

Evaluation of the Water Masks Generated by the SWOT Satellite and Comparison with Optical Sensors



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Introduction

The Surface Water and Ocean Topography (SWOT) mission, a collaboration between NASA and CNES, offers a novel opportunity to advance the monitoring of inland water bodies through high-resolution elevation and extent data, even under persistent cloud cover [1]. This is particularly relevant to Brazil, a country with extensive freshwater resources but significant challenges in monitoring water bodies at scale due to accessibility, cost, and the limitations of traditional methods. SWOT's Ka-band Radar Interferometer (KaRIn) overcomes many of these constraints by enabling high-resolution, cloud-independent measurements of water surface extent and elevation. While promising, the utility of many SWOT science products will depend directly on the quality of the water classification available in the raster and PixelCloud products. Initial observations indicate that the classification accuracy can be challenged under certain conditions, such as in the presence of specular ringing, dark water, and highly reflective surfaces like sandbanks [2]. In this context, this project proposes a systematic evaluation of water masks derived from the SWOT Raster 100m product, comparing them with established optical-based products such as OPERA (NASA/JPL).

Area and Methods

The areas of interest were selected to cover a range of distinct situations that can impact the water surface assessment. Figure 1 shows the site locations, as well as a table with the main contents in each selected scene. Dates were matched to minimize cloud cover on the Sentinel 2 scenery and guarantee a maximum of 5 days difference between SWOT and the reference mask.

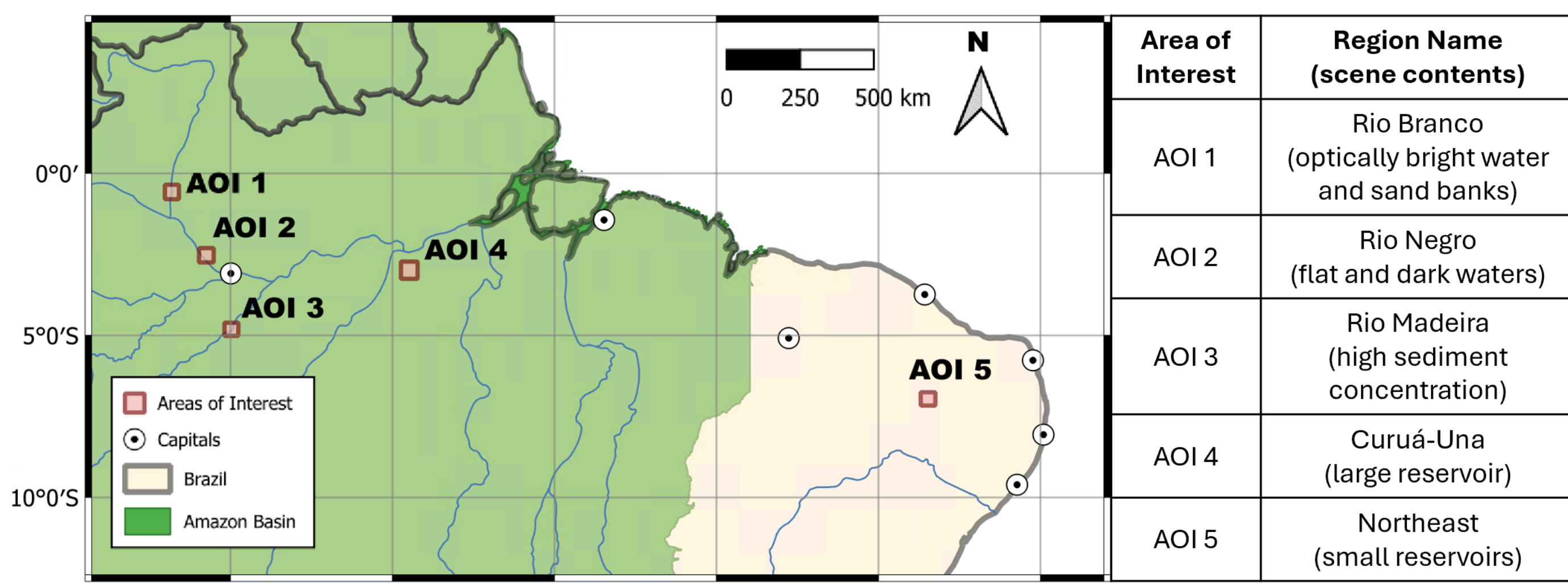


Figure 1: Areas of interest, corresponding dates and contents within each scene.

A fundamental premise for robust scientific validation is to use reference data of superior quality to the product being validated. There are two ways to ensure higher quality reference data: (i) using reference data with a higher resolution than the data being assessed; or (ii) using a measurement or interpretation method with greater accuracy than that used by the product [3]. In this project, the reference masks were produced with the Sentinel 2 multispectral imagery, through an interactive and supervised learning method. This method comprehends a random selection of training points, derived from the Scene Classification Layer (SCL), followed by a Random Forests classification. Besides the radiometry bands, the water indices NDWI and MNDWI were also included as input features. The masks were then refined by visual inspections that lead to adjustments in the training samples. Considering not all classes can be explained only by their radiometry, the final masks were cleaned and adjusted manually, ensuring water bodies greater than 0.5ha were represented correctly. The whole process is depicted in Figure 2.

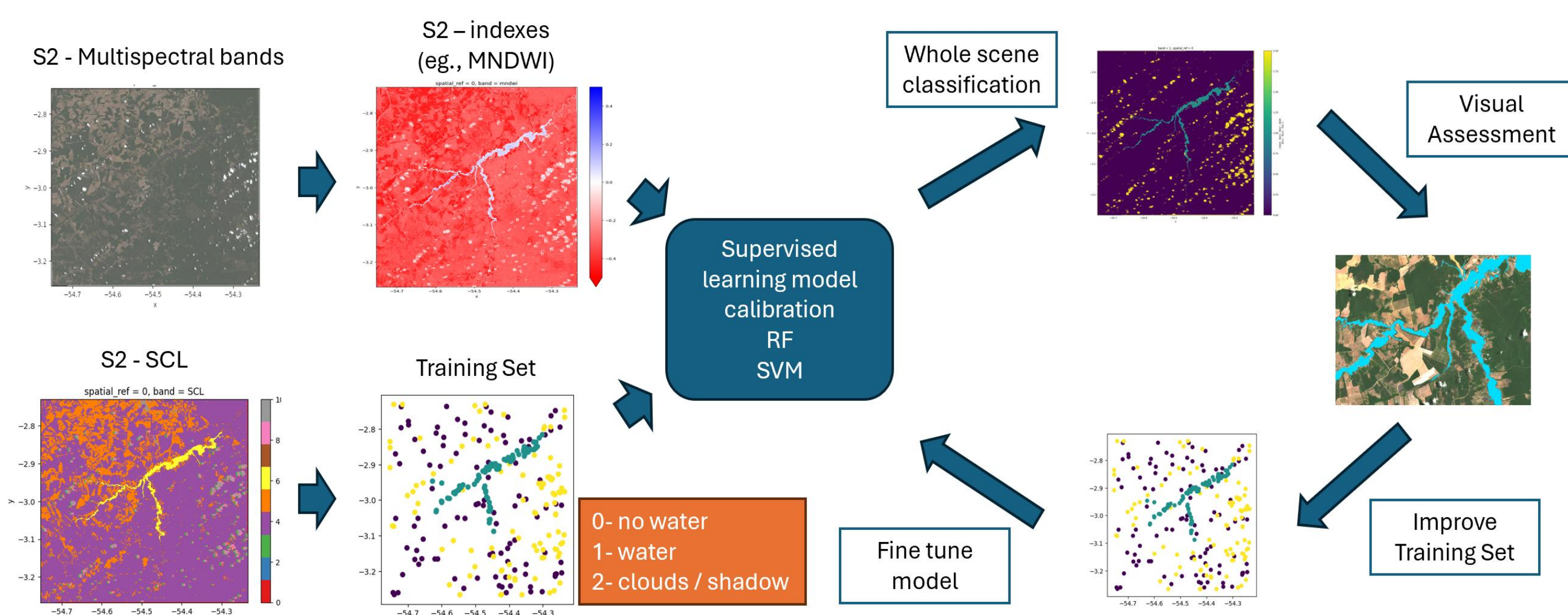


Figure 2: Interactive supervised methodology to produce the reference masks.

In addition to the reference masks, OPERA S2 and OPERA S1 products were also downloaded for each area of interest. Then, the SWOT raster with 100m of spatial resolution was used in this first part of the project. As the SWOT tiling is different from the S2 tiling, a mosaicking approach was conducted to ensure coverage of the entire AOIs (Figure 3).

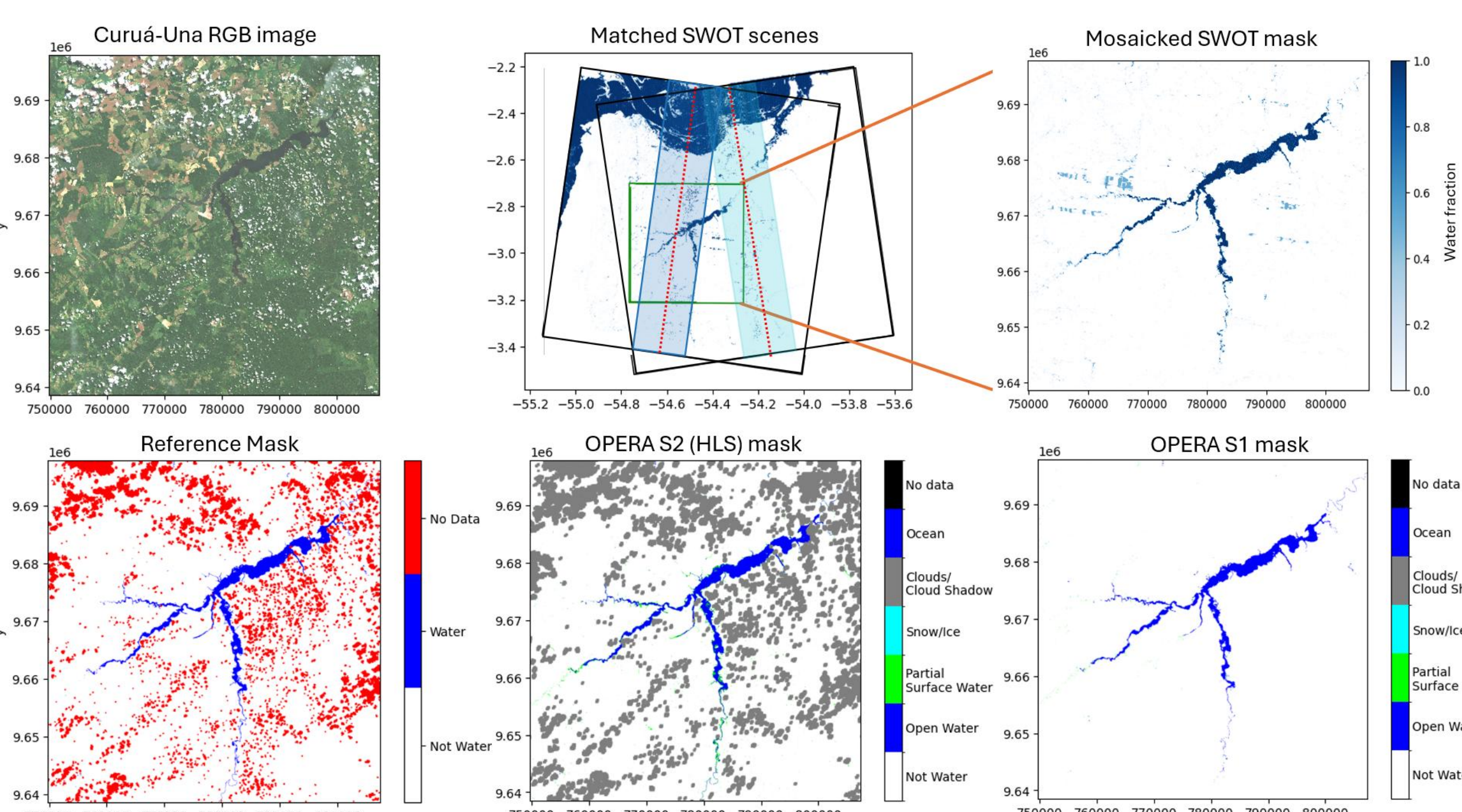


Figure 3: Curuá-Una scene, showing reference mask, OPERA masks and the SWOT mosaicking.

Preliminary Results

The first experiment compared all the masks to the reference ones, considering distinct scenarios on how the product flags were treated. OPERA S2 and S1 performed best without the inclusion of partial water pixels in their masks. For SWOT, the results excluding no data and excluding bad flags achieved similar results and were selected for the next experiments (Figure 4).

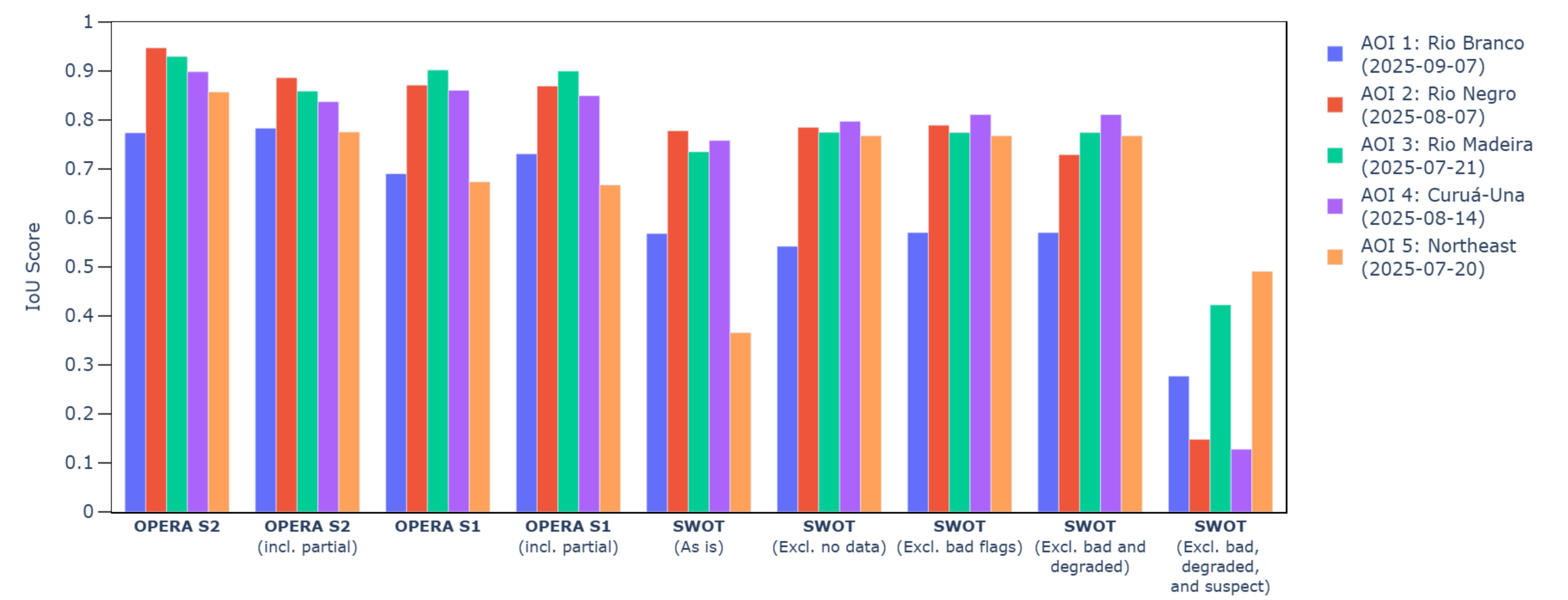


Figure 4: IoU metrics comparison across sites and flagging conditions.

To convert the water fraction available in the SWOT raster product into a binary water classification mask, it's necessary to select a threshold above which the pixel is considered water. The threshold was selected by testing values from 0 to 1, in 0.05 increments were tested for all sites. Figure 5, shows the median F1, IoU, Precision and Recall for each threshold. A threshold of 0.6 maximized the median F1 and IoU and was used as the best option for SWOT raster.

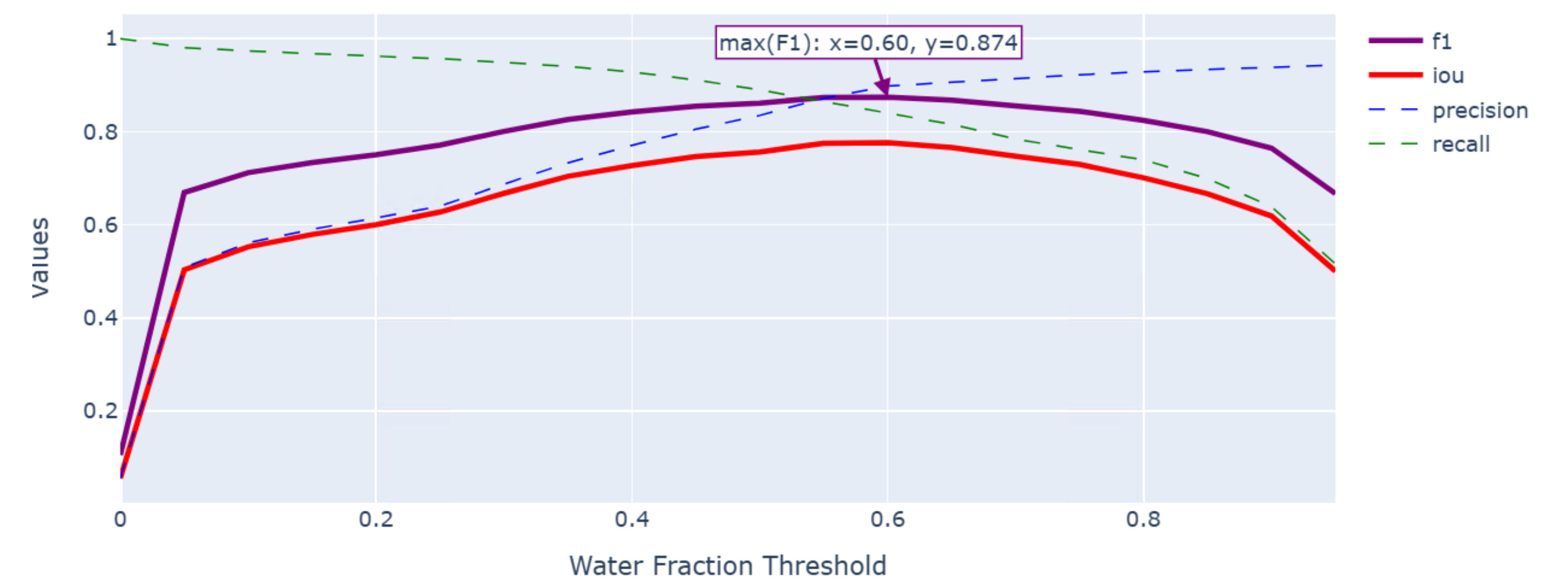


Figure 5: Median metrics calculated for different water thresholds across all the sites.

Initial results showed a good agreement between the reference mask and the OPERA S2, with median IoU of 0.899, followed by OPERA S1, with 0.861, and SWOT with 0.775. To test whether the agreement is related to the sensor a cross-validation was conducted considering each of the masks as the reference (Figure 6). Results are not exactly symmetrical due to the way no data is being handled in the reference masks. Additionally, the expected higher agreement between the radar sensors (OPERA S1 and SWOT) was not evident.

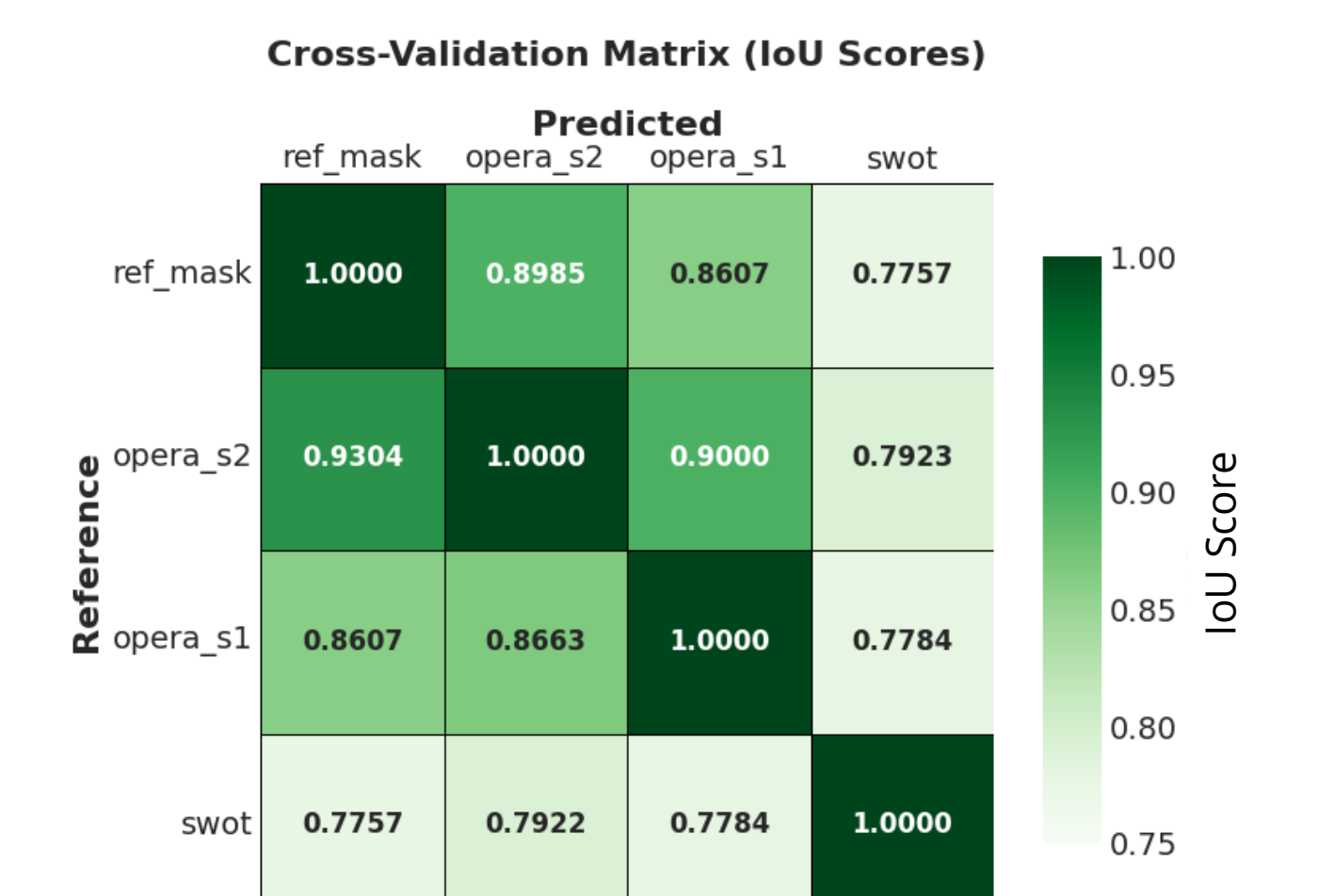


Figure 6: IoU values measured considering each mask as reference.

Finally, to assess the reason for the poor results obtained in the Rio Branco site, a more in-depth analysis has been conducted in the region. Visually, it can be noted that the SWOT raster misses part of the river Xeriuni, to the left of Rio Branco (Figure 7). Initial assessment, indicate that the occurrence of dark water (low backscatter signal) is most probable cause. Using the dark water flag to take these pixels into account, the IoU for this specific scene increased from 0.542 to 0.582, with a major improvement in the recall index (from 0.642 to 0.725).

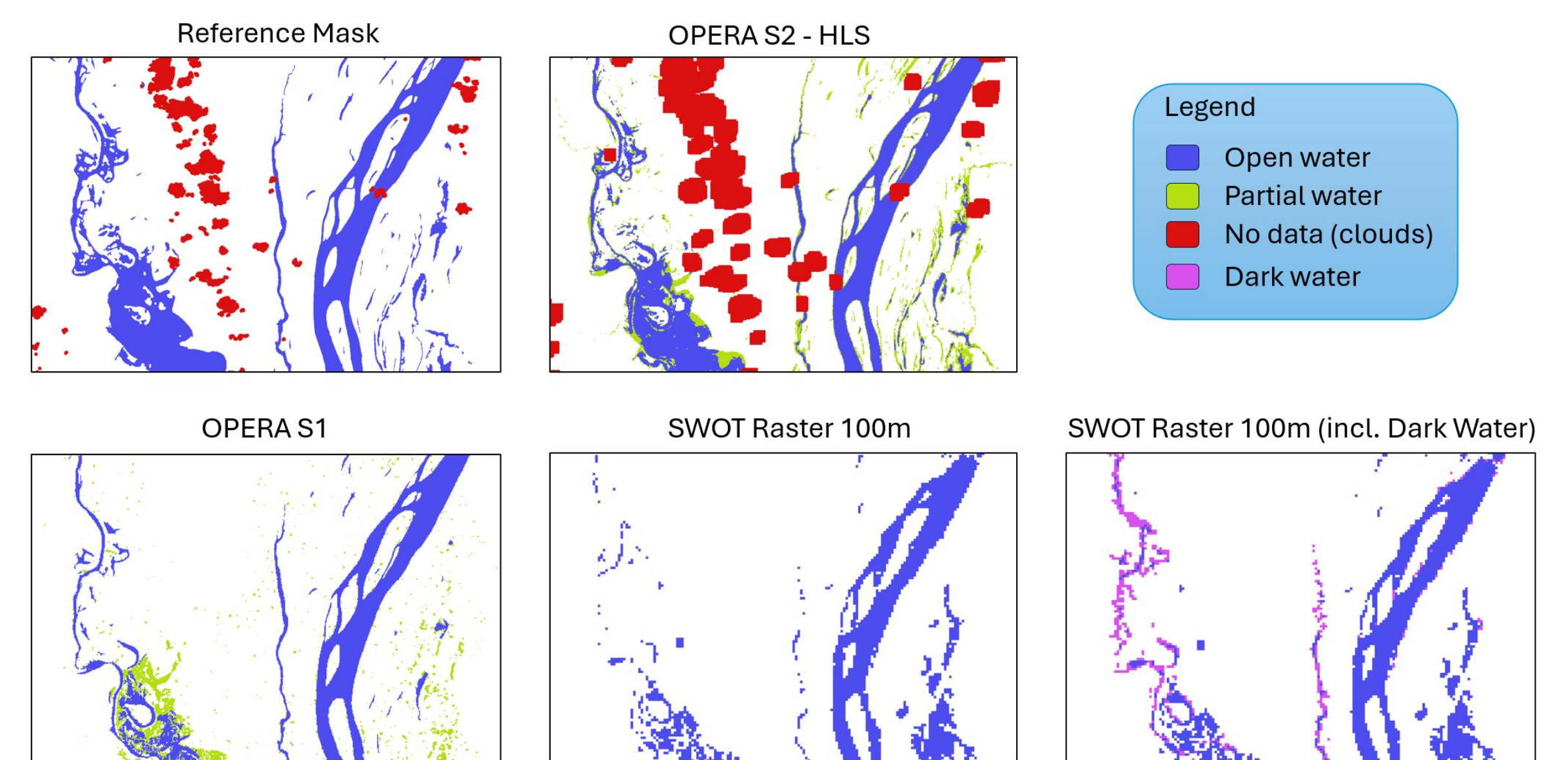


Figure 7: Water segmentation comparison in Rio Branco region.

References

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