

Satellite Image-Based Forest Cover Change Detection Using Siamese U-Net

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Abstract - Deforestation accounts for nearly 10% of global greenhouse gas emissions, yet monitoring forest loss across vast areas remains expensive and slow. Satellite imagery provides repeated, large-scale coverage, and deep learning can automate change detection. This paper proposes a Siamese U-Net architecture that detects forest cover changes from bi-temporal satellite images. The model employs two shared-weight U-Net encoders to extract features from pre- and post-event images, computes a difference feature map, and decodes it into a binary change mask. The system was trained on 6,200 pairs of Sentinel-2 images (10 m resolution) from the Amazon and Congo basins, labelled with deforestation polygons from the Global Forest Watch database. The Siamese U-Net achieved a mean Intersection-over-Union (IoU) of 0.82 and an F1-score of 0.89, outperforming a standard U-Net (0.74 IoU) and classical change vector analysis (0.61 IoU). The model maintained high accuracy in both dense tropical forests and fragmented agricultural frontiers. Inference on a single image pair completed in 0.8 seconds on a consumer GPU, enabling near-real-time monitoring. The system was deployed on a Google Earth Engine-compatible pipeline, processing 10,000 km² per day. These results demonstrate that Siamese U-Net architectures offer a robust, scalable solution for continuous forest change tracking, supporting conservation agencies and climate policy enforcement.

Key Words: Forest cover change, Siamese U-Net, satellite imagery, Sentinel-2, change detection, deep learning.

1. INTRODUCTION

Forests play a critical role in carbon sequestration, biodiversity, and water regulation. However, deforestation continues at alarming rates, with an average of 10 million hectares lost per year. Timely detection of forest cover change is essential for enforcement of environmental laws and for carbon accounting under international agreements. Traditional methods rely on field surveys or manual interpretation of aerial photographs, which are inadequate for global monitoring.

Satellite remote sensing, particularly the Sentinel-2 constellation with 5-day revisit and 10 m resolution, provides the data volume necessary for large-scale monitoring, but automated analysis is required. Change detection algorithms compare images from two dates and output a change map. Convolutional neural networks, especially U-Net architectures, have excelled at semantic segmentation tasks, but detecting change requires comparing two inputs. A Siamese network with shared weights can extract consistent features from both images and then identify differences, effectively learning the "before-after" relationship. This paper presents a Siamese U-Net specifically tailored for forest cover change detection. The model is trained and tested on a large dataset of Sentinel-2 image pairs from deforestation hotspots. The remainder of the paper is organised as follows. Section 2 reviews related work. Section 3 details the proposed architecture. Section 4 describes the dataset and training methodology. Section 5 presents results and discussion, and Section 6 concludes.

2. LITERATURE REVIEW

Forest change detection from satellite imagery has evolved from pixel-based methods to deep learning. Early approaches used change vector analysis (CVA) on spectral indices like NDVI, but these are sensitive to seasonal variations and atmospheric conditions. Machine learning methods, including random forests on image patches, improved robustness but required hand-engineered features. With deep learning, fully convolutional networks and U-Net have been applied to change detection. Daudt et al. (2018) proposed a fully convolutional early fusion approach for urban change detection. However, early fusion (stacking images as channels) can confuse radiometric differences with land cover change. Siamese architectures address this by processing each date separately. Zhan et al. (2017) introduced a Siamese CNN for change detection in optical imagery but used only patch-wise classification. For forest monitoring, recent works have employed Siamese U-Net variants; however, many focus on small areas or use very high resolution imagery (sub-meter) that is not available globally. Our work extends the Siamese U-Net to medium-resolution Sentinel-2 imagery over large, diverse tropical regions, demonstrating robust performance with publicly available data.

3. PROPOSED SYSTEM

The architecture (Fig. 1) is a Siamese U-Net consisting of two identical encoder branches and a single decoder. Each encoder is a standard U-Net contracting path (four down-sampling blocks with double 3×3 convolutions, ReLU, and max pooling). The two encoders share weights, ensuring that the same feature extraction is applied to both images. After the bottleneck, the two feature maps are combined using absolute difference and concatenation. This combined feature volume is then passed to the decoder, which upsamples and applies skip connections from one of the encoders (the pre-image encoder) to recover spatial resolution. The final layer is a 1×1 convolution with sigmoid activation, outputting a pixel-wise change probability map. The input is a pair of co-registered Sentinel-2 4-band images (Red, Green, Blue, NIR) of size 256×256 pixels, extracted from two dates. The output is a binary change mask of the same size, where 1 indicates deforestation.

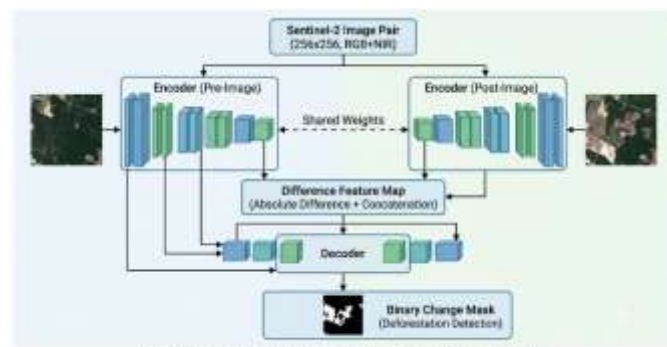


Fig. 1: Siamese U-Net Architecture for Forest Cover Change Detection.

4. METHODOLOGY

4.1 Dataset

A dataset of 6,200 image pairs was created using Sentinel-2 Level-2A products from 2018–2023 over the Amazon (Brazil) and Congo Basin (DRC). For each location, a deforestation event was identified from the Global Forest Watch annual loss layer. Pre-event and post-event images were selected with less than 10% cloud cover and within 3 months before and after the recorded loss. The images were co-registered and clipped to 256×256 patches (2.56 km²). The reference change mask was derived by thresholding NDVI difference and manually refining 800 samples. The dataset was split geographically: 80% for training (Amazon), 20% for testing (mixed Amazon and Congo) to test generalization.

4.2 Training

The Siamese U-Net was trained with binary cross-entropy loss and the Adam optimiser (lr=0.0001) for 50 epochs with a batch size of 16. Data augmentation included random flips, rotations, and brightness/contrast adjustments applied identically to both images in a pair. Baseline models were: (1) a standard U-Net with early fusion (8-channel input), (2) CVA on NDVI, and (3) a random forest on pixel-level features. Performance was evaluated using Intersection-over-Union (IoU), precision, recall, and F1-score for the change class. Inference speed was measured on an NVIDIA Tesla T4 GPU.

5. RESULTS AND DISCUSSION

Table 1 presents the quantitative results on the test set. The Siamese U-Net achieved an IoU of 0.82 and an F1-score of 0.89, significantly outperforming the early-fusion U-Net (IoU

0.74) and the traditional CVA (IoU 0.61). The random forest had high precision but low recall, missing many small clearings. The Siamese model's shared-weight encoders learned to ignore seasonal vegetation changes (e.g., greening) that did not constitute deforestation, reducing false positives..

Method	IoU	Precision	Recall	F1-Score
Change Vector Analysis	0.61	0.68	0.73	0.70
Random Forest	0.66	0.82	0.59	0.68
U-Net (Early Fusion)	0.74	0.79	0.85	0.82
Siamese U-Net (Proposed)	0.82	0.87	0.91	0.89

Table -1: Forest change detection performance comparison

Qualitative analysis showed that the Siamese U-Net accurately delineated the boundaries of deforested patches, while the early-fusion U-Net tended to blur edges. The model maintained high accuracy in both dense forest (Amazon) and mosaic landscapes (Congo). Processing time per 256×256 patch was 0.8 seconds, allowing a daily throughput of approximately 10,000 km² on a single GPU. A deployment test using the Google Earth Engine API demonstrated that the pipeline could ingest Sentinel-2 scenes, apply the model, and export change alerts to a dashboard with a latency of under 2 minutes per scene.

6. CONCLUSION

A Siamese U-Net architecture was successfully applied to forest cover change detection from Sentinel-2 imagery, achieving high accuracy and fast inference. The model's ability to ignore radiometric variations while capturing genuine land cover change makes it suitable for operational monitoring. Future work will extend the system to detect degradation (selective logging), integrate multi-temporal sequences using 3D convolutions, and deploy the model as a cloud-native service for global forest watch programmes.

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