Water Body Detection Using Remote Sensing

Laura Manuela Castañeda Medina
Daniel Felipe Torres Robles

February 24, 2025

1 Advantages and Drawbacks of Sensors for Water Body Detection

To effectively detect water bodies, we evaluated four types of remote sensing sensors: optical, Synthetic Aperture Radar (SAR), LiDAR, and SAR altimeters. Each sensor type offers different advantages and limitations, depending on the conditions and the application.

Optical Sensors

Optical sensors, such as those onboard satellites like Sentinel-2 and Landsat, operate in the visible and infrared regions of the electromagnetic spectrum. These sensors are particularly advantageous for water body detection because they provide high spatial and spectral resolution, making them ideal for indices such as the Normalized Difference Water Index (NDWI). Moreover, datasets from optical sensors are widely available as open access, which ensures accessibility for researchers and practitioners. Under favorable weather conditions, these sensors can effectively identify water features, leveraging the spectral differences between water and surrounding land or vegetation.

However, optical sensors face significant limitations. Their performance is highly affected by cloud cover, which can obscure the surface in regions prone to frequent precipitation. Additionally, these sensors are restricted to daytime operations as they rely on reflected sunlight for image acquisition. Another drawback is their struggle with mixed land-water pixels, such as those in densely vegetated wetland areas, where distinguishing water from vegetation becomes challenging.

SAR Sensors

SAR sensors, like those onboard Sentinel-1, provide an alternative by operating in the microwave region of the spectrum. Unlike optical sensors, SAR can acquire data regardless of weather conditions or lighting, making them ideal for regions with persistent cloud cover or for nighttime observations. SAR's ability to detect water boundaries with precision arises from the unique backscatter properties of water surfaces, which appear distinct from land or vegetation.

Despite these strengths, SAR sensors also have limitations. They generally offer lower spatial resolution compared to high-resolution optical sensors, which may reduce the clarity of fine-scale water features. Additionally, SAR data often require extensive preprocessing to reduce speckle noise, a characteristic granular pattern inherent to SAR imagery. This preprocessing increases the complexity of data analysis.

LiDAR and SAR Altimeters

LiDAR, which measures distances using laser pulses, and SAR altimeters, which focus on vertical measurements, have more specialized applications. LiDAR excels in generating highly accurate elevation models and is suitable for small-scale water body mapping or flood extent analysis. However, its limited coverage and high cost make it less practical for broad-scale studies. Similarly, SAR altimeters are optimized for measuring sea surface height and large-scale water level variations, making them more relevant for oceanographic studies than for detecting smaller inland water bodies.

Based on this evaluation, **optical sensors**, such as Sentinel-2, were selected as the primary choice for this study. Their high spatial and spectral resolution and their ability to calculate indices like NDWI make them highly suitable for water body detection. However, to address the limitations posed by cloud cover or nighttime conditions, SAR sensors, such as Sentinel-1, will serve as complementary tools. This combination ensures robust detection across a variety of environmental conditions while leveraging the strengths of both sensor types.

2 Sensor Selection: Single vs. Multi-Modal Approach

For the detection of water bodies, we have chosen to employ a multi-modal approach, combining the strengths of both optical and SAR sensors.

To overcome the mentioned limitations, SAR sensors will be used as a complementary tool. SAR operates in the microwave spectrum, allowing it to acquire data regardless of weather or lighting conditions. This capability makes SAR ideal for detecting water bodies in cloudy or dark conditions, where optical sensors are ineffective. SAR's unique backscatter properties further enhance its ability to delineate water boundaries, even in complex environments.

By combining these two sensor types, our multi-modal approach ensures robust detection under diverse environmental conditions. Optical sensors will serve as the primary source of high-resolution imagery, while SAR sensors will fill data gaps caused by cloud cover or insufficient light. This strategy allows for comprehensive and continuous water body detection, maximizing the strengths of both sensor technologies.

3 Image Source Selection: Open HR vs. VHR Commercial Data

For this study, we have chosen to use open High-Resolution (HR) images from the Sentinel-1 and Sentinel-2 satellites, available through platforms such as the Copernicus Open Access Hub and Google Earth Engine. These datasets offer the necessary spatial and spectral resolution for water body detection while being freely accessible, making them well-suited for academic research.

Sentinel-2 provides multispectral imagery at 10m resolution for key bands, enabling accurate calculation of water-specific indices such as the NDWI. Sentinel-1, on the other hand, delivers radar data that ensures reliable detection even under cloudy or nighttime conditions.

We opted against using Very High-Resolution (VHR) commercial satellite data from providers like TerraSAR-X or Pleiades for the following reasons:

- **Cost**: VHR datasets are expensive and not feasible within the scope of this project.
- **Coverage**: While VHR images offer finer resolution, HR data from Sentinel-1 and Sentinel-2 provide adequate detail for water body detection and cover larger areas efficiently.
- **Accessibility**: Open datasets are readily available and come with comprehensive tools for downloading and preprocessing, streamlining the workflow.

By leveraging the open HR datasets from Sentinel-1 and Sentinel-2, we ensure both cost efficiency and robust data quality, making them the optimal choice for this study.

4 Non-Learning Approach: NDWI for Water Body Detection

To detect water bodies without using learning-based methods, we employed the Normalized Difference Water Index (NDWI). This index utilizes the spectral properties of water, distinguishing it from land and vegetation based on the reflectance in the green and near-infrared (NIR) bands. The NDWI is calculated as follows:

$$\text{NDWI} = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}}$$

where the green band (e.g., Band 3 in Sentinel-2) typically has higher reflectance for water, and the NIR band (e.g., Band 8 in Sentinel-2) has significantly lower reflectance. Water bodies generally exhibit positive NDWI values.

Steps in the Analysis

1. **Data Preprocessing:** A Sentinel-2 Level-2A image covering a region with notable water bodies was downloaded. Preprocessing included cloud masking, atmospheric correction, and clipping to a specific Region of Interest (ROI).
2. **NDWI Calculation:** The NDWI was computed using the formula above, and a threshold (e.g., $\text{NDWI} > 0.3$) was applied to classify water pixels.
3. **Visualization:** The resulting binary mask was overlaid on the original image to visualize detected water bodies.
4. **Evaluation:** The accuracy of the detection was visually assessed against reference images or ground truth data.

Results and Discussion

The NDWI method effectively highlighted large water bodies, such as lakes and rivers. However, challenges arose in areas with mixed pixels, such as vegetation over water or shallow water regions. Additionally, shadows and cloud edges occasionally resulted in misclassifications, although preprocessing mitigated these effects.

This approach demonstrated that NDWI is a simple and computationally efficient method for water body detection, making it a reliable choice for initial analyses.

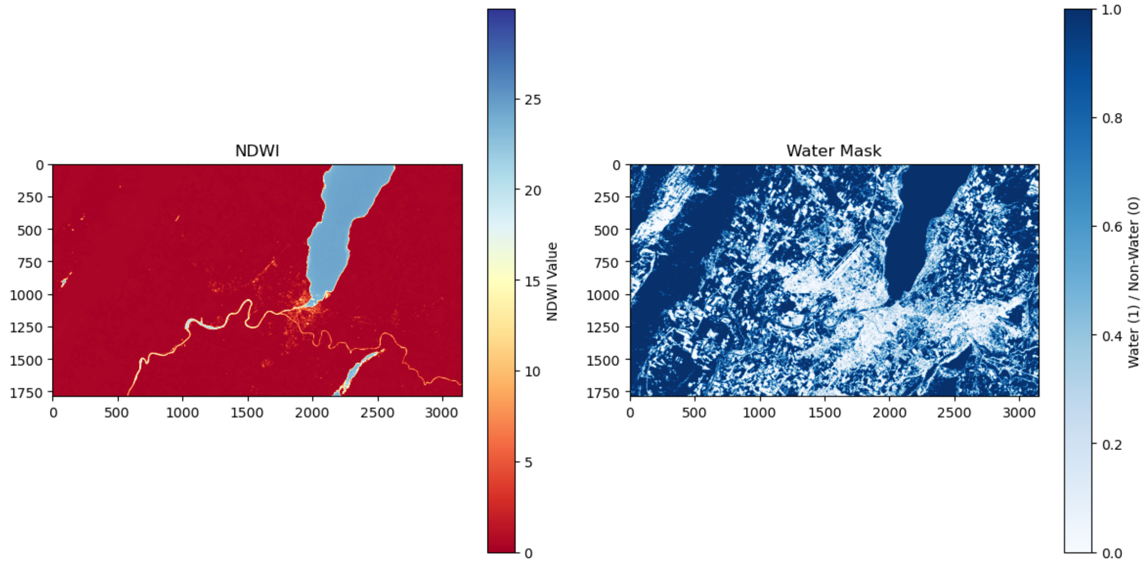

Figure 1: NDWI Map (left) and Water Mask (right) for the Lake Geneva region. The NDWI map shows positive values in blue indicating water bodies, while the binary mask highlights detected water regions.

NDWI Map

The NDWI map (left) correctly highlights the water bodies in the region, such as Lake Geneva and surrounding rivers. These areas are distinctly visible in shades of blue, representing positive NDWI values. The map also successfully captures small water bodies in the region, which demonstrates the effectiveness of the NDWI method in distinguishing water from land and vegetation.

Water Mask

The binary water mask (right), derived from applying a threshold to the NDWI values, identifies the major water bodies; however, it also includes false positives. Certain non-water areas, such as urban regions or vegetated surfaces, are incorrectly marked as water. This misclassification is likely due to the selected NDWI threshold value (e.g., 0.3), which may not be optimal for this dataset or geographic area. Additionally, while the NDWI map detects small water bodies, these features are often missed in the binary mask because they are either below the threshold or are lost among surrounding noise.

Strengths:

- Large water bodies, such as Lake Geneva, are well-detected in both the NDWI map and the binary mask.
- The NDWI map provides detailed information about smaller water features.

Limitations:

- The binary water mask fails to preserve smaller water bodies, which are overwhelmed by false positives in urban or vegetated areas.
- Thresholding introduces noise and misclassifications, highlighting the need for a more refined or dynamic threshold value.

5 Testing an Existing DL Dataset

For this analysis, we explored existing deep learning datasets relevant to water body detection. One such dataset, **Dynamic Earth Net**, provides annotated Sentinel-2 imagery for land cover classification, including water features.

Testing a Vanilla Methodology

To evaluate the potential of deep learning for water body detection, we propose testing a simple U-Net-based segmentation model on this dataset. The process involves:

1. **Dataset Preparation:** Sentinel-2 images are preprocessed and split into training, validation, and testing sets.
2. **Model Design:** A basic U-Net architecture is employed for semantic segmentation.
3. **Evaluation:** Model predictions are compared to ground truth annotations, and metrics such as IoU and F1-score are used to evaluate performance.

References

[1] W. Chan, N. Jaitly, Q. Le, and O. Vinyals, "Listen, attend and spell: A neural network for large vocabulary conversational speech recognition," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shanghai, China, 2016, pp. 4960–4964. [Online].