Flood mapping with optical and microwave satellite data: from indices to machine learning

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Supported by a NASA FINESST grant

Motivation

- Floods are the costliest natural disaster worldwide.
- A quarter of the global population is exposed to 1-in-100-year floods (Rentschler et al., 2022).
- Between 2000–2019, floods affected 1.6 billion people and caused $651 billion in damages (UNDRR, 2020).

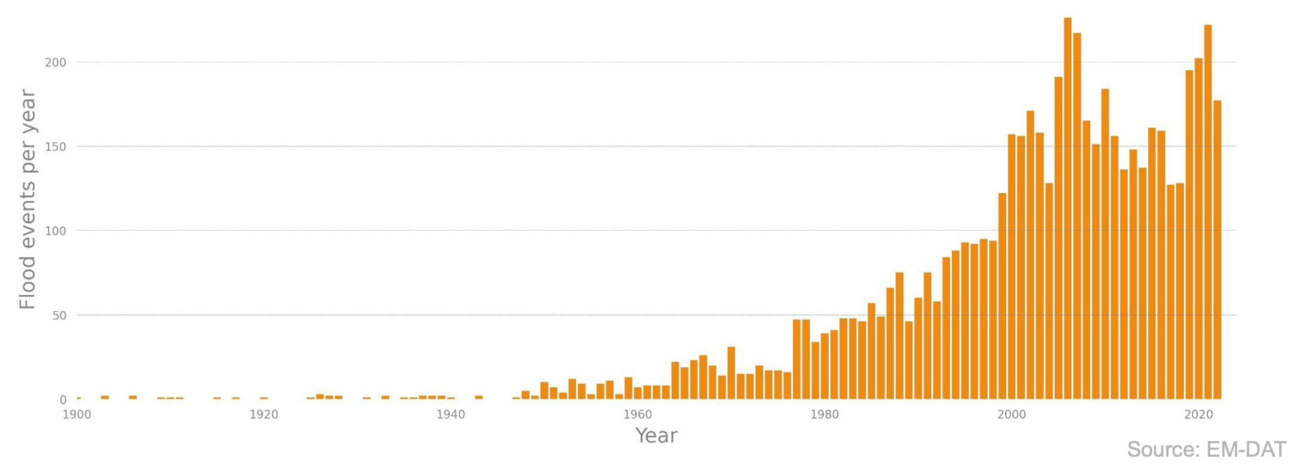

Figure 1. *Rising frequency of floods worldwide. Source: EM-DAT.*

- Nearly 89% of flood-exposed populations live in low- and middle-income countries.
- Reliable flood maps are essential for response, risk reduction, and climate adaptation.

Satellites for Flood Mapping

- Earth-observation satellites provide consistent, repeatable imagery for tracking changes in water and land.
- Optical sensors measure sunlight reflected from the Earth's surface.
- Radar (SAR) sensors actively send and receive microwaves, allowing imaging through clouds and at night.
- Combining both allows flood monitoring under all conditions.
- Freely available missions such as MODIS, Sentinel, and Landsat make global flood monitoring broadly accessible.

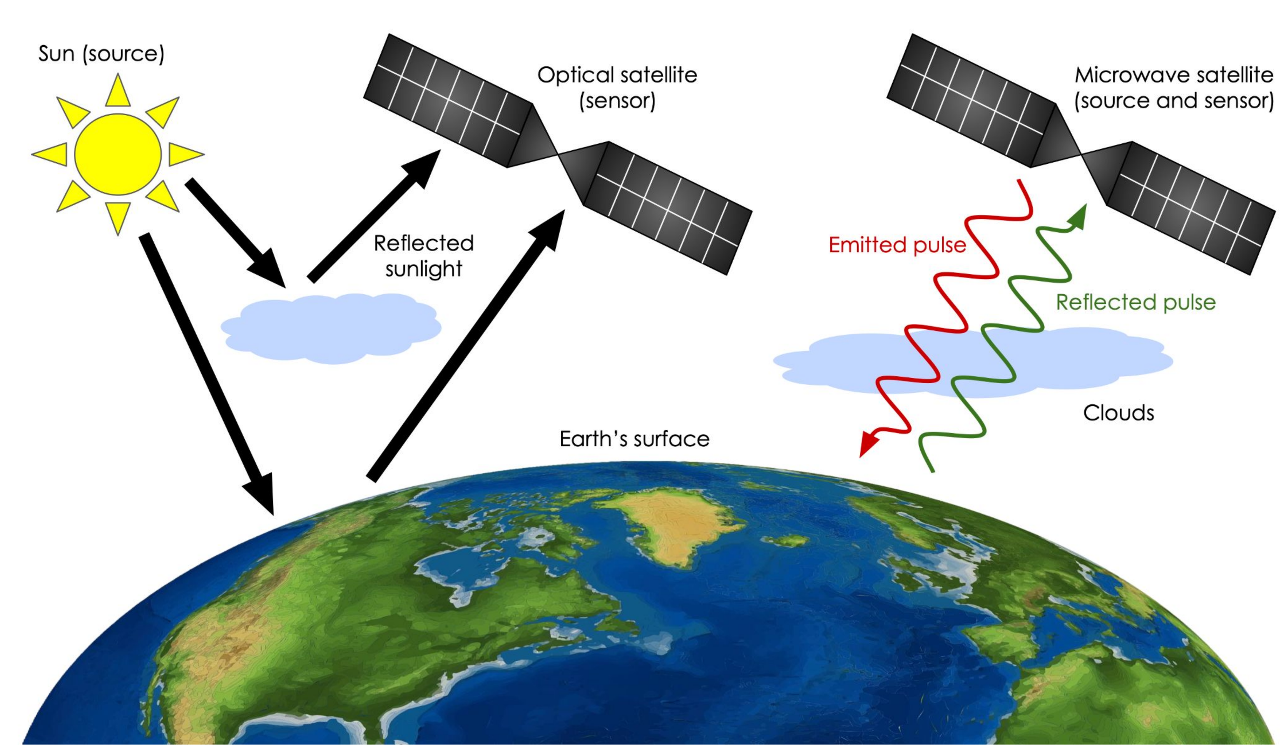

Figure 2. *Schematic illustration of optical and radar sensors used for flood mapping. Source: Tripathy et al. (2025).*

Optical vs Radar Satellite Sensors

- Optical data (e.g., Sentinel-2) is intuitive and ideal for clear-sky observations but fails under clouds.
- SAR data (e.g., Sentinel-1) works in any weather and at night, detecting surface roughness.
- Flooded surfaces appear darker in SAR imagery because smooth water reflects radar energy away from the sensor.
- Together, these sensors offer complete temporal coverage before, during, and after floods.

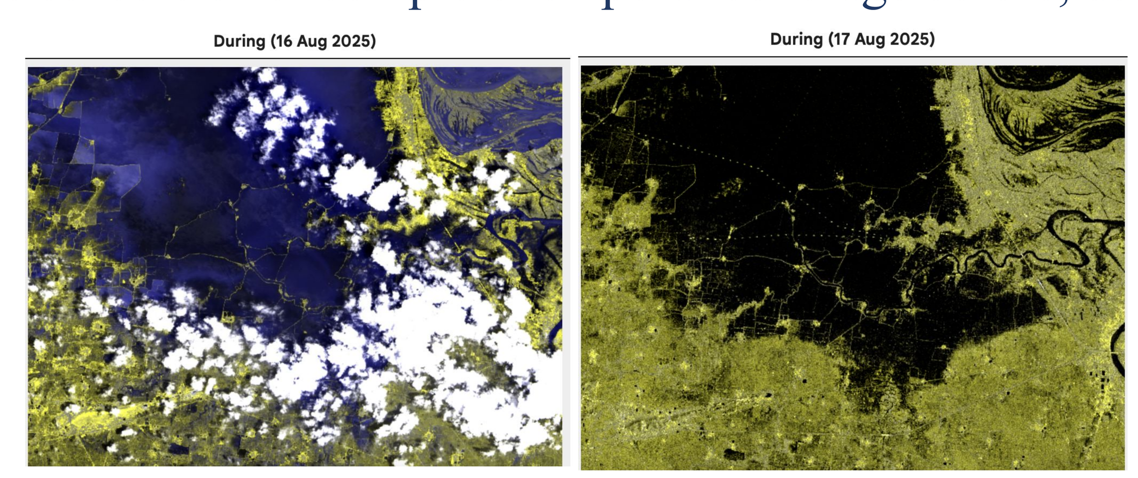

Figure 3. *Optical imagery (left) obscured by clouds; radar imagery (right) reveals flood extent through cloud cover*

Spatial Resolution: Coarse to Fine

- MODIS (250 m) provides wide-area monitoring suitable for continental-scale flood tracking.
- Sentinel-2 (10 m) resolves small rivers, floodplains, and urban inundation.
- Finer resolution increases local accuracy but demands greater storage and processing.
- Integrating multiple resolutions balances local detail with regional coverage.

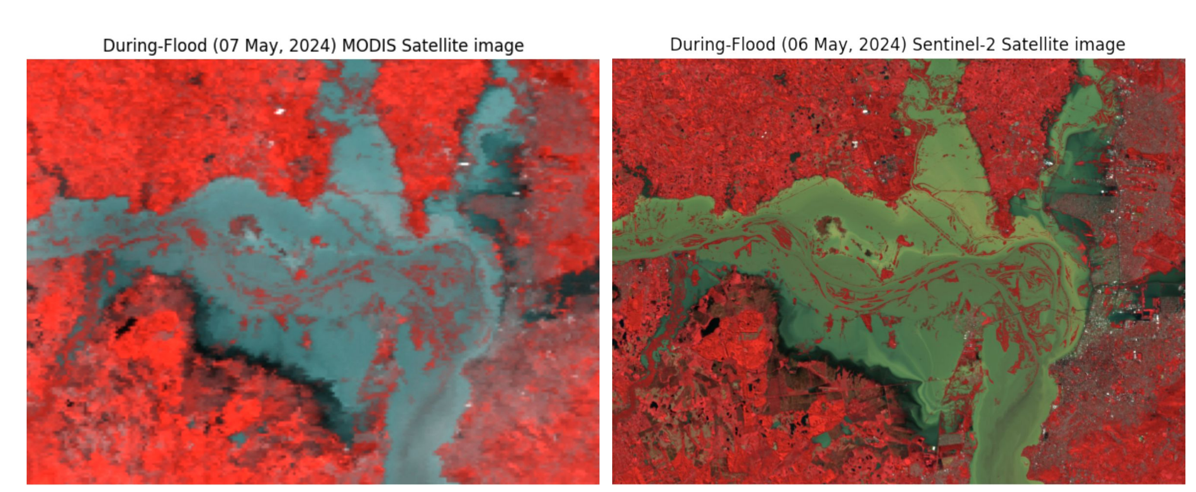

Figure 4. *MODIS (250 m) provides wide coverage, while Sentinel-2 (10 m) captures fine-scale inundation (Brazil, May 2024).*

References/ Further Readings

- UN Office for Disaster Risk Reduction (UNDRR). (2020). The Human Cost of Disasters: An Overview of the Last 20 Years (2000–2019).
- Rentschler, J., Salhab, M., & Jafino, B. A. (2022). Flood exposure and poverty in 188 countries. *Nature communications*, 13(1), 3527.
- Tripathy, P., & Malladi, T. (2022). Global Flood Mapper: a novel Google Earth Engine application for rapid flood mapping using Sentinel-1 SAR. *Natural hazards*, 114(2), 1341-1363.
- Rathore, J., Kumari, S., Tripathy, P., Mahto, S. S., & Lal, P. (2025). 2024 Brazil Floods: Mapping the extent and impacts in Eastern Rio Grande do Sul using geospatial techniques. *Natural Hazards Research*.

Flood Mapping Using Optical Data

- Compute the Modified Normalized Difference Water Index:
  MNDWI = (Green − SWIR) / (Green + SWIR).
- Threshold MNDWI values to classify water and flood extent.
- Effective in cloud-free conditions for pre- and during-flood comparison.
- Serves as a baseline and for training data generation.

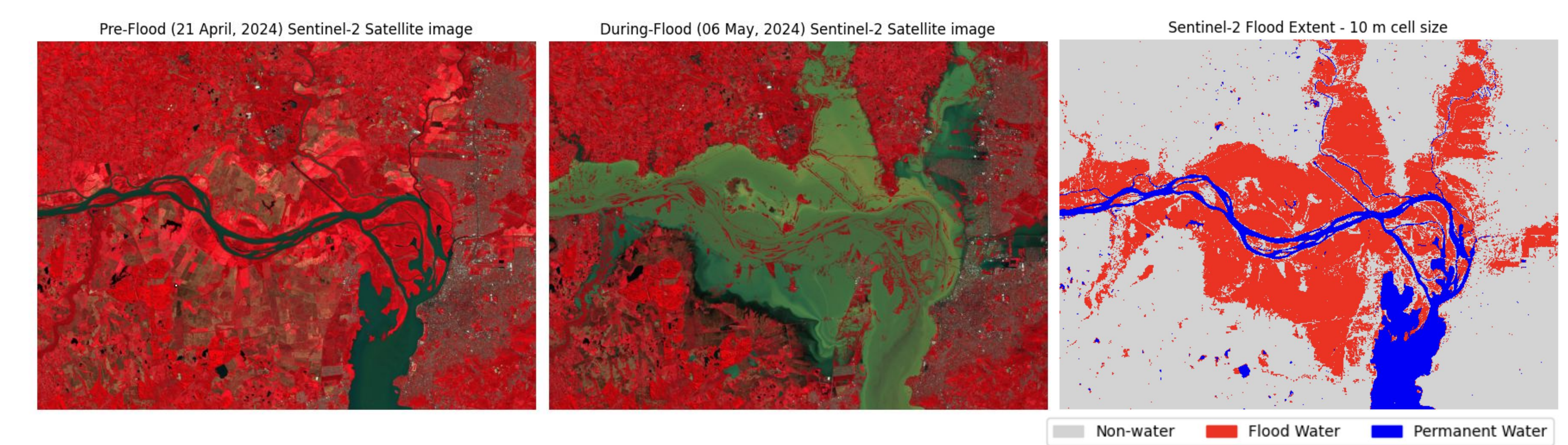

Figure 5. *MNDWI highlights flooded areas in Sentinel-2 imagery under clear-sky conditions.*

Flood Mapping Using SAR Data

- SAR captures backscatter intensity in VV and VH polarizations.
- Flooded areas show reduced backscatter relative to dry reference conditions.
- Band-ratio method: During / Pre-flood VV < 0.8 indicates inundation.
- Z-score method: Pixel-wise anomaly < −2.5 relative to dry-season mean.
- Spatial filtering (7×7) reduces speckle noise and smooths flood masks.

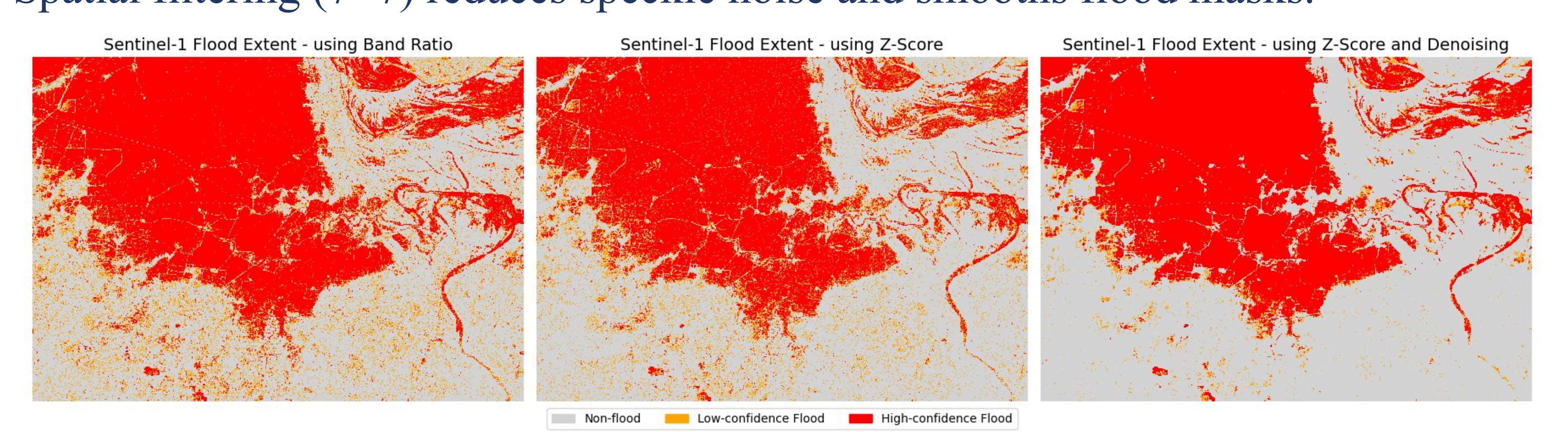

Figure 6. *Z-score anomaly mapping produces cleaner flood extent; denoising further refines the mask.*

Machine Learning for Flood Mapping

- Manual thresholds require case-specific tuning and expert supervision.
- Machine learning learns nonlinear patterns between VV/VH bands and flood labels.
- Models tested: Logistic Regression and Random Forest.
- Trained models predict flood extent in unseen regions without any further tuning.

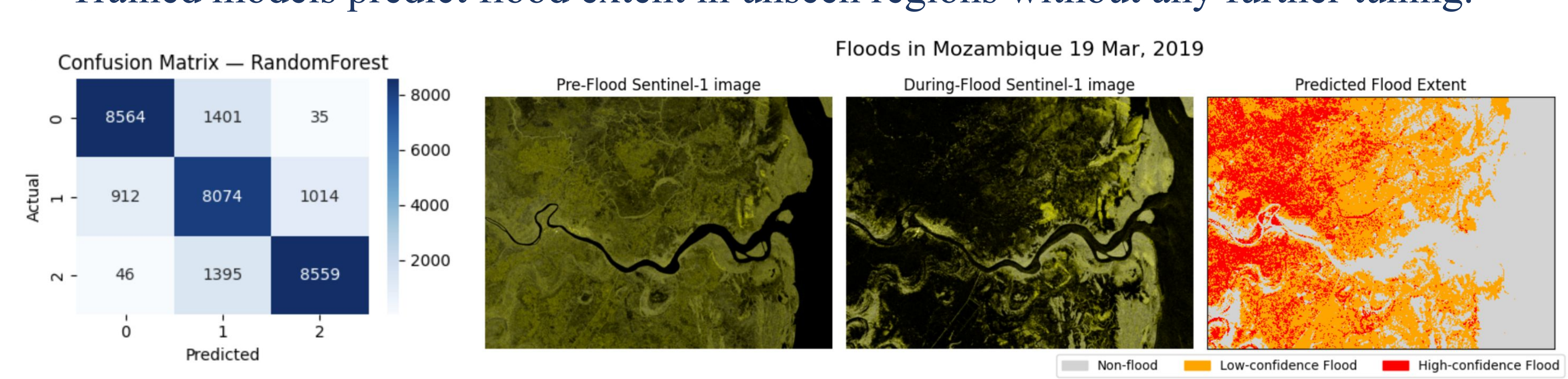

Figure 7. *Confusion matrix (left) and predicted flood extent (right) from trained Random Forest model.*