CTrees

Algorithm Theoretical Basis Document (ATBD)

# REDD+AI platform:

## High-Resolution Mapping of Tree Cover Loss And Degradation By Logging, Forest Fire And Road Construction using Planet Nicfi Images and Deep Learning

Version 1.0

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## Table of Contents


**Executive Summary** **2**
**1. Introduction** **3**
1.1. Scope and content 3
1.2. Area of interest 3
**2. Data** **3**
**3. Model** **4**
**4. Tree Cover Loss** **4**
4.1 Training and Prediction 5
4.2 Tree cover loss map 6
4.3 Tree cover loss limitations 7
**5. Degradation from Logging, Fire and Road Construction** **7**
5.1. Definition 7
5.2. Training and Prediction 9
5.3. Degradation maps 10
5.4. Limitations 12
**6. Data processing pipeline** **13**
**7. Validation** **14**
**8. Data Availability** **14**
**9. How to Cite** **14**
**10. License** **15**
**11. Final considerations** **15**
**12. References** **16**

## Executive Summary

CTrees is an non-profit non-governmental organization (NGO) created in 2022 by scientists and engineers with over 20 years of experience in tropical forests, and building global carbon monitoring systems and solutions that have informed climate change policies. Our leading experts work alongside public and private partners to provide operational data to national and state governments, project developers, investors, and decision makers.

The first version of this data product provides a detailed, high-resolution view of tree cover loss and forest degradation, attributed to specific human activities such as selective logging, forest fires, and road construction. While forest degradation can be a broad concept, we focus on the most pervasive human-induced disturbances in tropical forests that are traceable via satellite imagery. For the first time, these disturbances are directly attributed within a data product. We expect this will help the community better understand the dynamics of deforestation and degradation across pantropical forests. Furthermore, we plan to continually refine and enhance these datasets in future updates.

This Algorithm Theoretical Basis Document (ATBD) outlines the methodological framework used to generate these data layers, along with their known limitations. As a living document, it will be updated as new insights are gained and as limitations are addressed. Our dataset is derived from Planet NICFI imagery and is openly available for non-commercial use in education, research, and efforts to combat deforestation and forest degradation.

## 1. Introduction

### 1.1. Scope and content

This ATBD document describes the data and methods used to create maps of tree cover loss and degradation by selective logging, forest fire and road construction in the pantropical rainforests from 2016 to 2023, available on the CTrees REDD+AI platform.

### 1.2. Area of interest

Our study area is the land covered by pantropical evergreen forests (Figure 1). These are the areas where our models were run for the data products at v1.0.

Figure 1 - Pantropical evergreen rainforests.

## 2. Data

This work is based on the Planet satellite images over the tropics made available by the Norway's International Climate and Forest Initiative (NICFI, https://www.nicfi.no/) to help save the world's tropical forests while improving the livelihoods of those who live off, in, and near the forests [Planet2017]. The Planet NICFI images are multispectral satellite images containing red, green, blue, and near infrared bands at 4.77 x 4.77 m of spatial resolution for the Normalized Analytic Basemaps. The temporal resolution of the NICFI images is currently one month (Table 1), and they are a mosaic composite of the best daily acquisitions during the month. Consequently, Planet NICFI images are mostly cloud free, thus providing the best freely available multispectral dataset to monitor Land Use and Land Cover (LULC) changes in tropical regions. Each Planet NICFI tile corresponds to an area of 20 x 20 km. More than 61,000 Planet NICFI tiles overlap the area of interest, totalling more than 24.4 million km² of analyzed area. Imagery from Jan-Feb 2024 were used only for confirmation of detections.

Table 1 - Planet NICFI images characteristics.

| Time period | Type of composite | Number of composites |
|---|---|---|
| Dec. 2015 to Jun. 2020 | Biannual - every 6 months | 10 |
| Sep. 2020 to Feb. 2024 | Monthly | 42 |

### 3. Model

The first step to the creation of the map to monitor changes, is to segment the object of interest, i.e. tree cover, logging, fire and roads, and also additional objects to mask such as cloud and water, with high accuracy in the Planet NICFI images. To do this, a classical Unet model (Ronnenberger et al, 2015) is used which is a robust deep learning model for semantic segmentation tasks (Figure 2). This model was chosen because of its proven accuracy on the task (Wagner et al., 2019; Wagner et al., 2023; Dalagnol et al., 2023) and also because it is fast enough for training and inference, which enables us to scale our model to the pantropics.

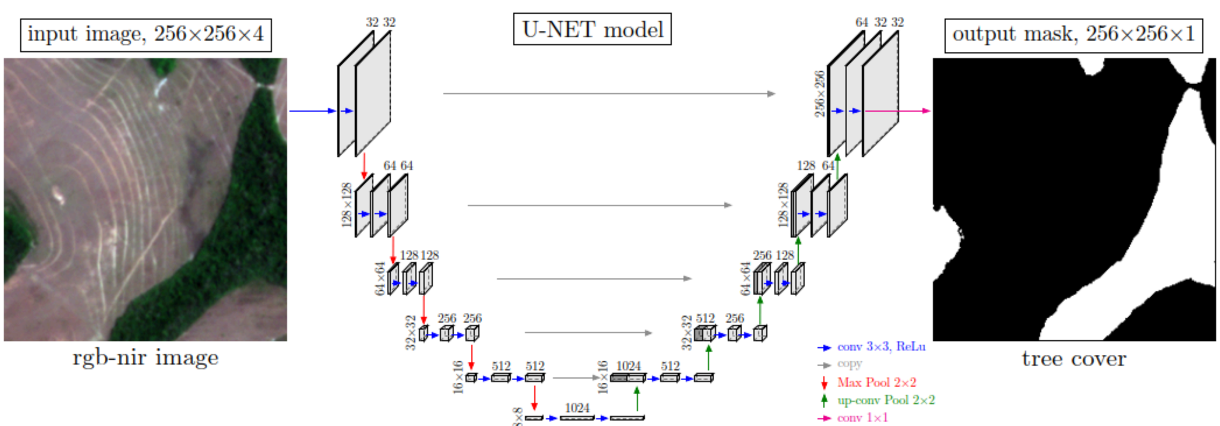


Figure 2. Architecture of the U-net model used to produce tree cover masks. Note that the same architecture is used for all of our models.

### 4. Tree Cover Loss

The theoretical basis for this layer comes from Wagner et al. (2023) paper. Since the publication of this paper, the model and postprocessing have been improved.

### 4.1 Training and Prediction

To train the U-net model for evergreen forest cover, we selected 130 Planet NICFI satellite images from different seasons, covering the region of Mato Grosso (Brazil) between September 2020 and September 2021. From these, we filtered out images with heavy cloud cover or poor lighting, leaving 75 usable images. We then used a deep learning method called the k-textures model to automatically segment these images into eight different classes, based on their visual characteristics. After reviewing the results, we kept 23 images where the forest segmentation was accurate. Any small errors were manually corrected, and the images were simplified into two categories: forest and non-forest (which included areas like agriculture, cities, water, and bare land).

Next, we trained an initial U-net model and applied it to all 130 original images. We excluded the 23 images used earlier and selected another set of 21 images with atmospheric challenges like clouds and haze. For these images, we manually adjusted the forest masks to ensure only clearly recognizable forests were labeled, while clouds and heavy haze were marked as non-forest.

Then, we trained a new version of the U-net model with this sample and applied it to all regions where we wanted the model to improve the performance in tropical forested regions, in shaded areas, and in forest with conspicuous phenology. For these images, we took the best forest mask and we manually adjusted them if needed.

After this final step, in total, we created a training set of 24,962 image patches (each 256x256 pixels) along with their corresponding forest/non-forest labels. Patches can include forest, background or both. We used 96 % of the patches for training and 4% for validation. The images were further processed with random flips to enhance the training data. This data augmentation, combined with the natural variety in weather and lighting across the different dates, prepared the images for the final U-net model training.

The loss function of the model was designed as a sum of two terms: binary cross-entropy and Dice coefficient-related loss of the predicted mask. We used the overall accuracy (i.e. the frequency with which the prediction matches the observed value) as the metrics to assess the model performance. The best model had a loss of 0.0353 and an overall accuracy (OA) of 0.9838.

Additionally to the tree cover layer, we also developed additional models for cloud, water and forest canopy height, using the same model architecture.

Then the predictions of tree cover, cloud, water and tree height were made for all the available Nicfi images. For the prediction, a border of 256 neighboring pixels containing the neighbor image's values or a mirroring image (if no neighbor image was present) was added on each side of the Planet tiles of 4096 x 4096 pixels. This border method was used to avoid border artifacts during prediction, a known problem for the U-net algorithm. Then, the predictions were made on the entire image and cropped to recover the original 4096 x 4096 pixels Planet tiles size.

Predictions and posprocessing were made on EC2 AWS instances (g5.xlarge and r6a.2xlarge) using ray on the anyscale platform.

### 4.2 Tree cover loss map

Here we detail the process used to generate the tree cover loss map displayed on the REDD+AI platform.

First, an evergreen forest baseline is created, consisting of pixels classified as evergreen tree cover at least once in the first four cloud-free observations. Additionally, a water mask baseline is created with pixels classified as water at least eight times in cloud-free pixels throughout the time series. A height baseline is also made for pixels with a tree height of at least 5 meters in four or more of the initial cloud-free images.

Then, the monthly tree cover loss map is generated. Tree cover loss is identified when pixels previously classified as forest become classified as non-forest due to complete forest removal. The initial detection of tree loss is labeled as unconfirmed, and it becomes confirmed if the pixel is classified as non-forest at least twice in the subsequent cloud-free images. Once tree loss is confirmed, the pixel is assigned the date of the first detection. If unconfirmed during the time series, the pixel reverts to a forested status. Tree loss detected towards the end of the time series, pending confirmation, is classified as a tree cover loss alert. Forested pixels that remain forested during the period are classified as 'Stable Forest'.

Our forest baseline voluntarily overpredicts forest cover to avoid missing any forested pixels. However, we have a method to remove the misclassified pixels in the forest baseline, as these pixels always appear as deforested in the initial dates. False detections of deforestation in the first dates, caused by an incorrect forest baseline, are eliminated using the water mask (for pixels classified as water) and the height mask (for pixels with a canopy height below 5 meters).

The final map displayed on the website is the annual aggregation of the biannual-to-monthly tree cover loss data and the stable forest layer.

### 4.3 Tree cover loss limitations

Main false detections of tree cover loss arise from the following: 1 - Deciduous forests that appear evergreen in the biannual Planet NICFI data, but their 2-3 month deciduousness begins to show when the NICFI data becomes monthly after September 2020, artificially increasing the tree loss count in 2020 or 2021 depending on the timing of the dry season; 2 - fires where crown damage is persistent and remains brown for several months exposing the soil; 3 - persistent shade in certain mountainous areas; 4 - artifacts due to cloud shading; 5 - geolocation errors in the NICFI images, especially in very cloudy environments, primarily affecting forest borders; 6 - extremely fragmented landscapes, such as agricultural areas or river islands, where small forests are more prone to false detection; and 7 - natural tree cover loss, such as windthrow, riverbed changes or extreme drought within evergreen forests.

Main tree loss omissions come from: 1 – unusual/rare forest types not included in the tree cover model training dataset, such as some forests in riverbeds in the Democratic Republic of the Congo; 2 - errors in NICFI images for 2-3 successive dates, where an image is produced over a forest but is blurry or contains artifacts not detected by our cloud model; 3 - extremely cloudy environments with fast-recovering vegetation, where forest regeneration occurs before a new cloud-free NICFI image is produced; and 4 - some deforestation with remaining trees and ground covered with dense green lower vegetation.

## 5. Degradation from Logging, Fire and Road Construction

The theoretical basis for these layers come from Dalagnol et al. (2023) paper. Since the publication of this paper, the model and postprocessing have been improved.

### 5.1. Definition

Forest degradation in tropical rainforests mainly consists of losses of tree cover and carbon storage, among other ecosystem services, which does not result in complete clearing of the forest (Figure 3). Here, we focus on human-induced disturbances that cause forest degradation by logging, forest fire, and road construction, which can be traceable using satellite imagery.

The *Degradation - Logging* layer measures forest degradation due to logging. In the tropics, logging includes selective logging, where trees are removed inside forests without clear cutting, over logging cycles that can last decades. Logged forests are expected to regenerate over time without additional tree removal. The *Degradation -*

*Logging* layer encompasses both legal and illegal logging. Logging can be legal in forest concessions where companies are required to follow rules of sustainable forest management. Illegal logging can result in severely increased levels of disturbance.

The *Degradation - Forest Fire* layer measures the area of burned forests, where the forest has been partially lost or its ecosystem services diminished. Areas subject to forest fire degradation often experience increased tree mortality and reduced productivity that can last from years to decades.

The *Degradation - Roads* layer measures areas degraded by construction of roads and trails, which can be used for transportation or for illegal activities. Roads are often connected to new deforestation and logging hotspots. Forests degraded by road and trail construction can regenerate over time if the road is no longer used.

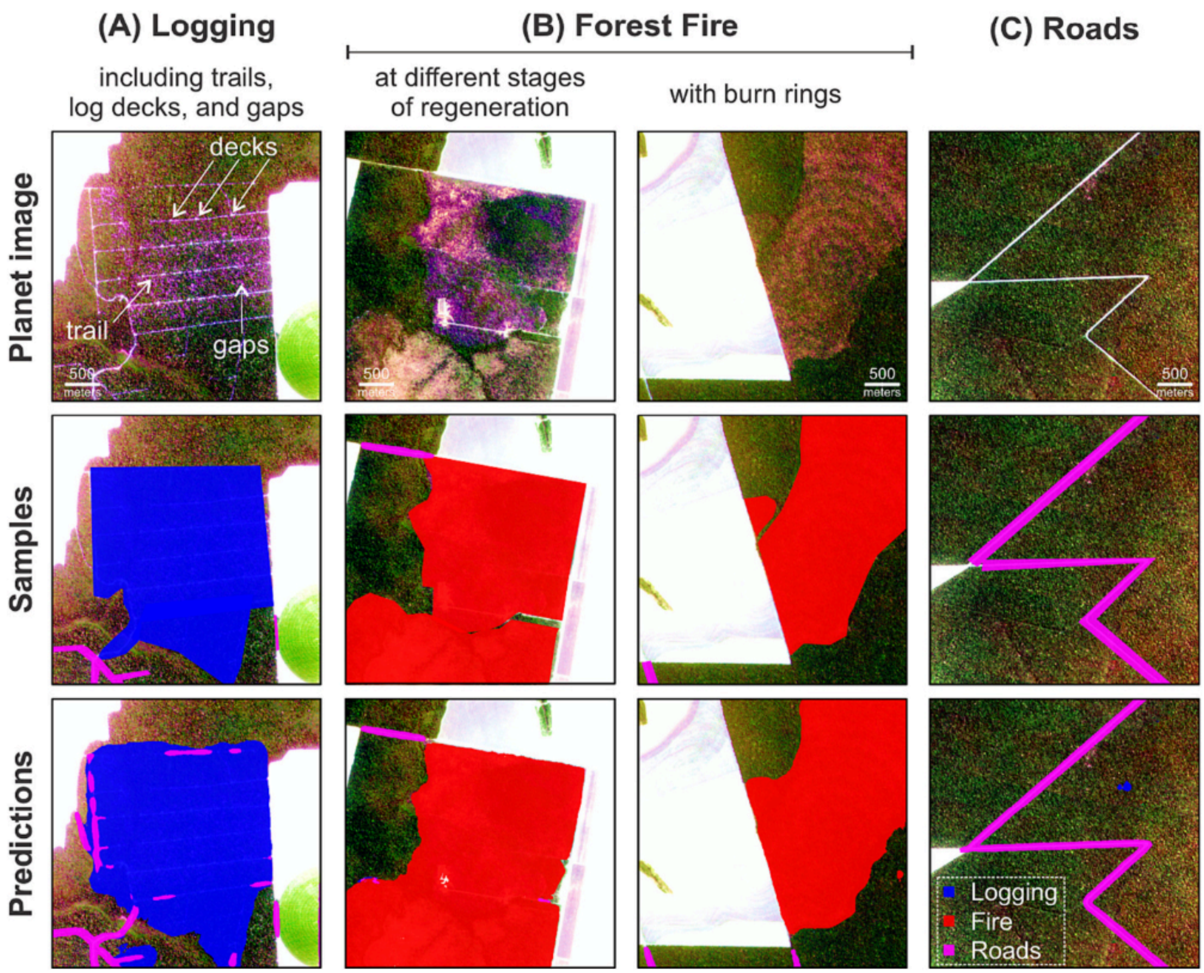


Figure 3 - Examples of (a) logging, (b) forest fire, and (c) road construction (Figure from Dalagnol et al., 2023).

### 5.2. Training and Prediction

The U-Net model was trained using imagery from over 500 NICFI tiles, comprising 138,736 image patches (256 x 256 pixels) for training and 35,115 patches for validation (Figure 4). Most samples were collected from the August 2021 mosaic due to the lower cloud cover typical of the Amazon dry season, but the dataset also included imagery from 20 other dates. The training samples were used to calibrate the model, while the validation samples helped select the best model based on the F1-Score metric. These samples were manually collected through visual interpretation of Planet NICFI imagery and vectorization of areas impacted by logging, fires, and road construction (as shown in Figure 3). For logging, vectors were created to encompass forest areas where at least two of the three key spatial indicators of logging—treefall gaps, logging decks, and trails—were observed (Figure 3a). It is important to note that the mapping of logging covers the entire boundary of the logged area similarly to a forest management or forest concession area, not just the individual pixels of complete clearing. For fires, we sampled all burned areas, not just forest fires, which were distinguished later during post-processing. During vectorization, forest pixels within burned patches were included, even if no apparent fire was observed, as they were likely impacted by the fires (Figure 3b). Compared to the models trained at Dalagnol et al. (2023) for Mato Grosso (Brazil), the training dataset significantly expands the sampling to include various forest environments across Amazonia, Congo basin and Southeast Asia. The model's configuration, training, and prediction processes were the same as done before in the paper and as explained in the tree cover loss section. After prediction, maps were filtered for cloud cover using a model trained to identify clouds in order to reduce false positives. For more detailed information, see Dalagnol et al. (2023).

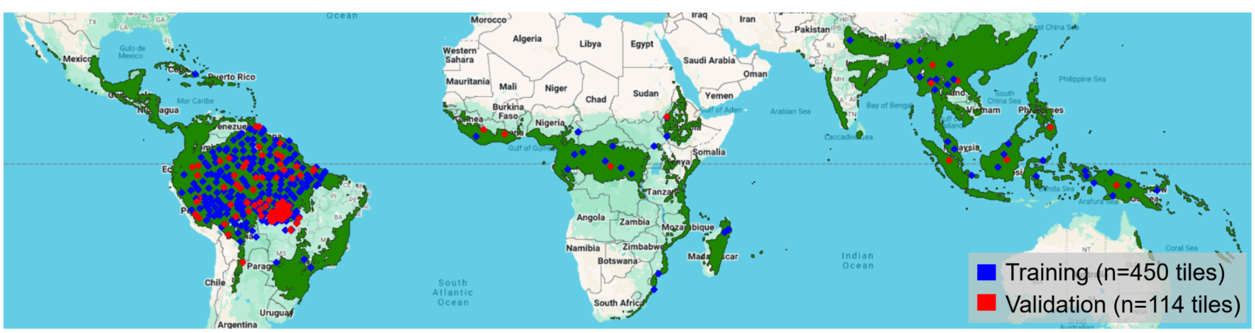


Figure 4 - Training and validation tiles used for the degradation layers.

### 5.3. Degradation maps

We aggregated the predictions into cumulative maps spanning from 2016 to 2023, where each pixel value represents the first biannual occurrence of degradation, measured at a six-month interval. To minimize false positives due to atmospheric effects, vegetation phenology, image artifacts (such as surface reflectance normalization issues, scan lines, and geolocation errors), and topographic effects, we implemented a confirmation logic. Our assumption is that true disturbances will continue to show some impact in subsequent images. Based on this, we applied a confirmation process to the monthly data (from September 2020 to the most recent date) for all layers. Specifically, logging and fire events required at least two detections within the following three months to be confirmed, while road construction required at least three detections in the same period. For the biannual data (from 2016 to June 2020), this confirmation process was applied only to the road construction layer, where at least two detections in the next three semesters were needed for confirmation. We did not apply this logic to logging and fire events in the biannual data, as these types of disturbances often show rapid vegetation recovery. In some cases, degradation effects from logging and fire disappear from imagery within six months, making it difficult to confirm their long-term impact. Meanwhile, the extra confirmation applied for roads was to minimize geolocation issues present in some NICFI mosaics, where in a subsequent image part of the mosaic could be displaced up to a few kilometers, resulting in 'double-roads' being mapped. This extra confirmation procedure significantly minimizes these effects. Exclusively for the confirmation of detections up to Dec 2023, we also employed imagery of Jan-Feb 2024.

The cumulative maps correspond to one map for each degradation type: logging, fire, and road construction. To achieve the final version of the maps, they went through visual quality assessment (QA) for some regions, where issues were identified and minimized through implemented quality controls (QC). Some of these were common errors among some of the layers (Table 2), and some were specific to each layer.

Table 2 - Common quality assessment and control implemented for each layer.

| **Quality Assessment** | **Layers** | **Quality Control** |
|---|---|---|
| Few false detections over water bodies | Logging, Fire, Road | Filtered detections overlapping water bodies using data from the global surface water (GSW) dataset v1.4 (Pekel et al., 2016) |
| Few false detections over urban settlements | Logging, Fire | Filtered detections overlapping urban settlements using data from the Global Human Settlement Layer (GHSL) |

| | | |
|---|---|---|
| | | dataset (Schiavina et al., 2023) |
| False detections over palm oil plantations | Logging | Filtered detections overlapping tree crop plantations and especially palm oil plantation using data from Du et al. (2022) |

**Logging :** The logging map was filtered to exclude stable non-forest areas using our tree cover loss map. Specifically, regions identified as non-forest in 2016 were used to filter out logging results, preventing false detections where logging appeared to overlap with non-forest areas. During quality assessment, we also observed that logging detections could falsely occur in regions where large trees were flowering, particularly in the Amazon. When many trees flower simultaneously, they create small circular areas with contrasting colors, which can resemble logging decks to the model. To minimize this issue, we applied a filter to retain only logging detections larger than 3 hectares. However, some of these issues persist and are scheduled for further investigation in future versions.

**Forest Fire :** To achieve the final map of forest fires, the fire map - which at this point represents any burned area - was filtered to exclude burns over non-forest areas and deforestation fires. This was achieved by intersecting our fire data with our tree cover loss data, removing any fires occurring in stable non-forest areas or areas where tree cover had already been lost before the fire. As a result, the final map primarily reflects burned areas that affect standing forest, henceforth called ‘forest fire’. Since our tree cover loss data may delay detection in cases where areas burn and regenerate quickly (especially in the early part of the time series, from 2017 to 2020), we also incorporated the Global Forest Change (GFC) tree cover loss data v1.11 for additional filtering. This ensures a more accurate representation of forest fires in the final dataset.

**Road Construction :** We found that road segments in the Planet NICFI imagery (~3 pixels in width) often appeared larger than their actual size. To address this, we applied image morphology techniques to progressively thin the road segments, approximating them to their center point — a process known as "skeletonization" using the `magick` R package (Ooms, 2024). For most roads, this process reduced their width to a single pixel. To better match what is observed in the Planet NICFI imagery, we then expanded the roads back to a three-pixel width by adding a one-pixel buffer on each side (Figure 5). Therefore, to roughly estimate road lengths, one should divide the area occupied by roads by three, and then divide by the data resolution (4.777314 meters). Additionally, we applied our own water model to reduce false detections over smaller river streams, which can sometimes resemble narrow roads in imagery. Some areas, particularly in Peru and western Amazonas (Brazil), were manually excluded due to the prevalence of small river streams that, due to their narrow and brown appearance, can easily be mistaken for roads or trails within the forest.

```
image_morphology('Thinning', 'Skeleton', iterations = 12)
```

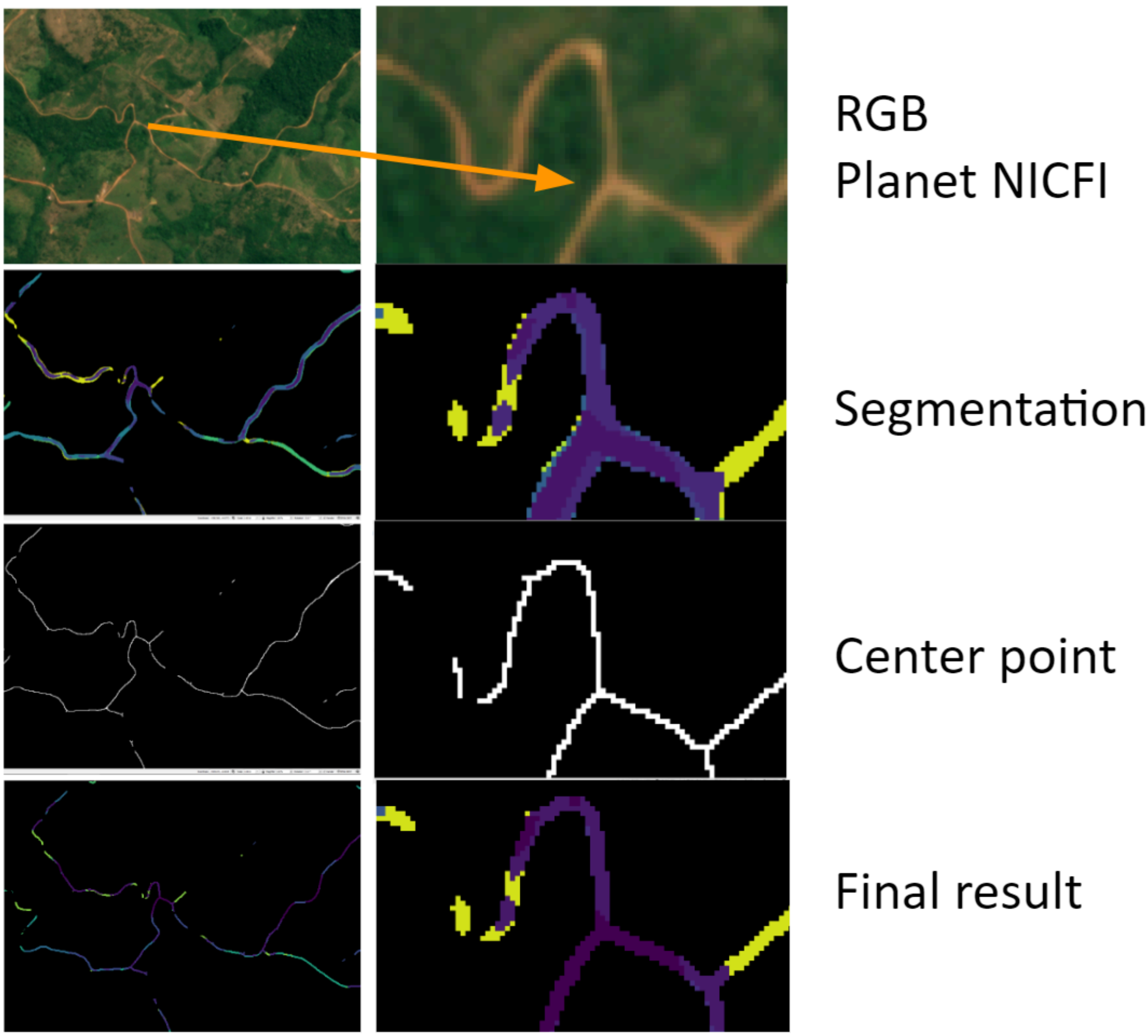


Figure 5 - Road construction post-processing. Planet NICFI imagery from June 2024.

### 5.4. Limitations

Since the prediction for the year 2016 includes any visible degradation that occurred in 2016 or earlier, we do not include it in the REDD+AI platform for logging and forest fire. However, we include roads from 2016 as they represent large pre-existing networks, included primarily for visualization purposes. That said, change rates should only be assessed starting from 2017.

False detections for logging may still occur in areas such as tree crop plantations, agroforestry zones, or during events of large-tree flowering. For forest fires, false detections might be seen in floodplains, deforested areas missed by tree cover loss data, over terrain features or drier forest environments where phenological changes make the vegetation appear brown, mimicking burn scars. False detections for road construction may also appear over small river streams where water masking was not entirely effective.

We plan to improve the AI models and post-processing techniques to enhance the quality of these datasets in future versions. However, it is not feasible to inspect every pixel across the pantropics, and thus we cannot guarantee that all issues have been identified or fully resolved. We welcome feedback to improve the accuracy of the maps.

## 6. Data processing pipeline

We developed a data processing pipeline using Amazon Web Services (AWS) cloud tools to scale our data products efficiently (Figure 6). This effort combined the multidisciplinary expertise of CTrees' science and engineering teams. Processing these large datasets was made possible through the use of high-end GPUs, orchestrated in a distributed manner using the Ray and Anyscale frameworks within the AWS cloud. The Planet NICFI dataset for our area of interest consisted of over 100 TB of compressed 8-bit data. To generate the final maps, we employed and integrated eight different AI models, including tree cover, degradation, cloud, and water cover mapping.

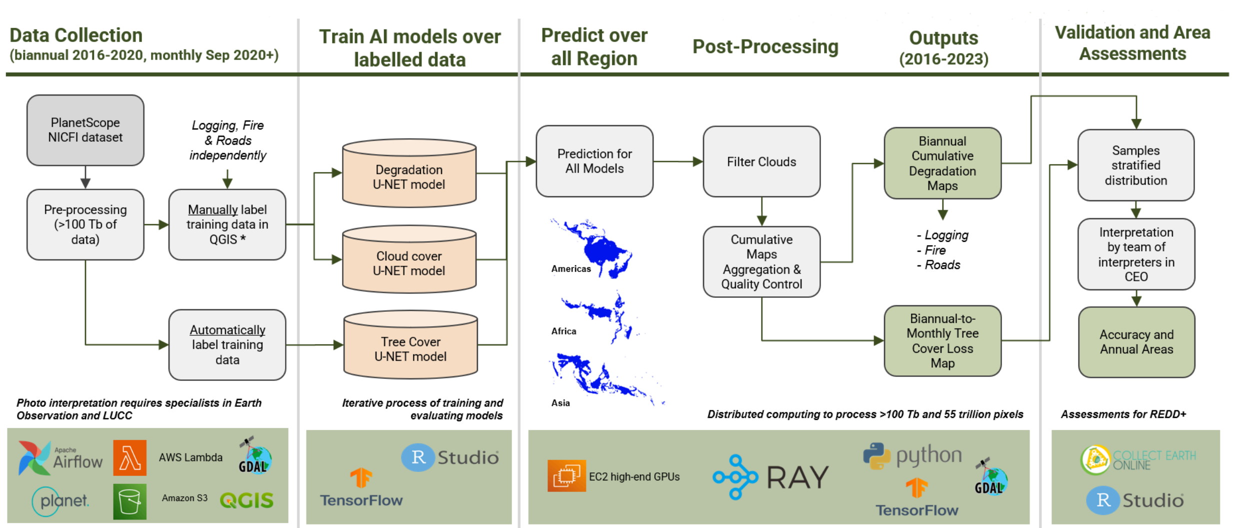


Figure 6 - Simplified representation of the data processing pipeline.

## 7. Validation

Validation of the data will be performed following good practices of map validation using a design-based stratified random sampling approach (Olofsson et al., 2014; Olofsson, 2021). We expect this to come with the next update of data in Q1 2025.

## 8. Data Availability

The datasets can be visualized at the CTrees REDD+AI platform www.ctrees.org/REDDAI. This platform also brings statistics at country, state, and municipalities levels. The underlying geospatial raster data can be accessed upon reasonable request through research collaboration for specific areas of interest. The entire dataset will not yet be available at this time, until we can finalize validation and further analysis of the datasets.

## 9. How to Cite

The preferred citation for the platform is :

> CTrees.org. (2024). **REDD+AI: Tree cover loss and degradation from logging, forest fire and road construction in tropical forests - v1.0**. https://www.ctrees.org/REDDAI/ (accessed on dd/mm/yyyy).

Bibtex version :

```
@Misc{CTreesREDD+AI2024,
  author = {CTrees.org},
  month  = oct,
  note   = {(accessed on dd/mm/yyyy)},
  title  = {REDD+AI: Tree cover loss and degradation from logging, forest fire
and road construction in tropical forests - v1.0},
  year   = {2024},
  url    = {https://www.ctrees.org/REDDAI/},
}
```

When using the datasets and platform in any way, please also cite these two papers below which provide the basis for the data and methods:

> Wagner, Fabien H., Ricardo Dalagnol, Celso H. L. Silva-Junior, Griffin Carter, Alison L. Ritz, Mayumi C. M. Hirye, Jean P. H. B. Ometto, and Sassan Saatchi. 2023. "**Mapping Tropical Forest Cover and Deforestation with Planet NICFI Satellite Images and Deep Learning in Mato Grosso State (Brazil) from 2015 to 2021.**" *Remote Sensing* 15, no. 2: 521. https://doi.org/10.3390/rs15020521.

Dalagnol, Ricardo, Fabien Hubert Wagner, Lênio Soares Galvão, Daniel Braga, Fiona Osborn, Le Bienfaiteur Sagang, Polyanna Da Conceição Bispo, Sassan Saatchi, et al. 2023. "**Mapping Tropical Forest Degradation with Deep Learning and Planet NICFI Data**." *Remote Sensing of Environment* 298: 113798. https://doi.org/10.1016/j.rse.2023.113798.

## 10. License

All data here are provided for reducing and reversing the loss of tropical forests, contributing to combating climate change, conserving biodiversity, contributing to forest regrowth, restoration and enhancement, and facilitating sustainable development, all of which must be Non-Commercial Use according to the Planet NICFI license (https://planet.widen.net/s/zfdpf8qxwk/participantlicenseagreement_nicfi_2024). Any publications, technical reports, models, or data products that utilize these datasets are required to cite the relevant papers and REDD+AI platform (refer to the 'How to Cite' section) and must acknowledge the Planet NICFI license.

## 11. Final considerations

This data product represents a significant step forward in supporting REDD+ initiatives by providing a high-resolution, satellite-based view of tree cover loss and forest degradation directly attributed to human activities such as selective logging, forest fires, and road construction based on CTrees' AI models and human expertise. By delivering clear and traceable data on these key drivers of forest degradation, the product enables more precise monitoring, reporting, and verification (MRV) for REDD+ efforts. This, in turn, can help countries and stakeholders better assess progress toward their deforestation and degradation reduction goals.

The ability to attribute specific causes of degradation enhances transparency and accountability, allowing for targeted interventions and informed policy decisions. While this is the first version, we are committed to improving the dataset over time, further enhancing its utility for the REDD+ community. With continuous updates, the product will evolve into an even more robust tool for understanding and helping to mitigate deforestation and forest degradation across the tropics, supporting global efforts to combat climate change and preserve critical forest ecosystems.

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