Mini Project Report

On

Flood Detection Using SAR Imagery: A Case Study of the 2018 Kerala Floods

Submitted By

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Certificate

This is to certify that the project, entitled Flood Detection Using SAR Imagery, is a bonafide record of the Mini Project coursework presented by the students whose names are given below during 2025 in partial fulfillment of the requirements of the degree of Bachelor of Technology in Data Science And Artificial Intelligence.

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1. Introduction

The 2018 Kerala Floods and the Role of Remote Sensing

The 2018 Kerala floods caused severe loss of life, displacement, and widespread damage. The disaster highlighted the need for timely, accurate flood inundation data to aid rescue, assessment, and recovery. Remote sensing, especially Synthetic Aperture Radar (SAR), is crucial in such situations due to its reliability during adverse weather.

SAR has a key advantage over optical sensors: it works regardless of cloud cover or time of day. Floods typically involve heavy rain and clouds, limiting optical imaging. SAR, using microwave energy, penetrates clouds and collects data day or night—vital for tracking rapidly changing flood conditions. As an active sensor, SAR sends and receives its own signals, ensuring consistent data capture.

Flood detection using SAR hinges on the contrast in radar backscatter: water surfaces reflect radar signals away, appearing dark in images, while land surfaces scatter signals, appearing brighter. This contrast helps identify flooded zones.

Google Earth Engine (GEE) supports large-scale SAR data analysis. Its cloud-based platform offers access to extensive satellite archives, including Sentinel-1 imagery, along with the computational power needed for processing. For events like the Kerala floods, GEE enables efficient flood mapping by simplifying data management and allowing rapid application of detection algorithms using pre-processed SAR data.

Sentinel-1 SAR Imagery for Flood Detection

The Sentinel-1 mission, operated by the European Space Agency, consists of two satellites (Sentinel-1A and 1B) providing continuous C-band SAR imagery at ~5.4 GHz (5.5 cm wavelength). This frequency offers a balance between atmospheric penetration and sensitivity to water and vegetation, making it well-suited for flood detection.

Sentinel-1 collects data in VV and VH polarization modes, both useful for flood mapping. VV typically shows low backscatter over calm water and is sensitive to vertical structures like vegetation, aiding detection in vegetated floodplains. VH captures rough surface and volume scattering, making it valuable in urban flooding where double-bounce effects between water and buildings enhance the signal. Using both VV and VH improves detection based on the flooding context.

The VV/VH backscatter ratio is another key indicator. Water usually shows a low ratio, and changes can reveal flooding or vegetation changes. This ratio also reduces effects from topography and sensor calibration, enhancing consistency.

Sentinel-1 GRD products, pre-processed for thermal noise removal, calibration, and terrain correction, are available in Google Earth Engine. The Interferometric Wide (IW) swath mode GRD data, with ~10 m resolution, is commonly used for regional flood mapping, including the 2018 Kerala floods. While SLC data includes phase info for interferometry, GRD's simplicity and lower noise make it ideal for mapping flood extents using pre- and post-event imagery.

2. Data And Methods

Preprocessing of Sentinel-1 SAR Imagery: Speckle Noise Reduction

Filter Name	Basic Principle	Key Advantages for Flood Mapping	Potential Disadvantages
Lee Filter	Locally adaptive filter using local mean and variance.	Effective speckle reduction in homogeneous areas.	Can blur edges and fine details.
Enhanced Lee Filter	Modification of the Lee filter with improved edge preservation.	Better at preserving edges compared to the standard Lee filter.	May not be as effective as Refined Lee in all scenarios.
Refined Lee Filter	Edge-adaptive filter using a non-square window aligned with local edge direction.	Excellent at preserving edges and fine details while reducing speckle noise.	Can be computationally more intensive than simpler filters.

Synthetic Aperture Radar imagery is inherently affected by speckle noise—a salt-and-pepper pattern caused by interference from scattered radar waves. This noise creates random pixel fluctuations, making it difficult to distinguish flooded from non-flooded areas based on backscatter intensity. As a result, speckle reduction is a crucial preprocessing step.

The Refined Lee Filter is a widely used adaptive method for reducing speckle in homogeneous regions while preserving edges and detail. Improving upon the original filter by aligning its window with edge direction, enhancing its ability to maintain important boundaries between flooded and dry zones. The filter uses local image statistics such as mean and variance to apply weighted average adapting to different image textures.

Performance is influenced by parameters like window size (commonly 3x3 to 7x7) and the number of looks, which estimates noise variance. Larger windows provide stronger smoothing but can blur critical features. Selecting optimal settings involves balancing noise suppression and detail preservation, typically through empirical testing tailored to Sentinel-1 data and the requirements of flood mapping.

Methodology for Identifying Flooded Areas Using VV/VH Band Ratio

Flood identification using Sentinel-1 SAR imagery can be effectively conducted by analyzing the VV/VH backscatter ratio, which accentuates differences in how water and land surfaces respond to radar polarizations. Calm water typically exhibits low backscatter in both VV and VH, but their ratio enhances contrast and mitigates the influence of varying incidence angles across the image.

In vegetated regions, floodwaters beneath the canopy can lead to increased VV backscatter due to double bounce between water surfaces and vertical vegetation structures, while VH responses vary depending on canopy density and structure. The VV/VH ratio helps distinguish between flooded vegetation, dry vegetation, and open water. Similarly, in urban environments, inundation alters scattering mechanisms—often increasing VH backscatter due to double bounce between water and building walls—making the ratio a valuable indicator for urban flooding.

A low VV/VH ratio generally signals flooding; however, the optimal classification threshold depends on local land cover and environmental conditions. A fixed threshold approach is commonly used, with the cutoff value determined empirically by analyzing known flood extents. Alternatively, multi-temporal analysis—comparing VV/VH ratios before and after the flood—can identify inundation through significant decreases. More advanced methods may involve adaptive thresholding or machine learning models that leverage additional SAR-derived features. Regardless of the technique, validation with ground-truth data remains essential to ensure classification accuracy.

Masking Permanent Water Bodies Using the JRC Global Surface Water Dataset

Accurate flood detection requires distinguishing temporary inundation from permanent water bodies like lakes, rivers, and reservoirs. The JRC Global Surface Water dataset offers 30-meter resolution maps derived from Landsat data (1984–2021) and includes useful bands such as water occurrence, recurrence, seasonality, and transitions.

It's long-term perspective helps identify consistently water-covered areas, which may appear as flooded in Sentinel-1 imagery due to low backscatter. The seasonality band, indicating the number of months per year water is present (0–12), is especially useful. A threshold—e.g., seasonality >10—can help classify permanent water pixels.

In Google Earth Engine (GEE), this involves importing the JRC dataset, selecting the seasonality band, creating a binary mask based on the chosen threshold, and applying this mask to Sentinel-1 flood maps. Multiplying the flood map by the inverse of the mask excludes permanent water bodies, improving focus on temporary flooding. Threshold choice is critical; a higher value (e.g., >10) ensures most permanent water is masked while retaining seasonally flooded areas relevant to the analysis.

Excluding Unlikely Flooded Areas Using Slope Information from USGS HydroSHEDS DEM

Topography significantly influences flood extent, water tends to accumulate in flat areas while steep slopes promote runoff. Incorporating slope data from Digital Elevation Model helps refine flood detection by excluding areas unlikely to flood. The USGS HydroSHEDS DEM, based on SRTM data and hydrologically conditioned, provides global elevation data at ~90 m resolution and is well-suited for hydrological analysis.

In Google Earth Engine (GEE), slope can be derived from the HydroSHEDS DEM using ee.Terrain.slope(), which calculates elevation change in degrees. A slope threshold can then be applied—studies have found that 0.28 degrees (~0.5%) works well for most DEMs. Pixels with slopes above this threshold are typically excluded from flood maps.

To integrate this in GEE, import the DEM, calculate slope, create a binary mask using the threshold, and apply the mask to the Sentinel-1 flood map. Multiplying the flood map with the slope mask filters out steep terrain, reducing false positives caused by radar artifacts like shadowing. However, the optimal threshold may vary by region and should be validated through testing, especially for complex terrains like in the 2018 Kerala floods.

Noise Reduction in Flood Maps Using Connected Component Analysis

After classifying flooded areas using the VV/VH ratio and masking out permanent water and steep slopes, the flood map may still show isolated pixels or small noisy patches. Connected Component Analysis (CCA) helps reduce these by grouping connected pixels and removing small, likely incorrect regions.

CCA labels each connected region in a binary image using either 4-connectivity (orthogonal neighbors) or 8-connectivity (includes diagonals). Small regions under a set pixel threshold are removed, helping refine the map by keeping coherent flooded areas and filtering out scattered noise.

Choosing between 4- and 8-connectivity impacts how regions are grouped—8-connectivity allows more merging, while 4-connectivity is stricter. Thresholds should be set based on image resolution and flood characteristics to balance noise removal and the preservation of true flood zones.

Calculating Flood Extent in Google Earth Engine

After refining the flood map, the next step is to calculate the flood's spatial extent. In Google Earth Engine (GEE), this involves combining the binary flood map (1 for flooded, 0 otherwise) with pixel area data. Since Sentinel-1 pixel sizes vary with geography, GEE's ee.Image.pixelArea() is used to account for these differences.

Multiplying the binary map by the pixel area image results in only flooded pixels holding area values. Then, reduceRegion() with ee.Reducer.sum() calculates the total flooded area within a region of interest. The result, in square meters, is converted to square kilometers by dividing by 1,000,000.

Accuracy depends on classification quality and resolution, but this method offers a solid estimate for assessing flood impacts and guiding response efforts.

3. Results and Discussions

Limitations of Using Sentinel-1 SAR Imagery for Flood Detection

Limitation	Description in the Context of Flooding	Examples of Affected Environments	Potential Mitigation Strategies
Urban Area Challenges	Complex backscattering due to buildings causes shadows, layover, and double bounce, leading to errors.	Densely built-up areas	Specialized urban flood detection algorithms, integration with LiDAR data.
Vegetated Wetland Issues	Signal interaction with canopy masks or is misinterpreted as inundation.	Marshes, forested wetlands	Multi-temporal analysis, use of different polarizations or SAR frequencies (e.g., L-band).
Impact of Weather Conditions	Strong winds roughen water surfaces, increasing backscatter and potentially underestimating flooding.	Open water bodies, coastal areas	Consider wind speed data during analysis.
Need for Ground Truth Data	Essential for validation and accuracy assessment of SAR-derived flood maps.	All areas	Comparison with optical imagery, field observations, official flood maps.
Temporal Resolution Limitations	6-day revisit might miss peak of rapid floods or have gaps in coverage.	Areas prone to flash floods	Combine with other satellite data sources with higher temporal resolution.

While Sentinel-1 SAR imagery offers major advantages for flood detection—like cloud penetration and all-weather, day-and-night coverage—it also presents notable limitations that affect flood mapping accuracy. In urban areas, complex backscattering from buildings and infrastructure creates challenges. Tall buildings can cause radar shadowing, leading to low backscatter zones that may be mistaken for water. Conversely, layover can obscure actual flood zones, while double scattering between water and building walls can create strong VH backscatter that's difficult to interpret and may cause false positives. Additionally, roads and tarmac may show low backscatter similar to water, complicating detection. Standard VV or VV/VH thresholding often proves inadequate in such areas, requiring algorithms that consider urban features.

In vegetated wetlands, radar interaction with dense canopy reduces the ability of C-band SAR to detect underlying water. Double bounce effects between water and vertical vegetation can also raise backscatter, risking overestimation or confusion with dry areas. Accurate mapping here may need multi-temporal analysis or alternative polarizations or frequencies (e.g., L-band).

Weather, especially strong winds, further complicates detection. Wind-roughened water surfaces increase backscatter, reducing contrast with dry areas and possibly leading to underestimation of flood extent. Thus, wind conditions during image acquisition must be factored into analysis.

Flood map accuracy using Sentinel-1 SAR heavily depends on ground-truth validation—via high-resolution optical imagery, field data, or official flood maps. This validation is essential, particularly for events like the 2018 Kerala floods, to confirm map reliability and understand limitations. Without it, assessing true accuracy is difficult.

Additional challenges include Sentinel-1's 6-day revisit time, which may miss peak inundation in short-duration floods, and geometric distortions in mountainous terrain that can skew mapping accuracy.

Analysis using Sentinel-1 SAR data processed in Google Earth Engine provided a quantitative view of the flood's extent:

Total area analyzed: ~230,820 hectares (Ha)

Flooded area: 1,360 Ha

Percentage flooded:(1360/230820)×100≈0.59%

While only 0.59% of the area was flooded, the effects were likely concentrated in vulnerable zones like lowlands and urban centers. Even small-scale flooding can cause major disruptions, economic losses, and displacement. Some areas may have experienced complete inundation.

This data allows for more detailed impact assessments, such as:

- Overlaying flood extent with population density to estimate affected individuals
- Comparing with land cover maps to identify affected agriculture and urban zones
- Analyzing flood distribution to highlight high-risk areas

Key Consideration: The accuracy of these numerical results hinges on the quality of the SAR-derived flood map, underscoring the need for ground-truth validation to ensure reliability.

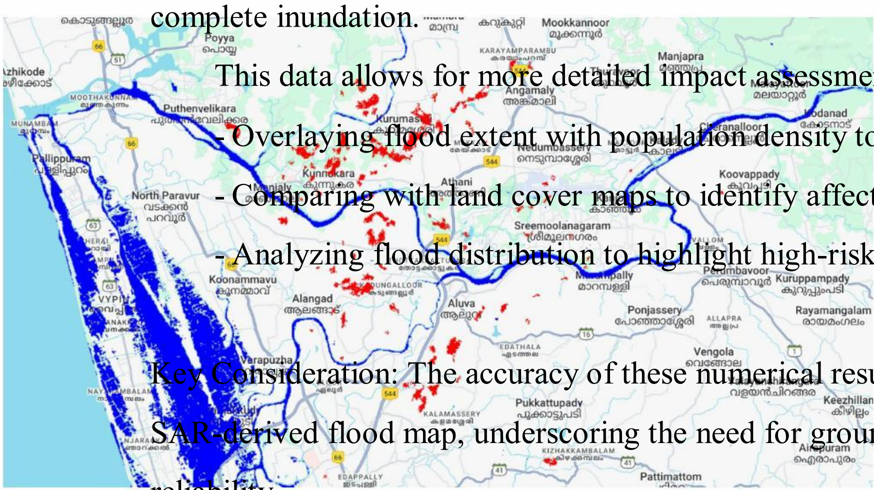


Figure Of Flood And Permanent Water Bodies Mapped On GEE, Where

- Blue Color : Indicated Permanent Water Bodies
- Red Color : Indicated Flood Impact

4. Conclusion

The analysis demonstrates that Sentinel-1 SAR imagery, processed via Google Earth Engine, is highly effective for automated flood detection, as shown in the 2018 Kerala floods case. Its C-band SAR capability allows cloud-penetrating, day-and-night observation, offering a key advantage over optical sensors. Using both VV and VH polarizations—especially the VV/VH ratio—proves useful for identifying flooded zones across diverse land covers. Preprocessing steps like speckle noise reduction with the Refined Lee filter enhance data clarity. Incorporating auxiliary datasets such as the JRC Global Surface Water dataset (to mask permanent water bodies) and slope data from the USGS HydroSHEDS DEM (to filter out improbable flood zones) refines detection accuracy. Noise reduction through connected component analysis and pixel-based flood extent calculations in GEE offer meaningful metrics for assessing flood impact.

Nonetheless, several limitations remain. In urban areas, complex backscattering poses classification challenges; in wetlands, vegetation canopies interfere with signal penetration. Weather factors like strong winds can alter backscatter from water surfaces, reducing detection precision. Sentinel-1's 6-day revisit time may miss short-term flood peaks. These issues highlight the need for further refinement to improve SAR-based flood detection.

Recommendations for Future Research and Methodological Enhancements:

Multi-temporal Analysis: Leverage pre- and during-flood Sentinel-1 imagery to detect significant backscatter changes linked to flooding.

Machine Learning: Apply ML models for improved flood classification using SAR features (VV, VH, VV/VH) and auxiliary data like DEMs and land cover.

Region-Specific Thresholds: Customize VV/VH thresholds to Kerala's terrain and land cover for more accurate results.

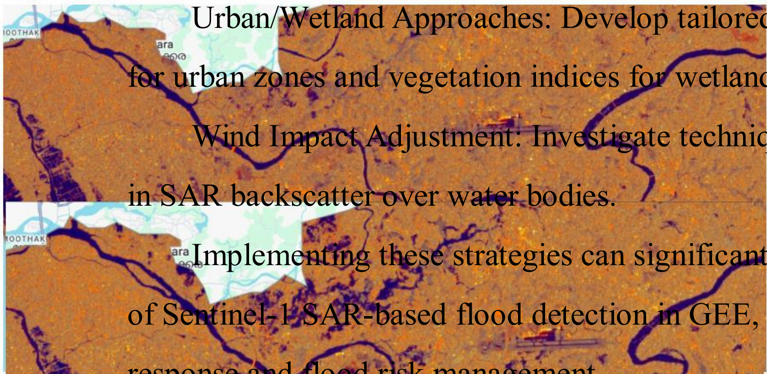
High-Resolution DEM Integration: Use finer DEMs (if available) to enhance terrain correction and explore flood depth estimation.

Rigorous Validation: Validate methods against ground-truth data from the 2018 Kerala floods to assess accuracy and refine techniques.

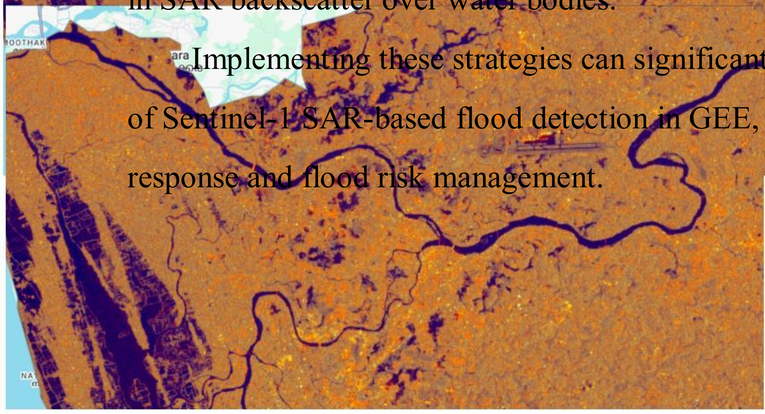
Urban/Wetland Approaches: Develop tailored methods using building footprint data for urban zones and vegetation indices for wetlands.

Wind Impact Adjustment: Investigate techniques to correct for wind-induced changes in SAR backscatter over water bodies.

Implementing these strategies can significantly improve the reliability and precision of Sentinel-1 SAR-based flood detection in GEE, making it a more robust tool for disaster response and flood risk management.



RGB Composite View: Before Image Of The Flood



RGB Composite View: After Image Of The Flood

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