

Assessing the Feasibility of Time-Series Integration for Large-Scale Forest Monitoring

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Abstract—Deforestation is a key contributor in reduced carbon sequestration and intensifying environmental impacts such as flooding and heat waves. This study explores the potential of incorporating time-series data into a forest monitoring system to enhance deforestation detection. The work utilizes the freely available Sentinel-2 satellite imagery. The effect of temporal information are analyzed in its influences in the classification and monitoring. The work focuses on the northern part of Thailand, Chiang Mai province, as the area was affected by severe flooding in 2024. Random Forest is adopted as the classifier of choice to monitor over a one-year period. The classifier implemented is proven satisfactory and is evaluated by known metrics such as Accuracy, F1-score, Precision and Recall. The study provides insights into the feasibility of time-series integration for large-scale, near real-time forest monitoring.

Index Terms—Deforestation Monitoring, Random Forest Classification, Remote Sensing, Sentinel-2, Time-Series Analysis

I. INTRODUCTION

Deforestation is a significant factor of environmental changes, contributing to phenomena such as climate change, fine particulate matter pollution, extreme heat waves, and flooding. A notable example is the 2024 flooding in northern Thailand, which affected 37 provinces, impacted over 18,000 households, resulted in 49 fatalities, and caused 28 injuries [1]. The economic losses were substantial but difficult to quantify. Investigations identified deforestation for mining activities and agricultural expansion as key factors exacerbating the disaster [2]. Illegal deforestation is not confined to specific regions but represents a global challenge. The scientific community has employed various strategies to address this issue, and recent advancements in high-resolution satellite imagery and machine learning have enabled large-scale deforestation monitoring. However, existing systems rarely incorporate time-series data for near real-time monitoring. In this study, monitoring of deforestation is done by mean of correct forest classification (i.e. whether deforestation had occurred) in areas of interest. The investigation is carried out whether incorporating multi-temporal data can improve the performance and stability of

a deforestation monitoring system. A Random Forest-based model trained on Sentinel-2 images is implemented to classify forest and non-forest areas across a one-year period. The study focuses on Chiang Mai, a northern province of Thailand as it suffered severe flooding in 2024 due to illegal logging [2]. By analyzing how time-series data influences classification accuracy and monitoring consistency, its potential to enhance large-scale deforestation detection and improve real-world monitoring applications can be assessed.

The rest of this paper is structured as follows: Section 2 reviews related work on deforestation monitoring using remote sensing and machine learning. Section 3 details the methodology which includes the data used and how the classifier (i.e. monitoring system) is implemented. Section 4 presents the results and analysis. Finally, Section 5 concludes the study and discusses potential future directions for improving forest monitoring systems.

II. LITERATURE REVIEW

In this section, previous and relevant research that leverage multi-spectral satellite imagery and machine learning techniques to enhance deforestation monitoring are reviewed. Traditional deforestation monitoring methods rely on manual observations of imagery and field surveys, which are labor-intensive, costly, and not scalable. These approaches also fail to provide real-time assessments over large areas, resulting in delayed responses to critical issues such as land use planning and illegal deforestation. The help of the recent advent of satellite imagery has significantly improved monitoring efficiency, with frequent revisit times (typically 3–5 days). It also reduced costs by eliminating the need for on-site inspections.

There are currently several missions for multi-spectral imagery at different temporal and spatial resolutions such as Planet Labs [3], Landsat [4], MODIS [5] and Sentinel-2 [6]. For deforestation monitoring, the temporal and spatial resolutions are essential to enable detecting the changes. This section reviews the relevant works in two perspectives, namely Landsat and Sentinel-2. Their main differences are:

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- 1) Spatial resolution: Landsat mission offers 30-meter resolution, while Sentinel-2 mission offers 10-meter resolution.
- 2) Data archive: Landsat mission (focused on mission 7 onward) provides images from 1999. Sentinel-2 provides images from 2016.

Another well-known satellite mission is Sentinel-1 which offers radar capability (i.e. visible under clouds) and has a revisit time of 6-12 days, depending on the regions. [7]. Sentinel-1 is referred to prolifically when the study areas are covered by clouds throughout the year which can render the ground surface invisible.

Deforestation predominantly occurs in tropical forests, such as the Amazon [8]–[11] and rainforests in Asia [12]. These regions are particularly affected by illegal logging and agricultural expansion, often driven by human settlements [12], [13]. Furthermore, rainforest deforestation has impacted the environment most severely. It does not only reduce carbon sequestration but also significantly decreases rainfall and exacerbates heat stress in affected areas [11], [14], [15]. The scientific community is urgently developing large-scale monitoring solutions that leverage satellite imagery and enhance detection capabilities through machine learning models. Understanding where deforestation occurs is essential, but equally important is how it is detected.

Deforestation monitoring methods can be broadly categorized into traditional machine learning and deep learning approaches. Traditional models such as Random Forest (RF) [16] and Support Vector Machines (SVM) [17] are commonly used for binary classification tasks, such as distinguishing forest from non-forest areas. While effective and computationally efficient, these models do not inherently capture spatial or temporal patterns, which limits their applicability in dynamic environments. In contrast, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks gained attention due to their ability to learn complex spatial and temporal dependencies from satellite imagery [10]. These methods often yield better visual results but require extensive labeled data and greater computational resources.

Several studies have employed traditional methods with success. Hoekman et al. [18] developed a rule-based system using Sentinel-1 data to detect deforestation at 6–12 day intervals, it achieved a false alarm rate below 1% and a missed detection rate under 19%. Yordanov et al. [19] combined pixel clustering and polygon-level classification to reduce processing time, achieving 90% accuracy in the Amazon forest. Potić et al. [20] applied SVM to monitor forests in Serbia. It highlighted the importance of red-edge bands in enhancing classification performance.

Deep learning methods offer greater flexibility. Bragagnolo et al. [21] used U-Net with Sentinel-2 imagery to delineate deforestation areas, achieving F1-scores between 0.75 and 0.92. Masolele et al. [22] benchmarked six architectures using Landsat time-series data and found that spatio-temporal models outperformed spatial- or temporal-only approaches. Their

findings emphasized the value of temporal context and regional consistency in improving classification accuracy.

In order to gain a better understanding of the trade-offs between traditional and deep learning approaches, performance in terms of accuracy, computational resources, and real-time monitoring capabilities are compared here. In conventional machine learning methods, most studies suggested RF to be the as the most effective algorithm for deforestation classification [23].

However, deep learning methods have attracted much attention for their accuracy in classification too. Guanyao et al. [24] reported that CNN outperformed SVM and RF by an average of 3% in accuracy, though this improvement was achieved by incorporating additional training samples during CNN training. In contrast, Caffaratti et al. found that RF and SVM delivered comparable performance to CNN while maintaining greater ease of use. However, they also noted that CNN outperformed RF and SVM in certain cases [25]. Similarly, Adarme et al. observed that while SVM’s accuracy was only 1–2% lower than deep learning models, it remained a viable alternative [8] due to its simplicity.

Beyond accuracy, the quality of the output images is also a crucial factor. De Bem et al. reported that while RF and CNN (along with its variations) achieved similar numerical performance, CNN produced visually superior results due to its ability to capture spatial dependencies between pixels. However, this advantage comes at a cost. CNNs require significantly more computational resources, such as GPUs, to accelerate the training process [10]. De Araújo et al. further affirmed this trade-off, demonstrating that although RF achieved slightly lower accuracy than CNN, it required considerably less inference time, even on edge devices (low-powered computing platforms) [26]. These findings underscore the practicality of deploying deep learning for large-scale deforestation monitoring while also emphasizing the cost considerations involved.

While both conventional machine learning and deep learning approaches have demonstrated effectiveness in deforestation monitoring, most existing methods rely on a limited number of selected image scenes rather than leveraging continuous time-series data. This limitation poses challenges, particularly during monsoon seasons when cloud cover obstructs optical satellite imagery, reducing the availability of usable data. This work is the first to investigate the impact of time-series data on deforestation monitoring performance and potential benefits of incorporating multi-temporal information. In the following sections, implementation, results, and their implications are discussed.

III. METHODOLOGY

The proposed method explores the impact of incorporating time-series data into deforestation monitoring, addressing the limitations identified in Section II. Traditional approaches often depend on a small number of manually selected cloud-free images, which require extensive curation and may be unsuitable for real-time monitoring, particularly during the

monsoon season. To investigate the feasibility of a more robust alternative, we employ a machine learning-based approach using Random Forest (RF) with monthly time-series Sentinel-2 imagery. The model is formulated as a binary classifier, distinguishing between forest and non-forest areas. Designed for efficiency and practicality, the model is trained once per year and applied for monthly monitoring, allowing us to assess the potential benefits of temporal information in deforestation detection.

A. Data Preprocessing

The satellite imagery used in this study is obtained from the Sentinel-2 mission, which provides 10 reflectance bands, including Near-Infrared (NIR) and Red-Edge—both proven to be significant for land use and land cover classification [20]. Despite its advantages, Sentinel-2 imagery is highly susceptible to cloud cover, which reduces the availability of usable daily data. To mitigate this issue, cloud masking is performed using the Scene Classification Layer (SCL) from the Sentinel-2 L2A product, where cloud-contaminated pixels were masked as "no data." However, this process can leave as little as 10% of the data usable in some cases. Then, the images are aggregated into monthly composites. Specifically, all scenes within a fixed period (e.g., April 1–30) are collected, and a per-pixel median is computed to create a cloud-free composite to ensure data continuity. In the aggregation process, the following vegetation indices are calculated, Normalized Difference Vegetation Index (NDVI), Chlorophyll Index (CI), Bare Soil Index (BSI), Normalized Difference Moisture Index (NDMI), and False Color Index (FCI) [27]. This aggregation approach significantly reduces data loss, improving the reliability of the monitoring process compared to traditional methods that rely on individual cloud-free images.

Fig. 1 and Fig. 2 illustrate the difference between a single daily scene and a monthly aggregated composite. As shown in Fig. 1, cloud cover obscures the upper portion of the image. In contrast, the monthly aggregation in Fig. 2 eliminates cloud interference, revealing underlying vegetation growth.

Five key vegetation indices—NDVI, CI, BSI, NDMI, and FCI are selected for the classification, instead of raw reflectance bands, as the latter are highly sensitive to terrain variations and elevation changes. Their values ranges from -1 to 1. The model is trained on a full year of data (January to December). Altogether, over 800,000 samples are collected for training and testing. During the training phase, any sample with missing values is simply discarded.

In this study, the work focuses on a region in Chiang Mai, a northern province of Thailand (MGRS T47QMA). The area was severely affected by the 2024 floods. Investigations linked the disaster to illegal logging in the surrounding mountains, making this an important case study for deforestation monitoring [2].

B. Random Forest-based Monitoring

Random Forest (RF) is chosen to be the classification tool in this study due to its robustness, interpretability, and proven



Fig. 1. T47QMA scene captured on 4th April, 2020.

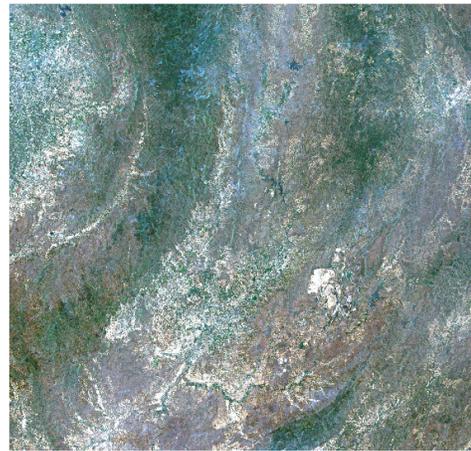


Fig. 2. T47QMA April aggregated in 2020.

effectiveness in deforestation classification as stated in the previous Section [23]. While RF does not inherently capture temporal correlations, time-series data can be incorporated by treating them as additional features during training.

The dataset is extracted from MGRS T47QMA (Chiang Mai, Thailand) for the year 2024. To ensure a spatially unbiased sample, a grid-based sampling strategy is applied in selecting a point every 100 pixels (1 km apart). This prevents nearby pixels from being included, therefore, avoiding unintentional spatial bias in the dataset.

The ground truth data is sourced from the Land Development Department of Thailand [28], which releases updated land cover information every 4–5 years, depending on the region, due to the surveying and correction processes involved. The dataset originally contained 131 land cover classes. Since this study focuses on binary classification, evergreen and deciduous forests are grouped as ‘forest’ and ‘non-forest’ otherwise. The label example is shown in Fig. 3 where the green color indicates the forest area.

In evaluation, the dataset is split into 70% training and 30% testing. The RF classifier is implemented using scikit-learn

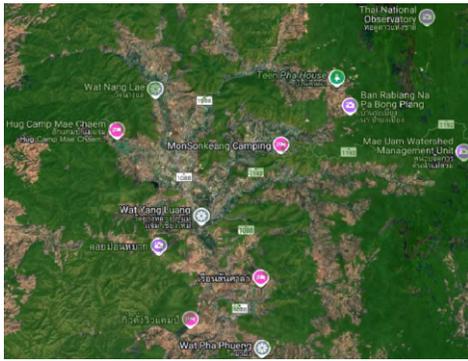


Fig. 3. Ground truth data example where green color indicates forests.

[29], with most parameters set to default, except `n_estimator` is set to 500 and `random_state` is set to 42.

This configuration ensures model stability and reproducibility, while maintaining a balance between computational efficiency and classification performance.

C. Evaluation Metrics

For this task, we evaluate the model using four key metrics: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of classification performance.

While accuracy provides a general measure of correctness, it can be misleading in imbalanced datasets. In this work, the T47QMA region contains a significantly higher proportion of forest pixels compared to non-forest pixels, which include urban, agricultural, and bare land areas. A model that simply predicts "forest" for most pixels could achieve high accuracy but fail to detect deforested regions effectively.

To address this, Precision, Recall, and F1-Score are included, which offer deeper insights into classification performance. Precision evaluates how many of the predicted forest pixels are actually forest, which is important for minimizing false detections. Recall measures the ability to detect all true forest pixels, ensuring that deforestation is not overlooked. Finally, F1-Score provides a balanced measure of precision and recall, making it useful for assessing the overall effectiveness of the monitoring system.

We outlined the complete framework of our deforestation monitoring approach, covering data preprocessing, feature selection, training strategy, and evaluation metrics. Additionally, we introduced a grid-based sampling strategy to mitigate unintended biases in model training. With the methodology established, we now present the experimental results and analyze the model's performance in detecting deforestation events.

IV. EXPERIMENTAL RESULTS

The experiments are conducted from January to November as stated. The primary focus is to assess the impact of temporal variations on model performance. Therefore, instead of testing with a full year's data, which would naturally yield the best

results, the behaviour of the model when data availability fluctuates throughout the year is of prime interest, e.g., inferring with data from January to March.

The accuracy of the model implemented, with only January data, without access to information from subsequent months (cf. Fig. 5) is notably low at 36%. Nevertheless, this is not unexpected as only one month of data is used. Due to this data scarcity, the model classifies nearly all areas as non-forest, as reflected in Fig. 4, where both precision and recall are 0 for the forest class. However, as additional monthly data became available (e.g., February), the performance of the model improve considerably, leading to an increase in recall to 0.45 (cf. Fig. 4). This is attributed to the detection of evergreen forests, which exhibit distinct spectral characteristics even in the early months.

From April to August, the model's performance stabilizes across all metrics. The overall accuracy is maintained at 70% and precision and recall of the forest class are 83% and 68%, respectively (cf. Fig. 4). Noted that this period covers Thailand's summer and rainy seasons. Typically, planting begins in May with peak vegetation growth occurring from July onwards, and harvesting taking place around November. As stated earlier, persistent cloud cover poses a significant challenge during the rainy season for conventional monitoring approaches. However, the aggregation process adopted in this study circumvents this issue, allowing the time-series model to maintain stable performance despite the reduced availability of cloud-free imagery.

A substantial improvement is observed in September when most crops had fully developed, allowing the model to better differentiate between deciduous forests and agricultural land. At this stage, the model achieves a precision of 84%, recall of 74%, and accuracy of 74%. Performance continues to improve in the following months, (reaching 87% in precision, and 88% in recall for forest class, and 85% in accuracy by the end of the study period.)

These results demonstrate that incorporating temporal information significantly enhances classification accuracy and model robustness, even though performance may be suboptimal in the initial months when limited data is available.

V. CONCLUSION AND FUTURE WORK

In this study, investigation into the integration of multi-temporal features for deforestation monitoring is conducted. The objective is to develop a robust and practical system capable of operating with minimal human intervention. The results demonstrate significant improvement in classification performance over time, highlighting the effectiveness of incorporating temporal information.

Based on findings, future work can be conducted in the following directions :

- 1) Incorporating additional data to mitigate early misclassifications.
- 2) Exploring additional vegetation indices that could enhance the distinction between crops and forests in the early months.

Classification Metrics Over Time (47QMA, 2024)

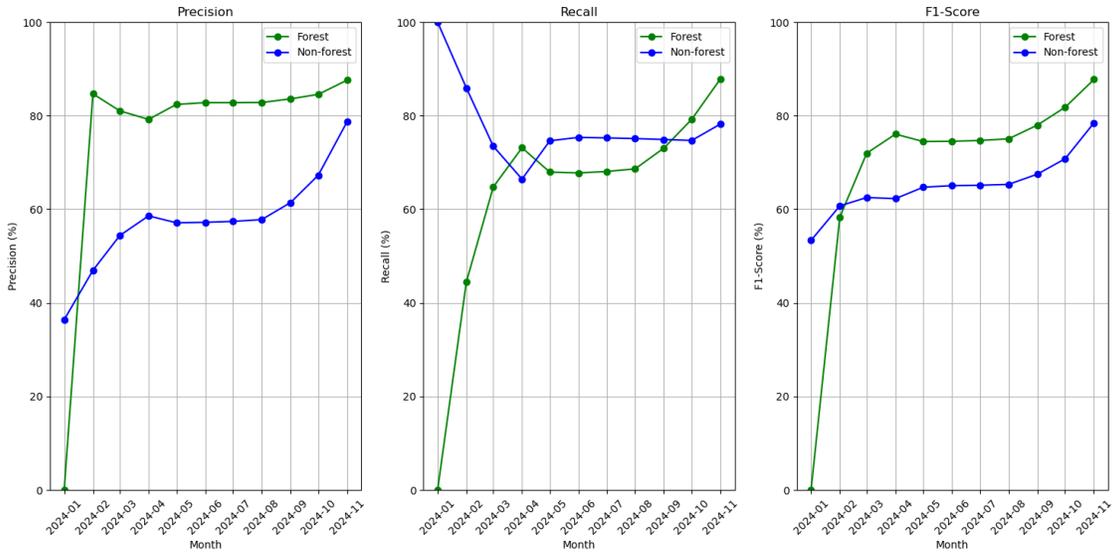


Fig. 4. Precision, Recall, and F1-score for forest and non-forest classification.

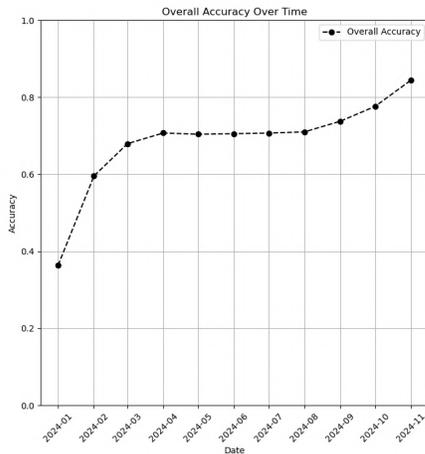


Fig. 5. Overall accuracy of the classification model.

3) Investigating alternative training strategies to address suboptimal performance during the initial months.

This study affirms the utilization of RF in deforestation classification and also indicates that conventional machine learning can be appropriate. Therefore, it may be prudent to gain an in-depth understanding of the task prior to selecting the tool. The study serves as a foundational step toward leveraging freely available satellite imagery for large-scale environmental monitoring. Further evaluation of the approach in this work can benefit from applying it to other areas such as Amazon forest.

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