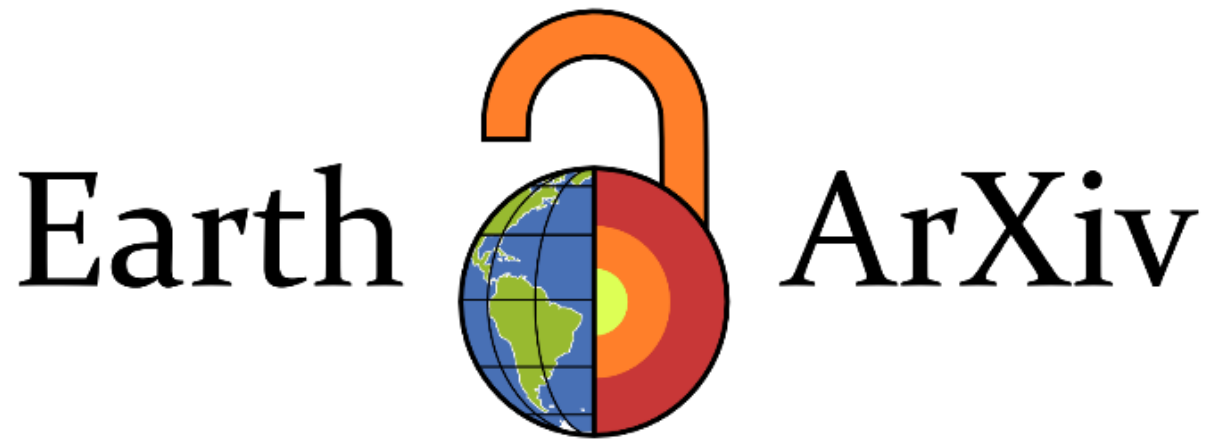




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Threshold Sensitivity and Reference Uncertainty in Sentinel-1 Inundation Mapping: The July 2021 Mahad Flood

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Abstract—Synthetic Aperture Radar (SAR) is widely used to map flood inundation under cloud cover, but backscatter-based mapping is sensitive to processing choices, and quantitative evaluation depends on reference data that are often unavailable. This paper examines both issues for the July 2021 flood at Mahad, Maharashtra, India. Three Sentinel-1A VV/VH scenes from one descending orbit, acquired on 10 July, 22 July and 3 August 2021, were used to derive backscatter change in Google Earth Engine. Candidate masks were generated with a fixed -2 dB threshold and with Otsu-derived thresholds (about -2.39 dB), after provisional exclusion of long-term water. The two masks covered approximately 10,8819 and 9,4349 km² with a mutual intersection over union (IoU) of 0.8670, which illustrates threshold sensitivity rather than accuracy. The NRSC Bhuvan portal displayed an inundation layer for 22 July 2021, but the original event-specific GIS data could not be obtained through the public access routes investigated, and a request sent to NRSC on 21 October 2026 had not been answered at the time of writing. As a documented workaround, the portal display was captured as a screenshot, georeferenced in QGIS using 11 ground control points, and converted to a provisional binary reference mask by RGB thresholding. On a common 662×649 grid, this reference contained 27,317 positive pixels (6.5590 km²) and the aligned Sentinel-1 shared candidate mask 38,597 (9.2675 km²); they shared 17,749 pixels (4.2617 km²), giving an IoU of 36.85%. This value measures spatial agreement with a screenshot-derived reference. It is neither the original NRSC product, nor independently verified ground truth, nor an estimate of flood-detection accuracy. The study is an exploratory analysis, not a validated flood-extent product or a risk assessment.

Keywords—Sentinel-1, SAR, flood mapping, threshold sensitivity, Otsu thresholding, reference-data uncertainty, Google Earth Engine, Mahad

I. INTRODUCTION

Mapping the extent of riverine flooding is difficult because inundation can evolve rapidly and because cloud cover frequently limits optical observation during the events of interest.

SAR sensors acquire data independently of sunlight and are less affected by cloud, and open water often returns low backscatter under suitable surface and viewing conditions, which has made SAR a common basis for flood mapping [1], [2]. The Sentinel-1 mission provides systematic C-band acquisitions that are openly available [3] and accessible at scale through cloud platforms such as Google Earth Engine [4].

Low backscatter is not unique to floodwater. Soil moisture, vegetation structure, surface roughness, radar shadow, local incidence geometry and terrain can all influence the observed signal, and built-up areas pose specific difficulties, so a backscatter-based classification can include non-flood surfaces and omit real inundation [2], [5]. Radiometric terrain effects are not removed by default in the Sentinel-1 GRD collection hosted in Earth Engine [6]. The result also depends on the threshold used: a fixed threshold is simple and reproducible, whereas histogram-based methods such as Otsu's method [7] derive a threshold from the data distribution, an approach that can be unreliable when the flooded class is a small fraction of the scene [8]. A smaller mapped area does not by itself indicate higher accuracy.

Evaluation introduces a second problem. Quantitative assessment normally requires an event-specific reference extent or other reliable observations [9], and errors in the reference data themselves can bias both apparent accuracy and estimated extent [10]. Where the original reference cannot be obtained, a publicly displayed map may provide contextual evidence, but extracting a mask from it adds uncertainty from georeferencing, cartographic rendering and colour classification. Agreement with such a reference is not independent validation.

The July 2021 flood at Mahad, on the Savitri River in Raigad district, Maharashtra, has been the subject of local

flood-mapping and case studies [11]–[13], and it provides a case in which both problems arise. The NRSC Bhuvan portal displayed an inundation layer for 22 July 2021 that was a natural candidate reference, but the underlying GIS product could not be obtained through the public routes we investigated. This paper (i) documents a temporal Sentinel-1 candidate-mapping workflow, (ii) shows how two thresholding rules change the mapped extent, (iii) documents in detail how a provisional reference mask was derived from the Bhuvan portal display when the original data were not obtainable, and (iv) quantifies agreement between the Sentinel-1 candidate mask and that provisional reference. It does not establish validated flood extent and is not a hazard–exposure–vulnerability risk assessment. We use the terms *Sentinel-1 candidate inundation* and *agreement with the screenshot-derived Bhuvan reference mask*.

II. LITERATURE REVIEW

A. Sentinel-1 SAR Flood-Mapping Workflows

Twele et al. [1] described a fully automated Sentinel-1 processing chain for near-real-time flood mapping that uses both VV and VH data and ancillary terrain information to limit false detections. Landuyt et al. [2] compared established pixel-based approaches (global and enhanced thresholding, active contour modelling and change detection) on SAR images of several flood events in the U.K. and Ireland and concluded that the most suitable method depends on the area of interest and its characteristics as well as on the intended use of the product. Methods evaluated on a single test case therefore cannot be assumed to transfer to a new setting. For built-up areas, which are not the focus of the present study, Zhao et al. [5] review the characteristics of floodwater in SAR images, the associated limitations of spatial and temporal resolution, and the limited availability of open reference datasets.

B. Fixed, Otsu and Adaptive Thresholding

Otsu’s method [7] selects the threshold that maximises between-class variance of a gray-level histogram and performs best when the histogram has two well-separated modes. In flood mapping the target class often covers only a small fraction of the image, so the histogram is frequently not obviously bimodal and parametric estimation becomes difficult; Chini et al. [8] addressed this with a hierarchical split-based approach that searches for tiles of variable size in which the two class distributions can be parameterised. Landuyt et al. [2] found that tiled thresholding was more robust than global thresholding, which performed well only on small subsets with clear bimodality. These findings bear directly on the present study: a scene-wide Otsu threshold applied to a change-difference histogram in which the flooded class is a minority need not correspond to a physically meaningful flood/non-flood boundary.

C. Terrain and Radar-Related Effects

SAR backscatter depends on local incidence geometry and terrain as well as on surface properties. The Sentinel-1 GRD

products in Earth Engine are pre-processed (orbit file, thermal-noise and border-noise removal and terrain correction), but radiometric slope correction and layover/shadow masking, which are required for analysis-ready backscatter under CEOS specifications, are not applied by default; Vollrath et al. [6] provide an angular-based slope-correction routine for Earth Engine for this reason. Auxiliary terrain information is also commonly used to constrain flood detection: the height-above-nearest-drainage (HAND) concept [16] underlies the exclusion of areas unlikely to flood in automated chains [1], and HAND-masked thresholding is among the approaches compared by Landuyt et al. [2].

D. Auxiliary Datasets

The JRC Global Surface Water dataset [14] describes the long-term occurrence of surface water, while terrain datasets such as SRTM [15] and MERIT Hydro [17] describe elevation and drainage. These provide susceptibility context and a means of excluding permanent water, but they are not event-specific flood maps.

E. Reference Data, Provenance and Agreement Metrics

Good-practice guidance for accuracy assessment emphasises the quality and provenance of the reference sample [9]. Foody [10] showed, for land-cover change, that error in reference data can bias estimates of both accuracy and extent, in either direction depending on whether errors are correlated with those of the map, and argued against treating reference data as “ground truth”. These considerations apply with greater force to a reference whose derivation is unknown. Overlap statistics such as the IoU (Jaccard index), precision, recall and F1 describe agreement between two masks; when one of them is itself uncertain they are *reference-relative agreement statistics* and not accuracy measures. For binary masks F1 and IoU are related by $F1 = 2 \text{IoU} / (1 + \text{IoU})$, so they carry the same information.

F. The July 2021 Maharashtra Floods

The July 2021 floods affected several parts of Maharashtra, and published work should be distinguished by location. Diwate et al. [18] analysed land-use/land-cover change in relation to the 2021 flood at Chiplun (Ratnagiri district), a different location and river system from Mahad; it is regional context only. For Mahad, Magar [11] mapped inundation along the Savitri River near Mahad for the 2005 and 2007 storm events using GIS tools, and Ghogare et al. [12] present a case study of the Mahad flood. Jadhav et al. [13] combined Sentinel-1 backscatter-ratio thresholding with Sentinel-2 NDWI filtering in Earth Engine for 2020–2024 and report an inundated area of 2,887.93 ha for the 2021 event from the combined SAR and NDWI data. That figure is not directly comparable with the areas reported here, because the study extent, sensors, thresholds and validation approach differ and we have not reproduced that work. Official event documentation is also available [19], [20], but it consists of reports rather than inundation rasters.

III. RESEARCH GAP AND CONTRIBUTIONS

A. Research gap

Published SAR flood-mapping work addresses automated processing chains, thresholding methods and their comparative evaluation, and the literature on accuracy assessment stresses reference-data quality. In practice, however, an event-specific reference is not always accessible, and the practical consequences of substituting a map displayed on a public portal for the original product (what processing is required, what uncertainty it introduces, and how the resulting agreement statistics should be read) are rarely documented step by step. This paper documents one such case. We did not conduct a systematic literature search, and we make no claim that the thresholding comparison or the screenshot-derived reference is methodologically novel.

B. Contributions

The main contributions of this work are:

- A documented temporal Sentinel-1 candidate-inundation workflow for the July 2021 Mahad flood.
- A comparison of a fixed -2 dB threshold and Otsu-derived thresholds, showing threshold sensitivity.
- A transparent, step-by-step record of the attempts to obtain the Bhuvan event layer and of the screenshot-derived reference-mask workaround, with an explicit account of the uncertainty it introduces.
- A grid-aligned four-class comparison with intersection, union and IoU, interpreted as agreement and not accuracy.
- Exploratory terrain context (elevation, slope, HND, UPA) for the candidate areas.

These are workflow contributions; no methodological novelty is claimed.

IV. STUDY AREA, DATA AND WORKFLOW

The study area covers Mahad and the surrounding Savitri–Gandhari river corridor in Raigad district, Maharashtra, India (Fig. 1). The Google Earth Engine region of interest (ROI) is bounded by 73.372° – 73.468° E and 18.035° – 18.125° N, with a nominal area of about 101.55 km^2 . The common three-date valid-observation footprint was about 101.23 km^2 , and the final QGIS comparison grid (662×649 pixels, about 15.495 m spacing, EPSG:32643) has a rectangular footprint of about 103.16 km^2 . These are three distinct spatial supports, and every area is reported with its own support.

The Central Water Commission (CWC) records extreme flooding at the Savitri River gauge at Mahad during 22–24 July 2021 [19], and an official event report dated 22 July 2021 is available [20]. The 22 July Sentinel-1 scene is treated as an *event-period* observation; it is not assumed to represent the flood peak. The only inundation layer identified for comparison was the one displayed on the NRSC Bhuvan Disaster Services flood portal [21].

Table I lists the datasets, and Fig. 2 summarises the workflow.

V. METHODOLOGY: SENTINEL-1 CANDIDATE MAPPING

A. Scene Selection and Filtering

Scenes were selected from COPERNICUS/S1_GRD by ROI, Interferometric Wide-swath (IW) mode, descending pass, relative orbit 136, and availability of both VV and VH. Within each date window the first matching image by acquisition time was used:

- 10 Jul 2021 (pre-event): S1A_IW_GRDH_1SDV_20210710T005513_20210710T005538_038708_049158_A40A
- 22 Jul 2021 (event-period): S1A_IW_GRDH_1SDV_20210722T005514_20210722T005539_038883_049695_2330
- 3 Aug 2021 (post-event): S1A_IW_GRDH_1SDV_20210803T005514_20210803T005539_039058_049BC7_1CE1

Only VV and VH were retained, and a neighbourhood-median filter (`focalMedian`, circular kernel, radius one pixel) was applied independently to each image. The workflow documented here used the collection as provided by Earth Engine and applied no additional radiometric slope correction, layover/shadow masking or HAND-based exclusion.

B. Temporal Change

Backscatter in dB, as represented in the Earth Engine collection, was differenced for each polarisation:

$$\Delta VV = VV_{22 \text{ Jul}} - VV_{10 \text{ Jul}} \quad (1)$$

$$\Delta VH = VH_{22 \text{ Jul}} - VH_{10 \text{ Jul}} \quad (2)$$

Negative values indicate lower backscatter on 22 July than on 10 July. Post-event changes were computed likewise as 3 August minus 22 July; a positive post-event change does not uniquely establish flood recession.

C. Common Support and Long-Term Water Exclusion

A common valid-observation mask was formed by intersecting the VV and VH masks on all three dates. Long-term water was provisionally defined from the JRC occurrence band [14] as pixels with occurrence $\geq 80\%$, an operational choice and not a universal definition of permanent water. The common support S_{common} is the set of pixels valid on all three dates and outside this long-term-water mask.

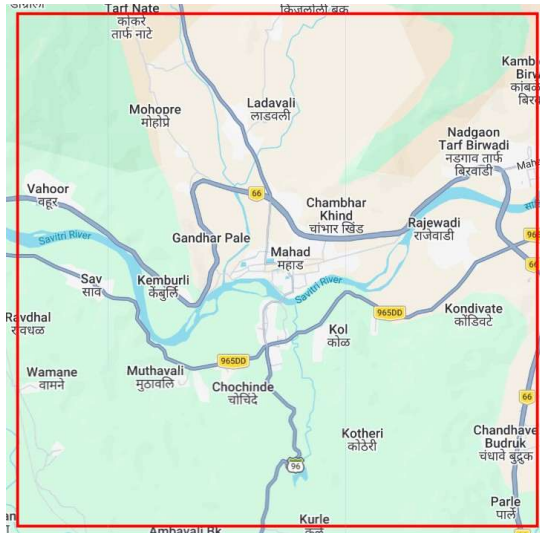
D. Fixed and Otsu-Derived Candidate Masks

The fixed-threshold candidate mask requires concurrent decreases of more than 2 dB in both polarisations:

$$C_{\text{fixed}} = (\Delta VV < -2) \wedge (\Delta VH < -2) \wedge S_{\text{common}}. \quad (3)$$

For the Otsu-derived mask, histograms of ΔVV and ΔVH were computed over valid three-date observations before JRC exclusion (maximum 128 buckets, minimum bucket width 0.1 dB, sample parameter 10,000, nominal scale 30 m). A custom implementation of Otsu’s method [7] selected the split maximising between-class variance, giving $T_{VV} \approx -2.390$ dB and $T_{VH} \approx -2.397$ dB:

$$C_{\text{Otsu}} = (\Delta VV < T_{VV}) \wedge (\Delta VH < T_{VH}) \wedge S_{\text{common}}. \quad (4)$$



(a) Google Maps view of the region of interest



(b) Sentinel-2 image of the region of interest

Fig. 1. Study-area context for Mahad and the Savitri River corridor, Maharashtra. The red outlines show the region of interest in the supplied images. Panel (b) is included for geographic context only and was not used in the Sentinel-1 flood analysis.

TABLE I
DATASETS, ROLES AND PRINCIPAL QUALIFICATIONS

Dataset (identifier)	Use	Qualification
Sentinel-1A GRD, IW, VV/VH (COPERNICUS/S1_GRD)	Pre-event, event-period and post-event backscatter comparison	Backscatter decrease is not uniquely attributable to floodwater; three dates do not establish the full event evolution
JRC Global Surface Water v1.4 (JRC/GSW1_4/GlobalSurfaceWater)	Provisional exclusion of long-term water (occurrence $\geq 80\%$)	Historical occurrence, not an event-specific flood map; approx. 30 m resolution
SRTM (USGS/SRTMGL1_003)	Elevation and slope context	Approx. 30 m; coarser than the nominal 10 m SAR analysis scale
MERIT Hydro v1.0.1 (MERIT/Hydro/v1_0_1)	Height above nearest drainage (HND) and upstream drainage area (UPA)	Approx. 90 m; context, not validation
NRSC Bhuvan flood portal display, 22 Jul 2021	Provisional reference mask from a georeferenced screenshot	Not the original GIS product or ground truth; unknown source metadata; rendering, georeferencing and colour-classification uncertainty

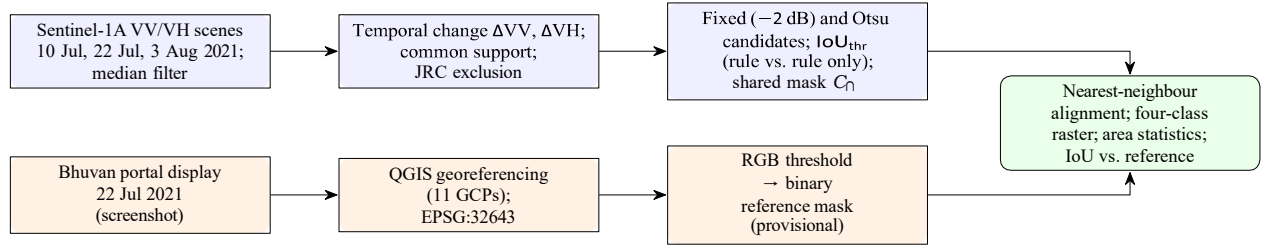


Fig. 2. Processing architecture: the Sentinel-1 candidate-generation path (blue) and the screenshot-derived reference-preparation path (orange) feed the aligned four-class comparison (green). The agreement between the fixed and Otsu masks (IoU_{thr} , blue path) compares two Sentinel-1 rules with each other, whereas the IoU against the reference (green) compares the shared Sentinel-1 mask with a provisional screenshot-derived mask. Neither represents independent validation.

Otsu's method gives a data-dependent split and does not inherently identify floodwater; as discussed in Section II, a scene-wide histogram in which the flooded class is a minority may not be clearly bimodal [8]. Agreement between the two masks was measured by

$$C_N = C_{\text{fixed}} \cap C_{\text{Otsu}}, \quad C_U = C_{\text{fixed}} \cup C_{\text{Otsu}} \quad (5)$$

$$\text{IoU}_{\text{thr}} = |C_N| / |C_U|, \quad (6)$$

which measures agreement between two rules and not accuracy. The shared mask C_N is the Sentinel-1 candidate mask carried forward to the reference comparison in Section VII. Areas were estimated in Earth Engine by pixel-area summation at a nominal scale of 10 m.

E. Exploratory Terrain Context

Elevation (SRTM [15]), slope (ee.Terrain.slope, degrees), height above nearest drainage (HND) [16] and up-

stream drainage area (UPA) from MERIT Hydro [17] were summarised (mean and median; nominal scale 90 m, maximum 10^9 pixels, tile scale 4) for four groups: shared candidates $C_{\cap}$, fixed-only, Otsu-only, and background $B = S_{\text{common}} \setminus (C_{\text{fixed}} \cup C_{\text{Otsu}})$. Because the source datasets are coarser than the SAR scale, these summaries are descriptive only.

VI. REFERENCE DATA: ACCESS ATTEMPTS AND THE SCREENSHOT-DERIVED MASK

The reference-data problem is central to the interpretation of this study, so the sequence of events is documented in full.

A. Why a Reference Was Needed

Comparing the Sentinel-1 candidate masks with an independent inundation extent is the only route, within the data available to us, to assess spatial plausibility. Two Sentinel-1 rules that differ by a fraction of a decibel necessarily agree with each other (Section VIII), so IoU_{thr} cannot establish correctness. The NRSC Bhuvan Disaster Services portal [21] displayed a Maharashtra inundation layer for 22 July 2021, the same date as the event-period Sentinel-1 scene, and was therefore identified as a potential reference for the Mahad flood.

B. Access Routes Investigated

We investigated the following public routes to the underlying event-specific data:

- 1) *Bhuvan Store service information.* The documented service table listed a Flood Hazard service (1998–2007) and Flood Annual Layers (1999–2010). These did not establish access to the 22 July 2021 event layer.
- 2) *WMS Manager.* In the interface we examined, the WMS Manager did not yield a usable event-specific endpoint.
- 3) *Portal help and download options.* The portal Help URL returned “Not Found”.

The original event-specific downloadable GIS data were therefore not obtained through the public routes investigated. These observations document the routes tested; they do not show that the dataset does not exist or is unavailable by other means. On 21 October 2026 we emailed the NRSC/Bhuvan team requesting the original GIS dataset or a supported service endpoint, together with metadata (sensor, acquisition date and time, resolution, coordinate reference system, derivation method and academic-use conditions). No response had been received at the time of writing.

C. The Screenshot Workaround

To avoid abandoning the spatial comparison, we used the only form of the layer that was accessible, its display on the portal. The procedure was:

- 1) The displayed layer was captured as a screenshot on 27 October 2026. At the time of capture, the browser zoom control was set to its maximum level, and the map displayed a scale indicator of 1,000 m.
- 2) The screenshot was georeferenced in QGIS using 11 ground control points.

- 3) The working raster was exported in EPSG:32643 on a 662×649 grid (X: 327,666.30–337,924.28 m; Y: 1,994,726.35–2,004,782.89 m; pixel size about 15.495 m).
- 4) The cyan inundation symbology was extracted with the QGIS Raster Calculator using $G > 150$, $B > 150$, $G - R > 40$ and $\alpha > 0$, producing a provisional binary reference mask.

This is a colour classifier applied to a cartographic rendering and not a flood-detection algorithm. The grid properties describe the processed screenshot raster, not the original Bhuvan product.

D. Uncertainty Introduced by the Workaround

The screenshot-derived mask is *not* the original NRSC GIS product and is *not* independently verified ground truth. Table II lists the sources of uncertainty that it introduces. None of them has been quantified in this study, and their combined effect on the mask, and hence on the agreement statistics, is unknown.

E. Interpretation Boundary

Consequently, any agreement statistic computed against this mask measures spatial agreement with a provisional screenshot-derived comparator. It is not an independent estimate of flood-detection accuracy, and disagreement cannot be attributed to the Sentinel-1 mask alone.

VII. GRID ALIGNMENT AND FOUR-CLASS COMPARISON

The shared Sentinel-1 candidate mask $C_{\cap}$ (about 10 m, EPSG:32643) was resampled in QGIS to the reference grid with nearest-neighbour resampling, which is appropriate for a categorical binary mask; CRS, extent, dimensions and pixel spacing were then checked. A four-class raster was built as

$$\text{class} = 2 \mathbb{I}[Bhuvan = 1] + \mathbb{I}[S1 = 1], \quad (7)$$

giving 0 = neither, 1 = Sentinel-1 only, 2 = Bhuvan reference only and 3 = both. An initial attempt was affected by an “Additional NoData” value of zero on the Bhuvan layer, which removed the legitimate background class; the setting was cleared and the operation repeated, yielding four classes and no NoData pixels. With n_1, n_2, n_3 the pixel counts of classes 1, 2 and 3,

$$\text{IoU} = \frac{n_3}{n_1 + n_2 + n_3}. \quad (8)$$

Precision, recall and F1 are computed treating the Bhuvan mask as a provisional comparator and are labelled *reference-relative agreement statistics*.

VIII. EXPERIMENTAL RESULTS

A. Threshold Sensitivity

Table III compares the two candidate masks on the original Earth Engine grid (nominal 10 m, after long-term-water exclusion). The smaller Otsu area does not indicate greater accuracy. Because both Otsu thresholds are more negative than -2 dB and the same support was applied, C_{Otsu} is expected to be a subset of C_{fixed} ; in that case IoU_{thr} equals the area

TABLE II
SOURCES OF UNCERTAINTY IN THE SCREENSHOT-DERIVED REFERENCE MASK

Source	Description	Possible effect
Unknown source metadata	Sensor, acquisition date and time, native resolution, coordinate system and derivation method of the displayed layer are unknown.	Temporal and spatial mismatch with the Sentinel-1 scene cannot be assessed
Map rendering	The portal display applies symbology, possible transparency, basemap blending and display-scale generalisation to the underlying data.	Altered colours and boundaries relative to the source data
Georeferencing	Position was fixed from 11 GCPs read from a screenshot; residuals measure fit to the control points, not absolute positional accuracy.	Systematic or local spatial offsets
RGB extraction	A fixed colour rule ($G > 150$, $B > 150$, $G - R > 40$, $\alpha > 0$) was applied to a rendered image.	Omission of blended or semi-transparent pixels; inclusion of similarly coloured non-inundation pixels
Spatial alignment	The Sentinel-1 mask (about 10 m) was resampled to the reference grid (about 15.5 m) by nearest neighbour.	Changes in pixel counts and boundary positions

TABLE III
FIXED AND OTSU CANDIDATE MASKS (GEE GRID)

Mask	T_{VV} / T_{VH} (dB)	Area (km ²)	IoU _{thr}
Fixed	-2 / -2	10.8819	0.8670
Otsu	-2.390 / -2.397	9.4349	
Fixed-only (derived)	–	1.4470	

TABLE IV
FOUR-CLASS COMPARISON ON THE ALIGNED GRID

Value	Class	Pixels	Area (km ²)	Share
0	Neither mask	381,473	91.5948	88.79%
1	Sentinel-1 only	20,848	5.0058	4.85%
2	Bhuvan only	9,568	2.2974	2.23%
3	Both masks	17,749	4.2617	4.13%
Total		429,638	103.1596	100.00%

TABLE V
DERIVED QUANTITIES ON THE ALIGNED GRID

Quantity	Pixels	Area (km ²)
Bhuvan reference positive	27,317	6.5590
Aligned Sentinel-1 positive	38,597	9.2675
Intersection	17,749	4.2617
Union	48,165	11.5648

ratio $9.4349/10.8819 \approx 0.8670$, consistent with the recorded value, and $C_{\cap} = C_{\text{Otsu}}$.

B. Agreement with the Screenshot-Derived Reference

Table IV gives the four-class statistics on the 662×649 grid (429,638 pixels; 103.1596 km²). GEE-grid areas are kept separate from areas on this aligned grid, because resampling from about 10 m to about 15.5 m changes pixel counts (for example, the Otsu candidate area of 9.4349 km² on the GEE grid corresponds to an aligned Sentinel-1 area of 9.2675 km²).

Table V gives the derived mask totals.

The aligned Sentinel-1 mask exceeded the reference by about 2.7085 km². The intersection was 17,749 pixels

TABLE VI
REFERENCE-RELATIVE AGREEMENT STATISTICS

Statistic	Value
IoU	0.3685 (36.85%)
Precision (S1 vs. reference)	0.460
Recall (S1 vs. reference)	0.650
F1	0.539

TABLE VII
EXPLORATORY TERRAIN SUMMARIES, SHARED CANDIDATES

Variable	Mean	Median
Elevation (m)	13.66	5.52
Height above nearest drainage (m)	8.106	0.624
Slope (°)	2.358	1.413
Upstream drainage area (km ²)	56.74	0.180

(4.2617 km²) and the union 48,165 pixels (11.5648 km²), so

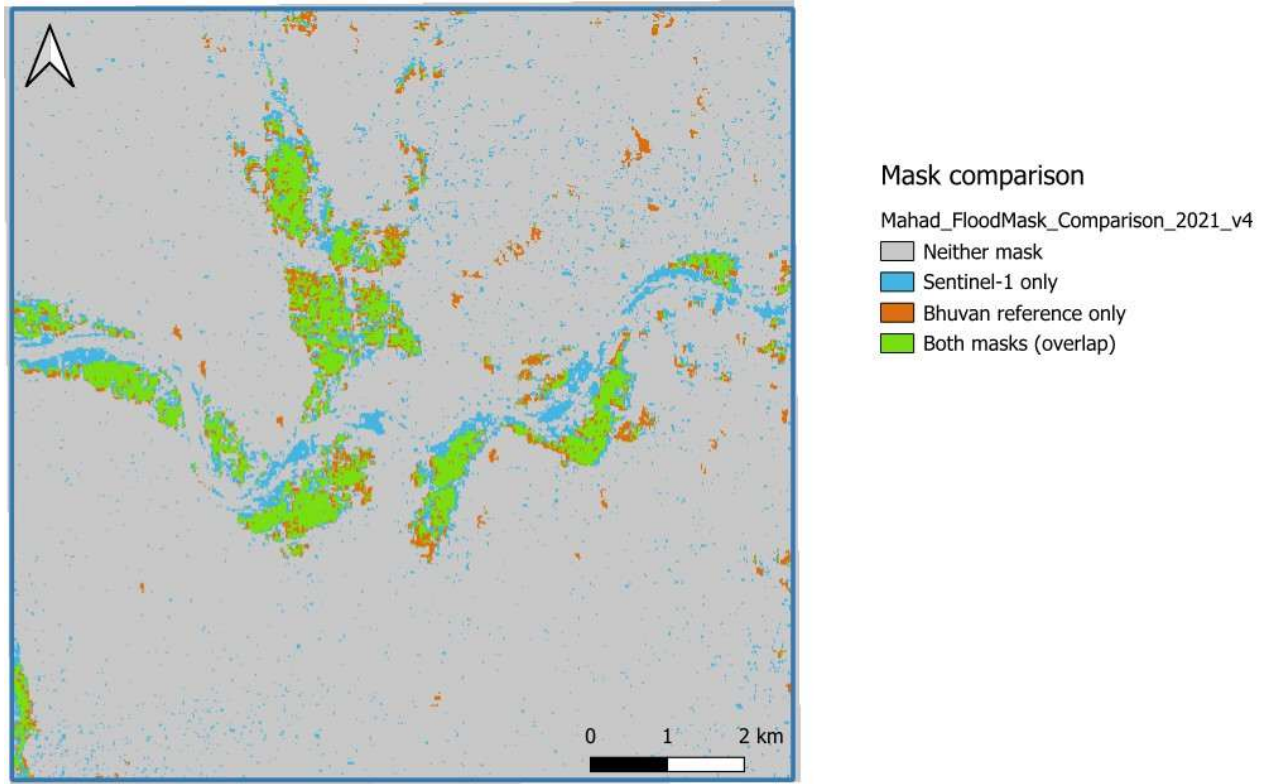
$$\text{IoU} = \frac{17,749}{48,165} \approx 0.3685 \text{ (36.85\%)} \quad (9)$$

The large “neither” class reflects the rectangular grid and is not an estimate of unflooded area. Table VI lists the agreement statistics derived from Table IV; they are reference-relative agreement statistics and must not be read as flood-detection accuracy. About 54% of Sentinel-1 positive pixels lie outside the reference and about 35% of reference positive pixels were not selected; these disagreement classes identify locations for further investigation and do not show which mask is correct.

C. Exploratory Terrain Summaries

Table VII gives the recorded summaries for the shared candidates. The medians indicate predominantly low-elevation, low-slope pixels close to the drainage network, and the large mean–median gaps for HND and UPA indicate right-skewed distributions. This does not show that the candidates are inundated, and statistics for the other groups are not in the handover report.

Sentinel-1 and Bhuvan Reference Mask Comparison — Mahad, July 2021



Bhuvan reference extent extracted from a georeferenced portal screenshot. Comparison indicates spatial agreement between masks and is not an independent validation of flood extent

Fig. 3. Four-class comparison of the Sentinel-1 shared candidate mask and the screenshot-derived Bhuvan reference for Mahad, July 2021. The map shows neither mask, Sentinel-1 only, Bhuvan reference only, and overlap. The reference is a provisional mask derived from a georeferenced portal screenshot; agreement with it is not independent validation of flood extent.

IX. DISCUSSION

A. Threshold Sensitivity

Moving from a fixed -2 dB rule to Otsu-derived thresholds of about -2.39 dB reduced the candidate area by roughly 13% (1.4470 km^2) while retaining most of the same pixels. The area changes because the change-difference distribution is continuous around these values: pixels whose decrease lies between about -2.0 and -2.4 dB in both polarisations are included by one rule and excluded by the other. Decreases of a fraction of a decibel may also arise from speckle residuals, soil-moisture change or differences in acquisition conditions, which this study does not quantify. Because the rules are nearly nested and differ by a fraction of a decibel, a high mutual IoU (0.8670) is expected and is weak evidence of correctness; it shows that the two rules agree with each other, not that either agrees with the true flood extent. Moreover, the Otsu histogram was computed scene-wide, where the flooded class is a minority and bimodality is not assured [2], [8], so the Otsu threshold should be read as a data-dependent split and not as a physically derived water threshold.

B. Agreement with the Bhuvan-Derived Reference

The IoU of 36.85% indicates partial spatial agreement. Several non-exclusive factors may contribute, which this study does not separate: (i) reference uncertainty: the unknown sensor, time and derivation of the Bhuvan layer, cartographic rendering, georeferencing error and RGB-threshold omission or inclusion (Table II), consistent with the general finding that reference-data error biases apparent agreement [10]; (ii) temporal mismatch: the Sentinel-1 scene was acquired at about 00:55 UTC on 22 July 2021, whereas the time of the data behind the Bhuvan display is unknown and the flood persisted over 22–24 July [19]; (iii) SAR limitations: backscatter decreases may arise from non-flood surfaces, while flooded vegetation or built-up areas may not give low backscatter [2], [5]; and no radiometric slope correction or layover/shadow masking was applied [6]; and (iv) resampling from about 10 m to about 15.5 m. The Sentinel-1-only class (about 5.0058 km^2) may therefore include genuine inundation absent from the reference as well as non-flood changes, and the Bhuvan-only class (about 2.2974 km^2) may reflect detection, rendering

or georeferencing differences. Because the reference is itself uncertain, neither mask can be called correct. Field evidence, high-water marks, optical imagery or the original official GIS layer would be needed to resolve these cases.

C. Terrain Context

The terrain summaries are consistent with candidates lying mainly on low, flat ground near drainage, but terrain variables are not unique indicators of flooding, were derived at coarser resolution (30–90 m) than the SAR data, and depend on the SAR-derived masks used to select pixels. The scattered detections away from the main corridor noted in the project records have not yet been inspected at large scale.

D. Limitations

The main limitations are: the reference derives from a screenshot, is not the original NRSC product and is not ground truth; RGB thresholding can omit or include features and GCP residuals do not establish absolute positional accuracy; backscatter change can result from moisture, vegetation, roughness, shadow and terrain as well as flooding; only three acquisition dates were used; candidate areas depend on the long-term-water rule, the Otsu histogram settings and the analysis scale (10 m for areas, 30 m for histograms, 90 m for terrain); and the study is not a hazard–exposure–vulnerability risk assessment.

E. Need for Independent Reference Data and Future Work

Future work, which is proposed and not yet done, includes obtaining the original Bhuvan layer or another independent reference (high-water marks, field survey, optical imagery), inspecting disagreement areas at large scale, testing additional dates and adaptive or tiled thresholding approaches, evaluating radiometric slope correction and HAND-based masking, and exposure analysis if a risk-assessment scope is retained.

X. CONCLUSION

A temporal Sentinel-1 workflow produced candidate inundation masks whose areas differ by about 1.45 km² between a fixed −2 dB threshold and Otsu-derived thresholds, illustrating threshold sensitivity. Because the original event-specific Bhuvan data could not be obtained through the public routes investigated, a provisional reference was extracted from a georeferenced portal screenshot, and the aligned Sentinel-1 shared candidate mask showed partial spatial agreement with it (IoU = 36.85%). Since this reference is not the original NRSC product and is subject to unknown source metadata and to georeferencing, rendering and classification uncertainty, the figure measures agreement and not flood-detection accuracy, and the candidate masks should not be described as validated flood extent. Obtaining the original event-specific data and independent reference evidence is the main priority for strengthening these results.

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DATA AND CODE AVAILABILITY

The project-specific Google Earth Engine scripts, processed GeoTIFFs listed in Appendix A, QGIS project and ground control point records are currently retained by the authors and have not yet been deposited in a public repository or archive. These materials are therefore not publicly accessible at the time of writing. The underlying Sentinel-1, JRC Global Surface Water, SRTM and MERIT Hydro datasets are accessible through their respective providers, as described in Table I. The Bhuvan portal display is third-party material. The screenshot and the reference mask derived from it are not redistributed with this manuscript, as permission for redistribution has not been obtained from NRSC.

APPENDIX A REPRODUCIBILITY FILE REGISTER

APPENDIX B GEOREFERENCING RECORD

The Bhuvan screenshot was georeferenced in QGIS using 11 ground control points (GCPs) and a first-order polynomial transformation. The individual GCP coordinates and residual records are retained in the project files. The recorded residuals are summarised in Section C of the methodology. These residuals describe the fit at the control points and do not establish absolute positional accuracy.

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TABLE VIII
FILES REQUIRED TO REPRODUCE THE COMPARISON

Filename	Purpose	Public status
MAHAD FLOOD PROJECT — STAGE 1A	Original Earth Engine script(s): scene selection, change, JRC exclusion, fixed/Otsu masks, areas, terrain summaries	Held by authors; not yet deposited
Mahad_Shared_Candidates_2021.tif	Original Sentinel-1 shared candidate mask (about 10 m)	Held by authors; not yet deposited
Mahad_Bhuvan_Georeferenced_3857_new_map_ROI_Clip.tif	Georeferenced screenshot on final comparison grid	Third-party display; not redistributed
Mahad_Bhuvan_CyanMask_new_map_ROI_Clip.tif	Screenshot-derived binary reference mask	Not redistributed unless permitted
Mahad_Shared_Candidates_2021_Final_Aligned_15m.tif	Candidate mask resampled to reference grid	Held by authors; not yet deposited
Mahad_FloodMask_Comparison_2021_v4.tif	Final four-class comparison raster	Held by authors; not yet deposited
Mahad_Flood_Comparison_Project.qgz	QGIS project with georeferencing, Raster Calculator expressions and comparison	Held by authors; not yet deposited
Result.png	Four-class comparison map (Fig. 3)	Held by authors

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