Detecting Deforestation via Transfer learning Image Segmentation

Anthony Wu
awu3@ncsu.edu
North Carolina State University
North Carolina, USA

Ophelia Sin
oysin@ncsu.edu
North Carolina State University
North Carolina, USA

Jheel Gala
jgala@ncsu.edu
North Carolina State University
North Carolina, USA

Venkata Sai Praveen Gunda
vgunda@ncsu.edu
North Carolina State University
North Carolina, USA

Abstract

With the increasing concern of forest degradation's impact on climate change, reducing deforestation has become critical in mitigating climate change and aiding forest preservation. The REDD+ (Reducing emissions from deforestation and forest degradation in developing countries) framework was established to aid these efforts by providing results-based payments for reductions in deforestation in developing countries. Though, some of these REDD+ projects in various different countries have been involved in skewing results by underestimating the effectiveness of projects. This work leverages the dataset of geographical boundaries from project sites provided by REDD+ projects to create another dataset of images within these boundaries. These images will be utilized to estimate the deforested area, which can subsequently be compared to the deforestation reported by REDD+ projects.

To estimate the areas of deforestation, an efficient modified U-Net model was used, featuring a symmetric encoder-decoder architecture and a fully convolutional network design. Skip connections were utilized to increase efficiency by reducing the need for complex computations in the later stages of training. Then a pre-trained model MobileNetV2 was used as the encoder, which reduced the amount of trainable parameters increasing efficiency of training.

Keywords

Deforestation, REDD+

ACM Reference Format:
Anthony Wu, Ophelia Sin, Jheel Gala, and Venkata Sai Praveen Gunda. 2024. Detecting Deforestation via Transfer learning Image Segmentation. In . ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

Conference'17, July 2017, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction and Background

Deforestation significantly contributes to climate change and forest degradation, making its reduction a global environmental preservation priority[3]. The REDD+ framework supports this by providing financial incentives to developing countries for reducing deforestation [8] [9]. Accurate monitoring and verification of deforestation levels are essential to ensure the effectiveness and integrity of these initiatives[14] [10].

Despite REDD+'s intentions, projects have faced criticism for potentially misreporting or overestimating their success in reducing deforestation, raising concerns about the framework's effectiveness and credibility [6][5]. Uncertainty in REDD+ carbon accounting further complicates the evaluation process. A survey of those involved in REDD+ reporting revealed widespread acknowledgment of the importance of including uncertainty estimates in reports, yet most felt their countries' current practices were insufficient. [11]. Advanced techniques such as Monte Carlo or Bayesian approaches are rarely used due to limited expertise, financial constraints, and lack of data [11]. This gap in technical capacity can lead to incomplete or inaccurate reporting of uncertainty in forest carbon accounting.

Existing methods for monitoring deforestation face several limitations, including reliance on potentially biased self-reported data and the lack of advanced models capable of analyzing large-scale geographical datasets efficiently[15]. While some studies have applied remote sensing techniques[18] [17], many have yet to incorporate deep learning architectures that can significantly improve accuracy and scalability in deforestation estimation.

Leveraging remote sensing, machine learning, and geographic datasets has emerged as a promising approach to assess forest cover and deforestation accurately [14] [10]. Recent advancements in deep learning techniques have shown promise in improving deforestation detection and monitoring. For instance, deep convolutional neural networks have demonstrated the ability to learn spatiotemporal patterns of deforestation from a limited set of freely available global data layers, including multi-spectral satellite imagery and historic deforestation maps [2].

Recent studies have explored various deep learning architectures for deforestation analysis, including U-Net, DeepLab V3, ResNet, SegNet, and FCN[14]. These models have enhanced the accuracy and efficiency in detecting deforestation patterns by employing multi-scale feature learning and fusion, enabling deep networks to comprehend contextual nuances across various scales[14].

A recent study[13] conducted an evaluation of a large-scale voluntary REDD+ project in Sierra Leoneusing a before-after-control-intervention (BACI) framework to assess the project's impact on deforestation rates and local economic well-being. The REDD+ project reduced deforestation in the buffer zone by approximately 1-percentage point compared to non-REDD+ communities[13]. However, the study emphasized the necessity of independent evaluations and standardized approaches to enhance the reliability of such assessments.

This work addresses the challenge of verifying deforestation data reported by REDD+ projects. Using the geographical boundaries provided [16], a dataset of images was created, masked and trained with U-Net model that employs a symmetric encoder-decoder structure and skip connections for computational efficiency. By integrating MobileNetV2 as a pre-trained encoder, the number of trainable parameters will be reduced, enhancing training efficiency. The results will enable a direct comparison of estimated deforestation areas with reported values, providing a transparent and scalable solution for improving the accountability of REDD+ projects.

The challenges ranging from reliance on self-reported data to insufficient use of advanced methodologies indicate significant gaps in monitoring, verifying, and accurately accounting for deforestation impacts. Addressing these issues is critical to improving the credibility and effectiveness of REDD+ initiatives.

2 Methods

Our project is novel for four reasons:

(1) A novel dataset was created from satellite images collected via the SentinelHub API. This curated dataset was not publicly available.
(2) Masks were manually created by our team using the GIMP software to delineate deforestation.
(3) Transfer learning using a modified U-Net model was applied on this novel dataset and metrics such as accuracy, loss and IoU were used to compare the predicted masks and the original masks.
(4) The IoU metric was modified in order to account for the images where the intersection between predicted and actual mask is zero. For instance, forested images has completely transparent mask.

To address the issues mentioned in the background section and the credibility and effectiveness of REDD+ initiatives, we propose to implement a modified U-Net model trained on satellite imagery and their respective masks. The final model generates masks which predict the deforestation area in satellite imagery capturing deforested regions.

In this project, we implemented a U-Net model using transfer learning to address the problem of image segmentation. The U-Net architecture was chosen for its ability to achieve precise localization by combining high-level contextual features with low-level spatial details through skip connections. Transfer learning was applied to leverage pre-trained weights from a backbone model, enabling efficient feature extraction and improved performance on our target dataset. Below, we describe the general approach that can be adapted to other datasets.

2.1 Architecture

2.1.1 *Encoder*.

(1) Pre-Trained Network
   - We replaced the encoder of the U-Net with MobileNetV2, a pre-trained convolutional neural network trained on the ImageNet dataset.
   - The encoder extracts hierarchical features from input images, starting with low-level spatial details and progressing to high-level semantic representations.

(2) Layer Freezing:
   - To reduce training time and prevent overfitting on small datasets, we experimented with freezing different layers of the encoder.
   - Layers closer to the input were frozen to retain low-level feature extraction capabilities, while deeper layers were fine-tuned to adapt to the new dataset.

(3) Feature Extraction:
   - The output feature maps from specific layers of the encoder were used as skip connections in the U-Net architecture.
   - These skip connections ensure that spatial information lost during downsampling is preserved and passed to the decoder.

2.1.2 *Decoder.*

(1) Upsampling Blocks:
   - The decoder consists of upsampling blocks that progressively increase the spatial resolution of feature maps using transposed convolutions.
   - Each upsampling block includes:
     – Transposed convolution layers for upsampling.
     – Concatenation with corresponding skip connections from the encoder.
     – Convolutional layers with ReLU activation for feature refinement.

(2) Final Output:

- Our final layer is Conv2DTranpose, which uses a transposed convolution operation to upsample feature maps.
- Since we're doing binary classification, we applied a sigmoid activation function to produce pixel-wise probabilities.

2.2 Rationale

(1) Transfer Learning is chosen instead of training a model from scratch because of the time constraints imposed by the course structure and the small dataset size.
(2) Although ensemble methods might provide better results, a CNN based architecture was chosen as it required less time to train. Specifically a U-Net was equipped to train a small dataset and produce good results. A U-Net based transfer learning model was simple to implement and yielded efficient results.
(3) While compiling the model, binary cross-entropy was chosen because the model has to differentiate between forested and deforested areas. Technically the model has to predict each pixel in the image as forested or deforested, making binary cross-entropy a better choice.

3 Plan and Experiment

3.1 Dataset

The dataset used in this project is generated based on the dataset compiled by West et al. 2023, containing geographical boundaries of Verified Carbon Standard (VCS) -certified REDD+ projects investigated. The original dataset included shapefiles of the 27 sites from 6 countries (Cambodia, Colombia, Democratic Republic of Congo, Peru, Tanzania, and Zambia). The images are collected from the Sentinel-2 L2A satellite (10-m resolution). We collected 1518 images during the summer months of 2016 to 2018 (June to August) using Sentinel Hub API [7]. The downloaded images were cropped to match the site boundaries. We then extracted 10 224 x 224 patches from each image. The image patches were reviewed manually – kept or discarded based on cloud coverage or existence of pixels with null values - and classified as forested or deforested. For our initial dataset, we retained 893 image patches.

To reduce the time spent on preparing the final dataset for this specific project, we randomly selected 121 224x224 images. The final dataset that was used for training the image segmentation model is shown in Figure 1. To accomplish our image segmentation task, masks were manually created using the GIMP. GIMP (GNU Image Manipulation Program)is a cross-platform image editor available for GNU/Linux, macOS, Windows and more operating systems. [1] The masks were created to mark deforested areas. Deforested areas were colored with black paint, whereas forested areas remain transparent. Figure 1 shows the total number of images per project site, as well as the deforested and forested breakdown.

Project	Total Images	Deforested Images	Forest Images
Colombia_1566	36	26	10
DRC_934	2	2	0
Peru_1067	39	39	0
Peru_1360	2	2	0
Peru_2278	1	1	0
Peru_844	16	1	15
Peru_944	4	4	0
Peru_958	1	1	0
Peru_985	2	2	0
Tanzania_1325	3	3	0
Zambia_1202	4	4	0
Zambia_1775	11	11	0

Figure 1: Number of images by project (Total images, deforested images, and forest images).

3.2 Preprocessing

The key data preprocessing steps are as follows. First, the original image and the mask were loaded using Tensorflow. While loading the mask, the alpha channel was extracted to facilitate the creation of binary masks (1=opaque, 0=transparent). The original images and the masks were in the TIFF format and contain the 3 visible channels (red, green and blue).In order to meet the model requirements, the images were converted to the PNG format. The images along with their corresponding segmentation masks were passed to TensorFlow's Dataset API to create the final dataset. This dataset was split into train, validation and test datasets with a split percentage of 70%, 10% and 20% respectively. To ensure efficient training and robust performance, the datasets were shuffled, batched, prefetched, and augmented.

3.3 Hypothesis

This project explores the possibility of applying transfer learning techniques in the case of a novel dataset of images with diverse topology including more variation in the patterns and their corresponding masks. These patterns could be hard to generalize by the model. We also wanted to investigate the effects of hyperparameter tuning and explore the different ways to improve the model's performance such as augmentation and L2 regularization. We also want to investigate different metrics such as IoU - Intersection over Union to evaluate the performance of the trained model. Irrespective of the results, it would be interesting to apply transfer learning techniques and verify the accuracy, loss, metrics such as IoU and robustness of the trained model over the novel image segmentation dataset.

3.4 Experimental Design

To address the hypothesis mentioned above, we will be using a modified U-Net. A U-Net consists of an encoder (downsampler) and decoder (upsampler). To learn robust features and reduce the number of trainable parameters, we will use a pretrained model—MobileNetV2—as the encoder. For the decoder, we will construct an upsample block. [4] The model will generate predicted masks. The predicted masks and actual masks will be printed alongside each other to visually compare the effectiveness of the model on the novel dataset. To demonstrate the performance of the model, different metrics can be tested such as accuracy which depicts the percentage of pixels correctly classified, loss which depicts the error made by the model, and Intersection over Union (IoU) metric that measures the overlap between the predicted segmentation and the ground truth segmentation i.e. Intersection Area over the Union Area. The hyperparameters used across all the experiments are L2 regularization at 0.001, 30 epochs for all the models using the early stopping criteria, and 6 layers present in the encoder which are also used for skip connections. These hyperparameters are based on the architecture mentioned in the tensorflow documentation [4] . As part of our experiments, we explored 1-Fold, 3-Fold and 5-Fold cross validation. We also compared the model's performance metrics after unfreezing 1, 2 and 3 deeper layers. We expect the model to perform better specifically when we unfreeze some layers in the encoder, as the weights will readjust to our dataset.

4 Results

To evaluate the results of the proposed U-Net model a series of test were conducted across the training and test datasets to compare results and understand the models performance. Bitwise accuracy was calculated by comparing predicted deforested areas with the ground truth comparing each individual pixel classification. The metric is defined as the ratio of correctly classified pixels to the total number of pixels, providing a final accuracy score.

$$\text{Accuracy} = \frac{\text{Number of Correctly Classified Pixels}}{\text{Total Number of Pixels}}$$

While bit wise accuracy provides an initial measure of the models performance, the loss metric provides deeper insights into how well the model's predictions align with the ground truth at a probabilistic level. By analyzing the loss values a more accurate conclusion can be made about the confidence and consistency of the model across the different datasets. For loss a simple binary cross-entropy was conducted as it fit the scenario the best, classifying a pixel as either deforested vs. non-deforested.

$$\text{BCE Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p_i) + (1-y_i)\log(1-p_i)\right]$$

To account for the influence of background (forested areas) on the bitwise accuracy score, the Intersection over Union (IoU) metric was calculated. This provides a clearer evaluation of how well the model predicted the deforested areas, compared to the ground truth, while completely ignoring the background. The IoU metric focuses solely on the deforested areas by considering only the ground truth mask and the predicted deforested mask, thus excluding the forested regions from the evaluation.

$$\text{IOU} = \frac{\text{Intersection}}{\text{Union}}$$

This approach offers a more accurate metric for this image segmentation task, as bitwise accuracy can be skewed by the correct classification of the forested areas, which dominates the background and artificially inflates the accuracy. By focusing only on the deforested areas, IoU ensures a more meaningful performance assessment. However, in cases where the mask is empty (i.e., the image is completely forested), the intersection will always be zero, which can lead to misleading results. To address this, a new approach for calculating IoU was adopted for such cases.

In these instances, IoU was calculated by taking the predicted areas of deforestation over the total number of pixels and subtracting 1 from the result. We found this method to be preferable to setting the IoU to either 1 or 0, as doing so would heavily skew the data towards one extreme, either falsely inflating or deflating the performance. This adjustment ensures a more balanced evaluation in cases where no deforestation is predicted.

K-fold cross-validation was used as it is more robust than simple model predict and can take advantage of small datasets by using all the data for training rather than just a percentage. It can also provide benefits in hyperparameter tuning, detecting overfitting, and reducing bias.

4.1 Results Visualization

These figures are provided as they are important to understanding the performance of the model. Each of these different images and predictions indicate key aspects of how the model is predicting.

The image in the top left of figure 2 does well in predicting areas of deforestation but fails to see the cloud as part of the background and instead labels the pixels as areas of deforestation. If images are not cleaned properly to avoid clouds it can skew the results of the model, causing worse scores for numeric metrics.

The image in the top right of the same figure is one already classified as forested meaning the ground truth mask will be empty, but the prediction still evaluates some of the area to be deforested. In

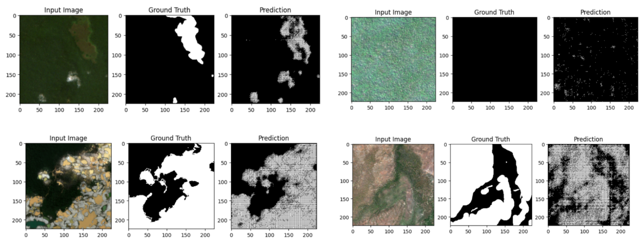

Figure 2: Model original images with ground truths and predicted deforested areas.

this case the accuracy and IoU values are unlikely to be significantly affected, as the model predicts very few deforested pixels relative to the entire image. The result is still important to note as it may effect the classification of the image as either forested or deforested if future work is done by taking predicted images with only no predicted deforestation as forested.

The bottom left image in the figure does exceptionally well in classifying the areas of deforestation as the predicted mask almost matches the ground truth mask. In cases where the image gives clear indication of the areas of deforestation with features such as vibrant colors and clear separation of forest and deforested the model is able to predict deforested areas with increased accuracy.

In the bottom-right image, the complex topology causes areas of deforestation to blend into forested regions, making it challenging for the model to accurately predict deforested areas. Even the ground truth is imperfect, as a flawless mask would require precise pixel-level classification, particularly in regions where deforestation and forest areas merge.

4.2 Results Discussion

After testing the model using k-fold cross validation the results were subpar and not up to the standard seen from previous works, where IoU values were upwards of 0.98[12]. Figure 3 below shows the average values of different metrics computed for each different model that was tested.

Metric	1-Fold	3-Fold	5-Fold	1-unfrozen Layer	2-unfrozen Layers	3-unfrozen Layers
Train Accuracy	0.839	0.749	0.814	0.868	0.859	0.856
Train Loss	0.319	0.477	0.365	0.272	0.284	0.287
Train IOU	0.438	0.093	0.197	0.404	0.349	0.430
Test Accuracy	0.816	0.693	0.755	0.860	0.818	0.836
Test Loss	0.432	0.624	0.624	0.349	0.391	0.375
Test IOU	0.443	0.290	0.290	0.409	0.321	0.358

Figure 3: Model Comparison using Result Averages

K-fold was computed for the model using 1-fold, 3-fold, and 5-fold along with metrics to compare against each other. After computing these values it was found that the best performing model was 1-fold with higher training accuracy(0.839), test accuracy(0.816), training IoU(0.438), and test IoU(0.443). Though 5-fold cross-validation should be more robust there could be various reasons why it performed worse than 1-fold cross-validation.

The small dataset likely caused each training fold to include only a limited portion of the data, resulting in insufficient training samples for the model to generalize effectively. This limitation can lead to poor performance and a higher likelihood of overfitting. In a 1-fold cross-validation setup, while overfitting to the training data is expected, the model has a better chance of capturing important patterns and achieving stronger results on the test set. Conversely, in 3-fold and 5-fold cross-validation, the smaller validation sets can produce noisy and unreliable performance metrics.

Notably, the 1-fold model generalized well to the test dataset, as evidenced by its higher IoU value on the test set compared to the training set. This supports the claim that the dataset is too small. The model’s better performance on the test set suggests it has not learned robust features from the limited training data, leading to overfitting. The lack of data also prevents the model from capturing the full variability of the dataset, reducing its ability to generalize effectively to new, unseen examples.

After testing K-fold the model was then modified to test 1-unfrozen layer, 2-unfrozen layers, and 3-unfrozen layers to provide more insight into the performance of the model. When testing 1-unfrozen layer performed the best, this can be the result of 2-unfrozen and 3-unfrozen layers overfitting as it may learn features that are not present especially since the dataset lacks variety with its small size. 1-frozen layer has an advantage in this case as the model can adapt to the task-specific features while leveraging the general features from the frozen layers.

The overall results suggest that the model’s performance is limited by the insufficient size of the dataset. The current dataset does not support more advanced training techniques, such as 5-fold cross-validation or unfreezing multiple layers (e.g., three layers). Expanding the dataset would likely enable these more complex models to outperform the current ones. Additionally, the IoU metric appears to be affected by inaccuracies in the pixel-level annotations of the masks. Even if the model successfully identifies deforested areas, the IoU may not reflect this accurately due to imprecise overlap between predicted and ground truth regions, resulting in misleading values for intersection and union. Prior work[12] using ensemble methods were able to get much better results but their dataset also contained images with exact mask to train their model on, resulting in much better results in IoU and accuracy. Without a properly robust dataset it is hard to judge the comparison between models in prior works compared to the model evaluated in this project.

5 Conclusion

This study presents a novel approach to detecting deforestation using transfer learning and image segmentation techniques. By leveraging a modified U-Net architecture with MobileNetV2 as the encoder, we aimed to create an efficient model for analyzing satellite imagery from REDD+ project sites. Our experiments with various cross-validation techniques and layer unfreezing strategies yielded insights into the model’s performance and limitations. The results indicate that while the model shows promise, its performance falls short of the high standards set by previous works in the field. Several factors contribute to this performance like limited dataset size, data variability and Model architecture. Despite these challenges, the study provides valuable insights into the application of deep learning techniques for deforestation detection in the context of REDD+ projects. The visual analysis of predictions demonstrates the model’s capability to identify clear instances of deforestation, while also highlighting areas for improvement, such as cloud detection and handling complex forest-deforestation boundaries.

In conclusion, while this study demonstrates the potential of deep learning approaches for monitoring deforestation in REDD+ projects, it also underscores the challenges inherent in working with limited and complex environmental data. By addressing these challenges and building upon the foundations laid in this research, future work can contribute to more accurate and reliable methods for assessing the effectiveness of forest conservation efforts worldwide.

6 Future Work

Moving forward, several avenues for improvement and future research emerge:

1. Expanding the dataset: Acquiring and incorporating more diverse satellite imagery from REDD+ project sites could significantly enhance the model’s performance and generalization capabilities.
2. Refining preprocessing techniques: Developing more robust methods for cloud detection and removal could improve the quality of input data and subsequent predictions.
3. Exploring alternative architectures: Investigating other state-of-the-art segmentation models or custom architectures tailored to deforestation detection may yield better results.
4. Incorporating multi-temporal data: Leveraging time-series satellite imagery could provide additional context for distinguishing between temporary and permanent deforestation.

7 Appendices

Metric	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average
Train Accuracy	0.813	0.815	0.834	0.818	0.788	0.814
Train Loss	0.363	0.343	0.322	0.372	0.426	0.365
Train IOU	0.205	0.189	0.213	0.233	0.0143	0.197
Val Accuracy	0.801	0.800	0.777	0.810	0.768	0.791
Val Loss	0.472	0.469	0.485	0.450	0.463	0.468
Val IOU	0.281	0.397	0.301	0.349	0.160	0.298

Figure 4: 5-fold cross-validation results

Metric	Fold 1	Fold 2	Fold 3	Average
Train Accuracy	0.7582	0.7874	0.7003	0.7486
Train Loss	0.4691	0.4186	0.5435	0.4771
Train IOU	0.0829	0.0909	0.1052	0.0930
Val Accuracy	0.7670	0.8225	0.7585	0.7827
Val Loss	0.4959	0.4015	0.5208	0.4727
Val IOU	0.3041	0.1801	0.0700	0.1847

Figure 5: 3-fold cross-validation results: train and validation accuracy, IoU, and loss with averages.

References

[1] [n. d.]. GIMP — gimp.org. https://www.gimp.org/. [Accessed 27-11-2024].

[2] [n. d.]. GitHub - PatBall1/DeepForestcast: Deforestation forecasting with deep convolution neural networks — github.com. https://github.com/PatBall1/DeepForestcast. [Accessed 27-11-2024].

[3] [n. d.]. Global Emissions and Local Deforestation Are Combining to Create Dangerous Levels of Heat Stress in the Tropics — wri.org. https://www.wri.org/insights/deforestation-heat-stress-tropics. [Accessed 26-11-2024].

[4] [n. d.]. Image segmentation | TensorFlow Core — tensorflow.org. https://www.tensorflow.org/tutorials/images/segmentation. [Accessed 27-11-2024].

[5] [n. d.]. REDD+ carbon and deforestation cuts in Amazon overestimated: Study — news.mongabay.com. https://news.mongabay.com/2020/11/redd-carbon-and-deforestation-cuts-in-amazon-overestimated-study/. [Accessed 26-11-2024].

[6] [n. d.]. REDD+ projects falling far short of claimed carbon cuts, study finds — news.mongabay.com. https://news.mongabay.com/2023/08/redd-projects-falling-far-short-of-claimed-carbon-cuts-study-finds/. [Accessed 26-11-2024].

[7] [n. d.]. Sentinel-2 L2A — docs.sentinel-hub.com. https://docs.sentinel-hub.com/api/latest/data/sentinel-2-l2a/. [Accessed 27-11-2024].

[8] [n. d.]. unfccc.int. https://unfccc.int/topics/land-use/workstreams/redd/what-is-redd. [Accessed 26-11-2024].

[9] [n. d.]. What is REDD+? - Coalition for Rainforest Nations — rainforestcoalition.org. https://www.rainforestcoalition.org/what-is-redd-2/. [Accessed 26-11-2024].

[10] admin. [n. d.]. Deforestation Remote Sensing and Monitoring — satpalda.com. https://satpalda.com/blogs/deforestation-remote-sensing-and-monitoring/. [Accessed 26-11-2024].

[11] Brett J Butler, Emma M Sass, Javier GP Gamarra, John L Campbell, Craig Wayson, Marcela Olguín, Oswaldo Carrillo, and Ruth D Yanai. 2024. Uncertainty in REDD+ carbon accounting: a survey of experts involved in REDD+ reporting. *Carbon balance and management* 19, 1 (2024), 22.

[12] Pradeep Kumar Das, Adyasha Sahu, Dias V. Xavy, and Sukadev Meher. 2024. A Deforestation Detection Network Using Deep Learning-Based Semantic Segmentation. *IEEE Sensors Letters* 8, 1 (2024), 1–4. https://doi.org/10.1109/LSENS.2023.3340562

[13] Mandy Malan, Rachel Carmenta, Elisabeth Gsottbauer, Paul Hofman, Andreas Kontoleon, Tom Swinfield, and Maarten Voors. 2024. Evaluating the impacts of a large-scale voluntary REDD+ project in Sierra Leone. *Nature Sustainability* 7, 2 (2024), 120–129.

[14] Imran Md Jelas, Mohd Asyraf Zulkifley, Mardina Abdullah, and Martin Spraggon. 2024. Deforestation detection using deep learning-based semantic segmentation techniques: a systematic review. *Frontiers in Forests and Global Change* 7 (2024), 1300060.

[15] Anthea L Mitchell, Ake Rosenqvist, and Brice Mora. 2017. Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification (MRV) systems for REDD+. *Carbon balance and management* 12 (2017), 1–22.

[16] Thales AP West, Sven Wunder, Erin O Sills, Jan Börner, Sami W Rifai, Alexandra N Neidermeier, Gabriel P Frey, and Andreas Kontoleon. 2023. Action needed to make carbon offsets from forest conservation work for climate change mitigation. *Science* 381, 6660 (2023), 873–877.

[17] Bertrand Ygorra, Frédéric Frappart, Jean-Pierre Wigneron, Thibault Catry, Benjamin Pillot, Antoine Pfefer, Jonas Courtalon, and Serge Riazanoff. 2024. A near-real-time tropical deforestation monitoring algorithm based on the CuSum change detection method. *Frontiers in Remote Sensing* 5 (2024), 1416550.

[18] Chuanwu Zhao, Yaozhong Pan, Xiufang Zhu, Le Li, Xingsheng Xia, Shoujia Ren, and Yuan Gao. 2023. Monitoring of deforestation events in the tropics using multidimensional features of Sentinel 1 radar data. *Frontiers in Forests and Global Change* 6 (2023), 1257806.

8 Meeting attendance

Date	Participants	Location
October 18, 2026	Anthony, Ophelia, Praveen, Jheel	Virtual (Zoom)
October 30, 2026	Anthony, Ophelia, Praveen, Jheel	Virtual (Zoom)
November 8, 2026	Anthony, Ophelia, Praveen, Jheel	Virtual (Zoom)
November 15, 2026	Anthony, Ophelia, Praveen, Jheel	In-person
November 24, 2026	Anthony, Ophelia, Praveen, Jheel	In-person