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Automatic Detection of Shoreline Change Using NDWI Based Image Segmentation Method

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ABSTRACT

Coastal areas are highly dynamic environments that undergo continuous changes due to natural processes and human activities. Monitoring shoreline dynamics is crucial for understanding coastal behavior and supporting sustainable management, particularly in regions experiencing rapid development such as Canggu Beach, Bali. This study focuses on detecting and analyzing shoreline changes using a combination of remote sensing and digital image processing techniques. Sentinel-2 satellite imagery from 2019 to 2024 was utilized to evaluate shoreline variations through the Normalized Difference Water Index method. Data processing was conducted using Google Earth Engine and Python, integrating several key stages including cloud masking, NDWI computation, image normalization, segmentation, and contour extraction. The extracted shoreline boundaries were converted into vector format and analyzed using transect-based measurements to quantify spatial changes, identifying areas of accretion and erosion along the coastline. The results revealed spatially varied shoreline movements, with an average annual change rate of 1.66 meters, reflecting moderate coastal dynamics influenced by both natural and anthropogenic factors. The developed automated method offers improved efficiency, reproducibility, and accuracy compared to traditional manual approaches. The integration of remote sensing and geospatial computation provides a replicable framework for continuous coastal monitoring, offering valuable insights for sustainable coastal zone management, erosion control, and environmental policy planning.

KEYWORDS;- *Shoreline change detection, NDWI, Sentinel-2, image processing, coastal monitoring.*

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I. INTRODUCTION

Coastal areas are dynamic environments that experience continuous changes due to natural and anthropogenic processes such as wave action, sea-level rise, sediment transport, and human development [1], [2], [3]. In recent years, Canggu Beach in Bali has undergone significant morphological alterations driven by tourism growth and coastal infrastructure expansion [4], [5]. These activities, coupled with natural erosion and accretion processes, have accelerated shoreline instability and increased the risk of coastal degradation [6], [7]. Understanding the spatial and temporal dynamics of shoreline change is therefore essential for sustainable coastal management and disaster mitigation in the region [8]. However, manual shoreline mapping methods remain time-consuming and inconsistent, limiting their ability to provide accurate and timely information for environmental monitoring [9].

Despite advances in remote sensing and geospatial technologies, a methodological gap persists in integrating multi-temporal satellite imagery with automated image processing to analyze shoreline dynamics efficiently [10]. Traditional approaches often rely on manual digitization or visual interpretation, which are prone to human error and lack temporal consistency [11]. Moreover, existing studies in Bali and other Indonesian coasts have primarily focused on broad-scale coastal vulnerability assessments rather than fine-scale, automated shoreline extraction using standardized computational frameworks. This gap highlights the need for a robust, automated, and replicable method capable of detecting shoreline changes with high spatial accuracy and temporal consistency.

Recent developments in remote sensing and digital image processing have introduced several state-of-the-art techniques for shoreline detection, such as the Normalized Difference Water Index (NDWI), edge detection algorithms, and contour-based vectorization. The NDWI, derived from Sentinel-2 imagery, provides a reliable spectral indicator for distinguishing water from land surfaces. When combined with segmentation and contour extraction methods implemented through Google Earth Engine (GEE) and Python, these techniques offer significant potential for large-scale, automated shoreline monitoring. However, few studies have optimized this integration for small-scale coastal environments like Canggu Beach, where high-resolution analysis is crucial for detecting subtle geomorphological changes.

This research lies in the increasing environmental and socio-economic pressures on Bali's coastal zones. Rapid coastal urbanization and the intensification of tourism-related activities have led to habitat loss, increased erosion, and reduced natural buffer zones. These issues are exacerbated by climate change-induced sea-level rise, making continuous and precise shoreline monitoring indispensable for informed coastal zone management [12]. Developing an automated method for shoreline detection not only supports environmental conservation efforts but also contributes to local and regional policy frameworks for sustainable coastal development [13].

This study lies in the integration of NDWI-based segmentation, image normalization, and contour extraction techniques within a combined GEE Python workflow. This hybrid computational framework automates the entire process from data acquisition and cloud masking to vector-based shoreline extraction and temporal change analysis. Unlike conventional manual approaches, this method enhances reproducibility, minimizes human bias, and provides consistent, high-resolution shoreline mapping across multiple years.

The aim of this research is to develop and implement an automated digital image processing method for detecting and analyzing shoreline changes along Canggu Beach, Bali, using Sentinel-2 imagery from 2019 to 2024. Specifically, the study seeks to (1) extract shoreline boundaries through NDWI-based segmentation and contour detection [14], [15], (2) quantify shoreline shifts and classify accretion and erosion zones using transect-based spatial analysis [16] and (3) visualize coastal change patterns to support evidence-based coastal management [17]. By combining remote sensing, image processing, and geospatial analysis, this research provides a replicable methodological framework for monitoring shoreline dynamics in other coastal regions facing similar environmental challenges.

II. RESEARCH METHODS

This study employs a digital image processing approach to detect, extract, and analyze shoreline changes in the Canggu Beach area, Bali. Image processing is performed on remote sensing data from Sentinel-2 imagery, which is processed using a combination of Google Earth Engine (GEE) and Python environments. The focus of this method is the application of segmentation techniques, edge detection, and contour-based spatial conversion that represent the boundary between land and water areas.

Data and Study Area

The study area is located along the coastal region of Canggu Beach, Badung Regency, Bali, with coordinates ranging from 115.130° E to 115.170° E and 8.700° S to 8.650° S. The data used are Sentinel-2 Surface Reflectance (SR) images obtained from Google Earth Engine (GEE) for the period between 2019 and 2024, with a cloud coverage threshold of less than 20%.

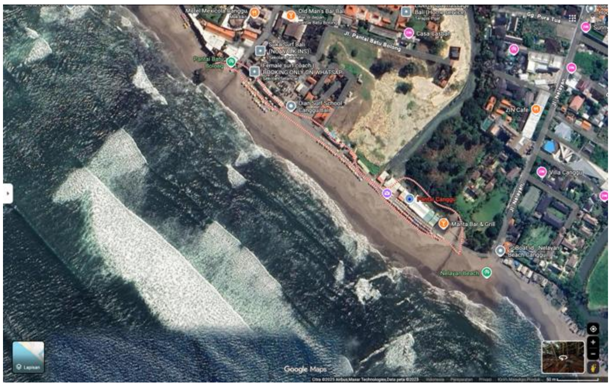


Figure 1. Study Area

Processing

The process of obtaining the Normalized Difference Water Index (NDWI) imagery began by collecting Sentinel-2 satellite data within the region of interest (ROI) for the selected years—2019 to 2024. To ensure consistency and minimize atmospheric disturbances, Sentinel-2 Level-1C and Level-2A surface reflectance products were used depending on the year of acquisition. Cloud and cirrus contamination were removed using a cloud masking algorithm based on the QA60 and SCL bands. After cloud-free images were obtained, the NDWI was computed using the normalized difference between the green band (B3) and the near-infrared band (B8), following the equation:

$$NDWI = \frac{B3+B8}{B3-B8}$$

The resulting NDWI images highlight open water bodies with positive values and suppress built-up and vegetation features. A threshold value of 0.05 was applied to classify water and non-water pixels, and a median composite was generated for each year to reduce temporal noise and residual cloud effects. The final NDWI and water mask images were then clipped to the ROI and exported for further spatial and temporal analysis of shoreline changes.

Normalization

The normalization process in this study is an essential step in preparing the NDWI (Normalized Difference Water Index) image data for coastline detection. After downloading the NDWI image from Google Earth Engine in GeoTIFF format, the raw pixel values are converted into a standardized scale ranging from 0 to 255 using OpenCV's normalization function. This process ensures that variations in pixel intensity are adjusted proportionally, allowing for consistent interpretation of water and non-water regions across different years. Normalization enhances the contrast between land and water surfaces, facilitating more accurate binary thresholding and contour extraction. By transforming the data into an 8-bit image format, subsequent image processing tasks such as thresholding and contour detection can be efficiently applied, leading to a more precise delineation of the shoreline boundary.

The obtained NDWI image has a continuous value range between -1 and +1 with a float32 data type. To facilitate processing using the OpenCV library, the pixel values are normalized to a range of 0–255 using the min–max normalization method.

$$I_{norm} = \frac{(I - I_{min})}{(I_{max} - I_{min})} x255$$

This step converts the image into an 8-bit (uint8) format, allowing it to be processed using binary segmentation techniques.

Segmentation

Segmentation is performed to separate water bodies and land areas into binary classes. A global thresholding method is applied using a fixed threshold value of 127, producing a two-class image: pixels with a value of 255 represent water areas, while pixels with a value of 0 represent land areas. This operation generates a binary map that highlights the transition boundary between the two classes—the primary candidate for the shoreline.

Contour Detection and Geometry Simplification

The boundary between land and water areas is identified using the find Contours from OpenCV, which extracts the edges of closed objects based on intensity differences. The contour with the largest area is considered the main shoreline contour. To reduce noise and refine the detection result, the contour is simplified using the Douglas Peucker algorithm. This algorithm removes insignificant points without altering the main contour shape, resulting in a smoother and more representative shoreline. The binary segmentation output is then converted into vector form through contour extraction to produce a land–sea boundary line.

Coordinate Transformation and Georeferencing

The coordinates of each contour point are initially in the image's pixel coordinate system. Therefore, a linear transformation is applied to convert pixel coordinates into geographic coordinates (longitude–latitude) based on the region of interest (ROI) boundaries. Subsequently, the detected geometry is reprojected into the UTM Zone 50S coordinate system (EPSG:32750) using the PyProj library, allowing for accurate measurement of distances and areas in meters.

Analysis of Accretion and Erosion Changes

Changes in shoreline position are calculated based on spatial differences between years, identifying areas of accretion (land gain) and erosion (land loss). The analysis employs several spatial operations: a 10-meter buffer is created to define the influence zone of each shoreline, a difference operation is performed to determine accretion and erosion areas, and the distance between shorelines is measured to calculate annual shoreline shifts. All computations are carried out in the UTM projection system to ensure accurate distance and area measurements.

The final stage involves visualizing the analysis results in thematic maps showing multi-temporal shorelines (2019–2024), accretion areas (in green), erosion areas (in red), and directional vectors with shoreline displacement distances between years. The visualization is generated using Matplotlib and GeoPandas, and the outputs are saved in both image (.png) and shapefile (.shp) formats for further spatial analysis.

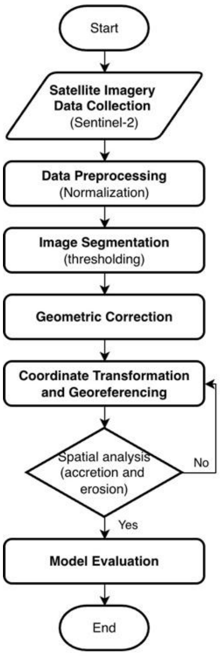


Figure 2. Image Processing Methods

III. RESULT VIEW

This research focuses on developing an automated method for shoreline change detection using satellite imagery and digital image processing techniques. The study utilizes data from Sentinel-2 satellites processed through Google Earth Engine (GEE) and Python to analyze coastal changes in Canggu Beach, Bali between 2019 and 2024. The main process involves calculating the Normalized Difference Water Index (NDWI) to separate land and water areas, followed by image segmentation and contour detection to extract the shoreline boundaries automatically. The extracted shoreline data are then compared across different years to identify areas experiencing accretion (land gain) and erosion (land loss). Using geospatial analysis, the system measures shoreline shifts and visualizes the results on thematic maps that show patterns of coastal change over time. This automated approach reduces the need for manual interpretation and provides a more efficient and consistent method for monitoring shoreline dynamics. This research demonstrates how combining remote sensing, image processing, and geospatial analysis can effectively support coastal monitoring. The method provides valuable insights for environmental management, disaster mitigation, and sustainable coastal planning, especially in regions vulnerable to erosion and sea-level rise.

Pre-Processing

The process begins by defining the Region of Interest (ROI) as a polygon representing the Canggu coastal area. Several parameters are initialized, including the observation years (2019 and 2024), the spatial resolution of 10 meters, and the NDWI threshold value set to 0.05.

Algorithm 1. Pre-Processing step

```
BEGIN
// 1. Define Study Area (ROI)
// ============================
Define polygon geometry for Canggu region as ROI
// ============================
// 2. Set Parameters
// ============================
Set YEARS = [2019, 2024]
Set SPATIAL_SCALE = 10 meters
Set NDWI_THRESHOLD = 0.05

Initialize COASTLINE_LIST as empty dictionary
Initialize STATS_LIST as empty list
```

```
// ============================
// 3. Define Cloud Mask Function
// ============================
FUNCTION maskS2Clouds(image):
   Select QA60 band (quality mask)
   Identify cloud and cirrus bit masks
   Create mask where cloud bits == 0 AND cirrus bits == 0
   Return masked image divided by 10,000
END FUNCTION
```

Two empty data structures—COASTLINE_LIST and STATS_LIST—are prepared to store extracted coastline data and corresponding NDWI statistics. A cloud masking function (maskS2Clouds) is then defined to remove cloud and cirrus noise from Sentinel-2 images. This function selects the QA60 band, identifies the cloud and cirrus bit masks, and retains only the cloud-free pixels. The image values are then scaled to reflectance by dividing them by 10,000, ensuring radiometric consistency for further analysis.

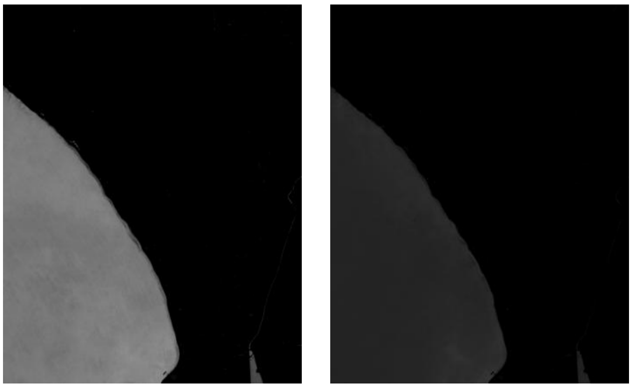
Algorithm 2. NDWI process

```
// ============================
// 4. Define NDWI Computation
// ============================
FUNCTION addNDWI(image):
   Compute NDWI = (B3 - B8) / (B3 + B8)
   Add NDWI as a new band
   RETURN image with NDWI band
END FUNCTION

// ============================
// 5. Loop for Each Year
// ============================
FOR each YEAR in YEARS DO:
   Define START_DATE and END_DATE for that year

   // Filter Sentinel-2 Collection
   Load Sentinel-2 (COPERNICUS/S2) dataset
   Filter by:
      - ROI boundary
      - Date range (START_DATE, END_DATE)
      - CLOUDY_PIXEL_PERCENTAGE < 60
   Apply maskS2Clouds function
   Apply addNDWI function

   // Generate Median Composite
   COMPOSITE = median of all images in collection (within ROI)

   // Compute NDWI and Water Mask
   NDWI_IMAGE = select NDWI band from COMPOSITE
   WATER_MASK = NDWI_IMAGE > NDWI_THRESHOLD

   // Extract Coastline (boundary between water and land)
   COASTLINE_VECTOR = reduce WATER_MASK to polygons (boundary extraction)

   Save COASTLINE_VECTOR in COASTLINE_LIST[YEAR]
   Display layers (Water Mask + Coastline)

   // ============================
   // Compute NDWI Statistics
   // ============================
   MEAN_NDWI = mean NDWI value within ROI
   WATER_AREA = total area of water mask (in hectares)

   Append to STATS_LIST:
      {
         'year': YEAR,
         'mean_NDWI': MEAN_NDWI,
         'water_area_ha': WATER_AREA
      }

   // ============================
   // Export Results
   // ============================
   Export WATER_MASK image to Google Drive as GeoTIFF
   Export COASTLINE_VECTOR as GeoJSON
```

```
END FOR
```

A function called addNDWI is defined to calculate the Normalized Difference Water Index (NDWI), using the green (B3) and near-infrared (B8) bands of Sentinel-2 imagery. The NDWI is computed as (B3 - B8) / (B3 + B8), and the result is added as a new band to the image collection. For each target year, Sentinel-2 Level-1C data are filtered based on the defined ROI, date range, and cloud coverage (<60%). The cloud mask and NDWI computation functions are then applied to all images in the filtered collection.

A median composite is generated for each year to reduce temporal noise and enhance surface consistency. From this composite, the NDWI band is selected and threshold using the predefined NDWI value (0.05) to produce a binary water mask, distinguishing water from land areas. The coastline is extracted by identifying the boundary between water and non-water regions, which is then vectorized and stored in COASTLINE_LIST for each year. The process also calculates statistical indicators—namely, the mean NDWI value within the ROI and the total water-covered area (in hectares)—which are appended to STATS_LIST. Finally, both the water mask and coastline vectors are exported to Google Drive as GeoTIFF and GeoJSON files, respectively, enabling further spatial analysis and visualization of coastline change over time.



2019 2024

Figure 3. NDWI Result

Transect Generate

After obtaining the NDWI (Normalized Difference Water Index), transects are created to quantitatively measure shoreline changes over time. The NDWI highlights water bodies and helps delineate the boundary between land and water. By generating transects—lines drawn perpendicular to the shoreline at regular intervals—it becomes possible to analyze spatial changes in the shoreline position across different time periods. Each transect serves as a reference line to calculate the rate and magnitude of shoreline movement, whether erosion or accretion, based on NDWI-derived water boundaries from multiple image dates. This method provides a systematic and precise approach to assess coastal dynamics and monitor shoreline evolution.

Figure 4. Transect Image

The transects were generated at 5-meter intervals, each with a total length of 500 meters. These transects were drawn perpendicular to the shoreline to serve as cross-sectional lines for measuring shoreline change. After all transects were created, a clip process was applied using the shoreline boundaries to ensure that only the portions intersecting the shoreline area were retained. This clipping step refines the dataset to include only relevant sections along the coast, ensuring that the analysis accurately represents shoreline changes within the defined coastal boundary.

Shoreline Change

The figure 5 show the spatial dynamics of shoreline change in the Canggu Beach area between 2019 and 2024, derived from the NDWI-based image segmentation and contour extraction process. The map overlay clearly depicts two temporal shoreline positions the red line representing the 2019 shoreline and the green line representing the 2024 shoreline. The overlaid lines highlight the extent of coastal accretion and erosion along the coastline over the five-year period.

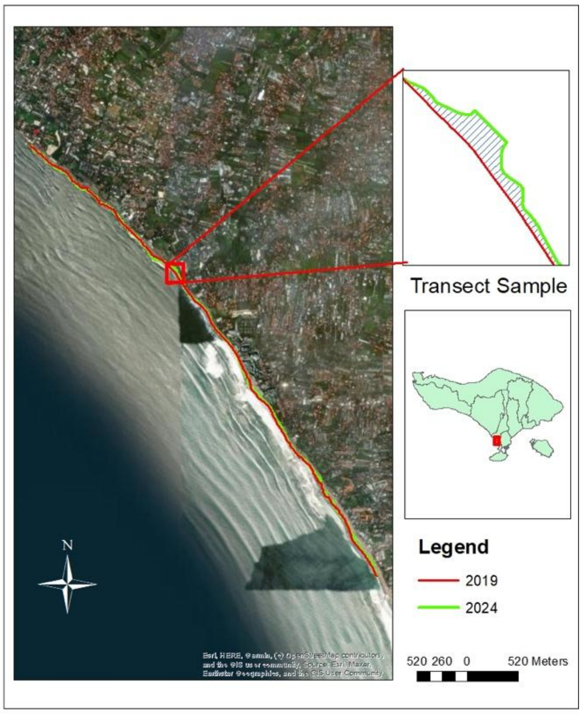


Figure 5. Shoreline Change Visualization (2019–2024) at Canggu Beach, Bali

Table 1. Shoreline Change Measurement

Baseline ID	Number of Transects	Length (m)		
		Minimum	Maximum	Average
1	133	0.06	25.93	11.47
3	3	6.04	7.46	6.8
6	52	0.4	23.42	9.87
7	2	33.22	53.08	43.15
8	98	0.2	36.72	10.89
10	3	1.73	5.49	3.75
11	40	0.05	14.92	9.78
12	2	13.83	15.01	14.42
14	100	4.71	15.54	10.52
15	63	1.24	20.24	9.67
16	70	0.3	5.43	2.92
17	3	2.89	3.78	3.34
19	53	0.07	9.49	5.51
20	3	6.62	7.16	6.93

22	23	0.65	15.52	7.52
23	1	1.04	1.04	1.04
24	2	0.98	3.16	2.07
25	110	0.58	31.22	11.84
26	160	0.03	16.1	5.47
28	26	0.05	5.61	2.42

Table 1 presents the summary of transect length data used for shoreline change analysis across multiple baseline segments in the Canggu Beach study area. A total of 988 transects were analyzed, with a minimum transect length of 0.026 meters, a maximum of 53.079 meters, and an average length of 8.31 meters. This wide range indicates varying shoreline dynamics along different coastal segments, reflecting the influence of both natural and anthropogenic processes on coastal morphology. On average, the annual shoreline change rate is estimated at 1.66 meters per year, suggesting that the shoreline in Canggu experiences a relatively moderate rate of accretion and erosion over time. Segments with longer transects, such as those under Baseline 7 (average length 43.15 m), represent highly dynamic coastal areas where erosion and sediment deposition occur more intensively. Meanwhile, shorter transects, particularly around Baselines 16 and 23, correspond to more stable coastal regions with limited shoreline movement. The dominance of transects within the range of 5–15 meters (observed in Baselines 1, 8, 14, 15, and 25) indicates that most parts of the coastline undergo moderate geomorphological changes, influenced by wave energy distribution, sediment availability, and human activities such as coastal construction and tourism development.

IV. CONCLUSION

This study successfully developed and implemented an automated shoreline change detection method using Sentinel-2 imagery and digital image processing techniques integrated within the Google Earth Engine (GEE) and Python environments. By applying the Normalized Difference Water Index (NDWI), image normalization, segmentation, and contour-based extraction, the research effectively delineated the land–water boundary and quantified shoreline dynamics in the Canggu Beach area between 2019 and 2024. The analysis revealed both accretion and erosion patterns along different coastal segments, indicating that Canggu Beach experiences moderate yet spatially varied shoreline movement influenced by natural coastal processes and human activities such as construction and tourism. The proposed method significantly improves efficiency and accuracy compared to traditional manual mapping approaches, reducing subjectivity and enabling consistent multi-temporal shoreline analysis. Furthermore, the integration of remote sensing and geospatial computation provides a replicable framework for continuous coastal monitoring, offering valuable insights for sustainable coastal zone management, erosion control, and environmental policy planning. This research demonstrates that combining NDWI-based segmentation with automated image processing can serve as a reliable and scalable tool for monitoring coastal dynamics in regions vulnerable to climate change and human-induced pressures.

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