Detecting Physiological Stress in Philippine Tropical Rainforest Canopies at the Genus Level: An Integrated Deep Learning Approach Using Fused Satellite Data

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Introduction

The tropical rainforest is the most biodiverse terrestrial biome on Earth, occupying only 18% of the total land but holding 62% of the world's terrestrial vertebrate species (Pillay et al., 2022). In the Philippines, tropical rainforests not only provide ecosystem services (e.g. carbon storage) but also significantly impact livelihood and culture, yet they are severely degraded by unsustainable human development (Bossy et al., 2025; Li et al., 2024; Wagner et al., 2023). Therefore, consistent monitoring is necessary to guide their conservation. Satellites are capable of broad forest monitoring but become unreliable in tropical rainforests due to frequent cloud cover (Bossy et al., 2025; Wagner et al., 2023). Fang et al. (2020) and Zarco-Tejada et al. (2019) noted that current satellite monitoring systems lack genus-specific tree health metrics which creates a gap between broad forest monitoring and genus-specific conservation. To bridge this divide, this study proposes a deep learning-based, genus-level detection system for physiological stress in rainforest canopies using fused satellite data. First, the study will sample and fuse Sentinel-1, Sentinel-2, NASA-ISRO Synthetic Aperture Radar (NISAR), and Biomass temporal satellite data from three Philippine tropical rainforests to investigate how the data can be optimized to contain only the most informative bands. Then, the study will train deep learning architectures with the prepared time-series data to investigate which structural and biophysical canopy traits are the most distinct and sensitive indicators for health and genus. Finally, the study will test the trained deep learning architectures against the ground truth datasets of each rainforest to measure their accuracy.

Review of Related Literature

Sentinel-1 is a synthetic aperture radar (SAR) that operates using the C-band. It records 10m backscatter coefficients in dual transmission polarizations of Vertical-Vertical (VV) or Vertical-Horizontal (VH) (Bossy et al., 2025; Li et al., 2024; Matsokane et al., 2025). Sentinel-2 is a multispectral optical satellite that operates using 13 spectral bands (Matsokane et al., 2025; Persson et al., 2018) including the red-edge spectral bands recorded in 20m spatial resolution (Polyakova et al., 2023; Zarco-Tejada et al., 2018, 2019). Both satellites have a 5-day revisit time (Persson et al., 2018), but unlike Sentinel-2, SARs like Sentinel-1 can penetrate clouds (Li et al., 2024; Matsokane et al., 2025). Biomass is a pioneer satellite that operates using a fully polarimetric P-band, allowing it to penetrate canopies and provide three-dimensional (3D) forest imagery (Kumar, 2025). It provides 200m resolution forest height maps with 3-day spacing between acquisition windows and yields 1-2 3D tomographic profiles of a location annually. NISAR operates using the L and S bands with a 6-day revisit time (Silva et al., 2021), offering 1 ha biomass maps for canopies with <100 t/ha above-ground biomass (AGB) (Quegan et al., 2019). Zarco-Tejada et al. (2018, 2019) used the chlorophyll-sensitive red-edge bands of Sentinel-2 to detect chlorosis in open-canopy conifer forests while Bossy et al. (2025) noted that fusing Sentinel-1 and Sentinel-2 data helped overcome limitations caused by cloud cover in tropical regions. Zarco-Tejada et al. (2018, 2019) also noted that the carotenoid content and phytochemical reflectance index (PRI) indicated stress responses in trees and that chlorophyll fluorescence quantified the net photosynthesis used to map stress hotspots. Fang et al. (2020), Matsokane et al. (2025), and Zarco-Tejada et al. (2018) expressed the role of structural indicators (e.g. leaf area index, canopy defoliation) as markers of foliage density to determine physical damage and seasonal variations among genera. Bossy et al. (2025) and Quegan et al. (2019) noted that canopy height and AGB captured vertical structure while Li et al. (2024) stressed the role of canopy cover in capturing small-scale disturbances (e.g. illegal logging). Tuominen et al. (2018) also noted that 3D features helped distinguish traits among different genera (e.g. crown architecture). Farmonov et al. (2023) used the Wavelet-Attention Convolutional Neural Network (WA-CNN) to extract the most informative bands from satellites. Polyakova et al. (2023) used Generative Topographic Mapping (GTM) to identify the probability distribution of dominant tree canopy species per pixel. Lin et al. (2024) used a hybrid VGG19/ResNet model to identify the composition of forests from hyperspectral images. Bossy et al. (2025) used vision transformers to incorporate structural information with canopy textures to map canopy heights. Zarco-Tejada et al. (2018, 2019) used radiative transfer models (RTMs) to identify biophysical traits and health baselines. Lastly, Manie et al. (2020) used the TensorFlow framework to implement a Long Short-Term Memory (LSTM) model for temporal data analysis while Bossy et al. (2025) and Wagner et al. (2023) noted the ability of U-Net to map tree cover and AGB. Overall, many studies have explored the potential of deep learning-integrated satellite forest monitoring, but a significant gap that remains is how deep learning can be integrated to forest monitoring in order to simultaneously provide health metrics and genus-level classifications.

Methodology

This study will undergo an experimental research design to measure the predictive accuracy of the proposed detection system to location-varied ground truth datasets. The data engine to be used is the NASA-ESA Multi-Mission Algorithm and Analysis Platform (MAAP) while the deep learning platform to be used is the TensorFlow framework. The Mt. Makiling dipterocarp, Mt. Banahaw montane, and Mt. Apo mossy rainforests will be selected due to their varying conditions. In line with Wagner et al. (2023), 6,510 evenly spaced satellite data forest patches (2,170 patches per forest) measuring 256^2 pixels each will be extracted using self-supervised segmentation through the k-textures model. Following a 70/30 training-validation ratio, 4557 patches will be used for training, and 1953 patches will be used for validation. 3190 patches of training data will be augmented using the k-textures model to center tree crowns and mask mixed pixels, reducing deep learning bias (Fang et al., 2020). Radiometric terrain correction model-enhanced data from Sentinel-1, NISAR, and Biomass will be used with Sun-Canopy-Senor+C model-enhanced data from Sentinel-2. The WA-CNN will be used to extract the most informative bands from the data, simplifying the deep learning process (Farmonov et al., 2023). The data will undergo temporal alignment, resolution alignment, flattening of convolution kernels, and fusion (Lin et al., 2024; Zarco-Tejada et al., 2019). Vision transformers, a hybrid model of GTM/Random Forest, and a hybrid model of VGG19/ResNet50 will be used to predict tree genera per pixel through structural and biophysical data (Lin et al., 2024). PROSPECT, 3D FLIGHT, and INFORM RTMs will be used to identify and compare healthy tree baselines with structural and biophysical data. U-Net will be used to assign semantic labels (e.g. forest/non-forest, moist/dry) to pixels. An LSTM model will be used for temporal data analysis. The deep learning models will be trained via self-supervised learning (Bossy et al., 2025) and validated using 10-fold cross validation (Gu et al., 2019; Persson et al., 2018; Tuominen et al., 2018). Lastly, the models' performance on localized datasets will be tested against independent reference data from the selected rainforests (e.g. Makiling Biodiversity Information System).

Conclusion

By integrating deep learning to fused satellite data, this system overcomes individual satellite sensor limitations to bridge the gap between broad forest monitoring and genus-specific conservation. If successful, this system will become a convenient tool to guide rainforest conservation in tropical regions by providing genus-level health metrics.

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