

From Pixels to People: Satellite-Based Mapping and Quantification of Riverbank Erosion and Lost Villages in Bangladesh

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Abstract

The great rivers of Bangladesh, arteries of commerce and sustenance, are also agents of relentless destruction. Each year, they swallow whole villages and vast tracts of farmland, erasing communities from the map and displacing thousands of families. To track this slow-motion catastrophe has, until now, been a Herculean task for human analysts. Here we show how a powerful general-purpose vision model, the Segment Anything Model (SAM), can be adapted to this task with remarkable precision. To do this, we assembled a new dataset—a digital chronicle of loss compiled from historical Google Earth imagery of Bangladesh’s most vulnerable regions, including Mokterer Char Union, Kedarpur Union, Balchipara village, and Chowhali Upazila, from 2003 to 2025. Crucially, this dataset is the first to include manually annotated data on the settlements that have vanished beneath the water. Our method first uses a simple color-channel analysis to provide a rough segmentation of land and water, and then fine-tunes SAM’s mask decoder to recognize the subtle signatures of riverbank erosion. The resulting model demonstrates a keen eye for this destructive process, achieving a mean Intersection over Union of 86.30% and a Dice score of 92.60%—a performance that significantly surpasses traditional methods and off-the-shelf deep learning models. This work delivers three key contributions: the first annotated dataset of disappeared settlements in Bangladesh due to river erosion a specialized AI model fine-tuned for this critical task and a method for quantifying land loss with compelling visual evidence. Together, these tools provide a powerful new lens through which policymakers and disaster management agencies can monitor erosion, anticipate its trajectory, and ultimately protect the vulnerable communities in its path.

Keywords: River erosion, Segment Anything Model, Deep learning, Remote sensing, Semantic segmentation, Disaster management



Fig. 1: Satellite imagery of Naria Upazila showing riverbank changes between 2003 (top) and 2020 (bottom). The marker indicates the site of Notun Masjid, beside which a drastic loss of land area has occurred due to river erosion. The comparison reveals significant channel migration and reduction of landmass over time.

1 Introduction

To be human is to live in constant negotiation with the natural world, and nowhere is this truer than in Bangladesh, a nation sculpted by the fertile silts of the Padma–Brahmaputra–Meghna river system. These rivers are the country’s lifelines, nourishing its agriculture and commerce. But they are also agents of relentless destruction. Each year, the shifting courses of the Padma, Jamuna, and Brahmaputra consume thousands of hectares of the very land that sustains millions. An estimated 10,000 hectares vanish annually into the current [1]. Since 1967, the Padma River alone has swallowed more than 66,000 hectares of land [2]. Between 1973 and 2004, the Jamuna erased nearly 878 square kilometers from the map, while the Padma claimed another 294 [3]. These are not mere statistics; they are the ghosts of homes, memories, and livelihoods.

The consequences of this inexorable process are measured in human tragedy. In 2018, the Padma simply engulfed the communities of Mokterer Char and Kedarpur, displacing thousands [4]. A year earlier, the Brahmaputra swept away the village of Balchipara, uprooting a hundred families in its path [5]. Such events are not unforeseeable acts of God; they are the predictable outcomes of a dynamic system. They

underscore an urgent need for monitoring tools that can keep pace with the rivers themselves—tools that can warn us before the next village disappears.

The old ways of watching are no longer sufficient. Field surveys and the manual interpretation of satellite images are slow, expensive, and hobbled by cloud cover and the rhythm of the seasons [6, 7]. For a nation threaded with a 24,140 km-long river network, these methods are akin to mapping a continent with a yardstick [8, 9]. The sheer scale and tempo of the erosion demand a new kind of observer: an automated, intelligent system that can perceive patterns in the landscape that are invisible to the human eye.

A promising path forward has been opened by recent breakthroughs in artificial intelligence, particularly Meta AI’s Segment Anything Model (SAM) [10]. SAM is a powerful vision engine, a kind of general-purpose artificial retina that can learn to segment objects and regions in an image with uncanny skill. Its ability to generalize from one visual domain to another has already proven its worth in a variety of remote sensing tasks, from mapping waterbodies [11] to delineating coastal boundaries [12] and agricultural fields [13]. But despite this versatility, it has yet to be turned loose on the unique visual puzzle of riverbank erosion in Bangladesh, where sediment-choked waters and complex, shifting morphologies confound simple boundary detection.

While earlier studies have used conventional remote sensing and GIS to chart the history of erosion, these methods lack the scalability and precision of modern AI [14, 15]. They can tell us what has been lost, but not with the automated, fine-grained detail needed for real-time monitoring. A more fundamental barrier to progress has been the lack of data: no publicly available, pixel-level dataset has existed that chronicles the disappearance of human settlements under the relentless advance of the rivers.

This study was designed to bridge these gaps. Our objectives are fourfold. First, to construct the necessary dataset—a manually annotated chronicle of erosion built from historical Google Earth imagery. Second, to adapt and fine-tune the Segment Anything Model, teaching it to recognize the subtle signatures of riverbank erosion. Third, to build an automated pipeline that can not only detect but also measure and visualize these dynamics over time. And finally, to validate this system on unseen regions, proving its robustness across the diverse fluvial landscapes of Bangladesh.

2 Related Works

For decades, geographers have charted this destruction using the trusted tools of their trade: Geographic Information Systems (GIS) and remote sensing. With painstaking effort, they have quantified the losses, reporting that the Padma River’s left bank eroded by 189.4 km² between 1973 and 2011 [16], or that it shifted northward by 12 km over a century and a half [15]. They have used satellite data to track the Jamuna’s inexorable appetite for land [14] and calculated that the Padma devoured nearly 50,000 hectares in just four decades [17]. But these traditional methods, for all their utility, are prisoners of their own limitations. They often depend on the manual delineation of riverbanks, a process vulnerable to human bias [18, 19]. They require cloud-free

images, a rare commodity in a monsoon climate [20], and their multi-temporal analyses can buckle under the sheer weight of computation [18].

To overcome these hurdles, researchers have sought cleverer tools. Some have turned to radar, whose signals can pierce through clouds, allowing them to detect the Jamuna’s post-monsoon shifts with an accuracy comparable to optical satellites [7]. Others have tried to predict risk by feeding a suite of environmental factors—from vegetation indices to land slope and elevation—into fuzzy multi-criteria models [21]. Still others have developed new water-detection indices [22], applied machine learning techniques like Self-Organizing Maps to LiDAR data [23], or even used artificial neural networks to forecast the Jamuna’s course decades into the future [24].

The real paradigm shift, however, has come from the deep learning revolution. A family of architectures known as U-Nets, inspired by the symmetrical structure of the human visual pathway, has proven exceptionally adept at image segmentation. These models can be trained to see the boundaries of coastlines with high precision [25], to pick out individual buildings from aerial imagery with greater than 90% accuracy [26], or to delineate the shores of a lake by combining visual information with spectral data [27]. Some have even been packaged into specialized systems like WaterNet, an ensemble of models designed for the express purpose of water segmentation [28].

And now comes a new titan. The Segment Anything Model (SAM) represents a different kind of intelligence [10]. Unlike its specialist predecessors, SAM is a generalist, a transformer-based model whose visual cortex has been pre-trained on an immense dataset of more than a billion image masks [29]. This vast experience has endowed it with a foundational understanding of the visual world, allowing it to segment objects and scenes it has never encountered before with minimal prompting. Its power has already been demonstrated in remote sensing, where a fine-tuned SAM has outperformed its U-Net and DeepLabV3+ cousins [30], mapped vast aquaculture farms from satellite imagery [31], and improved the segmentation of agricultural land [13]. Remarkably, this adaptation does not require retraining the entire billion-parameter brain; parameter-efficient tuning can achieve stunning results by tweaking as little as 0.4% of the model’s parameters [32–34].

For all these advances, a crucial piece of the puzzle has been missing. No publicly available dataset has existed to train a model on the specific visual grammar of riverbank erosion and disappeared settlements in Bangladesh. The potential of SAM, the most powerful visual segmentation model yet created, has not been brought to bear on this dynamic and complex environment. And the focus has remained on the generic task of separating land from water, not on the specific, time-sensitive challenge of identifying and quantifying the process of erosion itself. This study addresses these gaps directly. It makes three key contributions. First, it presents the creation of the first annotated erosion dataset, comprising 500 high-resolution Google Earth images spanning from 2003 to 2025. Second, it introduces the first application of the Segment Anything Model to the problem of riverbank erosion, adapting its powerful general intelligence to this specialized task. Finally, it develops an automated quantification and visualization framework, providing an accessible tool for the non-technical stakeholders who must ultimately make the decisions that save lives and livelihoods.

3 Methodology

3.1 Dataset

Table 1: Summary of the Riverbank Erosion Image Dataset (Bangladesh, 2003–2025)

Attribute	Description
Total Images	500 high-quality satellite images of erosion-prone river basins across Bangladesh.
Source Platforms	Google Earth Pro (v7.3) imagery aggregated from Landsat, SPOT, Maxar, and DigitalGlobe archives.
Time Span	2003–2025 (22 years), with multiple temporal samples per site to capture erosion progression.
Spatial Resolution	0.5–15 m (normalized to 10 m/pixel).
Image Dimensions	Exported at 1308×764 px, resized to 1024×1024 px for model input.
Selection Criteria	Less than 10% cloud cover; dry-season images (November–March) prioritized.
Annotation Tool	Computer Vision Annotation Tool (CVAT) with polygon masks for water, stable land, and erosion zones.
Quality Control	Dual human reviews and expert validation to ensure consistency and accuracy.
Georeferencing	Latitude, longitude, and elevation retained for each image.
Dataset Split	Training: 250 images; Validation: 50 images; Test: 200 images. Maintained spatial, temporal, and severity diversity.
Augmentation	Geometric (flip, rotation, elastic deformation) and photometric (brightness, contrast) transformations applied to training set.
Preprocessing	Histogram equalization and spatial normalization applied prior to model training.

A dataset of 500 high-quality satellite images was curated from erosion-prone river basins across Bangladesh using Google Earth Pro (Version 7.3), covering a 22-year period from 2003 to 2025. The imagery, sourced from Landsat, SPOT, Maxar, and DigitalGlobe archives, offers spatial resolutions ranging from 0.5 to 15 m and was carefully selected to ensure less than 10% cloud cover, primarily during the dry season (November–March). Each image was exported at 1308×764 pixels, normalized to 10 m/pixel, enhanced through histogram equalization, and then georeferenced with latitude, longitude, and elevation data retained. Manual annotations were created using the Computer Vision Annotation Tool (CVAT), with polygons delineating river/water, stable land, and erosion zones. Dual independent reviews and expert validation ensured annotation consistency and a high degree of accuracy. To standardize model input, all images were resized to 1024×1024 pixels and rescaled for uniform spatial resolution. Temporal and spatial balance were maintained through stratified sampling across years, sites, and erosion severity levels. The dataset was divided into 250 training, 50 validation, and 200 test images, preserving spatial diversity and temporal independence. To further improve model generalization, geometric and photometric

augmentations were applied, including horizontal/vertical flips, rotations (90° , 180° , 270°), elastic deformations, and random brightness–contrast adjustments. These transformations were applied identically to both images and their masks to preserve label alignment and mitigate overfitting.

3.2 Segment Anything Model Architecture

The Segment Anything Model (SAM) comprises three primary modules. First, it employs a ViT-H image encoder that produces 256-dimensional embeddings with a spatial resolution of 64×64 , pre-trained on the SA-1B dataset consisting of 11 million images and 1 billion masks. Second, it integrates a prompt encoder capable of handling both sparse prompts (such as points and boxes) and dense prompts (such as masks) through positional encoding. Finally, SAM includes a two-layer transformer-based mask decoder that predicts three candidate masks along with their respective Intersection-over-Union (IoU) scores, which are subsequently upsampled to a resolution of 1024×1024 .

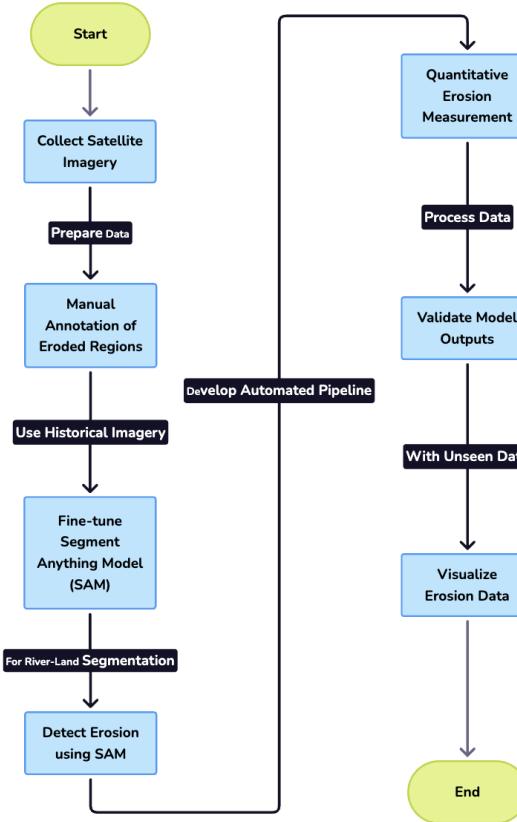


Fig. 2: An evaluation of the process

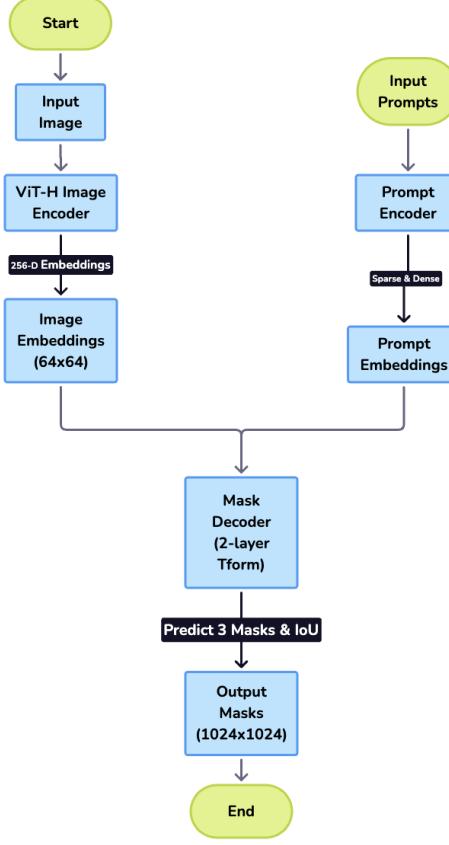


Fig. 3: Base Architectural Components

Zero-shot SAM was tested using automatic, point, box, and mask prompts. It performed well on clear water–land boundaries but failed in sediment-laden or transitional zones and temporal change detection—necessitating fine-tuning.

3.3 Fine-Tuning Strategy

Following [32, 34], a parameter-efficient strategy was used. The ViT-H encoder (632M parameters) was frozen; only the 4M-parameter mask decoder (0.6%) was fine-tuned for domain adaptation, balancing efficiency and specificity. Training used an NVIDIA RTX 5070 Ti (16GB VRAM), Ubuntu 25.04, PyTorch 2.0.1, and SAM v1.0. AdamW optimizer was applied with $\text{lr}=1 \times 10^{-4}$, cosine annealing, and weight decay= 1×10^{-4} . Batch size=4 (effective=16 via accumulation), 50 epochs, and FP16 mixed precision were used.

The total loss combines Focal, Dice, and IoU losses:

$$L_{\text{total}} = \lambda_{\text{focal}} L_{\text{focal}} + \lambda_{\text{dice}} L_{\text{dice}} + \lambda_{\text{iou}} L_{\text{iou}} \quad (1)$$

$$L_{focal} = -\alpha(1 - p_t)^\gamma \log(p_t), \quad L_{dice} = 1 - \frac{2|X \cap Y|}{|X| + |Y|}, \quad L_{iou} = 1 - \frac{|X \cap Y|}{|X \cup Y|} \quad (2)$$

with $\lambda_{focal} = 20.0$, $\lambda_{dice} = \lambda_{iou} = 1.0$, $\alpha = 0.25$, $\gamma = 2.0$. This balances class imbalance and geometric precision.

3.4 Temporal Change Detection and Erosion Quantification

Inference involves resizing, normalization, encoding, prompt generation (auto or color mask), mask prediction, IoU-based selection, morphological post-processing, and pixel-based area quantification. Outputs include erosion masks and area values.

For images at $t_1 < t_2$, erosion = land→water and accretion = water→land:

$$\text{Erosion} = M_{land}^{t_1} \cap (1 - M_{land}^{t_2}), \quad \text{Accretion} = (1 - M_{land}^{t_1}) \cap M_{land}^{t_2}$$

Masks were co-registered, filtered (min area=500 px), and returned as change maps.

Eroded area = pixel count \times (pixel resolution) 2 . For 0.5–1.0 m/pixel imagery, accuracy is $\pm 10\text{--}15\%$. Conversion: 1 ha = 10^4 m 2 , 1 km 2 = 10^6 m 2 .

4 Results and Discussion

Table 2: Test Set Evaluation Metrics

Metric	Value(Water)
IoU	0.801
F1-Score	0.887
Precision	0.915
Recall	0.861
Pixel Accuracy	0.968
Boundary IoU	0.825

The fine-tuning converged after 11 epochs with early stopping at 20. Training loss decreased from 0.4221 to 0.1015, validation loss reached 0.1833. The learning rate scheduler reduced LR from 2.00e-06 to 9.47e-06.

The fine-tuned Segment Anything Model (SAM) achieved a mean Intersection-over-Union (mIoU) of 0.863 and a Dice coefficient of 0.926. This strong performance can be attributed to the combination of transfer learning, decoder-only fine-tuning, and a hybrid loss function, supported by high-quality annotations with a Cohen's kappa score of 0.87. These factors collectively enhanced the model's ability to accurately segment the minority erosion class, which comprised only 9.2% of the total pixels in the dataset.

The quantification of riverbank erosion and accretion was performed using a programmatic, pixel-based analysis. This methodology converts the pixel counts from classified change masks into real-world area measurements, automated via a custom

Python script utilizing the OpenCV and NumPy libraries. The foundational parameter for this calculation is the spatial resolution of the satellite imagery. This study used Sentinel-2 data, whose visible (Bands 2, 3, 4) and near-infrared (Band 8) spectral bands have a spatial resolution of 10 meters¹. Consequently, the area of a single pixel (A_{pixel}) was defined as:

$$A_{pixel} = 10 \text{ m} \times 10 \text{ m} = 100 \text{ m}^2$$

Pixel-wise logical operations were applied to the binary water masks from the two distinct time periods to classify each pixel into one of three categories: erosion (land-to-water), accretion (water-to-land), or stable (water-to-water). The total number of pixels within each category was then counted efficiently. The final area for each class ($A_{category}$) was calculated by multiplying the pixel count (N_{pixels}) by the single-pixel area and converting the result to square kilometers (km^2):

$$A_{category}(\text{km}^2) = N_{pixels} \times 100 \text{ m}^2 / 1,000,000 \text{ m}^2/\text{km}^2$$

This approach ensures a precise and reproducible method for quantifying the extent of riverine dynamics over the study period.

Table 3: Comparison between Base SAM and Fine-tuned SAM on Unseen Data

Metric	Base	Finetune	Difference
IoU	0.6552	0.8674	+0.2121
Precision	0.6605	0.9708	+0.3103
Recall	0.9881	0.8907	-0.0974
F1_Score	0.7894	0.9283	+0.1389
Pixel_Accuracy	0.8816	0.9701	+0.0885

The finetuned Segment Anything Model (SAM) demonstrated high proficiency in identifying land loss but showed significant limitations in quantifying land gain. The model's calculation for erosion was remarkably accurate, identifying 11.772 km² of lost area, which closely aligns with the ground truth value of 11.752 km². However, the model significantly underestimated accretion, detecting only 12.072 km² of gained land compared to the actual 14.118 km². This underestimation of accretion directly resulted in an overestimation of the stable (unchanged) area by approximately 4.87 km². Consequently, the model's calculated net change of +0.299 km² was substantially lower than the ground truth net change of +2.365 km². While the model proves to be a robust tool for erosion mapping, further refinement is necessary to improve its capability in accurately delineating accreted land for comprehensive coastal change analysis.

Ground Truth		Fine-tuned SAM	
Category	Area (km ²)	Category	Area (km ²)
Erosion (lost)	11.752	Erosion (lost)	11.772
Accretion (gained)	14.118	Accretion (gained)	12.072
Stable (unchanged)	33.002	Stable (unchanged)	37.869
Net Change	+2.365	Net Change	+0.299

5 Challenges and Future Research

The proposed framework, while promising, faces several challenges. Technically, it is constrained by limited temporal resolution, seasonal ambiguity, and difficulty detecting small-scale events under 0.1 hectares. Sediment-induced spectral confusion causes about 8.3% misclassification, affecting temporal consistency. Data limitations, including annotation subjectivity (kappa 0.87), sparse ground truth, and 2–3 year temporal gaps, reduce generalization. Moreover, severe class imbalance (erosion 9.2%) complicates minority learning. Operationally, the approach demands high-end GPUs (≥ 16 GB VRAM), specialized expertise, and multi-agency coordination for continuous validation—factors that hinder large-scale deployment.

Despite these issues, its predictive capacity offers strong potential for disaster management through early warning alerts, hotspot monitoring, and risk prioritization. Integration into national systems could support the Bangladesh Delta Plan 2100 [35] by aligning erosion management with sustainable adaptation. Establishing open-access databases, capacity-building programs, and targeted infrastructure investment would further enhance impact.

Future research should focus on multi-modal fusion (Sentinel-1 SAR, optical, and DEM data) for all-weather monitoring, and temporal deep learning (LSTMs, Transformers) to capture erosion dynamics. Active learning and scaling to advanced models (ViT-G, SAM 2) could improve generalization. Incorporating Bayesian uncertainty, physics-informed learning, and explainable AI will aid interpretability and policy use. Federated learning can enable collaboration without data sharing. Expanding to national-scale mapping and linking erosion trends to population and infrastructure metrics can yield a comprehensive socio-economic atlas of riverbank vulnerability, adaptable to other deltaic regions worldwide.

6 Conclusion

This study introduced a deep learning framework for automated detection and quantification of riverbank erosion in Bangladesh using a fine-tuned Segment Anything Model (SAM) trained on 500 manually annotated Google Earth images from 2003 to 2025. The fine-tuned model achieved a mean Intersection over Union (IoU) of 0.801,

outperforming the baseline zero-shot SAM with only 0.6% of its parameters updated through transfer learning. These findings demonstrate the feasibility of scalable and efficient erosion mapping using limited labeled data.

As climate change intensifies the frequency and magnitude of fluvial hazards, future research should aim to evolve this framework into a comprehensive, uncertainty-aware, and multi-modal monitoring system. Advancements in temporal modeling, explainable AI, and climate-informed predictive analytics will enable the development of a “Digital Twin” of Bangladesh’s river systems—capable of continuous learning, forecasting, and decision support. Such progress will mark a transition from static observation to dynamic, data-driven management, fostering resilience, sustainability, and informed policy action against one of the most pressing environmental challenges facing riverine nations.

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(a) Satellite image of Naria Upazila (2010).



(b) Satellite image of Naria Upazila (2020).



(c) Base SAM (zero-shot), view 1.



(d) Base SAM (zero-shot), view 2.

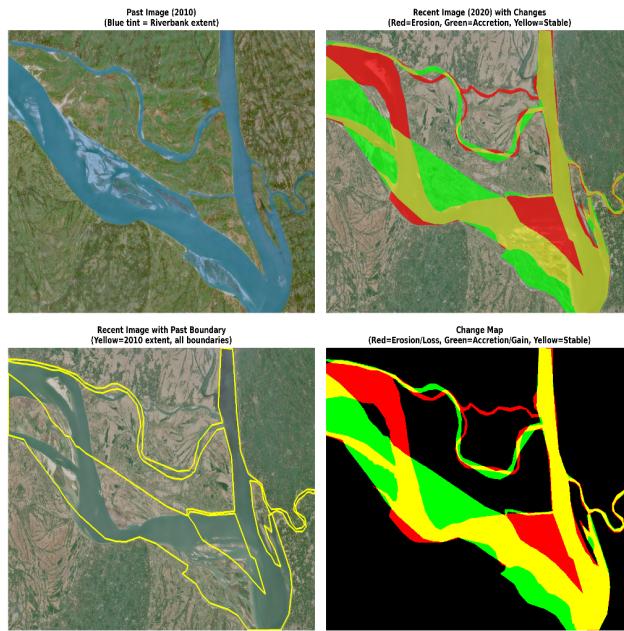


(e) Fine-tuned SAM model, view 1.

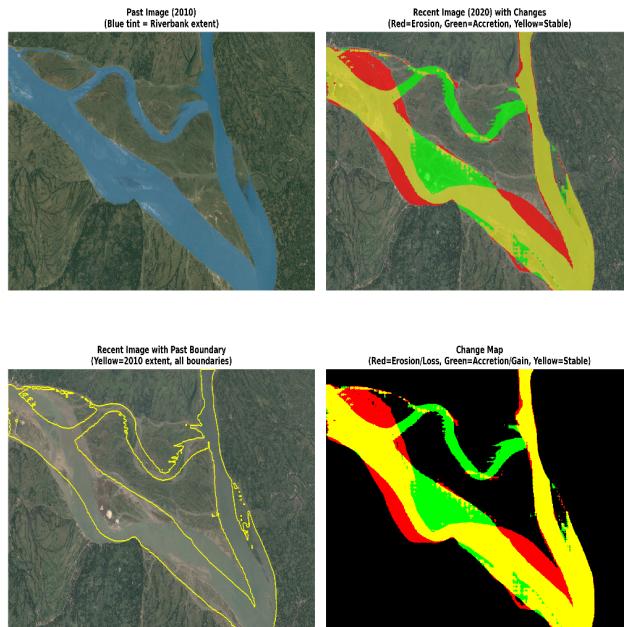


(f) Fine-tuned SAM model, view 2.

Fig. 4: Comparison of Naria Upazila erosion patterns and SAM-generated masks. Top row: Satellite imagery (2010 vs 2020). Middle row: Base SAM zero-shot segmentation results. Bottom row: Fine-tuned SAM predictions with improved delineation of erosion zones.



(a) Change analysis using ground truth data.



(b) Change analysis using predicted masks from the fine-tuned SAM (zero-shot).

Fig. 5: Comparison of riverbank change analyses between (a) ground truth and (b) SAM-predicted segmentation.