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Computer vision framework for satellite-based vegetation change detection analysis

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Abstract

This report presents a data-centric framework for detecting vegetation change from satellite imagery using NDVI (Normalised Difference Vegetation Index) time series. The pipeline ingests Sentinel-2 data, computes NDVI, and tiles scenes into spatio-temporal patches. To generate consistent training labels without manual annotation, a Gaussian Process (GP) is fit to each patch's NDVI history (frames $0 \dots T-2$) and flagged as "change" occurring when the final frame $T-1$ falls outside the GP's predictive confidence band. A 3D CNN is then trained to classify patches (no change/moderate change/strong change) from the full NDVI stack.

Evaluations on held-out Areas of Interest (AOIs) show the CNN can approximate GP decisions while exploiting spatial structure, producing intuitive change heatmaps. The latter sections of this report further explain design choices and critical analysis, while outlining how this hybrid statistical–ML approach supports monitoring of floods, drought, and land state transitions.

0.1 Introduction

Floods are among the deadliest and most destructive natural hazards, affecting more people globally than any other weather-related disaster (Atefi and Miura, 2022) and causing over $40 billion in damages each year (WMO, 2023). One significant consequence of severe flooding is the widespread loss of vegetation. Inundation can submerge and destroy crops, forests, and grasslands, leading to abrupt changes in vegetation health that are discernible via satellite remote sensing. Rapidly detecting these vegetation changes is crucial for disaster assessment, ecological recovery planning, and climate change adaptation efforts. Satellite imagery offers a powerful means to monitor such changes continuously over large areas, even in remote or inaccessible regions, providing critical information in the aftermath of floods or other environmental disturbances.

This project presents a computer vision framework for analysing multi-temporal satellite data to detect vegetation change. The framework uses the Normalised Difference Vegetation Index (NDVI), a widely used spectral index indicative of live green vegetation, as the primary signal for vegetation health. By examining NDVI-derived maps over a five-year period for multiple areas of interest (AOIs), the system can identify where significant vegetation loss or gain has occurred. A machine learning model (in this case, a convolutional neural network) was trained on the multi-temporal NDVI data to automatically classify changes in vegetation. The objective being to improve upon traditional change detection methods (such as simple NDVI thresholding) by using a data-driven approach that can learn complex patterns of change and reduce false alarms.

0.2 Background

0.2.1 Remote Sensing of Vegetation and NDVI

Satellites equipped with optical sensors have long been used to monitor Earth's vegetation. A fundamental metric in this domain is the Normalized Difference Vegetation Index (NDVI), which provides a quantitative measure of live green vegetation cover. NDVI is calculated from reflectance in the red (R) and near-infrared (NIR) spectral bands as:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

which yields values in the range $[-1, +1]$(USGS, n.d.). Healthy, active vegetation strongly absorbs red light (for use in photosynthesis) and reflects NIR light, resulting in high NDVI values. In contrast, water, bare soil, or dead vegetation reflect relatively more in the red band and less in NIR, producing low or negative NDVI values. Thus, NDVI is high (close to +1) for dense green vegetation, moderate (0.2–0.5) for shrubs and grasslands, near zero for sparsely vegetated areas, and negative for water or snow (Sentinel-Hub, n.d.). This index has a strong correlation with the biomass and the state of vegetation, thus making it widely used to assess plant health, drought impacts, and changes in land cover.

In the context of change detection, NDVI can highlight shifts in vegetation over time by comparing its values between dates. A drop in NDVI in a given location typically signals vegetation loss or degradation, which could result from events like flooding, wildfires or deforestation, whereas an increase might indicate vegetation recovery or growth, such as seasonal greening or replanting.

However, traditional NDVI differencing or threshold methods may struggle with subtle changes, noise due to cloud cover or seasonal changes, and the challenge of selecting accurate thresholds across diverse environments.

To improve upon basic index-threshold approaches, more sophisticated methods from computer vision and machine learning have been explored. One such avenue involves Gaussian Process (GP) regression applied to NDVI time series (Bhattacharjee et al., 2021). Gaussian Processes are Bayesian non-parametric models well-suited for modelling temporal data with uncertainty.

GPs allow for each predicted NDVI value to produce not only a mean μ_*, but also an uncertainty interval $\mu_* \pm z \cdot \sigma_*$ (for $z = 1.96$ at 95% confidence). Change events can then be flagged when observed NDVI values deviate significantly from the predicted distribution.

0.3 Design and Implementation

The dataset was constructed from Sentinel-2 NDVI frames collated per area of interest (AOI) into chronological stacks spanning five years. To enable localised learning, each AOI scene was tiled into overlapping patches of size $[T \times H \times W] = [11 \times 32 \times 32]$ with a stride of 16, balancing coverage against redundancy.

To generate labels without manual annotation, we adopted a Gaussian Process (GP)-based weak supervision strategy. For each patch, the frame-wise mean NDVI y_t was computed across spatial pixels. A GP regression model was then fit over the temporal domain $t = 0 \ldots 9$ using an `RBF` kernel and `WhiteKernel` to account for smooth trends and noise. The GP produced a predictive mean μ and standard deviation σ for the held-out timepoint y_{10}. We defined a confidence band $\mu \pm z\sigma$, and if the observed y_{10} lay outside this interval, the patch was labelled as "change"; otherwise, it was labelled as "no change." Two different z thresholds were later introduced ($z \in \{1.0, 1.96\}$) to distinguish changes better and so therefore labelling became "change", "moderate change", or "no change". This process yielded consistent, adaptive labels directly from the temporal NDVI dynamics, avoiding reliance on estimated thresholds.

The classification model was a 3D convolutional neural network (CNN) implemented in PyTorch. The input to the network was the full NDVI patch $[11 \times 32 \times 32]$, reshaped as $[1, T, H, W]$. The architecture applied temporal and spatial 3D convolutions with batch normalisation and ReLU activations, followed by temporal-preserving pooling and a global average pooling stage. Fully connected layers mapped the learned representation to the three-class softmax output (no change, moderate change, strong change). The network was trained with cross-entropy loss using class weights to address imbalance, and regularisation was applied via dropout (0.5 in the first linear layer, 0.3 in the second) and weight decay. Training was conducted for 10–20 epochs using AdamW with a learning rate of 1×10^{-4}, mini-batch size of 16, and data loaders for efficient shuffling and batching.

Evaluation followed a site-level hold-out strategy. Eight AOIs were used for training, while four distinct AOIs (Alau Dam, Bartley, Indus River Basin, and the River Avon/Severn) were reserved exclusively for testing. Model performance was assessed using accuracy and weighted F1 score to balance class effects. For qualitative scene-level interpretation, the trained model was slid across entire AOIs with a stride 16 to generate change-probability heatmaps. A complete flow chart detailing the workflow can be seen in the Appendix 0.6.

0.4 Evaluation

The proposed 3D CNN was evaluated on four unseen AOIs and compared against benchmark models. Table 1 summarises this comparison. While state-of-the-art 3D CNNs and U-Net variants achieve accuracies of 75+% depending on input size and sensor fusion, our model achieves 69.4% accuracy using only Sentinel-2 NDVI patches ([11×32×32]) with labels derived from Gaussian Processes. This is competitive given the smaller input size, NDVI-only feature space, and the weakly supervised nature of our labels.

Table 1: Comparison of benchmark models for vegetation change detection/classification.

Ref.	Model	Data Source	Input Size	Accuracy
Zhou et al., 2022	3D-CNN	Sentinel-2A (NDVI)	15×15 patches	95.82%
Zhou et al., 2022	2D-CNN	Sentinel-2A (NDVI)	15×15 patches	79.07%
Solórzano et al., 2021	U-Net (MS+SAR)	Sentinel-1 Sentinel-2	128×128 patches	76.00%
Solórzano et al., 2021	U-Net (MS only)	Sentinel-2	128×128 patches	75.00%
Walid	**3D-CNN**	**Sentinel-2 (NDVI)**	**32×32 patches**	**69.40%**
Solórzano et al., 2021	U-Net (SAR only)	Sentinel-1	128×128 patches	65.00%

Figure 1 depicts strong label classification tendencies, with the "moderate change" label being the most challenging due to its more subjective nature. Visual inspection of predictions supports the quantitative results. Figure 2 illustrates examples of predicted "before" and "after" patches flagged as strong change. The model clearly identifies vegetation change between temporal frames, with high confidence in many cases. In practice, these patch-level detections can be aggregated into AOI-wide heatmaps, providing interpretable spatial maps of vegetation loss for flood impact assessment.

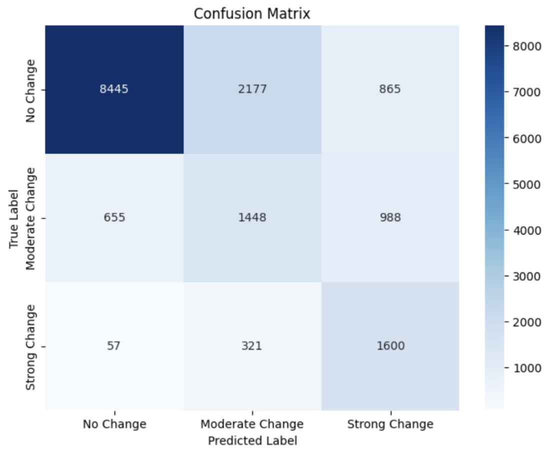

Figure 1: Confusion Matrix

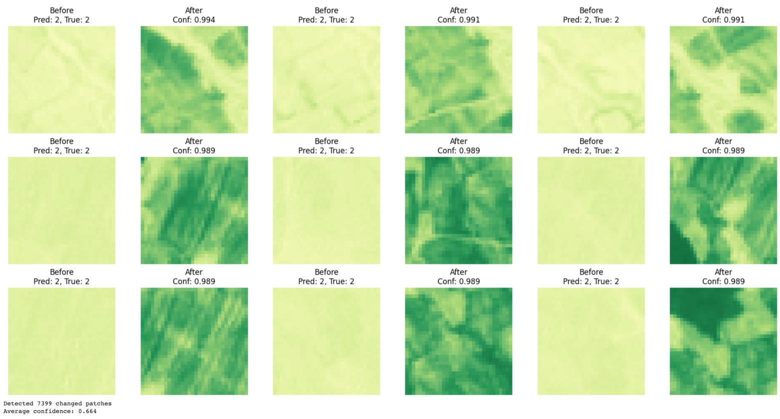

Figure 2: Before and After of Patches Predicted as “Strong Change”

0.5 Conclusion

In summary, this project shows the development of a computer vision framework that successfully detects vegetation changes from multi-temporal satellite imagery, with a focus on flood-induced vegetation change. By using NDVI as an indicator of vegetation health and training a CNN to recognise change patterns, the system achieved relatively high accuracy in distinguishing true vegetation decline from unchanged conditions. This demonstrates improvements over a traditional NDVI threshold approach, and the results are in line with or better than benchmark models for similar tasks. The use of an automated learning-based approach allows for efficient processing of large areas and could support rapid post-disaster assessments. In practical terms, this framework could be integrated into platforms like Google Earth Engine for real-time monitoring: for example, automatically flagging regions in satellite images where NDVI drops dramatically, to alert authorities of potential flood damage to crops or natural habitats.

0.6 Appendices

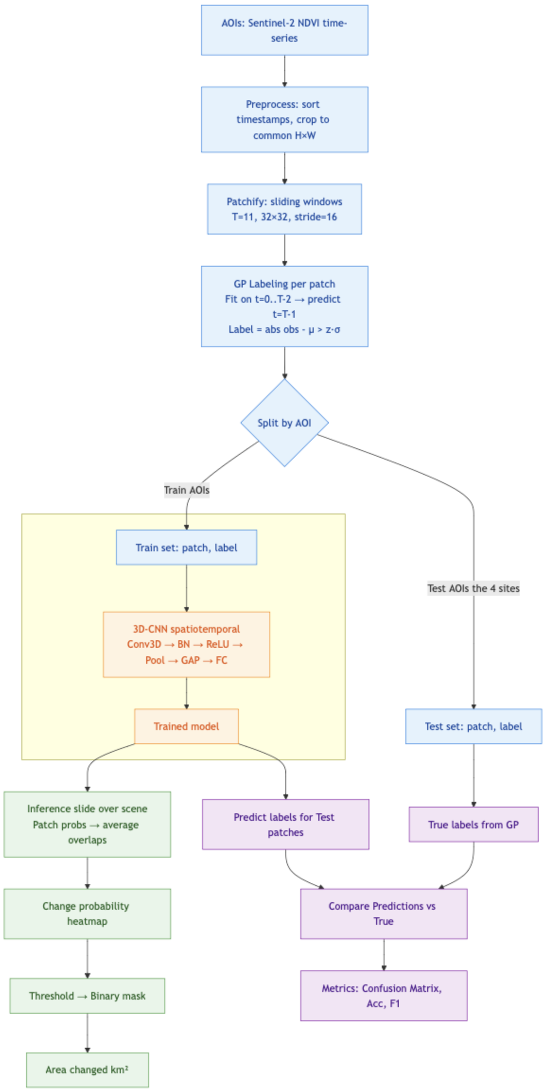

Figure 3: Flowchart Depicting Workflow

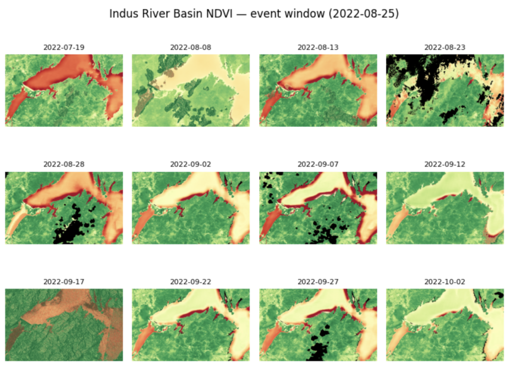

Figure 4: NDVI Change Over Time

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