Photovoltaic Power Plants – Appendix

Collection 10

Version 1 - BETA

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1 Overview

Photovoltaic (PV) energy systems convert solar radiation into electrical power through silicon-based modules. Both solar irradiance and the duration of the photoperiod influence the spatial arrangement and efficiency of these panels (Sampaio & González, 2017). PV installations usually come in two main types: centralized systems, found in places with lots of sunlight like dry areas and hills, and distributed systems, which are often set up on buildings like the roofs of factories or farms.

Innovative land-use integrations have emerged, notably agrivoltaic, aquavoltaic, and Photovoltaic systems, which combine energy generation with agricultural, fishery, and forestry activities. These multifunctional approaches contribute to local economic resilience and have shown potential to alleviate energy poverty. However, putting a lot of PV arrays in place can cause conflicts over land use and harm the environment, and it might affect how floods are managed when set up over inland water or on green hillsides.

In the Brazilian context, solar energy is particularly advantageous given the country's geographic positioning near the equator, which offers stable and intense solar radiation across most of its territory (Costa et al., 2023). The semi-arid northeast stands out for its high suitability for solar power generation. Initially favoring photovoltaic systems over concentrated solar power, Brazil's adoption of PV began in the 1990s and significantly accelerated after the national energy crisis of the early 2010s (Costa et al., 2023). Policy instruments such as public energy auctions and updated regulatory frameworks played a key role in this expansion.

Although solar energy development still faces barriers, including infrastructure limitations, financial constraints, and regulatory complexities, projections indicate a continued upward trend. Recent models forecast that by 2050, PV systems could supply over a third of Brazil's electricity demand. This trajectory is supported by declining technology costs, improved panel efficiency, and increasing integration with national climate policies aimed at reducing greenhouse gas emissions and enhancing air quality. Moreover, as climate projections indicate potential reductions in hydroelectric output due to altered precipitation patterns, the strategic coupling of solar with wind power is becoming increasingly vital for Brazil's long-term energy security and carbon neutrality goals (Sampaio & González, 2017; Zhang.et al., 2023).

The necessity for accurate mapping and continuous monitoring of PV infrastructures is increasing, driven by their rapid expansion and the need to assess environmental trade-offs. Remote sensing and geospatial technologies play a critical role in this context, supporting land-use planning, impact assessments, and system optimization (Creutzig et al., 2017).

In this sense, photovoltaic power plants, introduced in the new MapBiomas Collection 10, represent a newly mapped land use class across all of Brazil's territory. We use U-Net (Ronneberger et al., 2015), a CNN detection based on a deep learning approach. Below, we describe the technical information and methodological steps adopted for this mapping effort.

2 Methods

2.2 General processing

We developed a deep learning-based approach to map photovoltaic power plants across Brazil by integrating high-resolution NICFI PlanetScope imagery, U-Net convolutional neural networks, and cloud-based processing within Google Earth Engine (GEE) and local processing computing. Monthly cloud-free mosaics at a 4.77-meter resolution were aggregated into annual composites and combined with manually labeled training samples derived from a 5-kilometer buffer around known installations recorded in the ANEEL database. A U-Net model was trained on the Colab Pro+ platform using optimized hyperparameters and data augmentation techniques to improve generalization. The resulting classification outputs were exported as GEE-compatible assets. Post-processing involved spatial and temporal filtering, composite refinement, and resampling to a standardized 30-meter resolution grid. Final maps were validated and refined through spatial cross-referencing with official photovoltaic plant records and biome boundaries. All processing steps are illustrated in Figure 1.

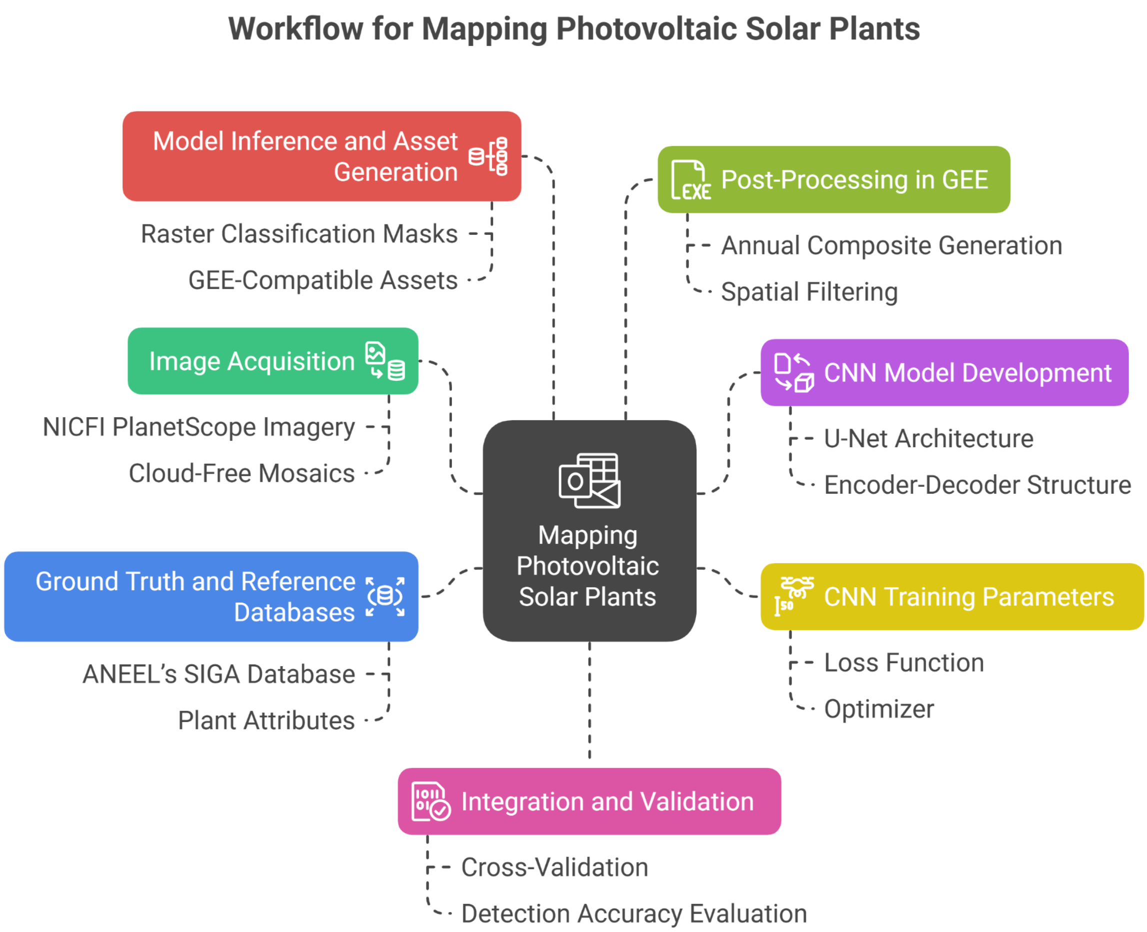

Figure 1. Processing workflow. All processing steps are represented using distinct colors to illustrate each stage of the methodology.

2.2 Image Acquisition

The Google Earth Engine (GEE) catalog provided access to high-resolution monthly mosaics (4.77 m spatial resolution) from the NICFI PlanetScope Tropical Regions program, covering the entire Brazilian territory. These mosaics were chosen because they are free of clouds and have consistent timing, which is important for finding both current and newly added photovoltaic systems.

For training and testing the model, image sections were taken from areas within a 5 km zone around known solar panel sites, as listed in the official database of Photovoltaic Power Plants kept by the Brazilian Electricity Regulatory Agency (ANEEL). Each image was paired with manually digitized masks delineating the extent of solar panel installations. These masks were created through visual interpretation of the Planet imagery, supported by ancillary geospatial data to ensure accurate labeling (Figure 2).

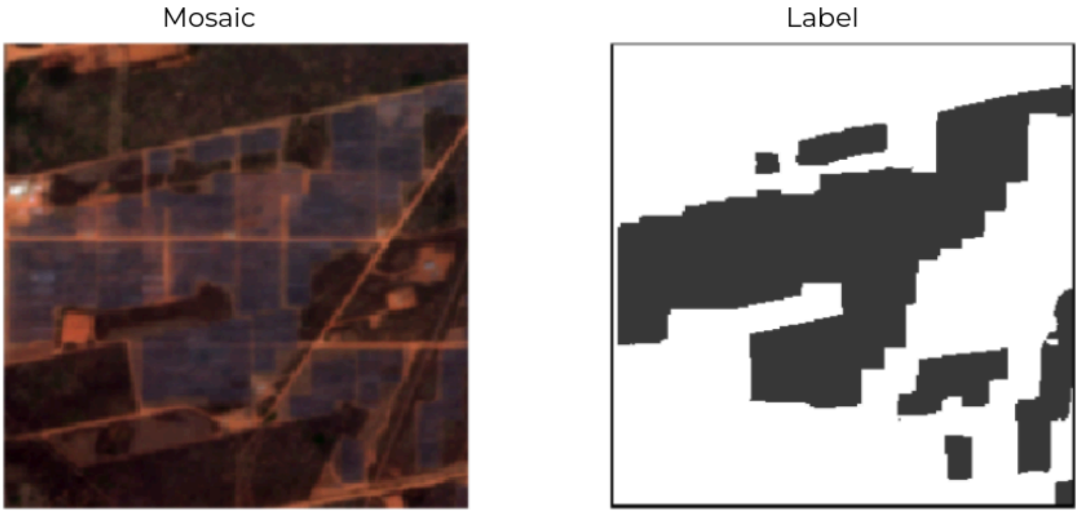

Figure 2. Patch of mosaic planet and their corresponding mask or label.

2.3 CNN model

A U-Net convolutional neural network was trained on the colab Pro+ platform to perform pixel-wise classification of photovoltaic structures (Figure 3).

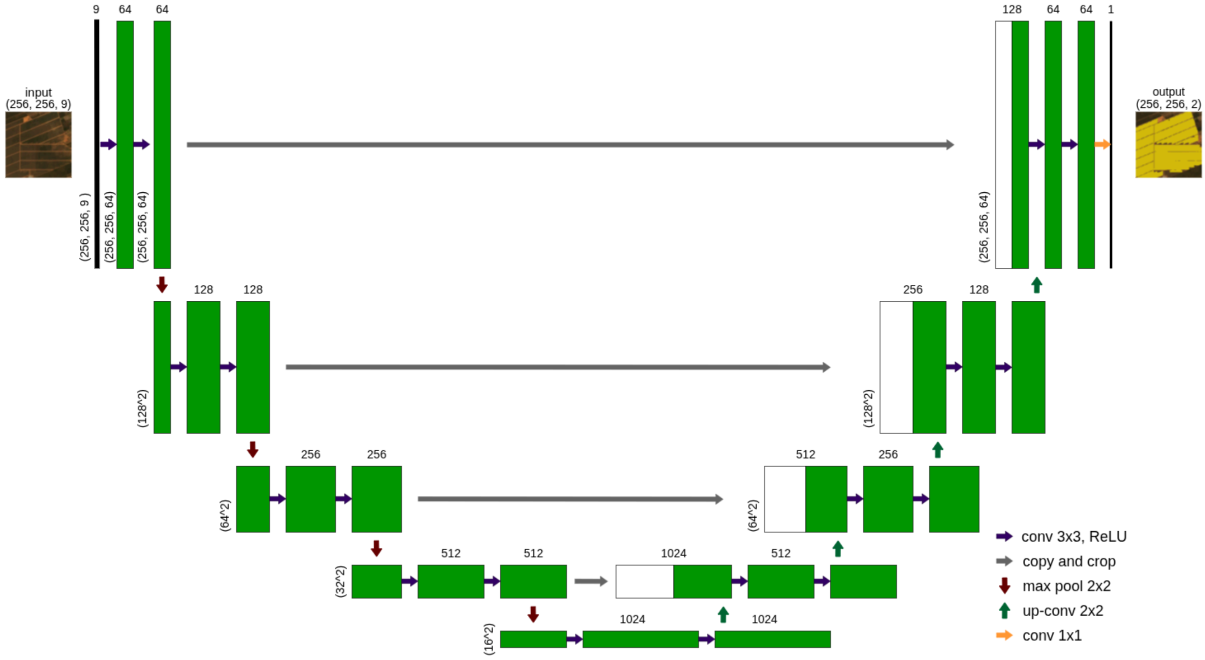

Figure 3. U-Net architecture used for photovoltaic solar plant segmentation. The model processes 256 × 256 × 9 input tiles and outputs a binary mask distinguishing photovoltaic panels from the background. It consists of an encoder for feature extraction, a decoder for upsampling, and skip connections for preserving spatial detail.

The architecture follows the encoder-decoder design (Figure 3), with skip connections to preserve spatial information:

- Input Size: 256 × 256 x 9 pixels
- Encoder: 4 convolutional blocks, each with 2 × (Conv2D + BatchNorm + ReLU) + MaxPooling
- Decoder: 4 upsampling blocks with transposed convolutions and skip-connections
- Output Layer: 1 × 1 convolution with sigmoid activation for binary classification (photovoltaic panel vs. background)

Compile Parameters:

- **Loss Function**: 'binary_crossentropy'
- **Optimizer**: Adam (learning rate: 0.0001)
- **Metrics**: tf.keras.metrics.MeanIoU(num_classes= 1)

Models Parameters:

- **Epochs**: 250
- **Batch Size**: 12

- **Steps_per_epoch**: 200
- **validation_steps** : 50
- **callbacks** : tf.keras.callbacks.ModelCheckpoint(monitor= 'val_mean_io_u', **save_weights_only**=False, save_best_only=True, save_freq=20)
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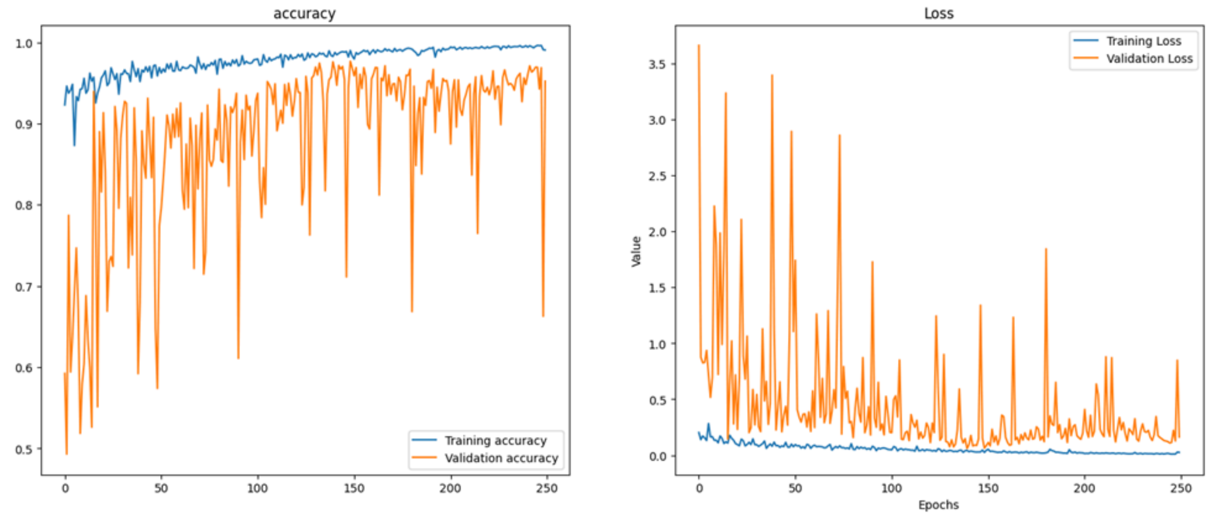

Figure 4. Training and validation performance of the U-Net model over a span of 250 epochs. The left plot shows accuracy and the right plot shows loss curves.

Figure 4 presents the training and validation performance of the U-Net convolutional neural network over 250 epochs. The left panel shows the evolution of accuracy, while the right panel depicts the loss values throughout the training process. The model demonstrates a consistently increasing trend in training accuracy, which stabilizes above 0.98 after approximately 150 epochs. Validation accuracy follows a more variable pattern, reflecting the diversity and complexity of the photovoltaic features in the test dataset. However, it generally remains above 0.85, indicating good generalization.

The loss curves on the right reveal a steady decrease in training loss, consistent with effective model optimization. The validation loss shows more ups and downs, especially in the early training stages, probably because of differences in the validation samples and the difficulty of identifying objects like small or partially hidden photovoltaic panels. Despite this variability, the overall trend suggests convergence, with validation loss frequently stabilizing below 0.5 in later epochs.

These results show that the U-Net model was very good at finding photovoltaic installations, and there was no major overfitting. The network was thus deemed suitable for deployment across large spatial extents in the Google Earth Engine environment.

3. Complementary database

The Brazilian Electricity Regulatory Agency (ANEEL) (ANEEL, 2016) maintains a database regarding Photovoltaic Power Plants (UFVs), and monitors, plans, and regulates solar energy generation in Brazil. This database is part of ANEEL's Generation Information System (SIGA) and provides structured data on all registered photovoltaic generation facilities, including those in operation or under concession/authorization processes.

The database includes detailed information on Photovoltaic Generation Units (UFVs), classified by type of concession (Authorization, Registration, or Concession), project development stage (in operation, under construction, authorized, etc.), and size of the facility. The main fields available are:

- Name of the power plant
- UFV code
- Location (Municipality, State, and Geographic Coordinates)
- Granted capacity (MW) and installed capacity (MW)
- Type of connection (AC or DC)
- Commercial operation start date
- Responsible company (project owner)
- Current project status (operational, under construction, etc.)
- Energy source type (Solar Photovoltaic)

4. Post-processing

For the solar plant maps, we classified the corresponding Planet mosaics from November of each year. Since the model was trained on the November 2024 mosaics and then used to predict all the November mosaics from 2016 to 2024, it consequently generated several commission pixels outside the regions with solar panels, especially in the years closer to 2016.

Once trained, the U-Net model weights were exported and used to generate predictions over large areas. The model inference was applied locally, and the classified rasters were converted to GEE-compatible assets.

We removed these noise or commission pixels using a temporal filter based on the 2024 map. The filter worked by removing pixels that were outside the 2024 solar panel area and did not persist in the years prior to the year being analyzed.

To upload data to Google Earth Engine (GEE), a script was used to export images from a local repository to Google Cloud in a format optimized for access via Cloud Storage. To facilitate processing, these images from the Cloud were saved into an `ee.ImageCollection` in a GEE *asset*, consolidating all country-wide data into a single image per year.

These images, with a spatial resolution of 4.7 meters, served as masks to create the map of Photovoltaic Power Plants (PVPs) at 30 meters resolution. For this, monthly Landsat 32-day mosaics (processed by GEE) were utilized. We selected the blue band and reclassified all its pixels to a value of 1. Subsequently, the `updateMask()` function was applied using the 4.7-meter PVPP layer. Through this procedure, the 30-meter pixels corresponding to PVPPs were reclassified into this specific class.

The following post-processing steps were applied within GEE:

- **Spatial Filtering**: Removal of isolated noise pixels and false positives via connected component analysis.

- **Temporal Filtering**: Monthly predictions were aggregated to identify persistent structures.

5. Integration with biomes and cross-cutting themes

The classified photovoltaic areas were checked against the ANEEL solar energy generation registry (minimum: ≥5000 kW), and an additional database was used to include small-scale distributed installations. This spatial intersection was used both to refine model training samples and to evaluate detection rates in underrepresented regions.

Figure 5 shows examples of how the U-Net model worked on NICFI PlanetScope images to find photovoltaic power plants. The panels are organized in triplets: the original RGB mosaics (left), the manually annotated ground truth masks (center), and the corresponding model predictions (right). The comparison showcases the model's ability to correctly identify Photovoltaic structures that exhibit diverse spatial configurations, which include large centralized solar farms and smaller distributed installations.

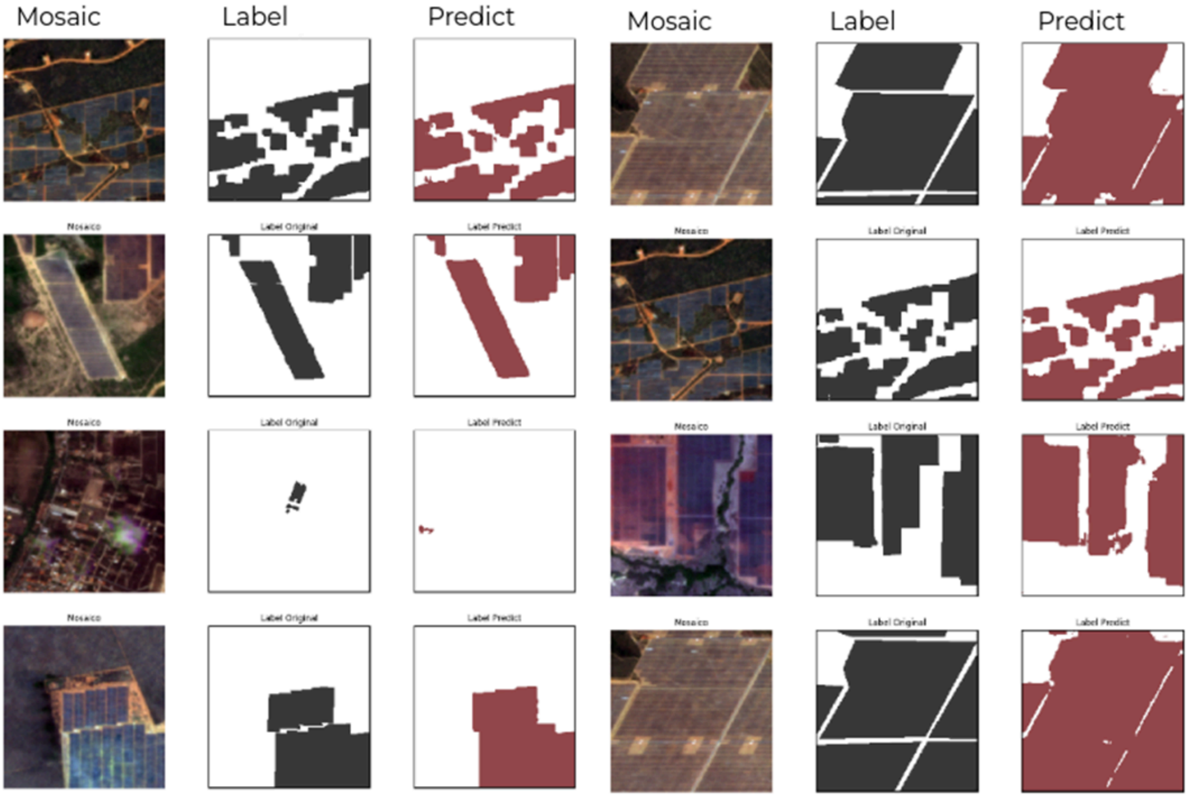

Figure 5. Visual comparison of input mosaics, ground truth masks, and U-Net predictions for the detection of photovoltaic power plants using NICFI PlanetScope imagery.

The results demonstrate strong agreement between predictions and ground truth across most samples, especially in clearly defined photovoltaic areas. Some challenges are observed in scenes with complex urban or agricultural backgrounds, where small installations may be confused with surrounding features or partially omitted in labeling. Despite these cases, the U-Net model generalizes well across varying landscapes and spectral conditions.

7 References

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