AI-based Validation of Deforestation Using High-Resolution Satellite Imagery in the Brazilian Amazon

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Abstract

Forests play an important role in the Earth systems for carbon sequestration and climate change mitigation, yet they have been increasingly disturbed by deforestation and forest degradation at an unprecedented pace. The Brazilian Amazon, for instance, experienced a 140% rise in deforestation from 2012 to 2020, with a record loss of 13,200 km² between August 2020 and July 2021. Alarmingly, 87% of 2019 deforestation alerts occurred on private properties, with 61% in legally restricted areas. Existing deforestation monitoring systems, such as PRODES and the Global Forest Change dataset, use about 30m resolution satellite imagery, which is insufficient for operational validation at fine scales. The Deforestation Alert System by Imazon leverages high-resolution PlanetScope data (3-4m) but faces challenges due to fewer spectral bands and variations in reflectance values across different satellite sensors and dates. As a result, current validation is based mainly on manual inspection which is highly time-consuming. To address the challenges and automate the validation process, this work develops a system based on deep learning – known for its ability to capture complex texture patterns in high-resolution images – to inspect and confirm new deforestation sites. Specifically, the system takes inputs from potential deforestation sites suggested by coarse-resolution products and uses a pair of PlanetScope images before and after the change at each site to determine new deforestation (excluding existing deforestation). Our results demonstrate that the new system achieves robust and high-quality accuracy under various test conditions.

1. Introduction

Forest plays an important role in the Earth systems for carbon sequestration and climate change mitigation. However, forests have been increasingly disturbed by deforestation and forest degradation at an unprecedented pace. Taking the Brazilian Amazon as an example, deforestation has been rapidly growing by 140% from 2012 to 2020, and between August 2020 and July 2021 alone, this region experienced a huge forest loss of 13,200 km², marking the highest deforestation rate in the past 15 years (Coelho-Junior et al., 2022). Moreover, a recent study indicates that 87% of the deforestation alerts in 2019 occurred on private properties, with 61% overlapping with legal restricted areas for forest removal, and only 0.1% were licensed forest suppression (MapBiomas, 2020). Altogether, these figures reveal the ongoing critical issue of illegal deforestation in the Brazilian Amazon, leading to the urgent need for automatically identifying deforestation to support effective environmental governance and restore regulatory control.

Past studies have made significant efforts to generate deforestation products. PRODES, the widely-used product of deforestation monitoring from the National Institute of Space Research of Brazil, generates clear-cut deforestation maps based on visual interpretation of satellite imagery and manual mapping (de Almeida et al., 2021). Similarly, the Global Forest Change dataset, the first global forest map at 30m resolution from the University of Maryland, provides consistent annual deforestation loss and gain since 2000 using data-driven decision tree classification methods (Hansen et al., 2013). However, both datasets are based on about 30m resolution satellite imagery, which is suitable for mapping the coarse-scale extent of deforestation and aggregated analysis but is insufficient to validate and confirm deforestation sites for operational use at high resolutions. Recently, MapBiomas Deforestation Alert, a well-established deforestation alert system for the Amazon Forest,

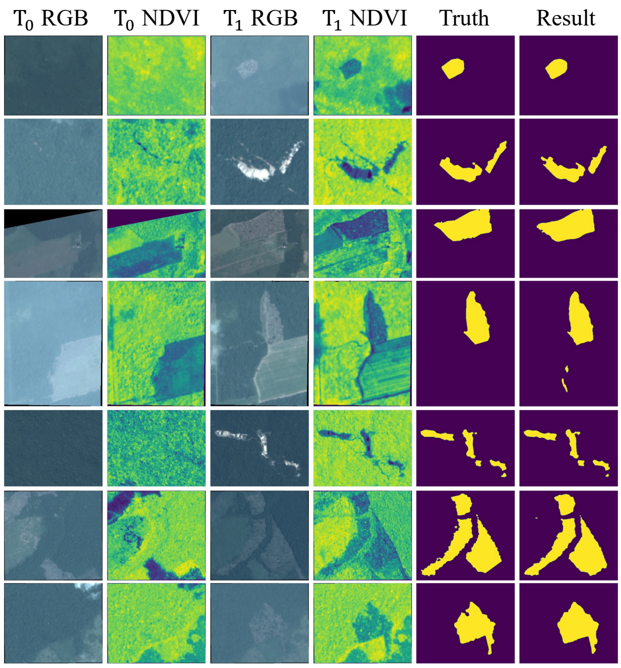


Figure 1. Results of AI-based deforestation validation.

utilizes the high-resolution PlanetScope data at about 3-4m resolution to validate deforestation sites (Mapbiomas, 2022). However, compared to conventional multispectral satellite imagery at moderate resolution, PlanetScope images have fewer bands, significantly more texture details from higher resolution, and variation in reflectance values across different satellite sensors and dates (Wagner et al., 2023; Pandey et al., 2021). These challenging characteristics suggest that conventional machine learning methods, which primarily depend on spectral features, may not be effective. As a result, current validation is based mainly on manual inspection, which is highly time-consuming.

To address the challenges and automate the validation process, this work develops a system based on deep learning – which has shown promising abilities in capturing complex texture patterns in high-resolution images (Persello et al., 2022; John and Zhang, 2022; Kattenborn et al., 2021) – to inspect and confirm new deforestation sites. Specifically, the system takes inputs from potential deforestation sites and uses a pair of PlanetScope images before and after the change at each site to determine if it is a new deforestation site (excluding existing deforestation). Our contributions are summarized as follows:

- We introduce a novel deep learning model to automate the validation of deforestation sites, leveraging the high spatial resolution of PlanetScope imagery to enhance detection accuracy.
- We conduct comprehensive experiments comparing traditional machine learning and popular deep learning methods for deforestation mapping, using various evaluation metrics to benchmark performance.
- We demonstrate the robustness and generalizability of our model by validating its performance on extensive datasets collected from the Amazon rainforest, highlighting its applicability in real-world deforestation monitoring.

2. Related Work

Deforestation monitoring has been a significant area of research, with various methods and products developed to track forest loss. Traditional machine learning methods, such as Decision Tree or Random Forest, have been widely used to generate deforestation maps using coarse- and moderate-resolution satellite imagery (Hansen et al., 2013; Grinand et al., 2013; Healey et al., 2018; Lesiv et al., 2022). Taking the Global Forest Change dataset as an example, a decision tree method is used to capture spectral patterns of forest and non-forest pixels, producing robust global deforestation loss and gain at a 30m resolution (Hansen et al., 2013). While these products offer valuable insights into large-scale deforestation patterns, their spatial resolution is limited, hindering the ability to detect smaller deforestation events and validate changes at finer scales.

Recent studies have incorporated higher-resolution imagery into deforestation monitoring using the Planet NICFI dataset which provides satellite imagery with approximately 3-4m resolution (Dalagnol et al., 2023; Wagner et al., 2023; Debus et al., 2024). However, traditional machine learning methods, primarily relying on spectral features, face challenges in extracting useful patterns from high-resolution pixels with fewer bands, variation of reflectance values, and more contexture details from neighbouring pixels (Wagner et al., 2023; Pandey et al., 2021). One promising solution is the application of deep learning models, which have shown state-of-the-art performance in semantic segmentation, particularly convolutional neural networks (CNNs) that can learn complex contextual patterns (LeCun et al., 2015; Chen et al., 2022; Wagner et al., 2023; Dalagnol et al., 2023). For example, Dalagnol et al. (2023) use the U-Net model to extract comprehensive contextual features through a symmetric encoder and decoder architecture, enabling high-quality deforestation mapping. However, these studies mainly focus on deforestation mapping using single-image inputs. Few studies address change detection, where only deforested regions are identified from a pair of images taken before and after a deforestation event. Detecting changes between images is important, as it allows for the identification of newly deforested regions based on a baseline of high-quality annual deforestation maps after extensive manual validation, thereby reducing redundant labour checks and enhancing environmental monitoring efforts.

3. Methods

3.1 Model Architecture

We use the U-Net architecture to identify deforestation changes between a pair of images at two different time steps. Fig. 2 shows the U-Net model, which consists of two parts, an encoder and a decoder, allowing the capture of contextual information at various scales (Ronneberger et al., 2015). The encoder passes input features through several blocks of convolutional layers, with the resolution gradually reduced using strides to learn multi-scale features. The decoder then up-samples coarse-resolution features through blocks of deconvolutional layers. To accurately recover fine details, the up-sampled features are concatenated with corresponding features from the encoder layers. At the final stage, we add a projection layer to output pixel-level classifications of deforestation changes.

In our setup, both the encoder and the decoder are comprised of 4 blocks each. For the encoder, each block includes two consecutive 3×3 convolutions, with the second convolution using a stride of 2 to halve the image size. Each convolutional layer is followed by a ReLU activation function. The decoder blocks consist of a 3×3 deconvolutional layer, followed by a 3×3 convolutional layer. After each deconvolutional layer, the feature map is concatenated with the corresponding encoder feature map of the same size, then followed by a 3×3 convolution layer. The final layer linearly projects the U-Net outputs into a probability map that indicates the "confidence" level in the deforested and non-deforested classes.

3.2 Loss Function

We train the network using the Dice loss, which is a widely used loss function for imbalanced datasets. In deforestation mapping, Dice loss helps the model focus on detecting the boundaries and extents of deforested areas, which can be sparser than no-change regions. Specifically, Dice loss measures the overlap between the predicted regions and the ground truth out of the union of both regions. The Dice loss is defined as:

$$\text{Dice Loss} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i + \sum_i g_i} \tag{1}$$

where p_i is the predicted deforestation region for pixel i, and g_i is the ground truth region for pixel i.

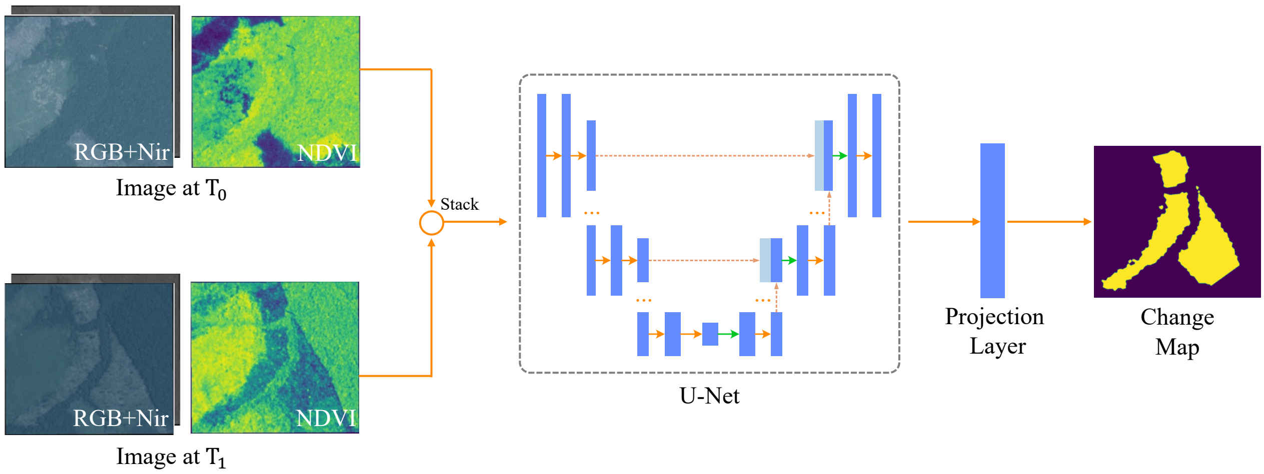


Figure 2. U-Net Architecture for deforestation validation.

3.3 Evaluation Metrics

To evaluate the performance of our deep learning model in deforestation mapping, we utilize four standard evaluation metrics in image segmentation tasks, including precision, recall, F1 score, and accuracy.

3.3.1 Precision Precision reflects the proportion of true positive predictions among all positive predictions. It is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

where TP is the number of true positives, and FP is the number of false positives. A higher precision means a lower false positive rate.

3.3.2 Recall Recall shows the proportion of true positive predictions among all actual positives in the dataset. It is defined as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

where FN is the number of false negatives. A higher recall means the model can classify a larger number of actual positives.

3.3.3 F1 Score The F1 score is the harmonic mean of precision and recall, showing a combined metric balancing both metrics. It is defined as:

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The F1 score is useful in imbalanced datasets by considering both false positives and false negatives and balancing the trade-off between over-segmentation and under-segmentation.

3.3.4 Accuracy Accuracy measures the proportion of all correct predictions (both true positives and true negatives) among the total number of predictions. It is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where TN is the number of true negatives. Accuracy demonstrates the overall performance of a model but might be misleading in cases of imbalanced class distribution.

4. Experiments

4.1 Data

In the experiment, we use the ground truth from the deforestation alerts dataset from MapBiomas (Mapbiomas, 2022), which is based on different forest monitoring systems (e.g., DETER, SAD, GLAD, SIRAD-X) to select PlanetScope imagery before and after deforestation and generate a more detailed deforestation polygon necessary to support law enforcement. Based on the identified deforestation sites from MapBiomas, we collected the corresponding high-resolution Planet NICFI imagery through Google Earth Engine (Team, 2017; Pandey et al., 2021). Specifically, we collected a pair of images representing before and after each deforestation site, each image having four bands including red, green, blue, and near-infrared.

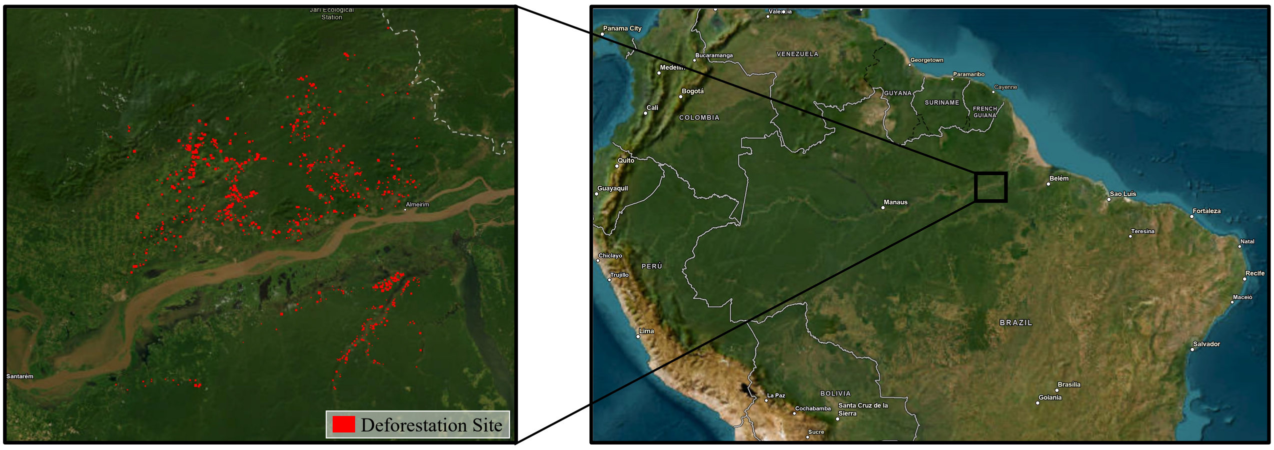
Fig. 3 shows the study area ranging from 55° to 52.5°W and -2.5°S to 0°, near the Amazon River, where deforestation is more likely to occur and be transported across the river. After data collection, we have a total of 1,912 images in the study area. We randomly split the dataset for training our models with 80% as training, 10% as validation, and 10% as testing.

4.2 Candidate Methods

We use the following candidate methods to demonstrate the performance of popular machine learning models in deforestation mapping.

- **Random Forest (RF):** A Random Forest classifier with 50 trees. We use all the other default parameters from the scikit-learn package.
- **Fully Connected Network (FCN):** A fully connected neural network with 5 hidden layers, each having 512 neurons followed by the ReLU activation function, and a linear output layer.
- **U-Net:** A convolutional encoder-decoder model for image segmentation (Ronneberger et al., 2015), and the architecture details are introduced in Sec. 3.1.

In the training stage, both deep learning models take images as inputs, while the Random Forest model uses single-pixel inputs. We trained deep learning models using the Adam optimizer with a learning rate of 0.0001. Dice loss was employed to



Study Area

The Amazon Forest Region

Figure 3. Deforestation sites collected in the study area (left), and the overall location within the Amazon Forest region (right).

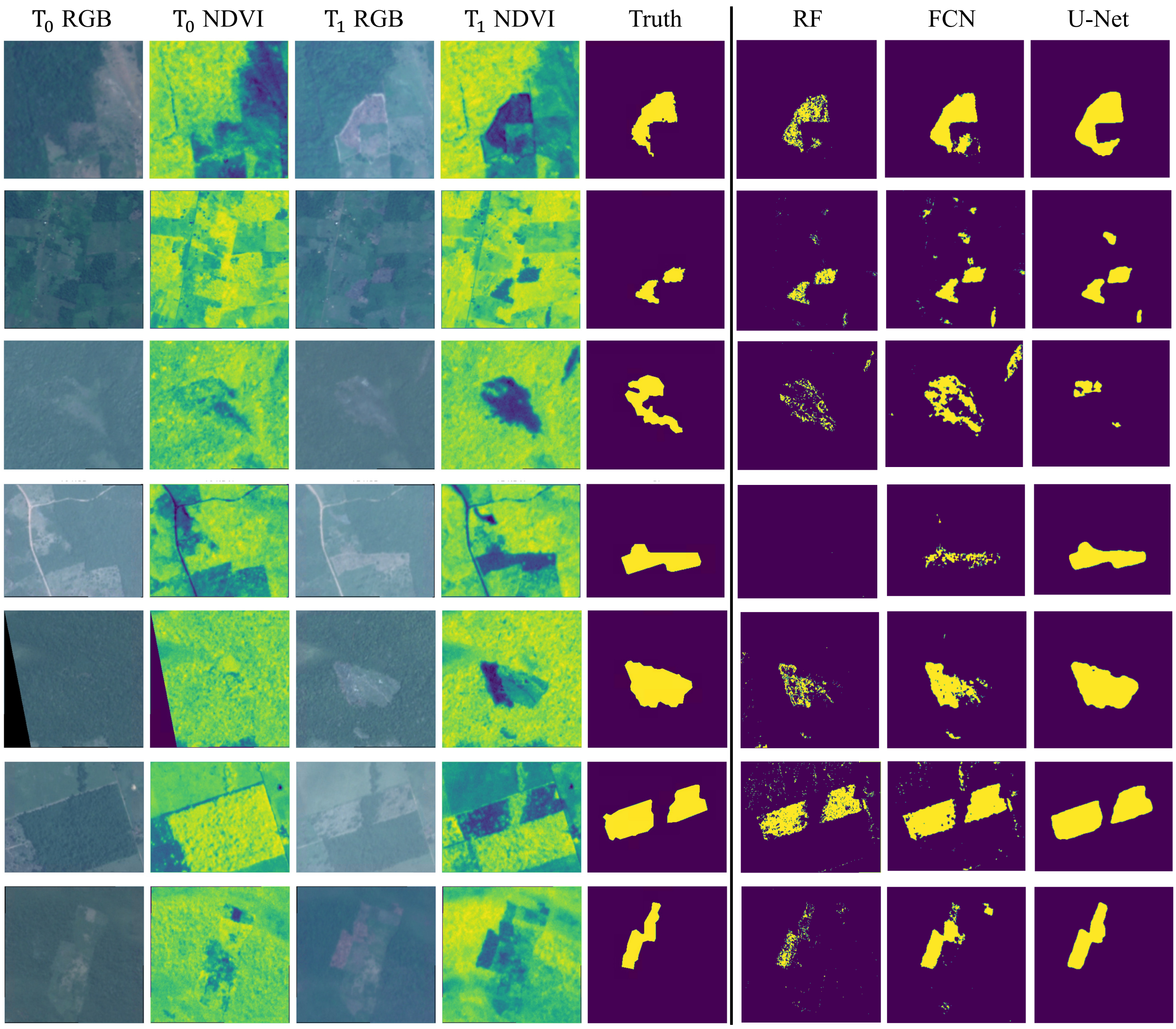


Figure 4. Visualizations of model's performance in detecting deforestation given a pair of Planet NICFI images taken before and after a deforestation event. Three candidate models are Random Forest (RF), Fully Connected Neural Network (FCN), and U-Net Model.

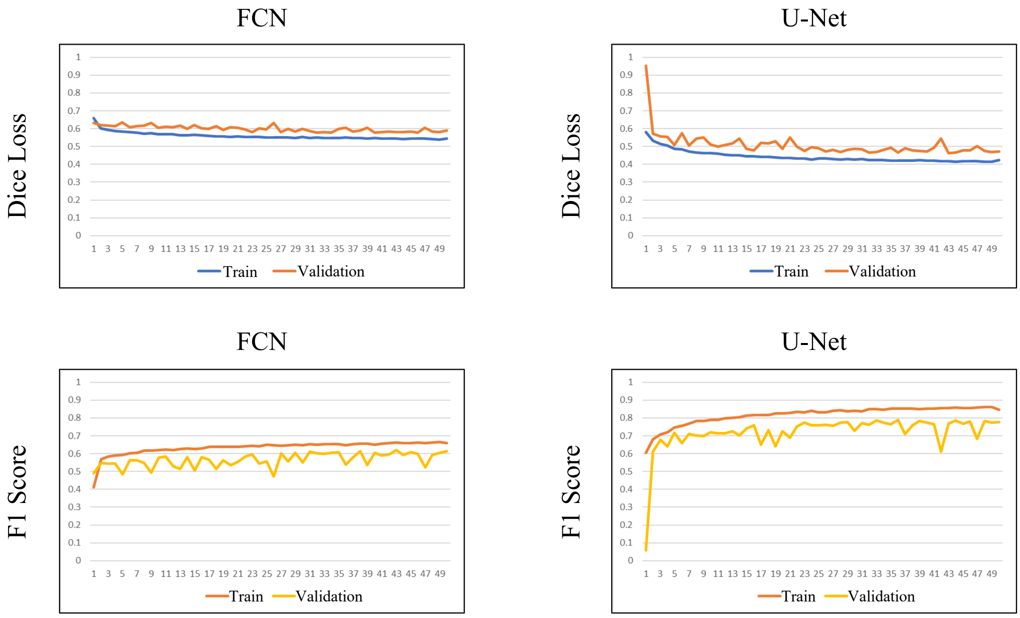


Figure 5. Changes of Dice loss and F1 score over 50 epochs for deep learning models.

handle class imbalance and improve the segmentation quality, particularly, in the case where the minority class (i.e. deforested region) significantly affects overall performance. To augment the training data, we applied various techniques such as random image rotations and random image flips horizontally or vertically. These augmentations not only increased the diversity of the training data but also potentially helped the models generalize better to unseen data by simulating different real-world conditions.

After 50 epochs of training, the best models were selected based on the highest F1 scores on the validation dataset, ensuring they achieved a balance between precision and recall. For the final evaluation, we used a hold-out test dataset, which the models did not see during the training and validation phases. This ensures an unbiased assessment of the models' performance on completely unseen data, providing a realistic measure of their generalization capabilities. The best models were evaluated on this test dataset using performance metrics including precision, recall, F1 score, and accuracy, implying how well the models can perform in practical applications.

4.3 Results

Table 1 shows the results of candidate methods on the test dataset across all the evaluation metrics. The U-Net model achieves the highest performance across all evaluation metrics. Its best performance can be attributed to its ability to effectively capture contexture patterns from high-resolution satellite imagery, making it more robust for identifying deforestation sites. In contrast, both RF and FCN demonstrate suboptimal performance as they primarily rely on the spectral features from single-pixel inputs, which can make it hard to capture the texture patterns in deforestation sites and are further limited by the fewer bands in PlanetScope images.

Figure 4 shows the deforestation masks produced by different methods in the test dataset, as well as the RGB and NDVI bands of images before and after deforestation. It can be seen that the removal of trees usually leads to lower NDVI values in deforestation sites. However, it is difficult to set a global threshold to differentiate the areas with and without deforestation. Moreover, the deforestation sites still have sparse trees in the middle, making it challenging to map the entire area. Comparing the results generated by different methods, U-Net shows the highest accuracy in delineating deforestation boundaries and provides a more continuous and complete mapping of the deforestation areas. FCN and RF, however, struggle to delineate clear deforestation boundaries and obtain a complete and continuous mapping of deforestation sites. This is mainly because they are based on single-pixel inputs, and thus cannot capture the context information necessary to remove the sparse trees in the deforestation sites. Furthermore, it is clear to observe the salt-and-pepper noise in the RF classification results, implying its limited ability to accurately classify satellite images at higher resolution.

Model	F1	Precision	Recall	Accuracy
RF	0.5505	0.6712	0.4665	0.9456
FCN	0.5833	0.4729	0.7608	0.9223
U-Net	**0.8251**	**0.7462**	**0.9226**	**0.9720**

Table 1. Overall performance of candidate methods in F1 score, precision, recall, and accuracy, where **Bold** fonts indicate best models and underline refers to runner-ups.

In figure 5, we demonstrate how dice loss and F1-score of different methods change on the training and validation datasets during the training process. It can be seen that both FCN and U-Net exhibit similar dice loss at the beginning, but as the training process goes on, the training and validation dice loss of U-Net decreases rapidly and finally arrives at lower values than FCN. On the F1-score, U-Net shows an obvious improvement on both training and validation datasets, while FCN shows a slow increase and quick hit to a performance plateau. This suggests that U-Net learns more efficiently than FCN on the deforestation mapping task.

5. Conclusions

Deforestation in the Brazilian Amazon has been increasing at an alarming rate, necessitating more efficient and accurate systems for monitoring and validation. Traditional deforestation monitoring systems often rely on coarse-resolution imagery that is insufficient to detect fine-scale deforestation events. Manual validation of high-resolution imagery, while more accurate, is highly time-consuming and labor-intensive. To address the challenges, we have developed a deep learning-based system that automates the validation process by leveraging Planet NICFI satellite imagery at a high resolution of 3-4m. Through experiments, we demonstrate that our system effectively captures complex texture patterns in the imagery, significantly improving the performance of deforestation detection. Our work represents an important step towards more efficient and effective environmental governance using high-resolution imagery, paving the way for better management and conservation of forest resources. Future work will focus on refining the model with more samples and extending its application to other forested regions worldwide.

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