EO–SAR Change Detection Analysis Report
Prepared by: ***Imagery Analyst – Ratnamala Ghosh***
Location: **Delhi**
Length: **4 pages**

1. **Introduction (study area description)**

The chosen Region of Interest (ROI) for this study is the Karachi Port, one of the busiest and most strategically significant maritime gateways in South Asia. As a major hub for commercial shipping, naval operations, and cargo logistics, Karachi Port experiences continuous vessel movement and infrastructural activity

2**. Datasets Used**

2.1 **Sentinel-1 (SAR)**

Product: Sentinel-1A GRD

Polarization: VV

Spatial Resolution: ~10 m

Acquisition Dates:

Pre-event: 2025-10-10

Post-event: 2025-10-22

Source: ASF Alaska Satellite Facility

2.2 **Sentinel-2 (Optical)**

Product: Sentinel-2 S2A/S2B

Bands Used: B02 (Blue), B03 (Green), B04 (Red), B08 (NIR) — 10 m

Acquisition Dates:

Pre-event: 2025-10-09

Post-event: 2025-10-12

2.3 **Region of Interest (ROI)**

Format: GeoJSON polygon

Purpose of ROI Selection:

To monitor ship movements, berth occupancy, and infrastructure changes, to detect abnormal vessel activity, potential illegal or unregistered ship movement, or operational anomalies.

3. **Data Acquisition (Automated)**

Scripts / Notebooks Used:

data_acquisition_sentinel2.ipynb – Uses Sentinelsat to programmatically download Sentinel-2 optical imagery

data_acquisition_sentinel1.ipynb – Uses ASF Search API (asf_search Python client) to download Sentinel-1 SAR imagery

Authentication & API Access:

Sentinel-2: Authenticates via Copernicus Data Space Ecosystem (CDSE) using OAuth Keycloak token with user-provided credentials.

[Note: Need to create an account on https://browser.dataspace.copernicus.eu/]

Sentinel-1: Authenticates with the ASF API using username and password, providing access to GRD products filtered by orbit and beam mode.

[Note: Need to create an account on https://urs.earthdata.nasa.gov/]

4. SAR Preprocessing (SNAP / QGIS)

Step	Description	Example Output Filename
1. Apply Orbit File	Improves geolocation accuracy by using precise orbit state vectors	# large data to upload
2. Thermal Noise Removal	Removes background thermal noise artifacts	# large data to upload
3. Radiometric Calibration (σ^o VV)	Converts digital numbers (DN) to backscatter values	# large data to upload
5. Range–Doppler Terrain Correction	Corrects geometric distortions using SRTM DEM and produces a geocoded image	# large data to upload
6. subset images	Subset according to ROI	subset_of_S1A_IW_GRDH_1SDV_20251010T133537_Orb_tnr_Cal_TC.data subset_S1A_IW_GRDH_1SDV_20251022T133537_Orb_tnr_Cal_TC.data
8. Re-subset (pixel matching two images)	Based on the model making need both images need pixel matching	subset_pixel_of_S1A_IW_GRDH_1SDV_20251010T133537_Orb_tnr_Cal_TC.tiff subset_pixel_S1A_IW_GRDH_1SDV_20251022T133537_Orb_tnr_Cal_TC.tiff

[Note: re-subsetting was needed for the same pixel matching of pre- and post-imagery]

5. Optical Preprocessing (QGIS/Python)

Step	Description	Example Output Filename
1. Band composite	B2, B3, B4, B8	# large data to upload
4. resample/ROI Clipping	Clipped to Karachi Port polygon	S2_merged_20251009_CLIP_pre.tiff S2_merged_20251012_CLIP_post.tiff

6. Change Detection Methods

6.1 **Sentinel2 (PCA-based change detection - Unsupervised Learning)**

Difference Image Calculation: Two Sentinel-2 satellite images were used: a **pre-event image** and a **post-event image**. Four spectral bands were extracted from each image and stacked into arrays of size $(4, H, W)$, where $H$and W $represent$ the spatial dimensions.

Principal Component Analysis (PCA): PCA is applied to the multi-band difference image to reduce dimensionality and highlight the most significant variance, which typically corresponds to areas of change.

Spectral Difference:

Each pixel location $\mathbf{x}$, a four-dimensional spectral difference vector was computed:

$$\mathbf{d}(\mathbf{x}) = \mathbf{I}_{post}(\mathbf{x}) - \mathbf{I}_{pre}(\mathbf{x})$$

A matrix of difference vectors $X \in \mathbb{R}^{N\times 4}$, where $N = H \times W$is the total number of pixels.

Thresholding and Morphological Filtering: After PCA, a threshold is applied to isolate significant changes, followed by binary morphological operations to remove noise.

To separate changed vs. unchanged pixels, an automatic statistical threshold was applied using the 95th percentile:

$$\tau = \text{Percentile}_{95}(PC_1^{abs})$$

The binary change mask is then:

$$M(\mathbf{x}) = \begin{cases} 1 & \text{if } PC_1^{abs}(\mathbf{x}) > \tau \\ 0 & \text{otherwise} \end{cases}$$

This selects only the strongest 5% of spectral changes in the scene.

Object Filtering: Region-based filtering is applied to focus on features of interest (ships in this case).

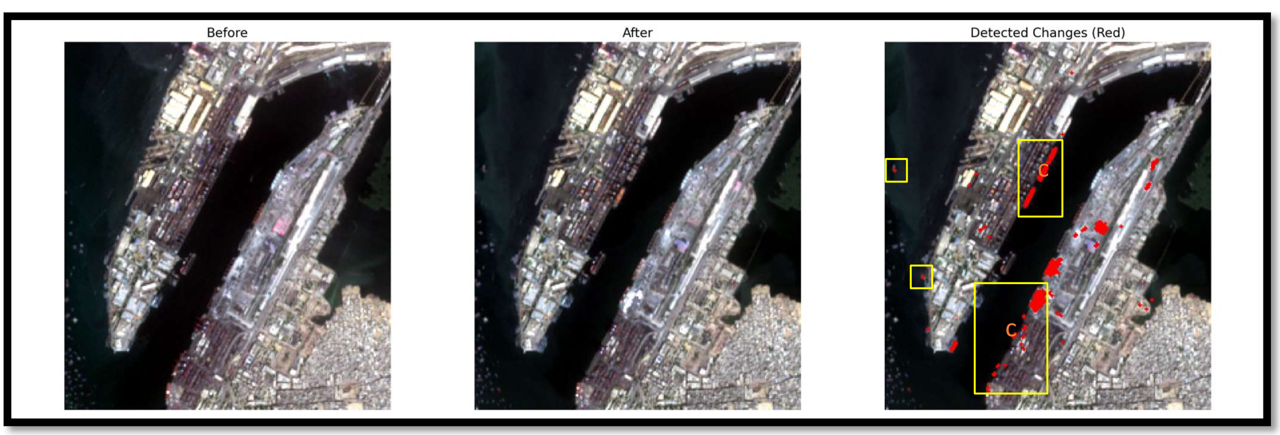
Each continuous region of the binary mask was labelled. For each region, its area (in pixels) was calculated.

Objects were kept only if their sizes fell within a predefined range:

$$A_{\min} \le A \le A_{\max}$$

This filters out noise, overly large objects, and shapes too small to represent valid targets (e.g., ships). Only regions with realistic physical sizes remain in the final mask.

Result:



[Note: detected areas geojson file saved inside Output folder (detected areas marked as yellow boxes)]

6.2 Sentinel-1 (Method 1- Object-pixel Based Unified Change Detection- Unsupervised approach)

Data Preparation: Pre-processed Sentinel-1 VV SAR images (pre-event and post-event) were loaded and converted to dB scale for consistent backscatter representation. Very low backscatter areas were masked to avoid false detections in water or shadows.

SAR intensity is typically analyzed on a **decibel (dB)** scale:

$$I_{\text{dB}} = 10\log_{10}(I)$$

Pixel-Level Analysis: Computed absolute difference between pre-event and post-event images. Identified pixel-level changes exceeding a percentile threshold (e.g., 96th percentile).

Speckle Reduction (Despeckling): SAR suffers from speckle noise, a multiplicative random phenomenon.
The code applies a uniform filter:

$$I_{\text{smooth}}(x,y) = \frac{1}{k^2}\sum_{i=-m}^{m}\sum_{j=-m}^{j=m} I(x+i, y+j)$$

Land–Water Separation Using Backscatter Physics:

Water has extremely low backscatter (smooth surface → specular reflection)

Land has higher and more variable backscatter (rough surfaces → diffuse reflection)

The code simply classifies water using:

$$\text{water}(x) = \begin{cases} 1 & \text{if } I_{\text{dB}}(x) < -20\text{ dB} \\ 0 & \text{otherwise} \end{cases}$$

Object Segmentation:

High-intensity regions in each image were segmented using thresholding and morphological operations to isolate individual objects (ships, bright infrastructure). Connected components labelling was applied to identify objects in pre- and post-event images.

Bright Object Extraction

For each image, a percentile threshold is computed:

$$T = \text{Percentile}_{95}(I_{\text{dB}}(\text{land}))$$

Objects above this threshold are considered “bright scatterers.”

Mathematically:

$$M(x) = \begin{cases} 1 & \text{if } I_{\text{dB}}(x) \geq T \\ 0 & \text{otherwise} \end{cases}$$

Connected-Component Labeling

Each connected region of pixels is treated as one scatterer:

$$\text{regions} = \text{ConnectedComponents}(M)$$

New or Missing Object Detection

A region in T_2 is marked as change if ***no overlapping region*** *existed in T_1:*

$$change(R_2) = \begin{cases} 1 & if\, R_2 \cap R_1 = \emptyset \\ 0 & otherwise \end{cases}$$

Object Radiometric Change

For each region:

$$\Delta = | \mu_2 - \mu_1 |$$

$$\Delta \geq \textit{Percentile}_{95}(| I_2 - I_1 |)$$

then the region is marked as changed.

Object-Based Change Detection:

Appearance: Objects present in post-event but absent in pre-event.

Disappearance: Objects present in pre-event but absent in post-event.

Pixel-Level Change Detection (Land)

For land-only pixels:

$$D(x) = \max\left(I_2(x) - I_1(x), 0\right)$$

A threshold is computed:

$$T_L = \text{Percentile}_{90}(D)$$

Change mask:

$$M_L(x) = \begin{cases} 1 & \text{if } D(x) \geq T_L \\ 0 & \text{otherwise} \end{cases}$$

Water Change Detection

Ships and water objects have strong positive backscatter differences.

The same pixel-level logic is applied but with a higher percentile threshold to avoid false alarms:

$$M_W(x) = \begin{cases} 1 & \text{if } D(x) \geq \text{Percentile}_{98}(D_{\text{water}}) \\ 0 & \text{otherwise} \end{cases}$$

Post-Processing: Small objects below a minimum area (e.g., 50 pixels) were removed to reduce noise. Morphological opening and closing cleaned up the binary mask.

Morphological filtering:

Opening (Erosion → Dilation)

Removes isolated speckle:

$$A \circ B = (A \ominus B) \oplus B$$

Closing (Dilation → Erosion)

Fills holes:

$$A \cdot B = (A \oplus B) \ominus B$$

Connected components smaller than a minimum area $A_{\min}$ are removed:

$$A = \{R \mid |R| \geq A_{\min}\}$$

Output & Visualization: Produced a binary change mask highlighting detected changes. Changes were overlaid in red on the post-event SAR image for visual inspection.

Mask change:

$$M_{final} = M_{land} \lor M_{water}$$

Change polygon extraction:

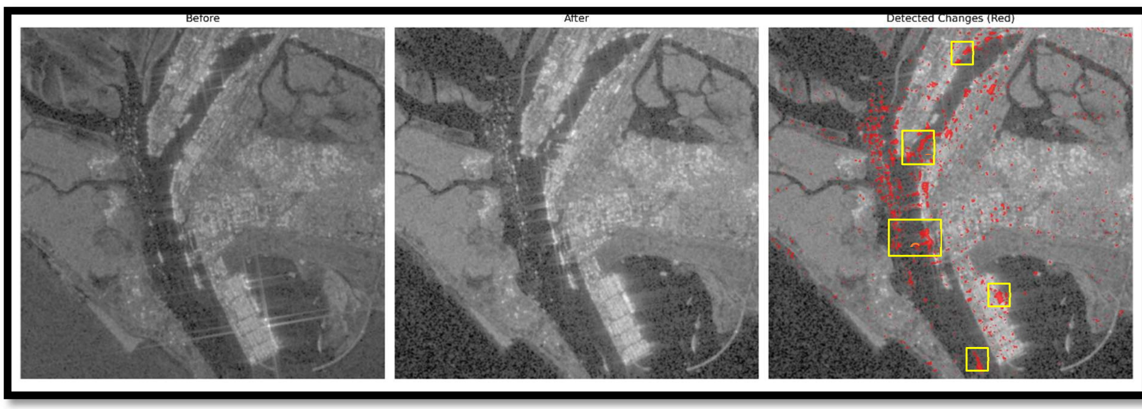
The raster mask is converted to vector polygons using raster-to-vector conversion:

$$\text{Polygons} = \text{shapes}(M_{\text{final}})$$

Only polygons whose area exceeds:

$$A_{\min} \cdot \text{pixel\_area}$$

Result:



[Note: detected areas geojson file saved inside Output folder (detected areas marked as yellow boxes]

7. Quality Checks:

Feature / Capability	PCA Optical Model	SAR Multi-Stage Model	Traditional ML (e.g., Random Forest, SVM)	Deep Learning (CNN / U-Net / Transformer)
Input Type	Optical RGB/NIR	SAR backscatter	Optical / SAR	Optical / SAR / Multi-sensor
Works Without Ground Truth	✅ (plausible detection)	✅ (plausible detection)	⚠️ (needs labelled data for training)	❌ (requires labelled datasets)

Feature / Capability	PCA Optical Model	SAR Multi-Stage Model	Traditional ML (e.g., Random Forest, SVM)	Deep Learning (CNN / U-Net / Transformer)
Detects Ships in Cloudy/Bad Weather	❌	✅	⚠️ (depends on input)	✅ (if trained on SAR/augmented data)
Detects Small Ships	⚠️	✅	✅ (if features selected properly)	✅ (CNN can learn small object features)
Detects Large Ships	✅	✅	✅	✅
Nighttime Detection	❌	✅	⚠️ (depends on sensor)	✅ (if trained on SAR/nighttime data)
Robustness to Noise	⚠️ (PCA sensitive to lighting)	⚠️ (SAR speckle can create false positives)	⚠️ (depends on features)	✅ (CNN can learn noise-robust features)
Computational Complexity	Low	Medium	Medium	High
Requires Training	❌	❌	✅	✅
Visual Interpretability	High	Medium	Medium	Low–Medium
Generalizability Across Scenes	Medium	High	Medium	High (if trained on diverse datasets)
Real-Time Capability	Medium	Medium	Medium	Low–Medium (depending on hardware)
Key Strengths	Simple, interpretable, and works without training	Works in all weather, night, and multi-stage robustly	Flexible, interpretable, and can combine features	High accuracy, can detect subtle patterns, and learns complex features
Key Limitations	Sensitive to clouds/shadows, small objects	Speckle noise requires	Needs labelled data, feature engineering	Requires large labelled

Feature / Capability	PCA Optical Model	SAR Multi-Stage Model	Traditional ML (e.g., Random Forest, SVM)	Deep Learning (CNN / U-Net / Transformer)
		tuning thresholds		datasets, heavy computation

8. Image Analysis:

Layer	Source / Input	Processing / Analysis	Output / Use for Ship Detection / Classification
Pre-Event Imagery (IMINT)	Sentinel-2 / SAR / Optical images	Visual inspection; radiometric normalization; DE speckling (SAR)	Baseline ship positions, port infrastructure layout; reference for comparison
Post-Event Imagery (IMINT)	Sentinel-2 / SAR / Optical images	Same preprocessing as pre-event; co-registration	Detects new, removed, or relocated ships; supports change detection
Change Detection Mask (IMINT)	Difference or PCA/SAR multi-stage results	Morphological filtering, thresholding, and connected component labeling	Highlights potential ship movements or new arrivals
Water / Land Mask (GEOINT)	SAR backscatter or optical indices	Thresholding, object-based classification	Separates navigable water vs land; reduces false positives
Ship Object Layer (GEOINT)	Detected change regions	Object-level filtering (area, intensity, shape, shadow analysis)	Candidate ship polygons or points; ready for further intelligence analysis
Ship Classification Layer (GEOINT/HUMINT/OSINT)	Ship object layer + visual characteristics + AIS/OSINT	Shape analysis, size estimation, signature matching, AIS cross-check	Differentiates between military vs commercial; identifies type (cargo, tanker, container, frigate, etc.), class, and possible vessel name if publicly known
Operational Context Layer (GEOINT/HUMINT)	Historical port activity, known trade routes, and intelligence reports	Pattern-of-life analysis, frequency of port visits, and docking duration	Explains why vessels are present: ongoing port activities, exercises, or logistical operations
Overlay on Georeferenced Map (GEOINT)	Detected ship layer + GIS basemap	Spatial context, port layout, navigation channels	Supports tactical awareness; allows tracking and identification
Temporal Change Layer (GEOINT)	Pre/post imagery comparison	Pixel-level and object-level change detection	Shows ship movement, arrivals, or departures over time

Layer	Source / Input	Processing / Analysis	Output / Use for Ship Detection / Classification
Metadata / Attribute Layer (GEOINT)	Derived from detection outputs	Area, centroid, intensity change, vessel type, class	Enables cataloguing, ship size estimation, classification, and further geospatial analysis

9. **Recommendations (Product & Workflow Improvements)**

9.1 **Technical Workflow Improvements: Automated Preprocessing Pipelines**, Integrate a sequential preprocessing workflow: download → calibration → speckle filtering → coregistration → change detection. **Quality Control Metrics** Include automatic metrics like the number of detected objects, total changed area, and signal-to-noise ratio. **Batch Processing & Logging,** enable batch processing of multiple ROIs with clear logs of thresholds used and outputs generated. Store intermediate outputs (despeckled images, masks) for reproducibility and debugging.

9.2 **Product / UI Improvements (tool):** Interactive Visualization, ability to switch layers between sensors interactively, hovering over the map shows lat/lon, pixel values, or changes intensity, statistics Panel, Filter Changes, batch Processing, change Animation, automatic reporting.

10. **Conclusion:**

This assignment demonstrates a complete, reproducible workflow integrating Sentinel-1 SAR and Sentinel-2 optical imagery for cross-sensor ship change detection and port activity monitoring at Karachi Port.