ECE-471 Remote Sensing Technical Memo

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Objective

The main goal of this project is to develop and evaluate flood mapping pipeline with remote sensing data and machine learning. A classification model was trained using the Sen1Flood11 public dataset to classify between flooded and non-flooded areas based on the satellite image features. Sentinel-1 SAR bands (VV and VH), NASA DEM elevation, and JRC Permanent Water Bodies data were used as input features. Then the trained model was applied to an unseen region, Matagorda County in Texas during the Hurricane Harvey event to generate a flood prediction map. Model performance was assessed through visual inspection of the prediction map along with the images before the flood and during the flood.

Background

Flood mapping is especially critical in hurricane-prone regions such as Texas, Louisiana, Mississippi, and Florida. An accurate and timely flood map plays a vital role in disaster management by allowing rapid identification of inundated areas, supporting emergency response efforts, and guiding infrastructure planning and mitigation strategies. Additionally, flood maps are valuable tools in the insurance industry for assessing and predicting flood risk.

Methodology

<u>Sen1Flood11 Dataset</u>

The Sen1Floods11 dataset provides the core training data for this project. It is developed by a public benefit corporation called "Cloud to Street" and offers a valuable collection of hand-labeled flood maps from 11 historical flood events across various regions of the world. The dataset includes co-registered Sentinel-1 synthetic aperture radar (SAR) imagery and pixel-level flood annotations, which makes it particularly well-suited for training machine learning models to recognize flood patterns.

Its global scope and variety of flood scenarios help improve the generalizability of models trained on it and allow them to perform well across different terrains and conditions. This dataset is especially useful in this project, as it provides clear examples of both flooded and non-flooded areas. In addition, Sen1Floods11 includes predefined training, validation, and test splits, which makes it much easier in model development process. Its standardized format and seamless integration with Sentinel-1 imagery make it an ideal choice for this project's flood mapping pipeline.

Feature Collection and Input Variables

The classification model was trained using various remote sensing features. These features are sent in as input variables along with the Sen1Flood11 data to enhance the model's ability to detect flood patters under different terrain or land cover conditions. This primary input features include the following:

- **Sentinel-1 SAR VV and VH Bands**

  VV and VH bands are dual-polarized SAR bands that are especially sensitive to surface roughness and moisture contents. Flooded areas typically exhibit a strong backscatter in VV and VH bands due to the specular reflection of radar waves on water surfaces. Including both bands helps capture variation between dry and flooded areas.

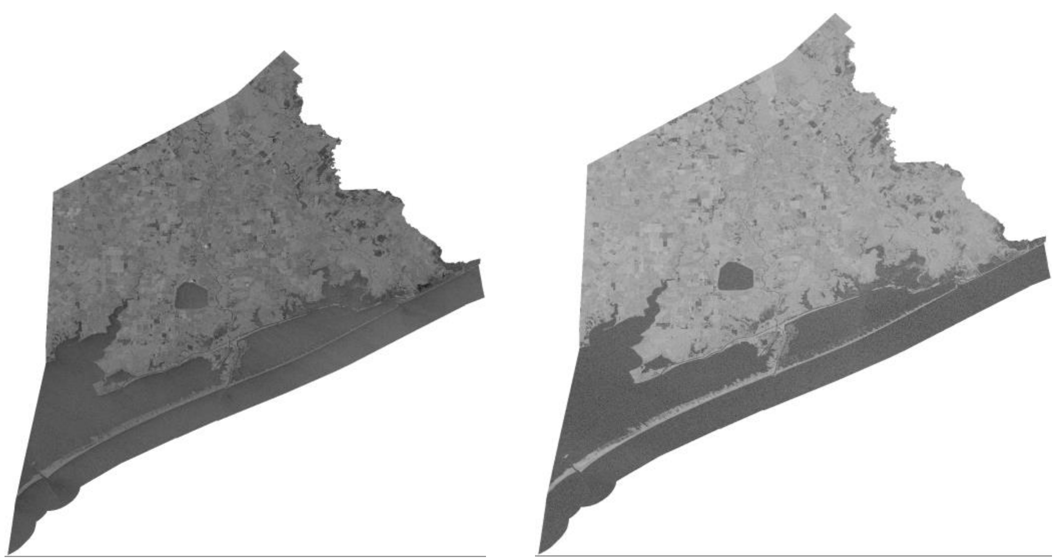

Figure 1: VV Band Imagery (Left) and VH Band Imagery (Right) of Matagorda County, Texas

- **NASA DEM Elevation**

Elevation data derived from NASA's Digital Elevation Model adds topographic context to the classification process. Since lower elevation areas are generally more prone to flooding, elevation data is an important predictive feature.

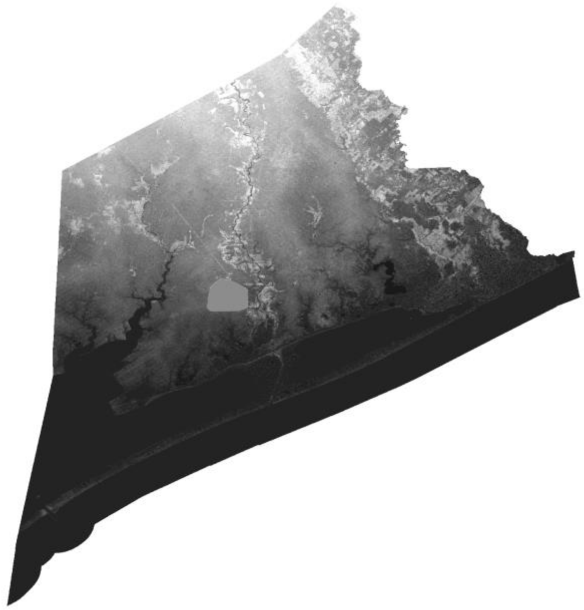

Figure 2: Elevation Imagery of Matagorda County, Texas. White pixels represent higher elevation, while darker pixels represent lower elevation.

- **Slope**

Slope is calculated from the DEM data and provides insight into the terrain's steepness. This shows the movement of water when the flood happens and areas that are more likely to accumulate water.

Figure 3: Slope Imagery of Matagorda County, Texas. White lines represent steeper slope.

- **JRC Permanent Water Bodies**

The JRC Permanent Water Bodies dataset was used in the post-training to mask out permanent water bodies. This dataset is critical to ensure the model to focus only on identifying temporary flood events. This distinction between static and dynamic water features improves classification precision and reduces false positives.

Figure 4: JRC Permanent Water Bodies Map of Matagorda County, Texas.

Together, these features create a multidimensional input space that allows the model to learn complex patterns associated with flooding, thereby improving prediction accuracy when applied to new regions such as Matagorda County, Texas.

Applying Model to Unseen Region

To evaluate the model's generalizability, the trained classifier was applied to an unseen region—Matagorda County, Texas—during the Hurricane Harvey event. Hurricane was one of the most devastating hurricanes in U.S. history that stroke Texas and Louisiana in August 2017. It brought record-breaking rainfall, with some areas receiving over 60 inches, resulting in widespread flooding across southeastern Texas. Matagorda County, located along the Gulf Coast, was among the regions significantly impacted by the storm's initial landfall and subsequent rainfall-driven flooding.

The trained model was deployed in this new region to generate a flood map based on the input features collected from Sentinel-1 SAR imagery (VV and VH), NASA DEM elevation and slope, and post-processed JRC Permanent Water Bodies data. A new feature stack was created for Matagorda County within the defined flood period of Hurricane Harvey (August 25 to 31), and the model was used to classify each pixel as non-water, floodwater, or permanent water. The resulting prediction map was then exported as a GeoTIFF file and analyzed using QGIS for visual inspection and comparison against a reference flood map.

Verification with Reference Map

To verify the flood prediction results, an independent reference dataset [1] was obtained from the Dartmouth Flood Observatory, which documented Hurricane Harvey flooding in Matagorda County through remote sensing analysis. The reference data was first processed by clipping it to the exact region of interest using a shapefile boundary, then a pixel-based classification algorithm was applied to convert the RGB reference map into a standardized three-class scheme (non-water, flood water, permanent water), seen in Figure 5, by identifying specific RGB value patterns (red pixels [224,0,0] for flood areas, blue pixels [48,117,255] for permanent water bodies). Since the reference dataset had different spatial resolution and projection parameters, a two-step spatial alignment process was employed involving reprojection to match the coordinate reference system of the prediction map, followed by nearest-neighbor resampling to ensure identical pixel dimensions and geographic positioning. This allowed for direct pixel-to-pixel comparison between the two datasets.

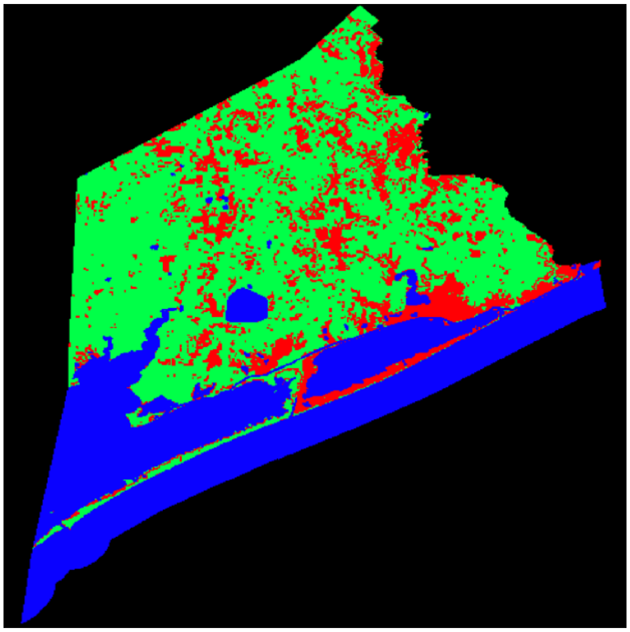

Figure 5: Classified Flood Map of Matagorda County During Hurricane Harvey Developed by Dartmouth Flood Observatory [1]

Result

Model Performance on Training and Validation Data

Performance of the trained classification model was assessed across three classes: Non-Water, Flood Water, and Permanent Water. As shown in figure 6 and 7, the model achieved an overall accuracy of 79%**.** Class-wise F1-scores were 0.82 for Non-Water**,** 0.69 for Flood Water**,** and 1.00 for Permanent Water, which indicates good performance in distinguishing non-water and flood water.

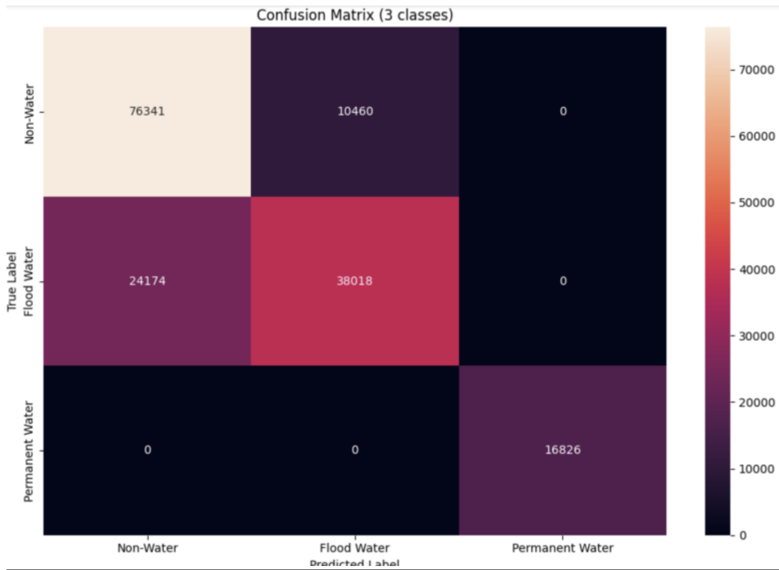

Figure 6: Confusion Matrix of Model Trained with Sen1Flood11 Data and Post-Processed with JRC Data

Classification Report (3 classes - Non-Water, Flood Water, Permanent Water):

	precision	recall	f1-score	support
Non-Water	0.76	0.88	0.82	86801
Flood Water	0.78	0.61	0.69	62192
Permanent Water	1.00	1.00	1.00	16826
accuracy			0.79	165819
macro avg	0.85	0.83	0.83	165819
weighted avg	0.79	0.79	0.79	165819

Figure 7: Classification Report of the Trained Model

However, the relatively lower recall for flood water suggests that while the model successfully identifies many flooded areas, some are still misclassified as non-water - likely due to backscatter similarity in complex or vegetated regions. Nonetheless, the model demonstrates strong overall classification capability and is robust enough for application to unseen data.

<u>Application to Matagorda County During Hurricane Harvey</u>

As shown in figure 8, the flood map generated by the model clearly identifies widespread flooding across low-elevation coastal and inland areas, with floodwater (in red) concentrated along river systems, flat farmlands, and urban zones.

Visual analysis of the prediction output shows that the model effectively captured both large flood extents and narrow flood trails. The spatial pattern of flooding closely aligns with known impacted areas during Hurricane Harvey. Although a formal accuracy assessment was limited by the lack of pixel-level ground truth for Matagorda County, the results are consistent with observed flood behavior during the event. This suggests that the model trained on Sen1Floods11 data can be transferred to real-world, large-scale disaster scenarios, providing timely and meaningful flood maps for emergency response and planning.

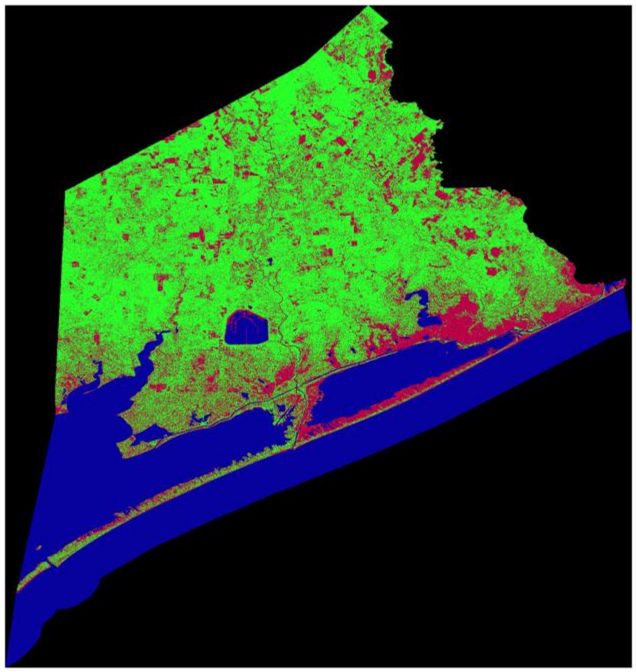

Figure 8: Flood Map of Matagorda County During Hurricane Harvey Generated with Trained Classification Model

Discussion

<u>Reference Map</u>

The validation of the flood prediction model using the reference map from the Dartmouth Flood Observatory [1] revealed important information about model performance and how different methodologies can drastically produce different results. Analysis of the aligned reference map using a confusion matrix, seen in Figure 9, showed that there was strong agreement for permanent water (93% recall) and non-water areas (79% recall), but weaker performance for temporary flood detection (52% recall, 43% precision).

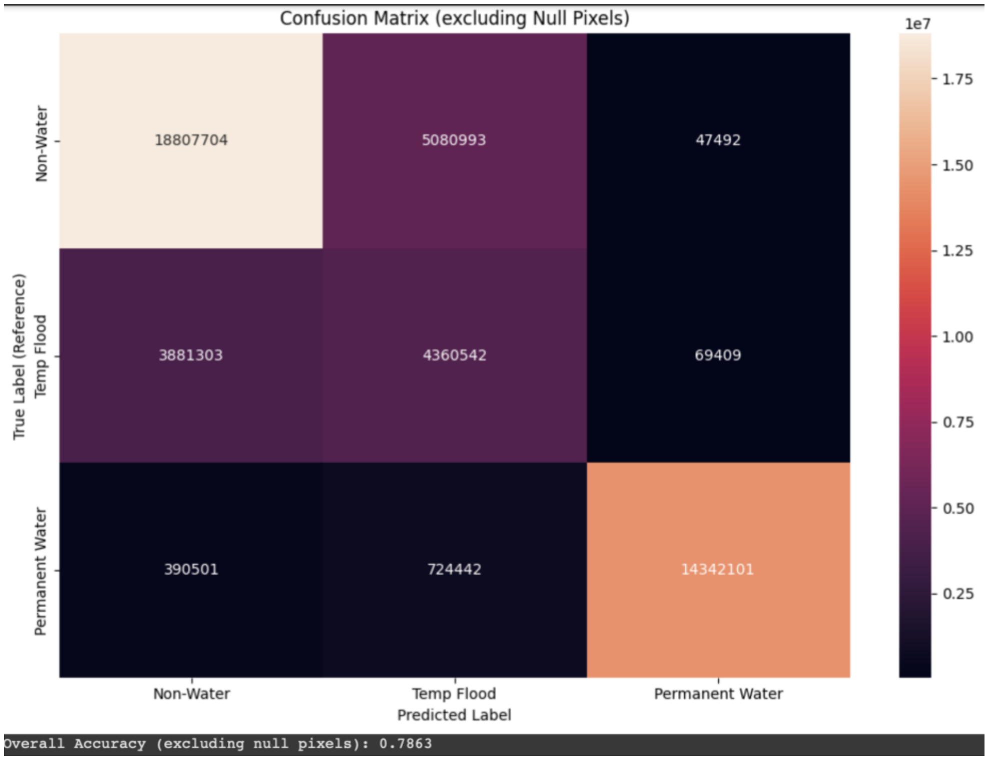

Figure 9: Confusion Matrix from Validation of Trained Model with Reference Map

This difference in accuracy comes mainly from using different methods to classify flood areas. The reference map used a simpler approach - applying a filter to smooth SAR images from before and after the flood, then using thresholds to find darker pixels (water) and calculate how much darker areas became during flooding. This manual method is quite different from our machine learning approach that combines SAR data (VV/VH), elevation, slope, and permanent water information to make predictions.

The lower accuracy for temporary flood areas is also affected by resolution differences, with the reference map being lower resolution than our model. This creates problems especially in border areas between flooded and non-flooded land, or where pixels contain a mix of both. Additionally, the manual threshold method depends heavily on which specific threshold values were chosen, potentially detecting different water depths than what our model learned to identify.

Because of these methodological differences, quantitative accuracy metrics alone provide an incomplete assessment. A more meaningful validation approach involves qualitative comparison of our model predictions with optical satellite imagery from Sentinel-2, which offers visual confirmation of flood extent patterns. While the statistical comparison with the reference data shows moderate agreement, the optical imagery provides clearer evidence of our model's effectiveness in capturing the spatial distribution of Hurricane Harvey flooding across Matagorda County.

Evaluation

Due to the low quality and limited resolution of the available reference flood map for Matagorda County, a quantitative accuracy assessment was not sufficient for evaluating the model’s real-world performance. Instead, a visual comparison was conducted using pre- and post-flood Sentinel-2 imagery, which offered clear insight into actual flood conditions on the ground. As shown in figure 10 and 11, by examining changes in the landscape, such as water pooling in fields and along river channels, the model's prediction map was visually assessed for consistency with observed flooding. The flood prediction map showed strong alignment with these visual cues, successfully capturing major inundated regions and water accumulation patterns. Although the output contained some scattered noise, it generally produced a coherent and realistic flood extent. This visual validation confirmed that the model performs reasonably well even when applied to complex, cloud-covered, and noisy environments like southeastern Texas during Hurricane Harvey.

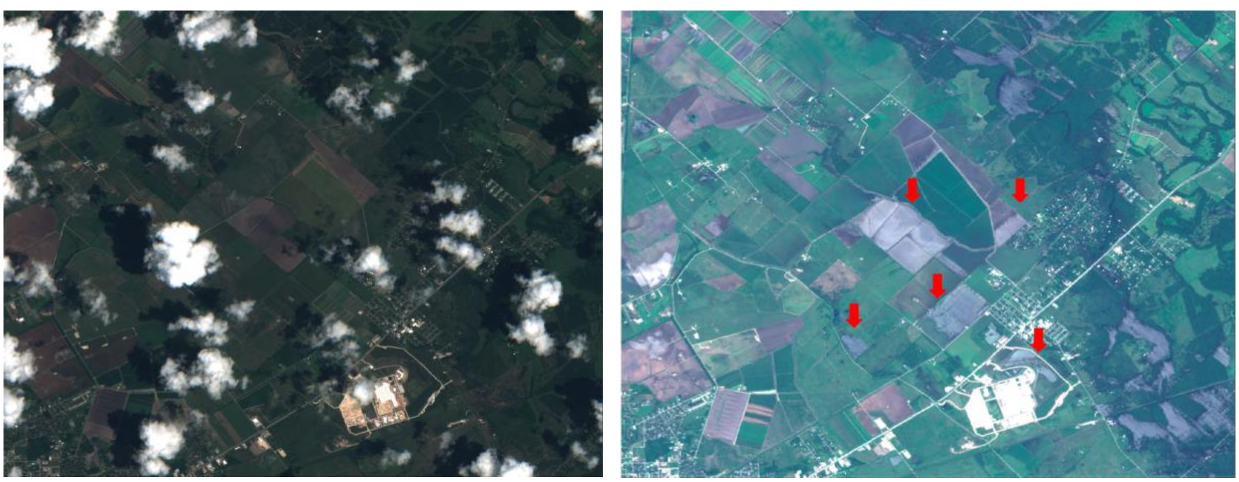

Figure 10: Sample Area of Matagorda County Before (Left) and After (Right) the Hurricane. Example of Flooded Areas are Indicated with Red Arrows

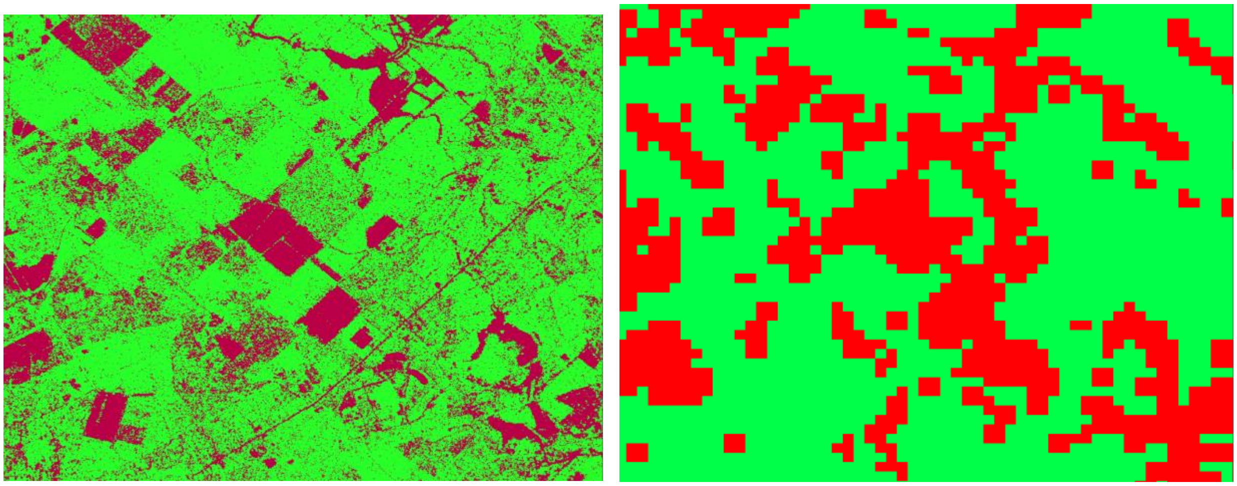

Figure 11: Flood Map Generated with Trained Model (Left) and Reference Map (Right) for Same Sampled Area with Figure 10

Future Work

While the current model demonstrates successful results, several areas remain for further development and improvement.

First, rather than relying solely on visual inspection to evaluate flood predictions, future work could incorporate Normalized Difference Water Index (NDWI) derived from Sentinel-2 imagery. NDWI would provide an independent spectral indicator of water presence, allowing for a more objective validation of whether the regions identified by the model are indeed flooded.

Second, current flood map includes some scattering noise. Applying post-processing speckle filters could help reduce these artifacts and produce cleaner, more spatially coherent flood boundaries.

Lastly, the model should be tested on additional historical flood events, especially those of smaller scale than Hurricane Harvey. Since Harvey was an extreme case, validating the model on moderate or minor flooding scenarios would help assess its generalizability and robustness across a broader range of hydrological events and geographic conditions.

References

[1] *2017 Flood USA 4510*.

(n.d.). https://floodobservatory.colorado.edu/Events/2017USA4510/2017USA4510.html