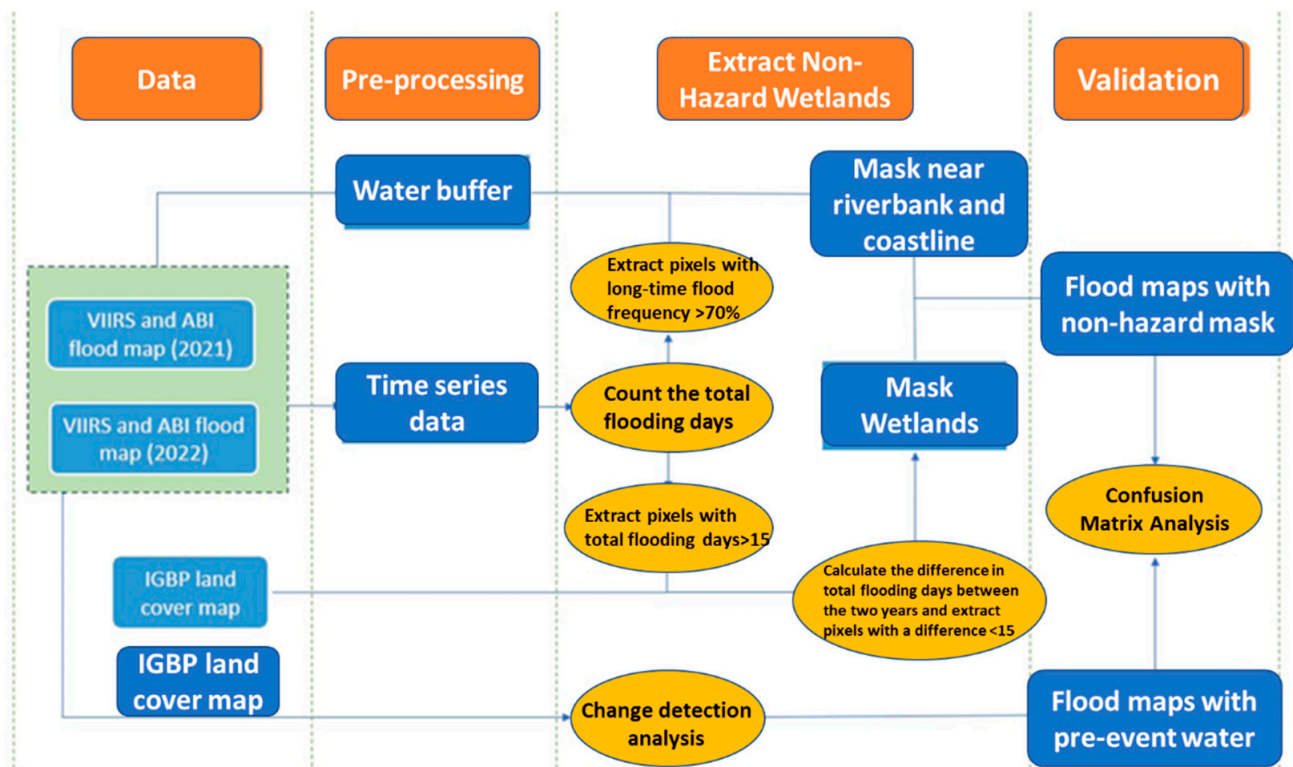
where  $p(x_i)$  represents the flood response frequency of pixel  $x_i$  over one year. Non-hazard water bodies exhibit a higher long-time flood frequency compared to real-hazard floods. A threshold of 70% ensures that pixels exceeding this are classified as non-hazard floodwaters. After determining the flood response frequency, all pixels within the water buffer range that exceed the threshold are extracted to form a non-hazard flood mask near riverbanks and coastlines.

To confirm and validate our results, we compared the results of this method with those obtained from the change detection analysis.

#### 2.3.5. Comparison with Change Detection Analysis

Flood maps before and after Hurricane Ida were compared to extract newly generated flood areas post-hurricane. The non-hazard flood masks generated from this study were overlaid onto the flood maps during and after the hurricane to extract the actual hazard flood areas. These results were then compared with those from the change detection analysis to evaluate the study's findings.

Figure 2 shows the flow chart for this study.

**Figure 2.** Data processing and analysis flow chart for this study.

### 3. Results

#### 3.1. Extraction of Wetlands from the VIIRS Five-Day Composite Flood Map

On 29 August 2021, Hurricane Ida, one of the strongest hurricanes ever recorded in the Gulf of Mexico, made landfall in Louisiana, United States. This Category 4 hurricane caused widespread power outages, impacting over a million households, and leaving the entire city of New Orleans without power. Hurricane Ida resulted in 26 deaths in Louisiana, with 11 casualties reported in New Orleans. Figure 3 shows two VIIRS flood maps for the Louisiana region: one before Hurricane Ida (upper) and one after Hurricane Ida (lower). The color bar ranges from green to red, indicating water fraction values from low to high. Brown denotes land, white shows snow, light blue represents ice, dark blue indicates normal open water, and gray represents clouds. The image reveals that even before Hurricane Ida's landfall, floodwaters already existed in many areas around Louisiana. Compared with the land cover map (Figure 1), these pre-existing floodwaters primarily align with wetlands, riverbanks, and coastlines. The post-Hurricane Ida flood map (Figure 3 lower) shows a significant increase in the extent of flood-affected areas compared to the pre-landfall flood map (Figure 3 upper).

By comparing and conducting a change detection analysis on flood maps before and after Hurricane Ida's landfall, we identified and labeled areas with floodwaters detected before the hurricane as "wetlands". In Figure 4, the turquoise blue regions represent these wetlands. This figure effectively illustrates the flood areas caused by Hurricane Ida and displays the water fraction values in various regions.

Figure 5 shows the post-hurricane flood map of Louisiana after overlaying the non-hazard flood mask generated in this study. Medium blue represents non-hazard floods in wetlands, while violet indicates non-hazard floods near riverbanks and coastlines. Observations reveal that applying the non-hazard flood mask effectively highlights the hazardous floods caused by the hurricane. The flooding from Hurricane Ida was primarily

concentrated around Lake Maurepas and Lake Pontchartrain, as well as Lafourche Parish to the south of Lake Salvador and Jefferson Parish to the southeast.

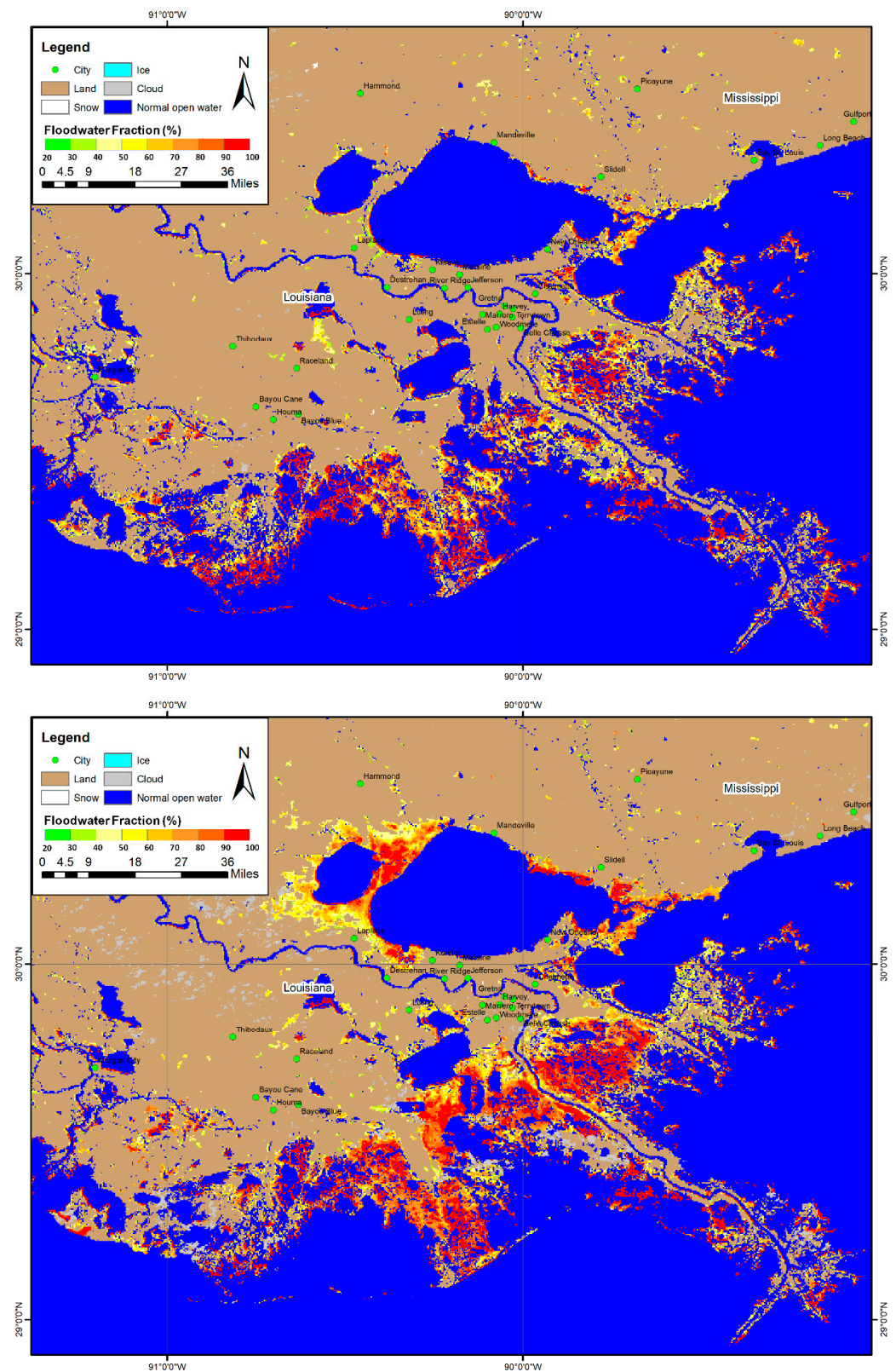


**Figure 3.** VIIRS five-day composite flood product for the Louisiana region: before Hurricane Ida (22–26 August 2021) (**upper**) and after Hurricane Ida (29 August–2 September 2021) (**lower**).

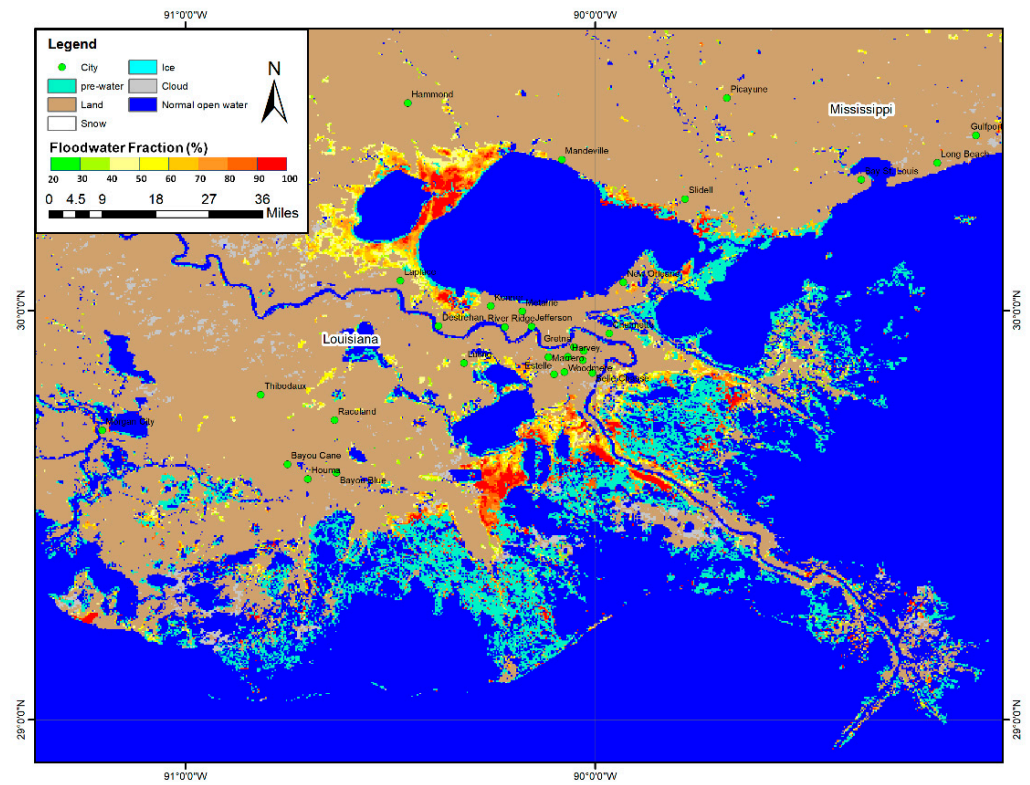


Figure 4. VIIRS five-day composite flood product showing wetlands in the Louisiana region.

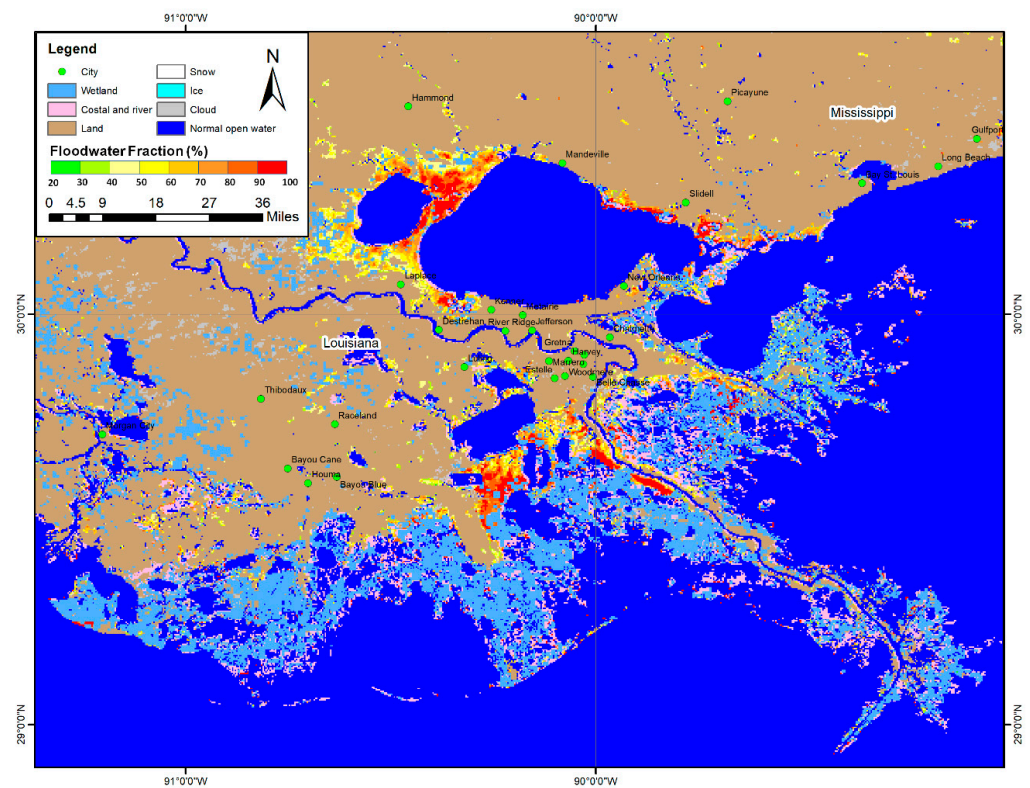


Figure 5. VIIRS five-day composite flood product highlighting the identified wetlands in the Louisiana region.

To further validate the results of this study, we compared the actual hazardous floods, excluding non-hazardous areas, with the floodwaters caused by Hurricane Ida, excluding the wetlands obtained through the change detection analysis. A matrix analysis was then conducted. Figure 6 shows the extent of the flood map used for the matrix analysis, which covers nearly all flood-prone areas in the Louisiana region. The confusion matrix is presented in Table 1.

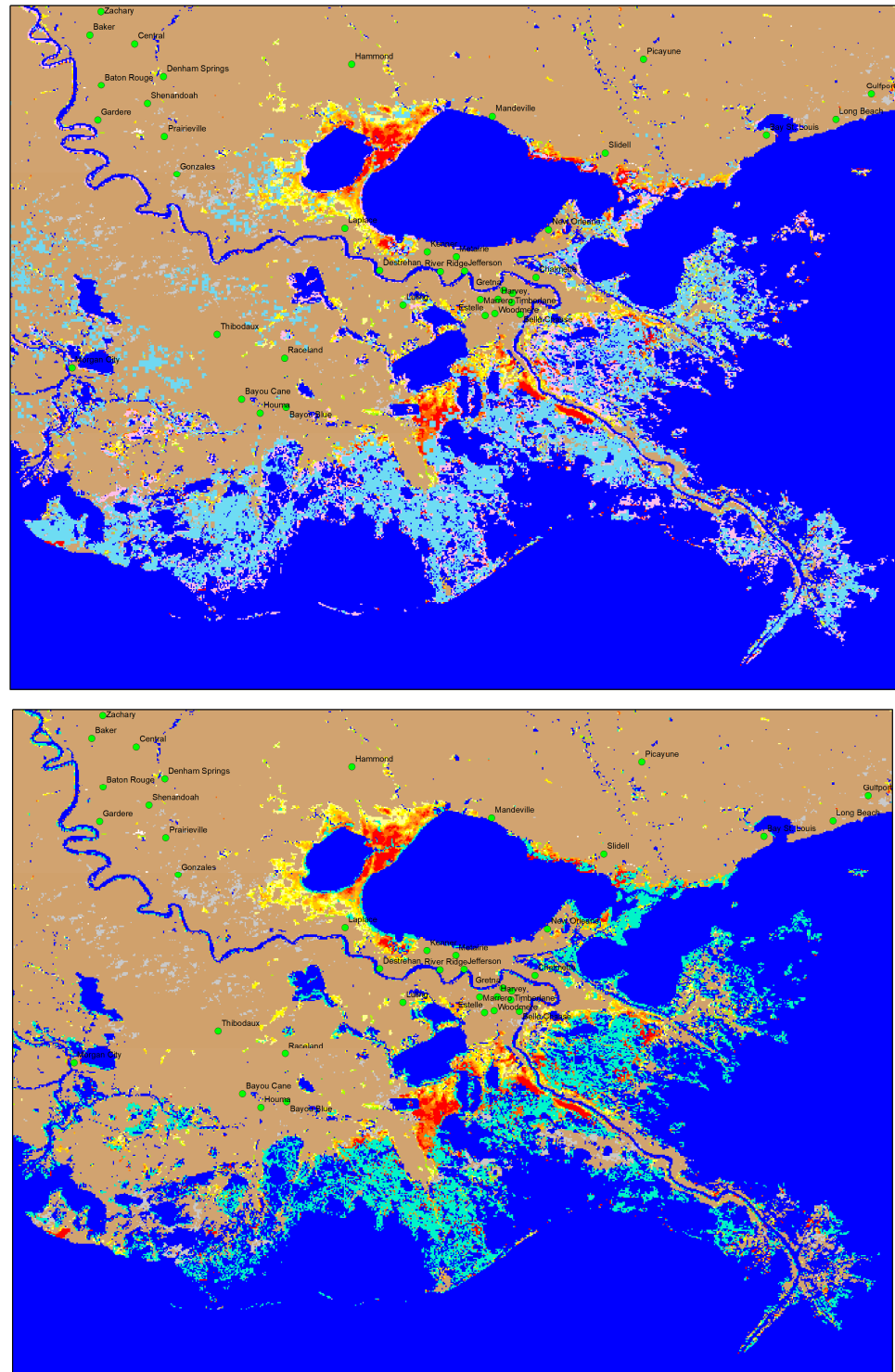


**Figure 6.** Map illustrating the confusion matrix analysis: flood map with the identified wetland mask (**upper**), and VIIRS five-day composite flood map showing wetlands (**lower**).

**Table 1.** Confusion matrix comparing hazard floods identified using the non-hazard flood mask developed in this study with wetlands and hazard floods in coastal Louisiana.

| Classification from This Study | Flood by Hurricane Ida | Wetlands     |
|--------------------------------|------------------------|--------------|
| Classified as a hazard flood   | 11,962 (TP)            | 2496 (FP)    |
| Classified as wetlands         | 5187 (FN)              | 293,555 (TN) |

Where TP represents True Positive, FN stands for False Negative, TN denotes True Negative, and FP indicates False Positive. The following metrics can be calculated using these definitions:

$$\text{Accuracy} = (TP+TN)/(TP + FP + TN + FN) \quad (4)$$

$$\text{Recall} = TP/(TP + FN) \quad (5)$$

$$\text{Precision} = TP/(TP + FP) \quad (6)$$

$$\text{F1 Score} = 2TP/(2TP + FP + FN) \quad (7)$$

The result from the confusion matrix analysis in the selected area shows an accuracy of 97.55%, precision of 82.74%, recall of 69.75%, and the F1-score of 75.69%. The significantly higher count of True Negatives compared to True Positives creates an imbalanced confusion matrix, which tends to overlook True Positives and inflates the accuracy metric. To address this issue, a sample is extracted for additional confusion matrix analysis, as shown in Figure 7.

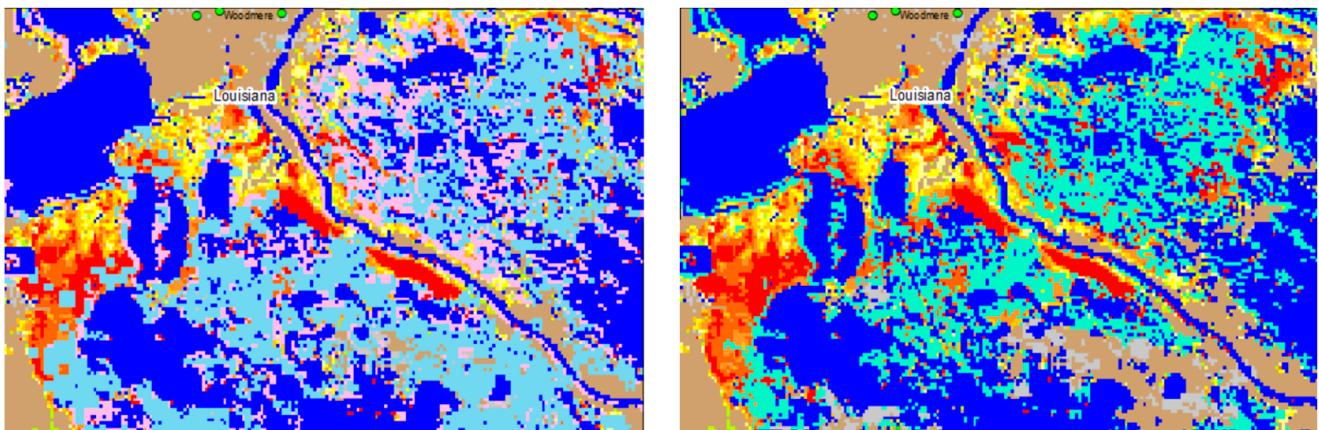
**Figure 7.** Sample for confusion matrix analysis: flood map showing identified wetlands marked in light blue (left) and flood map indicating wetlands marked in turquoise blue (right).

Table 2 displays the results of the confusion matrix analysis conducted on the sample, showing an accuracy of 91.58%, precision of 89.97%, recall of 66.73%, and an F1-score of 76.63%. The sample analysis significantly improved the matrix balance. While the F1-score values remained consistent across both analyses, there was a decrease in accuracy. However, this decrease is offset by a notable improvement in matrix balance, with the accuracy still being relatively high. Thus, the approach used in this study effectively excludes non-hazard floodwaters caused by wetlands.

**Table 2.** Confusion matrix for the sample hazard floods after applying the non-hazard flood mask in this study, compared with the hazard floods and wetlands in coastal Louisiana.

| Classification from This Study | Flood by Hurricane Ida | Wetlands    |
|--------------------------------|------------------------|-------------|
| Classified as a hazard flood   | 3677 (TP)              | 410 (FP)    |
| Classified as wetlands         | 1833 (FN)              | 20,704 (TN) |

### 3.2. Identification of Non-Hazard Floodwaters Due to Wetlands in GOES-R ABI Flood Products

Compared to VIIRS flood products, GOES-R flood data products have a lower spatial resolution (1000 m). To minimize cloud interference, VIIRS products use a five-day synthesis method, combining current-day data with observations from the previous four days. This approach reduces cloud cover in flood maps. On the other hand, GOES-R data typically experiences less cloud interference and provides high temporal resolution and frequent observations, thus mitigating the impact of clouds on data. For this study, we selected GOES-R ABI data from the day with the least cloud cover before and after Hurricane Ida for analysis, as shown in Figure 8.

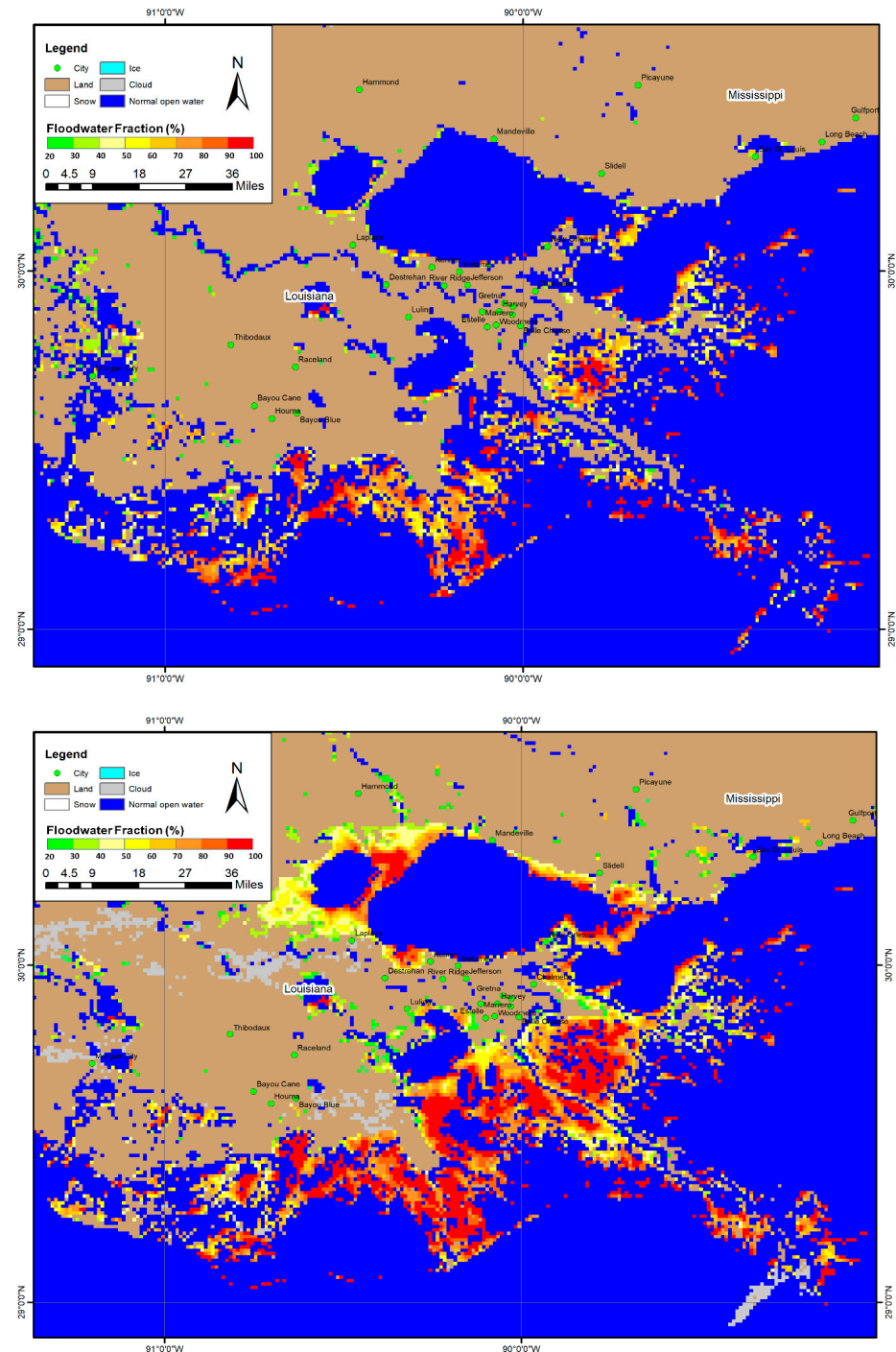


**Figure 8.** GOES-R ABI flood product in the Louisiana coastal region: before Hurricane Ida (25 August 2021) (**upper**) and after Hurricane Ida (31 August 2021) (**lower**).

[illegible]

Figure 10 shows the flood map from GOES-R ABI data, dated 31 August 2021, after applying the non-hazard floodwater method due to wetlands following Hurricane Ida. The map differentiates between hazard and non-hazard flood areas. To further assess the feasibility of this study, we extracted data within the same range for confusion matrix analysis. Figure 11 illustrates the sample range used for this analysis: Figure 11 (left) shows the flooded areas after applying the non-hazard flood mask, while Figure 11 (right) depicts the pre-event floodwater or wetlands identified through change detection analysis.

**Table 3.** Confusion matrix for the sample hazard floods with non-hazard flood masks from this study, compared to hazard floods and pre-event water in coastal Louisiana using GOES-R ABI data.

| Classification from This Study | Flood by Hurricane Ida | Wetlands  |
|--------------------------------|------------------------|-----------|
| Classified as a hazard flood   | 622 (TP)               | 16 (FP)   |
| Classified as wetlands         | 394 (FN)               | 2092 (TN) |

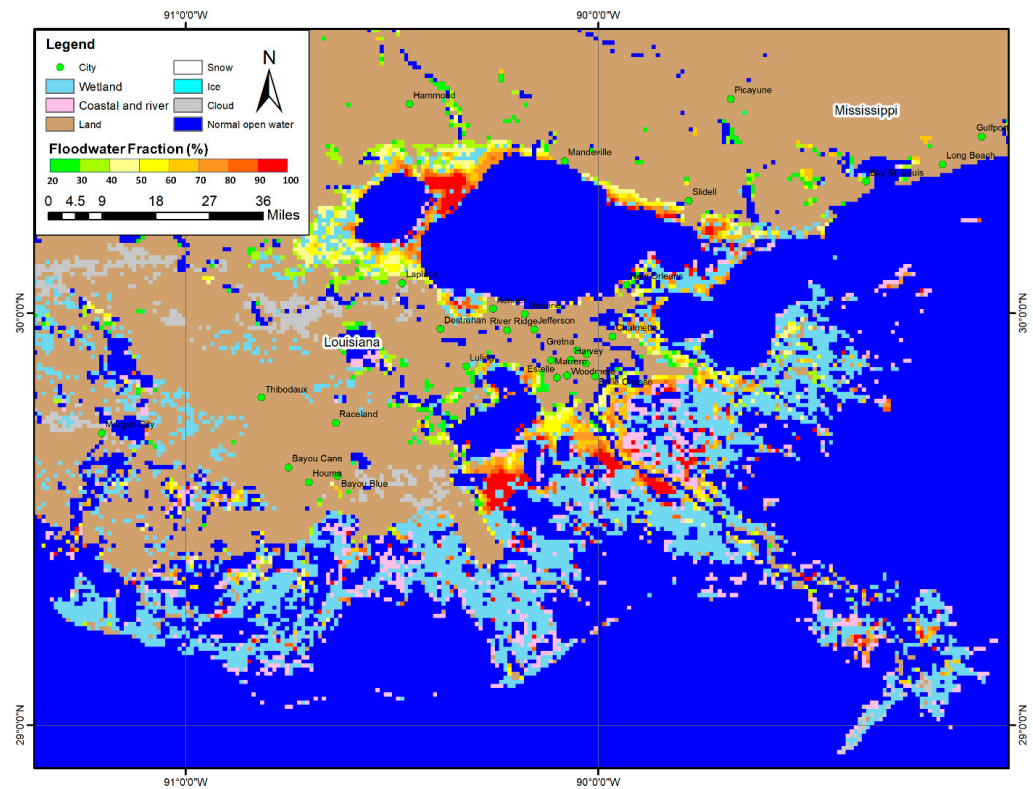


**Figure 10.** GOES-R ABI flood product with the identified wetlands for the Louisiana coastal region.

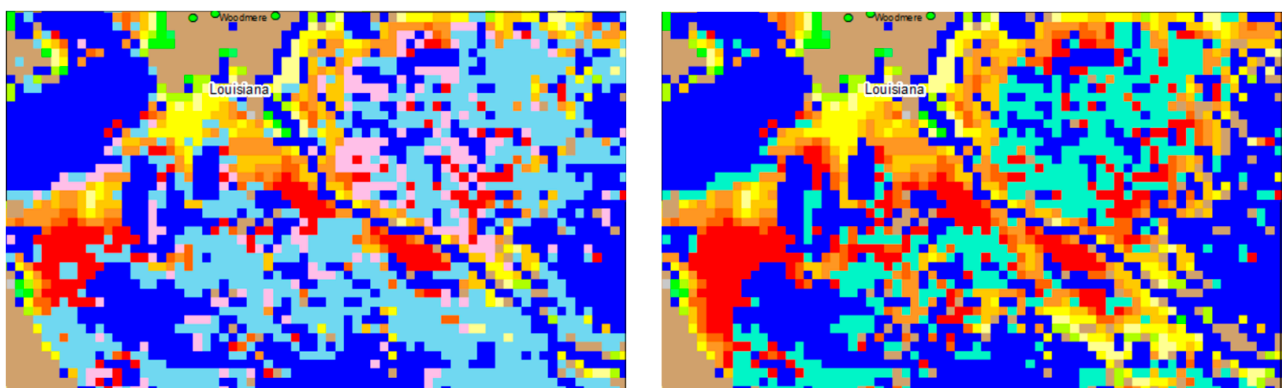


**Figure 11.** Sample for confusion matrix analysis of GOES-R ABI data: flood map highlighting identified wetlands in light blue (**left**) and flood map showing wetlands in turquoise blue (**right**).

### 3.3. Comparison with the Sentinel-1-Based Flood Mapping from the Operational Copernicus Global Flood Mapping System

It is interesting to compare our findings with the Global Flood Monitoring (GFM) flood extent product from the Copernicus Emergency Management Service (CEMS). The GFM system offers continuous tracking of global flood events by rapidly processing and analyzing all incoming Sentinel-1 Synthetic Aperture Radar (SAR) satellite images in near real-time (NRT) [58]. Compared to our VIIRS products, the GFM Product provides much higher spatial resolution, and the SAR can deliver stable data under cloud cover and adverse weather conditions. However, the Sentinel-1 has limited spatial coverage and a low temporal resolution with a 12-day revisit time, whereas our VIIRS product offers a temporal resolution of one day. Therefore, Sentinel-1 may miss detecting floods caused by extreme weather events and may not be able to capture the full duration of flooding.

There was only a total of 12 days in 2021 and 19 days in 2022 with valid flood extent data in the Louisiana region. The 2021 data have significant gaps, particularly missing data during the time of Hurricane Ida in August and September. This may be due to the limited spatial coverage and long revisit time of Sentinel-1 observations. Another reason may be that the GFM product uses an exclusion mask, covering all pixels where SAR data cannot provide reliable flood delineation. This occurs when the SAR sensor is unable to receive any signals from the ground surface due to obstruction by high vegetation canopies [58]. When wetlands are covered with vegetation and mixed with water, the radar signals from water may be obstructed by vegetation, particularly in the C-band [40,41], making it challenging for SAR to provide reliable flood detection under vegetation. As illustrated in Figure 12, no flood detection is available in the exclusion areas, which include both the hazardous flooding caused by Hurricane Ida and wetlands covered by vegetation. Therefore, the methodology developed in this study cannot be applied to the CEMS GFM product for extracting wetlands in Louisiana.

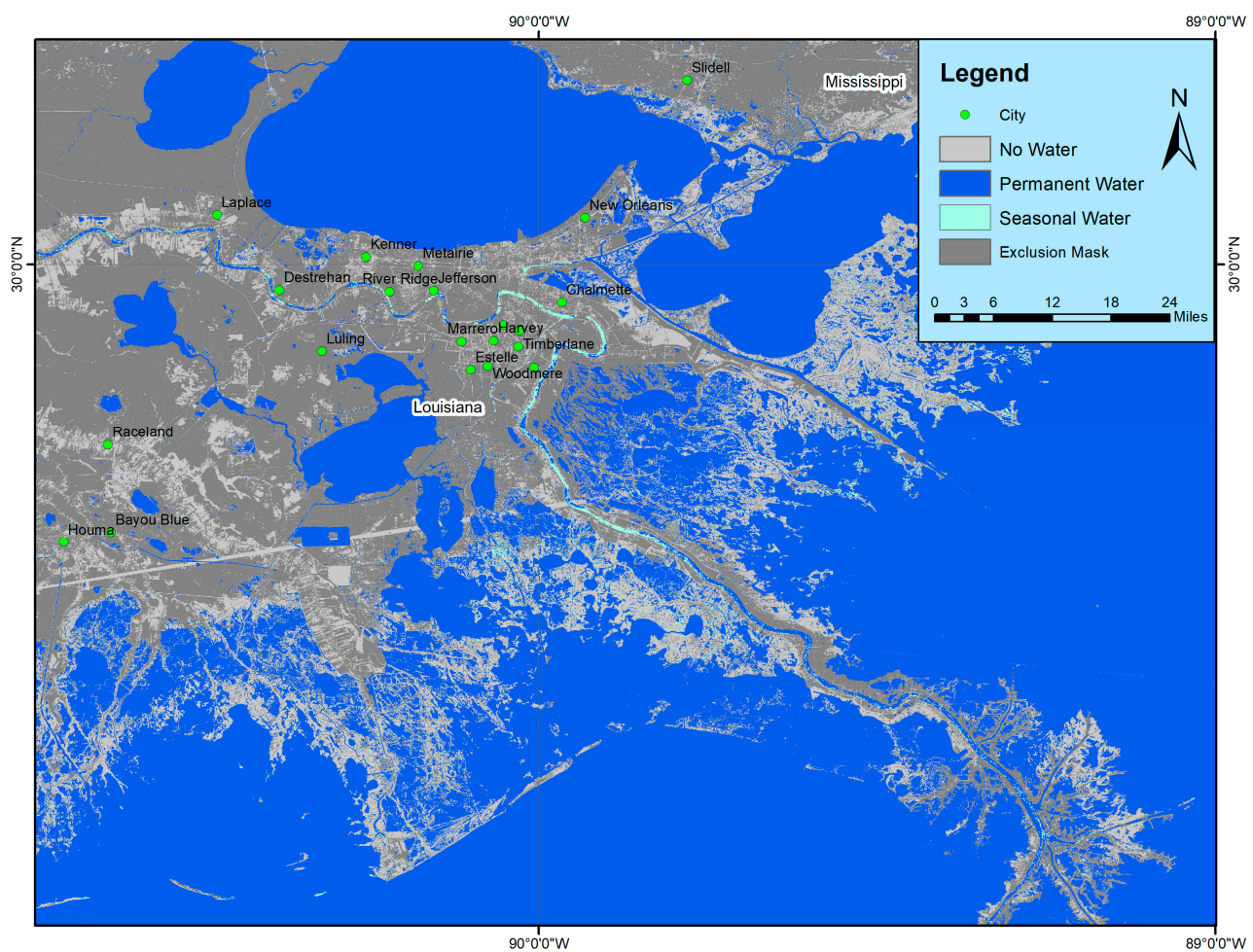


**Figure 12.** The GFM product Exclusion Mask for 2022 in coastal Louisiana.

We can only apply a long-time frequency analysis to the 2022 GFM data. Flood frequency for 2022 is calculated for each Sentinel-1 pixel (Figure 13). In the 2022 GFM product, floods primarily occurred in Lafourche County and Plaquemines County, with some pixels exhibiting very high flood frequencies greater than 80% throughout the year. These high frequencies are most likely attributed to non-hazard floods due to wetlands, as noted in our study, but are significantly less than those in the VIIRS and GOES-R flood products. There are two main reasons for this result. First, the GFM reference water mask includes not only permanent water but also seasonal water. As shown in Figure 13, the seasonal water is similar to wetlands in our study, while some segments of rivers are also

classified as seasonal water by the GFM reference water mask. Second, the GFM product cannot provide reliable flood detection in areas with high vegetation, which are excluded by the Exclusion Mask (Figure 12).

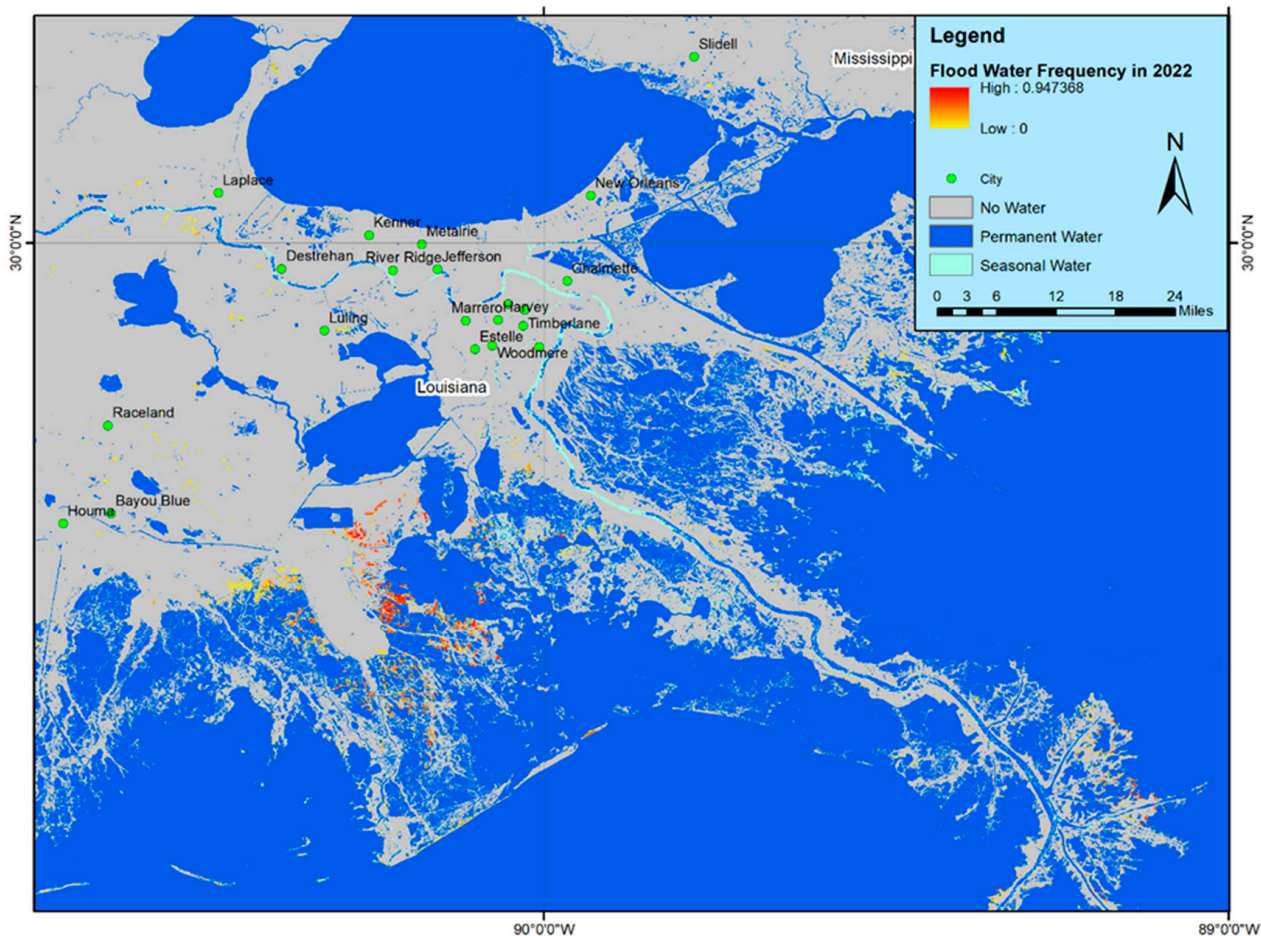


**Figure 13.** Flood Water Frequency in 2022 for the GFM flood extent product in Louisiana State.

From this comparison and analysis, we find that the GFM flood extent product has the advantage of minimizing potential false positives, although some still remain—such as those due to wetlands as appeared in our operational optical sensor-based flood products, which is the problem this study aims to address. The GFM flood extent product may exclude real hazardous floods that are filtered out by the exclusion mask because the Sentinel-1 cannot provide reliable flood detection in urban areas, flat and impervious areas, and densely vegetated areas.

### 3.4. Cross-Evaluation of the Model with Sar-Based Flood Mapping by Microsoft

A cross-evaluation of the model using the SAR-based flood mapping provided by Microsoft is conducted. Figure 14 shows the flooding caused by Hurricane Ida from the Microsoft SAR-based flood mapping, which also suffers false positive problems. Several factors may cause false positives in SAR data. To filter potential false positives, Microsoft conducted a post-analysis using auxiliary data, including soil moisture data, digital elevation models (DEM), land surface temperature, and land cover mapping [48]. They used elevation (specifically slope) to filter terrain shadow, which is solved and masked in VIIRS and GOES-R flood products [53]. Land surface temperature is used to remove freeze-thaw false positives in SAR data, while snow and ice are identified in VIIRS and GOES-R flood products. Soil moisture levels below a certain threshold were excluded as false positives. As shown in Figure 14, the filtering process removes false positives (shown in turquoise

blue) not related to Hurricane Ida, most likely due to wetlands in the Louisiana region. Compared to the VIIRS data, the flood areas identified in the Microsoft SAR flood map are much smaller than those detected in the VIIRS and GOES-R flood products. For instance, the areas between Lake Maurepas and Lake Pontchartrain were covered by floodwaters in the VIIRS products (Figures 4 and 5) and GOES-R flood products (Figures 9 and 10), but no floods were detected in the Microsoft SAR flood map (Figure 14). Moreover, we performed a confusion matrix analysis (Table 4) between the operational VIIRS flood products and the Microsoft SAR-based flood mapping. The accuracy (0.8179) is over 80%. This high accuracy is mainly due to the large number of True Negatives (TN). While other metrics, like precision (0.1099), recall (0.2816), and F1-score (0.1580), are quite low. The high accuracy and the large number of TNs suggest that the wetlands identified in this study align well with the false positives filtered by Microsoft.

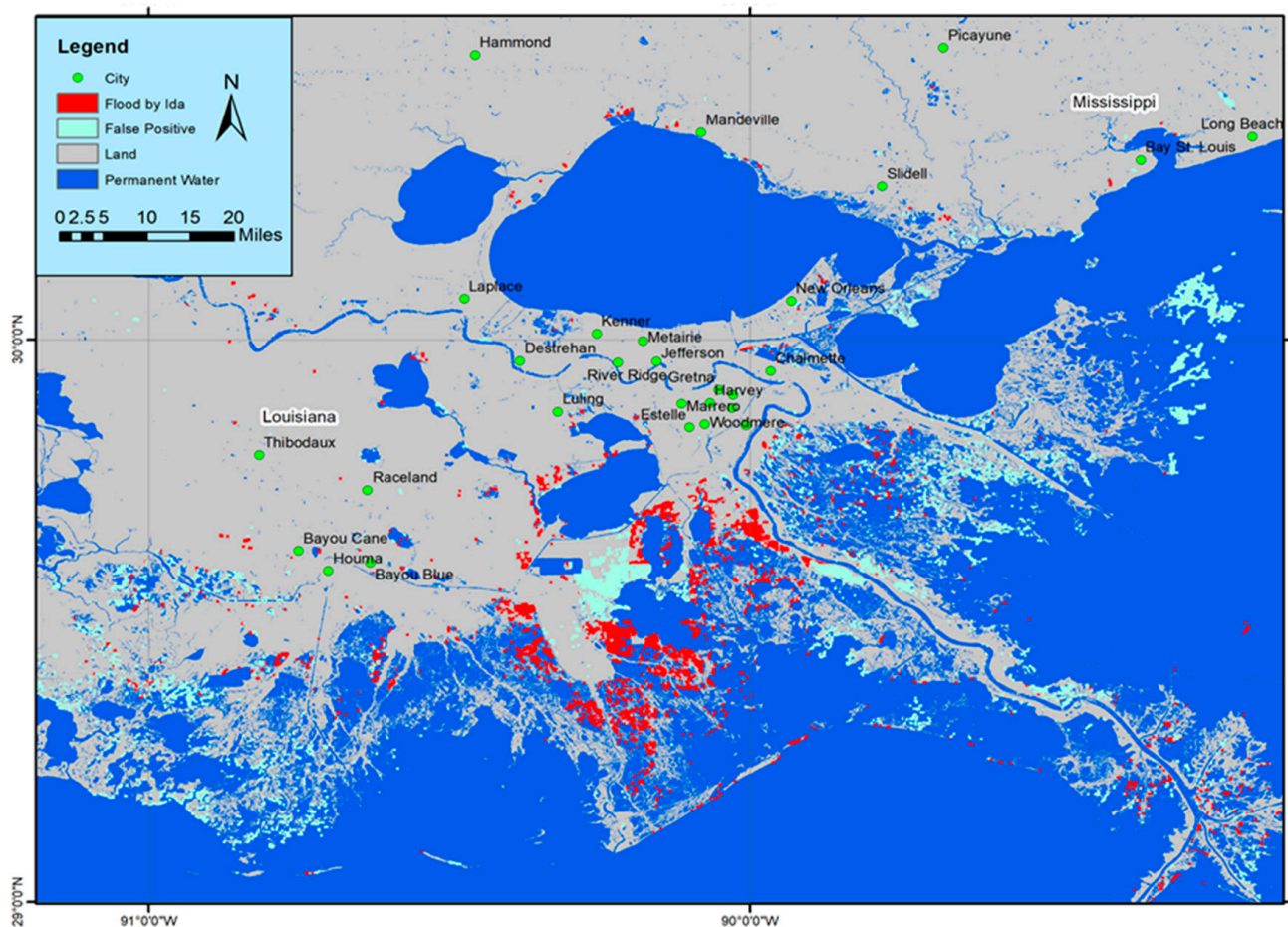


**Figure 14.** SAR-based flood mapping of Hurricane Ida flooding using AI by Microsoft.

**Table 4.** Confusion matrix for the VIIRS flood products and the identified Wetlands from this study, compared to the SAR-based flood mapping provided by Microsoft in coastal Louisiana.

| VIIRS Classification          | Hurricane Flood from SAR by Microsoft | False positives (Wetlands) from SAR by Microsoft |
|-------------------------------|---------------------------------------|--------------------------------------------------|
| Classified as hurricane flood | 455 (TP)                              | 3687 (FP)                                        |
| Classified as wetlands        | 1161 (FN)                             | 22,321 (TN)                                      |

VIIRS detected more hurricane flooding than SAR, as shown by the False Positives (FP) in Table 4. This result may be due to the flooding caused by Hurricane Ida occurring primarily within the exclusion areas defined in the Global Flood Mapping (GFM) exclusion mask, as illustrated in Figure 12. According to the Copernicus GFM documentation [58], the exclusion mask indicates all areas where SAR observations cannot reliably delineate floods because the SAR sensor is unable to receive signals from the ground surface due to obstruction by high vegetation canopies. The SAR radar waves are scattered, absorbed, and reflected when penetrating dense vegetation layers, making it difficult to accurately detect water under dense vegetation.

#### 4. Discussion

To create satellite-based flood maps, water bodies are first identified from satellite imagery. Floodwaters can be detected by comparing pre-event and post-event water classification maps. However, in an operational setting, such comparisons are often impractical. Instead, operational flood products are generated by comparing water classification maps with permanent or normal water bodies. This approach may misclassify certain water bodies, such as wetlands, as floodwaters because they are not considered permanent or normal water. The VIIRS and GOES-R ABI flood products are widely used by the NWS and the International Charter Program for flood monitoring and FEMA for emergency response and rescue operations. However, these products sometimes mistakenly identify wetlands as floodwaters, even without actual flooding. These wetland floodwaters usually do not result in property damage or fatalities, but they can complicate flood assessment and decision-making. This study seeks to distinguish non-hazardous floodwaters due to wetlands from actual hazardous floods from hurricanes in the Louisiana coastal region. For VIIRS data, four AOIs are necessary to cover the Louisiana wetlands, while one AOI is sufficient for the GOES-R data.

This study concentrated on a specific region in the Louisiana coastal area, where the threshold method was effective. Future research will expand this approach to global coverage for VIIRS flood products and complete coverage for GOES-R flood products, including regions in North and South America. Artificial Intelligence (AI) techniques, such as decision trees and deep learning algorithms used in our current flood algorithms [1–3], will be employed to automatically determine dynamic threshold values across different conditions and regions.

The method developed in this study is designed to work with operational VIIRS and GOES-R flood products. Compared with the Sentinel-1-based flood mapping from the operational Copernicus GFM system, optical sensor-based flood mapping provides the advantages of wide area coverage and high temporal resolutions, which enable catching real-hazard floods. The GFM flood extent product provides the advantage of minimizing potential false positives by including Seasonal Water in the Reference Water Mask. The GFM flood product may miss real hazardous floods, like the flooding due to Hurricane Ida, because coastal Louisiana is located in the Unclassified areas in the Exclusion Mask, which covers urban areas, flat and impervious areas, dense vegetation, sandy surfaces, and topographic effects. Since SAR-based flood data in 2021 and 2022 are very scarce in the study region, the method developed in this study cannot be applied to SAR-based flood products.

Future works are planned to generate non-hazard flood masks, including wetlands, all over the globe and provide them to users as Quality Control (QC) flag files for combined use with the operational flood products. Once the routine flood product applies this non-hazard flood mask over the detected flood areas, the accuracy of hazard flood detection in operational VIIRS and GOES-R flood products shall be greatly improved.

Another plan is to replace the MODIS global water mask data [46] in the current operational VIIRS and GOES-R flood products with the reference water mask data from the operational Copernicus Global Flood Mapping system to filter seasonal water as well as permanent water to avoid potential false positives due to seasonal water.

Recently, some researchers have introduced physically based approaches [59,60] to identify and differentiate geomorphic and hydrographic features (channel, floodplain features, wetlands, etc.) in drainage basins. These methods could offer a future direction for this research through comparative analysis to address this issue.

## 5. Conclusions

This research used VIIRS five-day composite and GOES-R ABI flood products to identify non-hazard floodwaters due to wetlands in the Louisiana coastal area.

Flood cases in Louisiana resulting from Hurricane Ida were used to demonstrate the differentiation between non-hazard floodwaters from wetlands and real, hazardous floods caused by hurricanes. Since Hurricane Ida made landfall in 2021 and there were no major flood events in this region during 2022, VIIRS and ABI flood data from these two years were selected. The difference in annual total flooding days between 2021 and 2022 was calculated and combined with long-time flood frequency to distinguish non-hazard floodwaters due to wetlands from real, hazardous floods caused by the hurricane.

Long-time flood frequency was calculated from the 2-year VIIRS and GOES-R ABI flood products to identify non-hazard floodwaters. The results were compared with change detection analysis during major flood events and showed good agreement. For the VIIRS data, the confusion matrix analysis indicated an accuracy of 91.58%, precision of 89.97%, recall of 66.73%, and an F1-score of 76.63%. For the GOES-R ABI data, the confusion matrix analysis demonstrated an accuracy of 86.88%, precision of 97.49%, recall of 61.22%, and an F1-score of 75.21%. Compared to the analysis for the VIIRS flood data, both the accuracy and F1-score values for the GOES-R ABI flood data decreased due to lower spatial resolution but remained within a feasible range.

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## References

1. Sun, D.; Yu, Y.; Goldberg, M.D. Deriving water fraction and flood maps from MODIS images using a decision tree approach. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2011**, *4*, 814–825. [CrossRef]
2. Sun, D.; Yu, Y.; Zhang, R.; Li, S.; Goldberg, M.D. Towards operational automatic flood detection using EOS/MODIS data. *Photogramm. Eng. Remote Sens.* **2012**, *78*, 637–646. [CrossRef]

3. Li, S.; Sun, D.L.; Yu, Y.; Csiszar, Y.; Stefanidis, A.; Goldberg, M.D. A New Short-wave Infrared (SWIR) Method for Quantitative Water Fraction Derivation and Evaluation with EOS/MODIS and Landsat/TM data. *IEEE Trans. Geosci. Remote Sens.* **2013**, *51*, 1852–1862. [\[CrossRef\]](#)
4. Li, S.; Sun, D.; Goldberg, M.D.; Sjoberg, B.; Santek, D.; Hoffman, J.P.; DeWeese, M.; Restrepo, P.; Lindsey, S.; Holloway, E. Automatic near real-time flood detection using Suomi-NPP/VIIIRS data. *Remote Sens. Environ.* **2018**, *204*, 672–689. [\[CrossRef\]](#)
5. Li, S.; Sun, D.; Goldberg, M.D.; Sjoberg, B.; Satya, K.; Lindsey, D.; Hoffman, J.P.; DeWeese, M.; Connelly, B.; McKee, P.; et al. A downscaling model for derivation of 3-D flood products from VIIIRS imagery and SRTM/DEM. *ISPRS J. Photogramm. Remote Sens.* **2022**, *192*, 279–298. [\[CrossRef\]](#)
6. Sharifi, A.; Kalin, L.; Hantush, M.M.; Isik, S. *Wetlands: Earth's Kidneys*; Lamar, J., Lockaby, B.G., Eds.; Auburn Speaks; Auburn University: Auburn, AL, USA, 2013; pp. 140–143.
7. EPA: Term. Available online: <https://www.epa.gov/cwa-404/how-wetlands-are-defined-and-identified-under-cwa-section-404> (accessed on 24 May 2024).
8. Barducci, A.; Guzzi, D.; Marcoionni, P.; Pippi, I. Aerospace wetland monitoring by hyperspectral imaging sensors: A case study in the coastal zone of San Rossore Natural Park. *J. Environ. Manag.* **2009**, *90*, 2278–2286. [\[CrossRef\]](#)
9. Neyland, R. The Effects of Hurricane Rita on the Aquatic Vascular Flora in a Large Fresh-Water Marsh in Cameron Parish, Louisiana. *Castanea* **2007**, *72*, 1–7. [\[CrossRef\]](#)
10. Wang, Y. Seasonal Change in the Extent of Inundation on Floodplains Detected by JERS-1 Synthetic Aperture Radar Data. *Int. J. Remote Sens.* **2004**, *25*, 2497–2508. [\[CrossRef\]](#)
11. Kiage, L.; Walker, N.; Balasubramanian, S.; Babin, A.; Barras, J. Applications of Radarsat-1 Synthetic Aperture Radar Imagery to Assess Hurricane-Related Flooding of Coastal Louisiana. *Int. J. Remote Sens.* **2005**, *26*, 5359–5380. [\[CrossRef\]](#)
12. Ramsey, E., III; Lu, Z.; Suzuoki, Y.; Ragoonwala, A.; Werle, D. Monitoring Duration and Extent of Storm Surge Flooding Along the Louisiana Coast with Envisat ASAR Data. *IEEE Trans. Geosci. Remote Sens.* **2011**, *4*, 387–399.
13. Keddy, P.A. *Wetland Ecology: Principles and Conservation*, 2nd ed.; Cambridge University Press: Cambridge, UK, 2010; p. 497.
14. Keddy, P.A.; Campbell, D.; McFalls, T.; Shaffer, G.; Moreau, R.; Dranguet, C.; Heleniak, R. The wetlands of lakes Pontchartrain and Maurepas: Past, present and future. *Environ. Rev.* **2007**, *15*, 43–77. [\[CrossRef\]](#)
15. Lamb, B.T.; Tzortziou, M.A.; McDonald, K.C. A Fused Radar–Optical Approach for Mapping Wetlands and Deepwaters of the Mid–Atlantic and Gulf Coast Regions of the United States. *Remote Sens.* **2021**, *13*, 2495. [\[CrossRef\]](#)
16. Philipson, W.R. *Manual of Photographic Interpretation*, 2nd ed.; American Society for Photogrammetry and Remote Sensing: Falls Church, VA, USA, 1996; 2440p.
17. Bartlett, D.S.; Klemas, V. In situ spectral reflectance studies of tidal wetland grasses. *Photogramm. Eng. Remote Sens.* **1981**, *47*, 1695–1703.
18. Kearney, M.S.; Rogers, A.S.; Townshend, J.R.G.; Rizzo, E.; Stutzer, D.; Stevenson, J.C.; Sundborg, K. Landsat imagery shows decline of coastal marshes in Chesapeake and Delaware Bays. *Eos. Trans. Am. Geophys. Union* **2002**, *83*, 173. [\[CrossRef\]](#)
19. Kulawardhana, R.W.; Thenkabail, P.S.; Vithanage, J.; Biradar, C.; Islam, M.A.A.; Gunasinghe, S.; Alankara, R. Evaluation of the wetland mapping methods using Landsat ETM+ and SRTM data. *J. Spat. Hydrol.* **2007**, *7*, 62–96.
20. Ozesmi, S.L.; Bauer, M.E. Satellite remote sensing of wetlands. *Wetl. Ecol. Manag.* **2002**, *10*, 381–402. [\[CrossRef\]](#)
21. Frohn, R.C.; Reif, M.; Lane, C.; Autrey, B. Satellite remote sensing of isolated wetlands using object-oriented classification of Landsat-7 data. *Wetlands* **2009**, *29*, 931–941. [\[CrossRef\]](#)
22. Couvillion, B.R.; Barras, J.A.A.; Steyer, G.D.D.; Sleavin, W.; Fischer, M.; Beck, H.; Trahan, N.; Griffin, B.; Heckman, D.; Catharine, S.; et al. Land Area Change in Coastal Louisiana from 1932 to 2010. *U.S. Geol. Surv. Sci. Investig.* **2011**, *3164*, 12.
23. Phinn, S.R.; Menges, C.; Hill, G.J.E.; Standford, M. Optimizing remotely sensed solutions for monitoring, modeling, and managing coastal environments. *Remote Sens. Environ.* **2000**, *73*, 117–132. [\[CrossRef\]](#)
24. Elmore, A.H. Remote Sensing of Tidal Freshwater Marsh Elevation, Channels, and Vegetation Structure. Master's Thesis, University of Maryland, College Park, MA, USA, 2008; Supervised by Professor Katharina Engelhardt.
25. Campbell, A.; Wang, Y.; Christiano, M.; Stevens, S. Salt Marsh Monitoring in Jamaica Bay, New York from 2003 to 2013: A decade of change from restoration to hurricane sandy. *Remote Sens.* **2017**, *9*, 131. [\[CrossRef\]](#)
26. Gilmore, M.S.; Wilson, E.H.; Barrett, N.; Civco, D.L.; Prisloe, S.; Hurd, J.D.; Chadwick, C. Integrating multi-temporal spectral and structural information to map wetland vegetation in a lower Connecticut River tidal marsh. *Remote Sens. Environ.* **2008**, *112*, 4048–4060. [\[CrossRef\]](#)
27. Hurd, J.D.; Civco, D.L.; Gilmore, M.S.; Prisloe, S.; Wilson, E.H. Coastal marsh characterization using satellite remote sensing and in situ radiometry data: Preliminary results. In Proceedings of the American Society of Photogrammetry and Remote Sensing 2005 Annual Conference, Baltimore, MD, USA, 7–11 March 2005.
28. Klemas, V. Using Remote Sensing to Select and Monitor Wetland Restoration Sites: An Overview. *J. Coast. Res.* **2013**, *289*, 958–970. [\[CrossRef\]](#)
29. Langley, J.A.; Megonigal, J.P. Field-based radiometry to estimate tidal marsh plant growth in response to elevated CO<sub>2</sub> and nitrogen addition. *Wetlands* **2012**, *32*, 571–578. [\[CrossRef\]](#)

30. Lopes, C.L.; Mendes, R.; Caçador, I.; Dias, J.M. Assessing salt marsh extent and condition changes with 35 years of Landsat imagery: Tagus Estuary case study. *Remote Sens. Environ.* **2020**, *247*, 111939. [\[CrossRef\]](#)
31. Van Beijma, S.; Comber, A.; Lamb, A. Random forest classification of salt marsh vegetation habitats using quad-polarimetric airborne SAR, elevation and optical RS data. *Remote Sens. Environ.* **2014**, *149*, 118–129. [\[CrossRef\]](#)
32. Lamb, B.T.; Tzortziou, M.A.; McDonald, K.C. Evaluation of Approaches for Mapping Tidal Wetlands of the Chesapeake and Delaware Bays. *Remote Sens.* **2019**, *11*, 2366. [\[CrossRef\]](#)
33. Mahdianpari, M.; Salehi, B.; Mohammadimanesh, F.; Homayouni, S.; Gill, E. The first wetland inventory map of newfoundland at a spatial resolution of 10 m using sentinel-1 and sentinel-2 data on the Google Earth Engine cloud computing platform. *Remote Sens.* **2019**, *11*, 43. [\[CrossRef\]](#)
34. Jones, J.W. Improved automated detection of subpixel-scale inundation-revised Dynamic Surface Water Extent (DSWE) partial surface water tests. *Remote Sens.* **2019**, *11*, 374. [\[CrossRef\]](#)
35. O'Connell, J.L.; Mishra, D.R.; Cotten, D.L.; Wang, L.; Alber, M. The Tidal Marsh Inundation Index (TMII): An inundation filter to flag flooded pixels and improve MODIS tidal marsh vegetation time-series analysis. *Remote Sens. Environ.* **2017**, *201*, 34–46. [\[CrossRef\]](#)
36. Brisco, B.; Kapfer, M.; Hirose, T.; Tedford, B.; Liu, J. Evaluation of C-band polarization diversity and polarimetry for wetland mapping. *Can. J. Remote Sens.* **2011**, *37*, 82–92. [\[CrossRef\]](#)
37. Brisco, B.; Ahern, F.; Murnaghan, K.; White, L.; Canisus, F.; Lancaster, P. Seasonal change in wetland coherence as an aid to wetland monitoring. *Remote Sens.* **2017**, *9*, 158. [\[CrossRef\]](#)
38. Kasischke, E.S.; Bourgeau-Chavez, L.L. Monitoring south Florida wetlands using ERS-1 SAR imagery. *Photogramm. Eng. Remote Sens.* **1997**, *63*, 281–291.
39. Lang, M.W.; Kasischke, E.S. Using C-band synthetic aperture radar data to monitor forested wetland hydrology in Maryland's coastal plain, USA. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 535–546. [\[CrossRef\]](#)
40. Ramsey, E.; Werle, D.; Suzuoki, Y.; Rangoonwala, A.; Lu, Z. Limitations and Potential of Satellite Imagery to Monitor Environmental Response to Coastal Flooding. *J. Coast. Res.* **2012**, *280*, 457–476. [\[CrossRef\]](#)
41. Kim, J.-W.; Lu, Z.; Jones, J.W.; Shum, C.K.; Lee, H.; Jia, Y. Monitoring Everglades freshwater marsh water level using L-band synthetic aperture radar backscatter. *Remote Sens. Environ.* **2014**, *150*, 66–81. [\[CrossRef\]](#)
42. Hird, J.N.; DeLancey, E.R.; McDermid, G.J.; Kariyeva, J. Google earth engine, open-access satellite data, and machine learning in support of large-area probabilistic wetland mapping. *Remote Sens.* **2017**, *9*, 1315. [\[CrossRef\]](#)
43. Slagter, B.; Tsendbazar, N.-E.; Vollrath, A.; Reiche, J. Mapping wetland characteristics using temporally dense Sentinel-1 and Sentinel-2 data: A case study in the St. Lucia wetlands, South Africa. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *86*, 102009. [\[CrossRef\]](#)
44. Huang, W.; DeVries, B.; Huang, C.; Lang, M.W.; Jones, J.W.; Creed, I.F.; Carroll, M.L. Automated extraction of surface water extent from Sentinel-1 data. *Remote Sens.* **2018**, *10*, 797. [\[CrossRef\]](#)
45. Bioresita, F.; Puissant, A.; Stumpf, A.; Malet, J.-P. A Method for Automatic and Rapid Mapping of Water Surfaces from Sentinel-1 Imagery. *Remote Sens.* **2018**, *10*, 217. [\[CrossRef\]](#)
46. Carroll, M.; Townshend, J.; DiMiceli, C.; Noojipady, P.; Sohlberg, R. A New Global Raster Water Mask at 250 Meter Resolution. *Int. J. Dig. Earth* **2009**, *2*, 291–308. [\[CrossRef\]](#)
47. Copernicus Emergency Management Service Global Flood Monitoring Product User Manual. 2020. Available online: <https://emergency.copernicus.eu> (accessed on 24 September 2024).
48. Misra, A.; White, K.; Nsutezo, S.F.; Lavista, J. Mapping Global Floods with 10 Years of Satellite Radar Data. To be submitted.
49. Chen, Y.; Huang, C.; Ticehurst, C.; Merrin, L.; Thew, P. An evaluation of MODIS daily and 8-day composite products for floodplain and wetland inundation mapping. *Wetlands* **2013**, *33*, 823–835. [\[CrossRef\]](#)
50. Notti, D.; Giordan, D.; Caló, F.; Pepe, A.; Zucca, F.; Galve, J.P. Potential and Limitations of Open Satellite Data for Flood Mapping. *Remote Sens.* **2018**, *10*, 1673. [\[CrossRef\]](#)
51. Sun, D.; Yang, T.; Li, S.; Goldberg, M.; Kalluri, S.; Helfrich, S.; Sjöberg, B.; Zhou, L.; Zhang, Q.; Straka, W.; et al. Hazard or Non-Hazard Flood: Post Analysis for Paddy Rice, Wetland, and Other Potential Non-Hazard Flood Extraction from the VIIRS Flood. ISPRS J. Photogramm. Remote. Sens. **2024**, *209*, 415–431. [\[CrossRef\]](#)
52. Li, S.; Sun, D.; Yu, Y. Automatic cloud-shadow removal from flood/standing water maps using MSG/SEVIRI imagery. *Int. J. Remote Sens.* **2013**, *34*, 5487–5502. [\[CrossRef\]](#)
53. Li, S.; Sun, D.; Goldberg, M.D.; Sjöberg, W. Object-based automatic terrain shadow removal from SNPP/VIIRS flood maps. *Int. J. Remote Sens.* **2015**, *36*, 5504–5522. [\[CrossRef\]](#)
54. Huang, C.; Zhan, C.; Csiszar, I. VIIRS Surface Type Algorithm Theoretical Basis Document. 2023; 61p. Available online: [https://www.star.nesdis.noaa.gov/JRSS/documents/ATBD/ATBD\\_VIIRS-SurfaceType\\_v2.2.pdf](https://www.star.nesdis.noaa.gov/JRSS/documents/ATBD/ATBD_VIIRS-SurfaceType_v2.2.pdf) (accessed on 24 September 2024).
55. Belward, A.; Loveland, T. The DIS 1 km land cover data set. *Glob. Chang. News Lett.* **1996**, *27*, 7–9.
56. Hurricane Ida. Available online: [https://en.wikipedia.org/wiki/Hurricane\\_Ida](https://en.wikipedia.org/wiki/Hurricane_Ida) (accessed on 24 September 2024).
57. Joint VIIRS-ABI Floodwater Fraction Map Products. Available online: <https://gis-fema.hub.arcgis.com/apps/8332b01063a949399ba846e93e6e26f/explore> (accessed on 24 September 2024).

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58. The GFM Product Definition Document. Available online: <https://extwiki.eodc.eu/GFM/PDD> (accessed on 24 September 2024).
  59. Bernard, T.G.; Davy, P.; Lague, D. Hydro-Geomorphologic Metrics for High Resolution Fluvial Landscape Analysis. *J. Geophys. Res. Earth Surf.* **2022**, *127*, e2021JF006535.
  60. Costabile, P.; Costanzo, C.; Lombardo, M.; Shavers, E.; Stanislawski, L.V. Unravelling spatial heterogeneity of inundation pattern domains for 2D analysis of fluvial landscapes and drainage networks. *J. Hydrol.* **2024**, *632*, 130728. [[CrossRef](#)]

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