Food and Agriculture Organization of the United Nations

BAMBOO RESOURCES ASSESSMENT

A methodological approach using SEPAL with case studies in Asia

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Abbreviations

BI	Bamboo Index
CCDC	Continuous Change Detection and Classification
CEO	Collect Earth Online
CHT	Chittagong Hill Tracts
ESRI	Environmental Systems Research Institute
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
FRA	FAO Global Forest Resources Assessment
GCVI	Green Chlorophyll Vegetation Index
GEE	Google Earth Engine
GLCM	Gray-Level Co-Occurrence Matrix
INBAR	International Bamboo and Rattan Organisation
LSWI	Land Surface Water Index
MTCI	MERIS Terrestrial Chlorophyll Index
NDFI	Normalized Difference Fraction Index
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NFI	national forest inventory
NIR	near-infrared
RF	random forest
SEPAL	System for Earth Observation Data Access, Processing and Analysis for Land Monitoring
SRTM	Shuttle Radar Topography Mission
SWIR	short-wave infrared
VH	vertical transmit, horizontal receive
VV	vertical transmit, vertical receive

Units

ha	hectare(s)
m	metre(s)
mm	millimetre(s)
tC/ha	tonnes of carbon per hectare

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Executive summary

Bamboo is one of the fastest-growing species, distributed widely across some of the most biodiverse and carbon-rich areas of the tropics and subtropics in Africa, Asia and South America. With an estimated area of 35 million ha (FAO, 2020) and more than 1 600 species recorded (INBAR, 2021), bamboos are very versatile plants suitable for multiple uses.

Despite the recognized range of benefits and potential, bamboo has often not been managed sustainably or used effectively in many countries. The main reasons are related to the lack of information about countries' bamboo resources, as well as insufficient knowledge about bamboo uses, products and commercial potential, and ecosystem service values, particularly regarding climate change. The Global Forest Resources Assessment (FRA) of the Food and Agriculture Organization of the United Nations (FAO) in 2020 showed that only 23 countries reported information on bamboo resources, despite that methodologies and technical tools are available for the assessment of bamboo forest cover, stock and carbon sequestration.

The underlying rationale for this study is that knowledge of the status and extent of bamboo resources is crucial for evidence-based decision-making and policymaking for sustainable management, conservation, restoration and economic development through the harvesting of bamboo forests to properly capitalize on their potential.

This study proposes a simple and practical approach to mapping bamboo on a large scale in Southeast Asia with the help of cloud-computing tools, including FAO's System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL) and Google Earth Engine (GEE). It integrates freely available satellite data, including Sentinel-1 and Sentinel-2 time-series data from 2022 to August 2024, with a focus on mid-March to mid-April 2024, Shuttle Radar Topography Mission (SRTM), and global canopy height datasets.

The study combines Continuous Change Detection and Classification (CCDC) time-series analysis with both optical and radar data, and incorporates multiple vegetation indices – the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Chlorophyll Vegetation Index (GCVI), MERIS Terrestrial Chlorophyll Index (MTCI), and Normalized Difference Fraction Index (NDFI) – as well as texture and topographical features. A key methodological innovation is the use of time-series data to extract phenological characteristics, such as amplitude and phase, from spectral and vegetation indices, such as near-infrared (NIR), short-wave infrared (SWIR), red-edge bands, NDFI and EVI, in order to improve classification accuracy. A random forest (RF) classifier with optimized 40–100 trees provides enhanced bamboo detection capabilities and the use of Collect Earth Online (CEO) for training sample collection enhances classification reliability.

This study provides a detailed map of bamboo distribution in selected countries; the analysis of the results revealed some ecological insights. Bamboo is found growing at mid-elevations of 300–750 m on moderate slopes of 8–17 degrees and in areas with intermediate rainfall of 2 000–3 000 mm per year. Its adaptability to semi-arid conditions, steep slopes and degraded lands indicates its dual function as an ecological stabilizer and climate-resilient species in soil stabilization, erosion control and in the fight against desertification.

The country case studies show that the methodology is very efficient, with overall accuracy of 90–95.95 percent and kappa coefficients of 0.81–0.89. These metrics show the efficiency and quality of the approach in correctly identifying bamboo growth in different ecosystems and terrains. The high kappa values also further support the agreement between the model predictions and the reference data, making this methodology very suitable for large-scale bamboo mapping.

Limitations exist, including challenges in species-level identification due to insufficient species-specific ground-truth data, as well as challenges in classifying the many species of bamboo across various categories.

Future efforts should include collaboration with local country teams while expanding assessments to other countries and regions, incorporating species-specific ground-truth samples, and leveraging other existing bamboo data at country level.

This research establishes a robust framework for bamboo mapping, combining advanced technologies, open-access platforms, and collaborative tools. It sets the stage for informed decision-making, promoting sustainable bamboo resource management and fostering ecological and socioeconomic resilience in Southeast Asia.


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Introduction

Bamboo and its importance

Bamboos are a group of evergreen perennial plants belonging to the subfamily *Bambusoideae* of the grass family *Pocaceae*. Bamboo is one of the fastest-growing species, distributed widely across some of the most biodiverse and carbon-rich areas of the tropics and subtropics in Africa, Asia and South America. With an estimated area of 35 million ha (FAO, 2020) and more than 1 600 species recorded (INBAR, 2021), bamboos are very versatile plants suitable for multiple uses. It is estimated that bamboo has over 10 000 possible uses, including for livelihood subsistence and applications with high economic potential.

Bamboo forests have also proved to be a strategic resource for countries to combat the negative effects of climate change. Estimates of carbon stock of bamboo forests range from 94 to 392 tC/ha. Depending on species and management regimes, annual carbon sequestration of bamboo forest can reach 25 tC/ha annually (Yuen *et al*., 2017). Most large-diameter bamboo species grow faster than fast-growing tree species. Importantly, bamboo forests can be harvested selectively with no damage to the environment and harvested culms will be replaced by new culms within a year. With modern technology, bamboo products can be made very durable, lasting for 30 years or more, and can be a sustainable substitute for other materials, such as plastic, wood, aluminium, polyvinyl chloride (PVC), concrete and metal. Furthermore, bamboo has proved to be a very good species for restoring degraded land and conserving soil and water; it can also play an important role for climate change adaptation, especially in bamboo-based smart agricultural systems.

Bamboo is typically found among the poorest communities in the tropical and subtropical belt, where it is customarily used for daily subsistence. New product processing can build on existing skills and offer producers a wide range of options, increasing their flexibility in times of market stress. In addition, bamboo's lightweight and linear-splitting nature makes it comparatively easier to process than timber. This provides farmers, many of whom are women, with opportunities to engage in initial processing, increasing their share in value addition towards the production of an array of high-value end uses as commodities.

Various countries in Asia, as well as Africa and Latin America, already have experiences promoting the bamboo sector with significant contributions to employment generation across entire value chains. Activities related to the management of bamboo forests, harvesting, pre-processing and processing has created employment and a sustainable source of income for rural communities.

Problem statement and research gap

Despite the recognized range of benefits and potential, in many countries, bamboo has often not been managed sustainably or used effectively. The main reasons are related to the lack of information about countries' bamboo resources, and insufficient knowledge about bamboo uses, products and commercial potential, as well as about its ecosystem service values, particularly regarding climate change. The FRA in 2020 showed that only 23 countries reported information on bamboo resources, despite methodologies and technical tools available for the assessment of bamboo forest cover, stock and carbon sequestration.

The process of mapping bamboo in Southeast Asia is challenging because bamboo is spectrally like other vegetation types and the region has frequent cloud cover, a diverse landscape with limited ground-truth data on bamboo species and limited bamboo maps both at the global and national level. These problems limit the effectiveness of precise and scalable bamboo resource assessments for policy development and sustainable management.

The underlying rationale for this study is that knowledge of the status and extent of bamboo resources is crucial for evidence-based decision-making and policymaking for sustainable management, conservation, restoration and economic development through the harvesting of bamboo forests to properly capitalize on their potential.

The role of the International Bamboo and Rattan Organisation in bamboo mapping

The promotion of sustainable bamboo conservation and utilization through comprehensive assessments has been a major contribution by the International Bamboo and Rattan Organisation (INBAR) towards global bamboo resource management. The organization carried out remote-sensing assessments to map bamboo resources across multiple countries, such as China, Ethiopia, Ghana, India and various Southeast Asian nations. The mapping efforts have provided informative and useful information that assists in policy development, sustainable practices, and helping communities that depend on bamboo. Even though INBAR assessments provide valuable primary information, the objective of this study is to build upon existing knowledge by streamlining bamboo methodologies using freely available remote-sensing satellite images in SEPAL with a user-friendly approach.

Literature review

The use of remote sensing and geospatial technologies has changed the way bamboo resources are mapped in Southeast Asia. In previous studies, bamboo mapping was done through conventional field surveys, an approach used by Dransfield and Widjaja (1995) for mapping different types of bamboos and their habitats. However, such field surveys were limited as they were not very efficient in covering large and hard-to-reach areas (Watanabe *et al*., 2018).

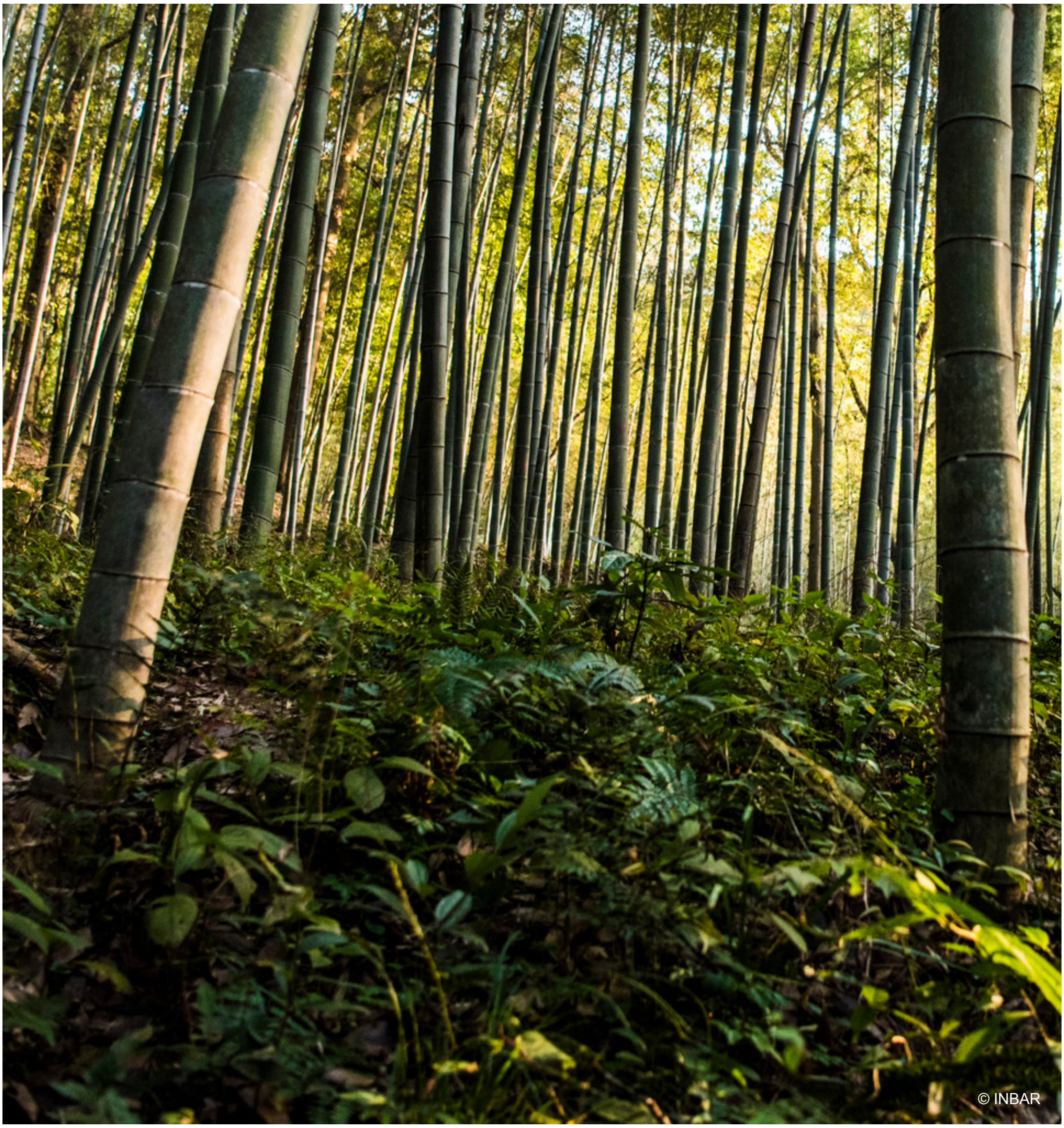
Remote-sensing approaches using optical satellite images, especially from Landsat and Sentinel-2 missions, have been employed for mapping bamboo in Southeast Asia. For instance, Landsat-8 Operational Land Imager (OLI) data were employed to distinguish bamboo from other plants based on spectral signatures in Viet Nam (INBAR, 2019). In the same manner, in Thailand, Sentinel-2 images were employed to determine the occurrence of some important species, such as *Dendrocalamus asper* and *Bambusa blumeana* (Amatyakul, Orozco and Bunschoten, 2023). Although the use of optical images proved useful, limitations exist because bamboo is similar to other plants, especially in the mixed landscapes of Southeast Asia.

To overcome these challenges, researchers have combined sensor datasets and sophisticated classification algorithms. The application of machine-learning techniques – such as support vector machines (SVMs) (Cortes and Vapnik, 1995), artificial neural networks (ANNs) (Bishop, 1995), and RF classifiers – has been found to substantially enhance the classification accuracy in complex environments (Belgiu and Drăguţ, 2016). Among these, RF is the most used because it is fast and robust. However, methods such as support vector machines are known to be costly and require a lot of resources and proper settings (Foody and Mathur, 2004; Huang *et al*., 2002). In the same manner, the optimization of artificial neural networks is also difficult due to time-consuming parameter tuning and the large number of topologies available (Abdolrasol *et al*., 2021).

The integration of radar imagery with optical data has further enhanced the ability to detect bamboo, especially in areas with sparse optical data due to persistent cloud cover. The need for combining Sentinel-1 synthetic aperture radar (SAR) and Sentinel-2 optical data to achieve better bamboo mapping in Viet Nam was well demonstrated by Xiang *et al*. (2023). The high spatial and spectral resolution of Sentinel-2 is better than that of Landsat because it has SWIR and NIR bands, which are very useful in distinguishing bamboo from other land cover categories (INBAR, 2019). Moreover, the use of spectral and textural characteristics of passive and active sensors, together with topographical, climatic, edaphic, and phenological data, improves the classification accuracy in the diverse environment (Venkatappa *et al*., 2020).

Vegetation indices used in bamboo mapping include NDVI, EVI, Normalized Difference Moisture Index (NDMI), Bamboo Index (BI) and GCVI. These indices increase the capacity to separate bamboo from other plant communities through the utilization of spectral and physiological characteristics (Tamang *et al*., 2022; Yebeyena *et al*., 2024). For instance, NDVI is still being employed as a key indicator in distinguishing vegetated and non-vegetated zones (Feng *et al*., 2023); GCVI is especially useful for demonstrating the chlorophyll contribution in the vegetation differences. The initial studies, including those on Moso bamboo in China, revealed that the inclusion of phenological layers – such as EVI changes, red-edge shifts, and their slopes – was efficient (Li *et al*., 2019; Feng *et al*., 2023). New technologies like high-resolution images based on light detection and ranging (LIDAR) and unmanned aerial vehicles (UAVs) have also enhanced the bamboo mapping efforts to determine the culm level distribution, biomass and species identification (Zhou *et al*., 2022).

The major constraint of their application in Southeast Asia is the high cost and the unavailability of such technologies in many countries. Despite the above achievements, there are still large gaps in the current distribution of bamboo. At present, many Southeast Asian countries have no up-to-date information on the distribution of bamboo, which hinders their ability to conserve and manage these resources. These gaps must be addressed in future work by combining remote-sensing technologies, machine-learning approaches, and field data collection to guarantee the sustainable management of bamboos in the region.



Objectives

The objective of this work is to enhance the current approach for mapping bamboo across Southeast Asia by proposing a simple method that uses freely available satellite imagery and two main platforms: SEPAL and GEE. The overall purpose is to address the present gap in the easily obtainable bamboo data by sharing more detailed information on the distribution of bamboo in the region. This effort aims to help those who require transparent, collaborative and evidence-based tools to be able to make the right decisions on the management and use of bamboo in a sustainable manner.

The methodology presented in this study aims to maximize the use of optical and radar imagery to avoid the drawbacks of cloud cover. The bamboo distribution maps and analysis produced will be useful to researchers, policymakers, and local people in supporting the transparent management of sustainable resources.

In addition, this study will not only enhance the current knowledge on bamboo mapping methodologies but also address the lack of data in different regions. Ultimately, this study aims to provide stakeholders and government counterparts with information needed to make decisions on bamboo planting, harvesting and conservation, as well as encourage sustainable practices to improve people's livelihoods and environmental sustainability.

Study area

In this study, the proposed methodology was tested and applied to selected bamboo-rich countries in Southeast Asia.

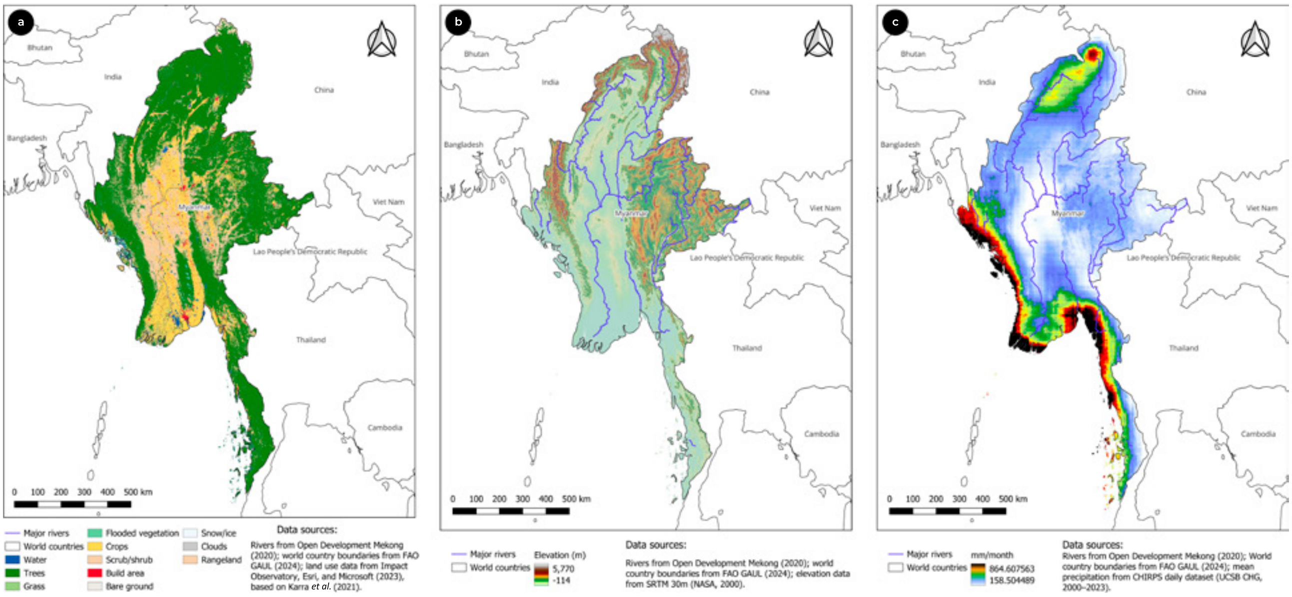
Myanmar

Myanmar is a country with high ecological diversity and variety of habitats, along with various land cover classes (Figure 1a). From the Himalayan belt in the north to the tropical lowlands in the south, Myanmar offers a suitable terrain for the investigation of bamboo. Bamboo is widely distributed throughout Myanmar, impacting the environment, economy, and culture of the country. Myanmar is one of the countries with the third-largest estimated area of bamboo, after China and India, and has the highest number of naturally growing bamboo species at 8 percent of the global total (FAO, 2010). The northern part of Myanmar is characterized by steep terrain and dense forests, particularly in Kachin and Shan States (Figure 1b). The area is rich in bamboo species that grow alongside the broadleaf forests (Zhou *et al*., 2011). Due to the temperature and altitude gradient, this region is significant for investigating natural bamboo growth in forests without anthropogenic influence. The central dry zone, Mandalay and Magway, are different from the previously mentioned areas, as bamboo is either cultivated or maintained in agroforestry systems constituting an asset for local people; its products are used for building, handicrafts and energy (FAO, 2015). The eastern highlands of Shan State have a combination of agricultural land and forested areas. They are part of the natural ecosystem but are also extensively used in farming systems to control soil erosion (Liese and Köhl, 2015). The southern coastal areas, particularly Tanintharyi and Mon States, are endowed with tropical rainforests which are suitable for bamboo growth due to the warm and humid climate. Bamboo is linked with other tropical plants and mangroves in the coastal zone and offers important ecosystem functions which include carbon sequestration and conservation of biological diversity (Yuen *et al*., 2017). The Rakhine Yoma (Arakan Mountains) is a major mountainous tract in western Myanmar extending from the northern Chin State to the southern coast of Rakhine State. This area is primarily characterized by its hilly terrain, high species richness, and large areas of bamboo growth, making it an important area for bamboo mapping. The Rakhine Yoma is home to extensive bamboo tracts, particularly *Melocanna baccifera*, which dominates the landscape in many areas. These bamboo forests act as an ecosystem to support wildlife, including the Asian elephant (*Elephas maximus*) and the Arakan Forest turtle (*Heosemys depressa*), both listed as endangered species.

Tropical monsoon climate prevails in Myanmar; the year is divided into three seasons: the hot season from March to mid-May, the rainy season from mid-May to October, and the cool season from November to February. The southwest monsoon is quite active, and most parts of the country receive more than 4 000 mm of rainfall during the year, the maximum being June to August (Figure 1c). The climate and physical geography of the country are quite diverse, which has led to the development of different types of ecosystems, such as tropical rainforest, deciduous forest and mangrove; thus, many types of bamboos are found in the country.

The FAO (2005) bamboo resource assessment for Myanmar reports 963 000 ha in 1990, 895 000 ha in 2000, and 859 000 ha in 2005. Meanwhile, the Forestry Department has pointed out that there are 1.78 million ha of commercial-grade bamboo forests located in Bago and Tanintharyi regions, as well as Rakhine State, according to the Ministry of Environmental Conservation and Natural Resources data. This shows that the current bamboo data is inconsistent. Also, the absence of current bamboo data in the 2020 FRA further supports bamboo mapping efforts.

Figure 1. Myanmar: Land cover (ESRI 2023) (a), elevation SRTM (b), and mean precipitation (May–October 2024) (c)



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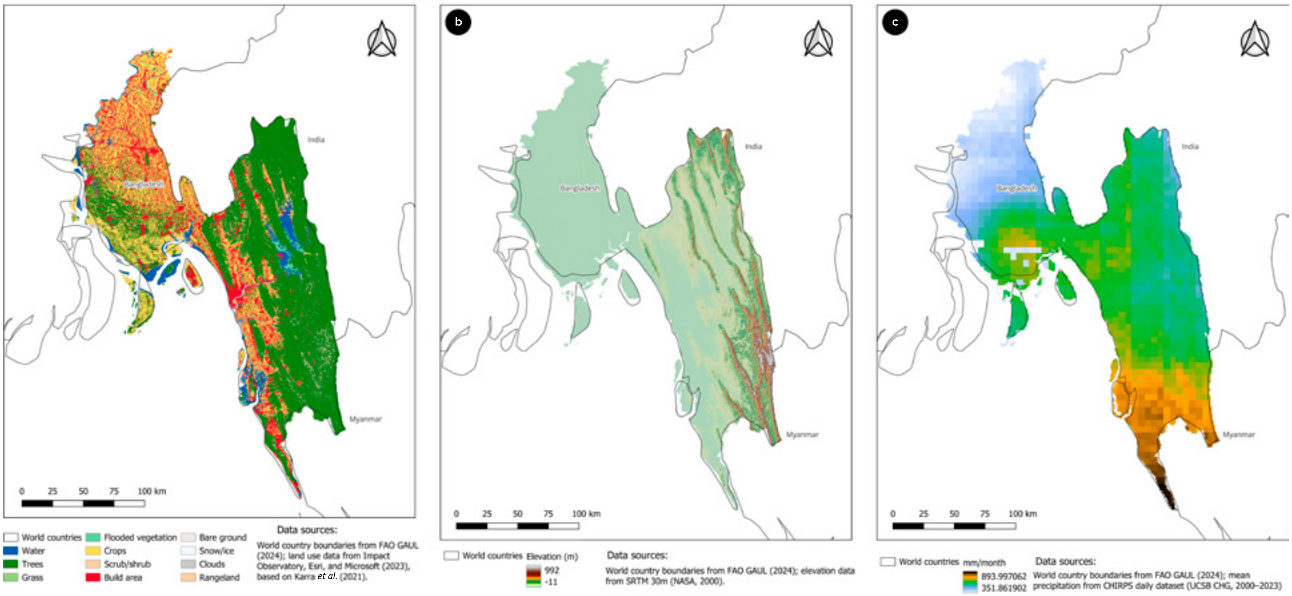
See References for data sources.

Chittagong Division–Bangladesh

Bangladesh is among the leading bamboo-producing countries; the Chittagong Hill Tracts (CHT) is one area with abundant natural bamboo growth (FAO, 2010). Chittagong is a region of significant ecological diversity and varied habitats, and bamboo is particularly important for the economy and culture of its inhabitants. For these reasons, the Hill Tracts in the southeast of Bangladesh and the coastal belt along the Bay of Bengal is a suitable area for the investigation of bamboo distribution.

The CHT, consisting of Bandarban, Rangamati and Khagrachari districts, is a hilly and forested region (Figure 2a). This area is rich in bamboo species that grow along with tropical evergreen and semi-evergreen forests (FAO and INBAR, 2006). The region is important for the purpose of understanding the natural growth of bamboo due to its location at different elevations and climates (Figure 2b and Figure 2c), as well as with minimal human interference. The region holds a major part of the country's bamboo resources, most of which is *Melocanna baccifera* (Banik, 2020). *Melocanna bacciferia* is found growing wild in the forests of northeastern India and moves south and east to Sylhet and the CHT. It then travels southeast to Arakan, Yoma Hills, across the border from Pathein and Pyay and into the Rakhine State of Myanmar (Banik, 2016, 2020). Bamboo is cultivated or naturally found in the central and southern part of Chittagong in agroforestry systems or in village homesteads. The importance of bamboo in economic activity, particularly in construction, furniture and handicrafts, means it is a vital source of income for rural people (Huang, Davis and Townshend, 2002). Bamboo also acts as an erosion controller on the hill slopes, making it an ideal species for sustainable land management practices. The World Bamboo Resource report by INBAR and FAO (2005) indicated that the area under bamboo in Bangladesh was 80 000 ha in 1990, 86 000 ha in 2000, and 83 000 ha in 2005, with Chittagong region being one of the largest contributors to this area. However, the mapping of bamboo in the CHT poses challenges due to the complex terrain and vegetation structure.

Figure 2. Chittagong: Elevation SRTM (a), land cover (ESRI 2023) (b), mean precipitation (May–October 2024) (c)



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See References for data sources.

Thailand

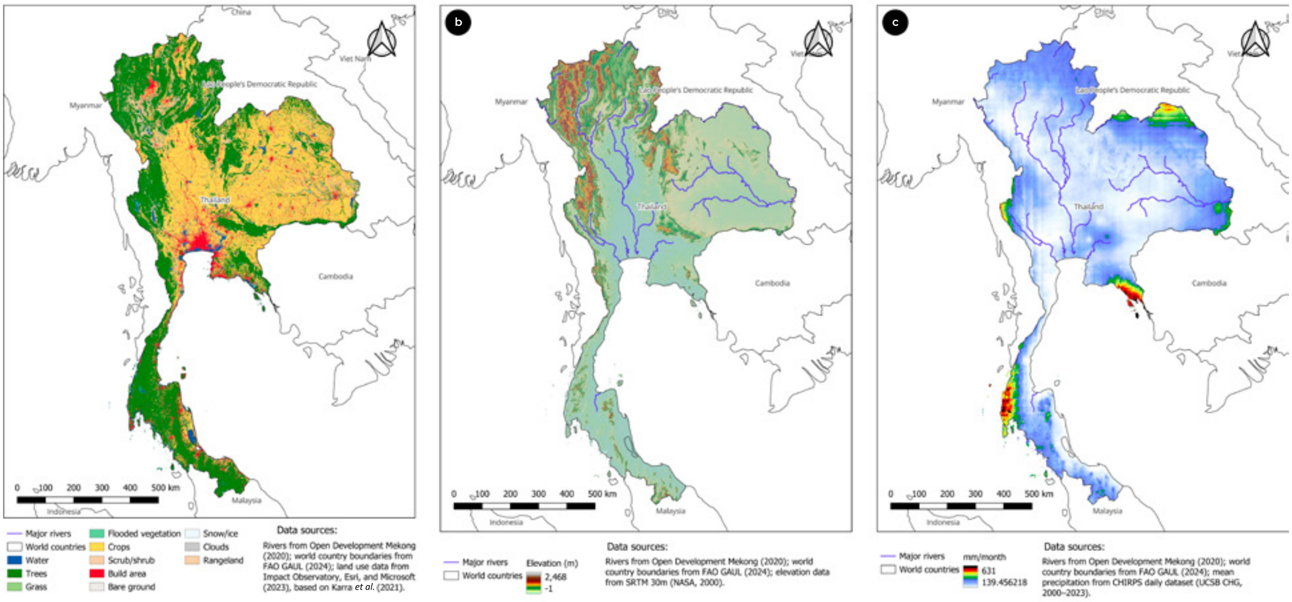
Thailand is a country with significant ecological diversity and different habitats, from the highlands in the north to the lowlands in the south (Figure 3b). Bamboo is commonly found growing naturally and being cultivated across the country; it is an important part of the environment, economy, and cultural traditions of the people. Thailand is among the biggest producers of bamboo in Southeast Asia; there are vast natural stands of bamboo in different parts of the country, especially in the northern and western highlands (FAO, 2010).

According to the Bamboo Value Chain Analysis in Thailand report by the Thailand Environment Institute (2021), there are about 69 species of bamboo in 17 genera in Thailand, which is about 5 percent of the total number of bamboo species in the world (Chanpuypetch *et al.*, 2023). In Thailand, the forests are divided into five types of forests: evergreen forest, deciduous forest, dry dipterocarp forest, mixed forest and mangrove forest. The northern and western highlands, especially around Chiang Mai, Mae Hong Son, Tak and Kanchanaburi provinces, are considered as important study areas because of the presence of dense natural bamboo stands.

Marod *et al.* (1999) indicated that these zones are rich in diverse bamboo species that grow alongside the tropical evergreen and deciduous forests. This region is significant to understand the natural growth patterns of bamboo species with little or no human interference due to the gradient in altitude and climate (Figure 3c), including *Dendrocalamus membranaceus* and *Bambusa spp.*, which are found in these territories and are important for local people's livelihoods and conservation wildlife efforts.

The central plains are situated along the Chao Phraya River Basin and are divided into agricultural fields and small fragmented forests (Figure 3a). These ecosystems contain naturally growing bamboo, as well as bamboo cultivated to prevent soil erosion and as a rural income source for people (Gajaseni and Gajaseni, 1999; Charoenlerkthawin *et al.*, 2022). By focusing on Thailand's bamboo-rich landscapes, this study aims to enhance the knowledge of bamboo's ecological roles and its potential contributions to sustainable development and conservation.

Figure 3. Thailand: Land cover (ESRI 2023) (a), elevation SRTM (b), mean precipitation (May–October 2024) (c)



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See References for data sources

Methodology

The bamboo mapping process follows the following main steps:

1. satellite data collection and pre-processing;
2. time-series analysis of optical and radar data using the CCDC algorithm;
3. extraction of vegetation indices, textural features and topographic information;
4. training sample collection; and
5. classification using the RF machine-learning algorithm.

The Continuous Change Detection and Classification algorithm

Time-series analysis of satellite imagery is a powerful tool for assessing land cover dynamics and improving the accuracy of land-use classification. By utilizing key metrics extracted from data series, this approach minimizes detection errors and misclassifications by reducing the impact of seasonal and interannual variations, atmospheric conditions (such as clouds and mist), and artifacts present in multitemporal satellite image composites. However, in the past, high computation demands and time-intensive processing limited its application, particularly for large areas when using local desktop computers.

The advent of GEE, a cloud-based geospatial analysis platform leveraging Google Cloud computational resources, has enabled large-scale and long-term time-series assessments that were previously impractical. Among the algorithms employed in GEE for time-series analysis is the CCDC algorithm, developed by Zhu and Woodcock in 2014 (Zhu and Woodcock, 2014). This algorithm has demonstrated its potential for mangrove identification in Myanmar, specifically in the Ayeyarwady Delta and Tanintharyi regions, by the Satellite Monitoring System developed as part of the Myanmar Mangrove UN-REDD programme.[1]

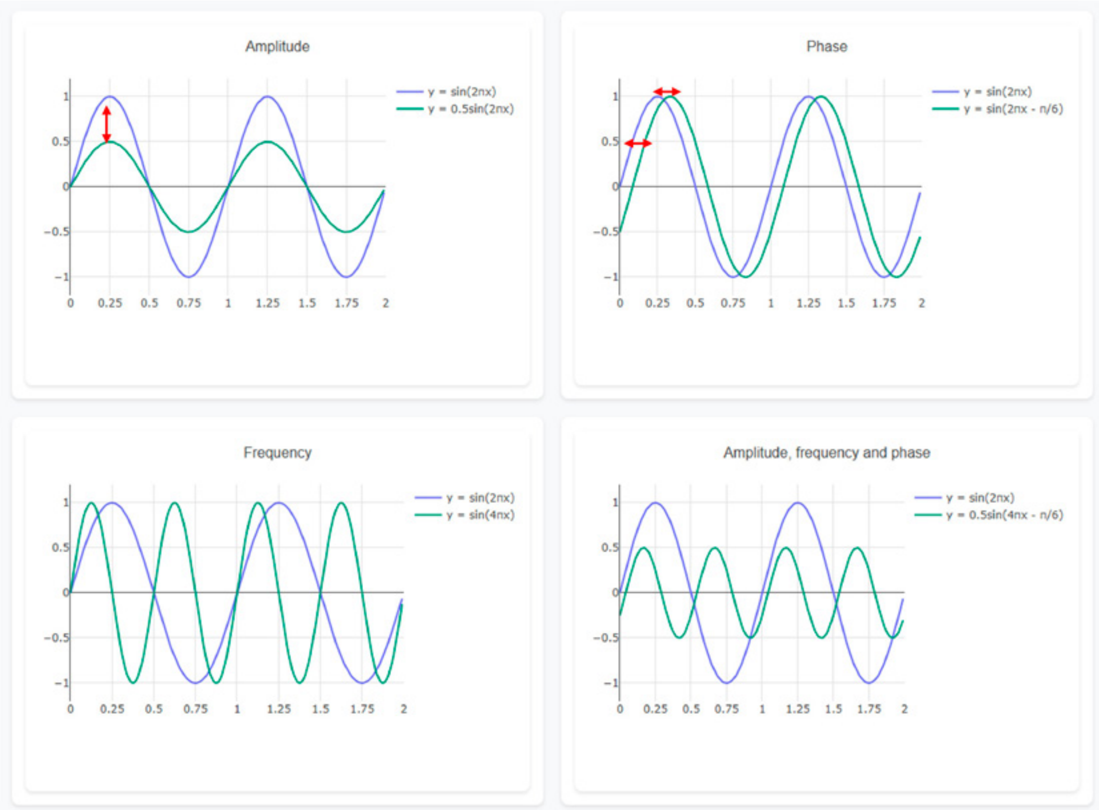
A key advantage of the CCDC-based classification is its ability to analyse not only single values, but entire time series of data from a pixel. The algorithm models the time series and identifies three types of changes:

1. seasonal changes: captured through harmonic regression coefficients (amplitude, phase, frequency; see Figure 4);
2. gradual changes: detected using a trend coefficient (slope); and
3. abrupt changes: identified as breakpoints.

The harmonic regression and trend components are particularly useful for distinguishing phenological behaviours, enhancing the precision of land cover classification.

[1] The UN-REDD programme refers to the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries.

Figure 4. Harmonic regression coefficients from a CCDC slice that capture phenological behaviour



Note: The use of "y", "sin", "π" and "x" mean "y", "sin", "π" and "x", respectively.

Leveraging SEPAL for bamboo mapping

Using the CCDC algorithm in GEE requires advanced programming skills. However, FAO's SEPAL platform simplifies this process by providing user-friendly tools with graphical interfaces.

SEPAL is a free, open-source, cloud-based computing platform designed for customized land and forest monitoring applications. It allows users to access and process large amounts of geospatial data, perform complex spatial analyses, create maps, and detect land cover and land-use changes, without requiring programming expertise. By leveraging GEE's computing power, SEPAL integrates algorithms like CCDC, enabling users to efficiently conduct time-series analyses and generate advanced mapping products. Its intuitive interface makes it accessible to users with limited technical skills.

SEPAL provides two key tools for CCDC analysis:

1. Create a CCDC asset from a time series: Generates an image collection from a selected satellite and period, detects change points, and models stable time segments.
2. Create a slice of a CCDC asset for a specific date: Visualizes and exports model coefficient values for a chosen date, including phenological metrics, for further classification.

By simplifying complex analyses, SEPAL improves accessibility and efficiency in bamboo mapping and other large-scale land monitoring projects. Another key advantage of SEPAL is that it reduces reliance on expensive proprietary software and specialized technical expertise, making it particularly valuable for bamboo mapping in developing countries and organizations with limited research capacity.

In this study, SEPAL enabled accurate bamboo classification and the rapid generation of detailed distribution maps, demonstrating its effectiveness for large-scale mapping efforts. It also helped overcome challenges such as cloud cover and spectral confusion, which are common in traditional mapping methods.

Data collection and preparation

Satellite data collection and pre-processing

Bamboo exhibits distinct spectral characteristics and is particularly sensitive in the red region between early-spring and late-summer. This period is optimal for data acquisition, leading to improved precision and a higher detection accuracy (Qi *et al.*, 2022; Feng *et al.*, 2023). The use of spectral bands and vegetation indices enhances the ability to distinguish bamboo from other land cover types (Yebeyena *et al.*, 2024). Although data collection during other seasons is possible, it presents challenges. For instance, low vegetation cover in the dry season affects spectral responses (Xiang *et al.*, 2023), while spectral similarities with other vegetation types in late-summer and early-autumn create classification difficulties (Lu and Weng, 2007).

In this study, four remote-sensing datasets were employed for bamboo forest mapping: optical bands from Sentinel-2, radar bands from Sentinel-1, SRTM 30 m digital elevation data, and the ETH global canopy height model (2022).[2]

For time-series analysis, a CCDC asset was generated from Sentinel-2 data covering the period from 1 January 2021 to 31 July 2024. The pre-processing steps included surface reflectance correction, cloud detection using quality assurance (QA) bands, and masking of clouds, shadows, and snow. A Sentinel-2 CCDC slice was extracted from mid-March to mid-April 2024, providing spectral band values, vegetation indices (NDVI, EVI, and NDFI), and phenological characteristics such as magnitude, phase, amplitude, and slope.

Similarly, the Sentinel-1 processing workflow involved geometric terrain correction, application of Lee speckle filtering, and outlier removal before generating a CCDC Sentinel-1 slice for April 2024.

To further improve bamboo detection, several commonly used vegetation indices were incorporated, including:

- GCVI: NIR/(Green – 1)
- MTCI: ID
- Water Stress Index (SI): (NIR–SWIR)/(NIR + SWIR)
- BI: (NDVI–SI)/(NDVI + SI)

Additionally, Gray-Level Co-Occurrence Matrix (GLCM) texture analysis was applied, and key extracted features suggested by Zhou *et al.* (2022) and Yebeyena *et al.* (2024) were included:[3]

- Gray contrast: Measures image contrast.
- Variance: Assesses the spread of gray-level distribution.
- Gray inverse difference moment: Evaluates pixel homogeneity.

These vegetation indices and texture features were integrated into the classification framework to enhance the distinction between bamboo and other vegetation types based on both spectral and morphological characteristics. Table 1 compiles the data considered in the classification.

[2] ETH refers to the Federal Institute of Technology.

[3] The spelling of the word "gray" remains consistent throughout the publication, in order to align with the spelling of "Gray-Level Co-Occurrence Matrix (GLCM)".

Table 1. Input satellite data for the classification

Source	Spectral bands/indices/variables/features	Coefficients
Sentinel-2 CCDC slice	Blue, Green, Red, NIR, SWIR1, SWIR2, Red-edge bands	Value, slope, phase and amplitude for each band
	Brightness, Greenness, Wetness, NDVI, NDMI, NDFI, EVI	
	Additional vegetation indices (GCVI, MTCI, SI, BI)	
	GLCM features (Gray contrast, Variance, Gray inverse difference moment)	
Sentinel-1 CCDC slice	Vertical transmit, vertical receive (VV), Vertical transmit, horizontal receive (VH)	Value, slope, phase and amplitude for each band
SRTM	Elevation, Slope and Aspect	
Lang *et al.* (2023) global canopy height data	Canopy height (10 m)	

Training sample data collection

The collection of training sample data started with the national forest inventory (NFI) – where present – as the source of bamboo and land-use data, providing a good starting point for accurate and robust bamboo mapping. However, the NFI bamboo training samples were insufficient to cover the entire country (both for model fitting and validation).

Non-bamboo training samples

Non-bamboo training samples were automatically generated from common agreement of existing land cover datasets, including Environmental Systems Research Institute (ESRI) Land Cover Maps, Dynamic World, and national land cover datasets. These samples primarily represent cropland, water, and urban areas. This approach minimized manual effort while ensuring a diverse and robust training dataset. While the non-bamboo training samples could be generated automatically, bamboo-specific samples required a more manual and detailed approach due to the lack of complete global and national bamboo maps.

Bamboo training samples

Before collecting bamboo-specific training samples, the temporal spectral profiles of the NFI bamboo dataset were reviewed to understand the characteristics of the bamboo species in the region. This preliminary analysis provided valuable insights for guiding the subsequent sampling process.

Bamboo-specific training samples were collected through manual visual interpretation using CEO, with high-resolution imagery from Google Satellite, Planet, and Sentinel, providing the visual confirmation for bamboo identification. To aid in distinguishing bamboo from other vegetation types, tools like **Geo-Dash** were used to generate time-series plots (for example, NDFI, NDVI, EVI), which proved crucial in discriminating bamboo from other tree species. These time-series analyses captured bamboo's phenological cycle, highlighting a typical decline in values in April, which is characteristic of certain bamboo species.

The **NDFI chart** was particularly effective for bamboo discrimination, as bamboo species exhibit seasonal trends with a noticeable decline in April, while evergreen forests maintain stable NDFI values year-round. This analysis helped to deepen our understanding of the temporal variations in bamboo imagery and ensured accurate definition and classification of bamboo in the training dataset.

Thus, by integrating the NFI dataset, automated sample collection, and manual interpretation, we were able to develop a comprehensive and precise set of training samples for bamboo mapping across the study areas.

Bamboo mapping process

Multisource data integration

To improve the accuracy of bamboo mapping, this study employed a multisource data approach. The analysis utilized freely available multispectral satellite imagery from Sentinel-1 (radar) and Sentinel-2 (optical). Additionally, ETH global canopy height data (Lang *et al.*, 2023) and SRTM 30 m resolution digital elevation model (DEM) data were incorporated to differentiate bamboo from other species based on their vertical structure.

Vegetation indices and phenological metrics

We employed eight vegetation indices commonly used in vegetation research:

- NDVI
- LSWI
- GCVI
- MTCI
- NDFI
- BI
- EVI
- NDMI

To enhance the accuracy of bamboo mapping, the CCDC algorithm within SEPAL was applied to generate time-series data, including phenological parameters such as amplitude, phase, and slope, derived from seasonal growth patterns observed in Sentinel-2 and Sentinel-1 imagery.

Integration of textural and structural features

For more precise bamboo detection, texture features from the GLCM, including contrast, variance, and inverse difference moment, were integrated into the analysis. These features provided information on horizontal morphology. Additionally, Sentinel-1 radar data provided structural information, especially in regions with persistent cloud cover or complex terrain, such as mountainous areas. The integration of topographic data (elevation, slope, location) and canopy height further refined the classification framework, improving the accuracy of bamboo detection.

Random forest classification and probability mapping

An RF classifier was used to generate bamboo probability maps by combining spectral, textural, and phenological information as input datasets. The training samples were divided into 70 percent and 30 percent for model training and validation, respectively.

Based on the initial probability map, an additional 500 samples were collected using stratified random sampling in areas with a predicted bamboo presence probability greater than 0.5, as well as in the 0.4–0.5 range. These samples were visually interpreted using **CEO**, supported by high-resolution imagery, including Planet data (3–5 m resolution) and time-series vegetation indices such as EVI, NDVI and NDFI. Following the integration of these new samples into the training dataset, the classification model was re-run to produce the final bamboo distribution map.

An RF classifier is an ensemble machine-learning algorithm that constructs multiple decision trees and aggregates their outputs to improve accuracy and reduce overfitting. Each tree is trained on a random subset of the training data (70 percent of the training samples), and the final prediction is made through majority voting. The "bag fraction" determines the proportion of training data used per tree, defining the size of the random subset ("bootstrap sample"). For instance, with a bag fraction of 0.7, each tree is trained on 70 percent of the dataset, randomly selected with replacement.

Hyperparameter tuning

To enhance model accuracy, hyperparameter tuning was performed by optimizing parameters such as the number of trees and bag fraction. Increasing the number of trees generally reduces variance but increases computation time, while a higher tree count improves stability but does not always enhance accuracy.

To systematically determine optimal values, a programmatic approach was adopted to test a range of parameters (Gandhi, 2022). Cross-validation (divided into 70 percent and 30 percent) was used to fine-tune these parameters, aiming to minimize computational cost while maximizing accuracy. We began with 10 trees and an initial bag fraction of 1.0 (where each tree is trained on a full bootstrap sample) and selected 90 trees that used a bag fraction of 1.0 (Figure 28).

Figure 5. Hyperparameter tuning

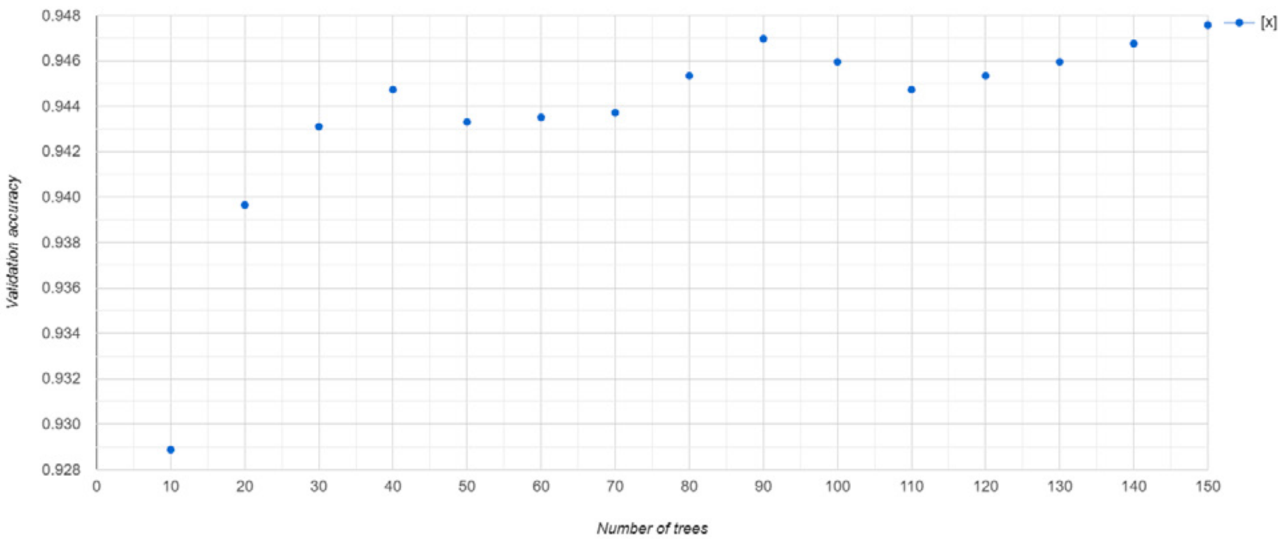
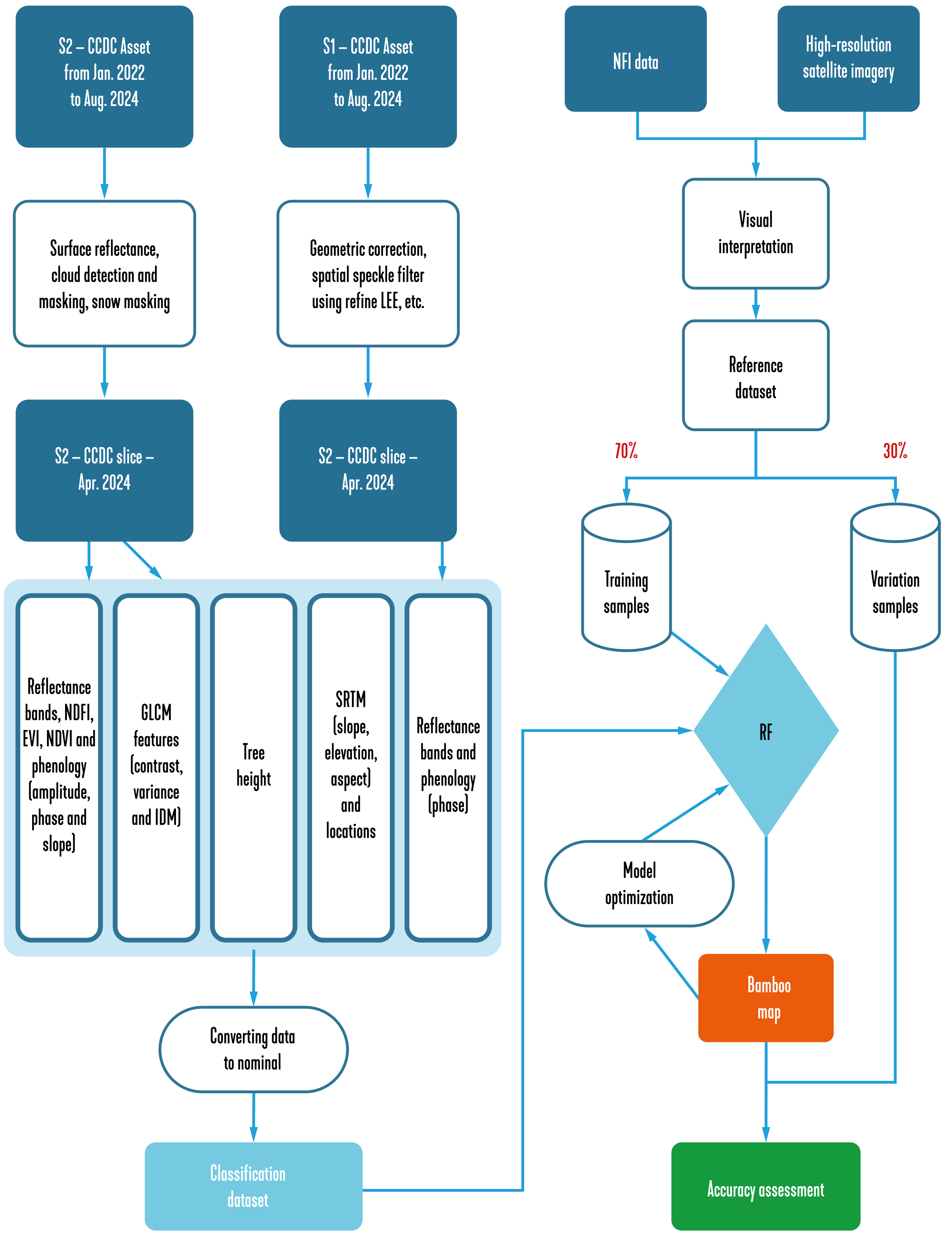


Figure 6. Methodology workflow for the bamboo extent mapping



Notes: "S1" and "S2" refer to Sentinel-1 and Sentinel-2, respectively. "LEE" refers to the Lee filter or Lee algorithm found in SEPAL. "IDM" refers to "inverse difference moment".

Results and discussion

Importance of time-series data

Single-date satellite imagery makes it challenging to distinguish bamboo from other vegetation types, as it often grows alongside evergreen forests, grasslands, and perennial crops, which share similar spectral responses (see Figure 7). However, CCDC time-series data revealed that phenological differences can play a crucial role in bamboo identification. Specifically, the amplitude and phase of the SWIR1 and SWIR2 bands, along with those of the NDFI and EVI vegetation indices, consistently emerged as the most significant factors in the classification model across all regions.

These findings emphasize the importance of temporal vegetation dynamics in distinguishing bamboo from other species. This distinction is particularly evident in CCDC asset graphics, which highlight unique phenological trends. Bamboo exhibits a characteristic EVI trend, reaching its lowest point in mid-May before gradually rising to a peak in early-September, with a 40 percent change (Figure 8). In contrast, evergreen forests maintain stable EVI values throughout the year (Figure 10), while grasslands and deciduous forests display different but less pronounced variations (Figure 9).

Although spectral signatures alone may be insufficient for accurately classifying bamboo, integrating time-series data – particularly through CCDC analysis – significantly enhances the model's ability to differentiate bamboo from other plant types. The results confirm that phenological features are consistently essential for bamboo classification across regions, underscoring their critical role regardless of geographic location.

Figure 7. Single-date imagery average spectral signature of different land cover samples

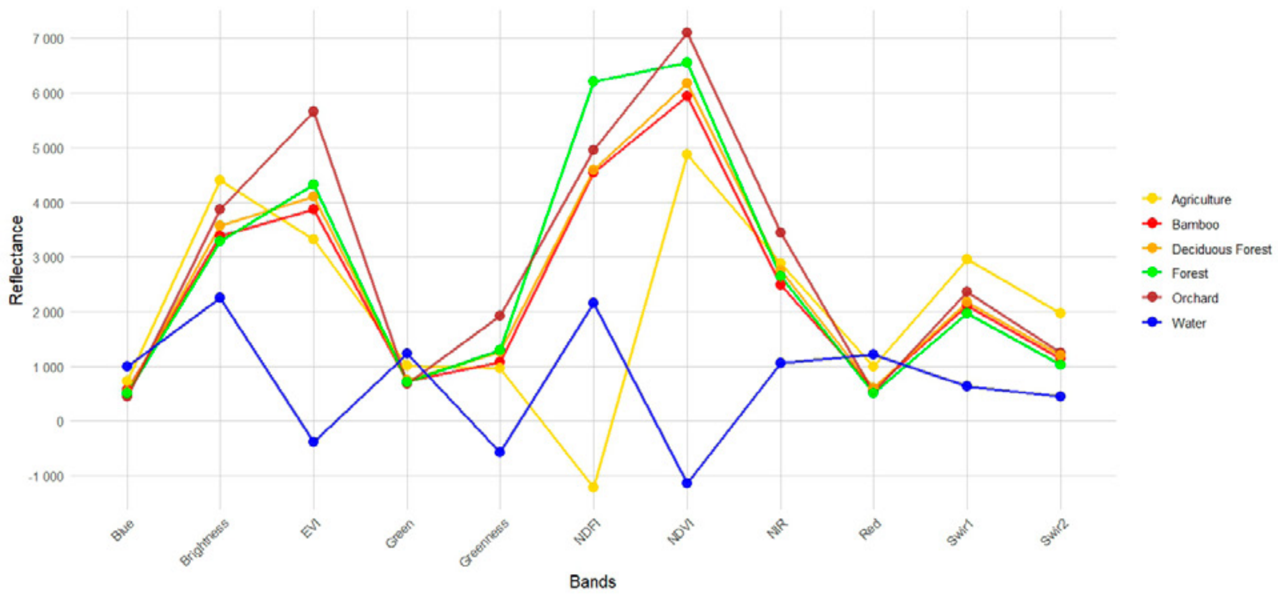
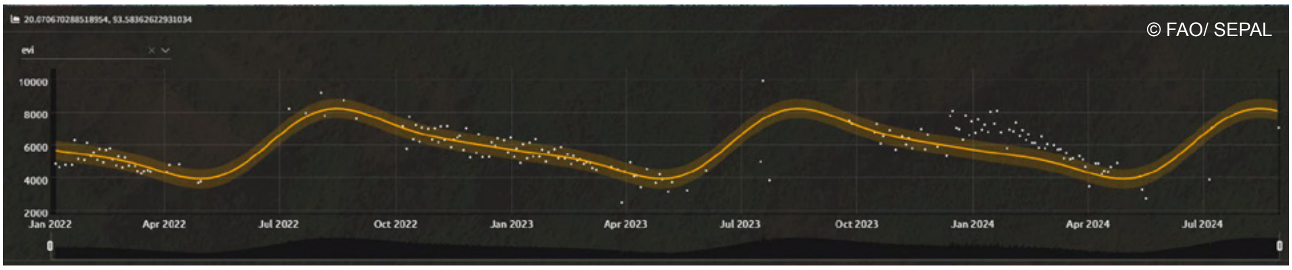
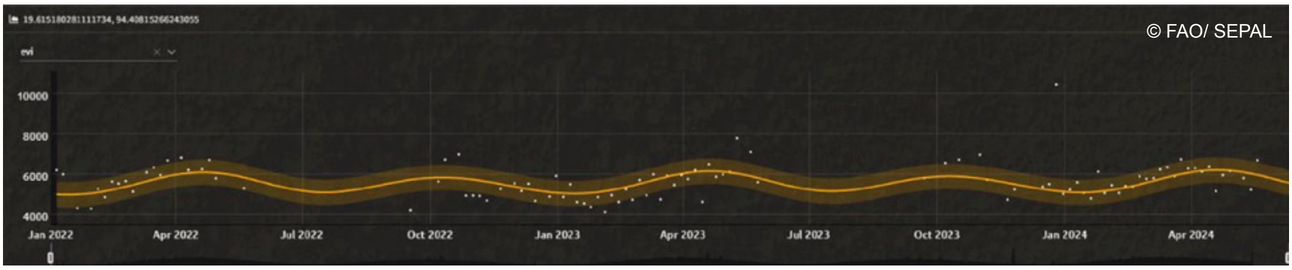


Figure 8. Sentinel-2 CCDC asset EVI spectral signature of a bamboo sample



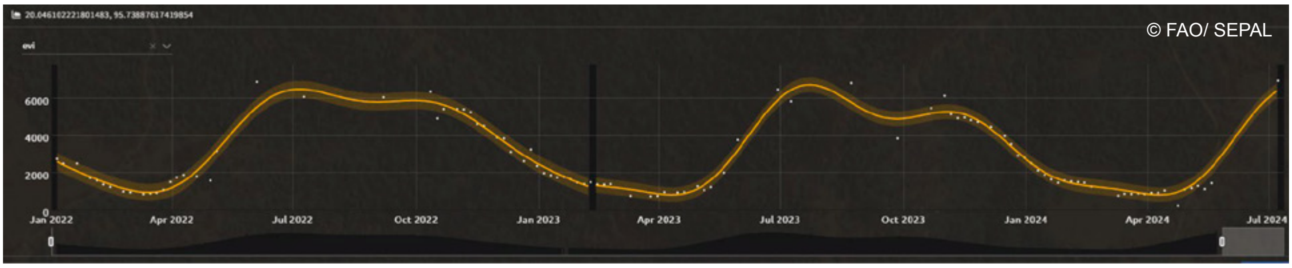
Sources: Authors' own elaboration made in SEPAL (http://sepal.io).

Figure 9. Sentinel-2 CCDC asset EVI spectral signatures of an evergreen forest sample



Sources: Authors' own elaboration made in SEPAL (http://sepal.io).

Figure 10. Sentinel-2 CCDC asset EVI spectral signatures of a deciduous forest sample



Sources: Authors' own elaboration made in SEPAL (http://sepal.io).

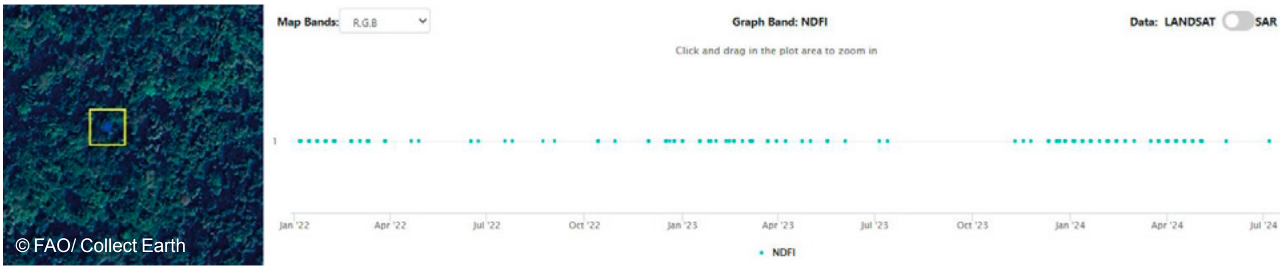
The role of Collect Earth Online

Collect Earth Online, an open-source platform for interpreting high-resolution satellite imagery, proved to be valuable for training sample collection and land cover classification. In addition to facilitating the visual interpretation of high-resolution imagery from sources such as Planet and Google Earth satellites, the platform enables direct analysis of time-series data. This capability improves the understanding of changes in the pixels of training samples over time.

For example, as shown in Figure 11, the NDFI of evergreen forest pixels remains constant for two years unless deforestation occurs. In contrast, Figure 12 illustrates that bamboo forests exhibit seasonal trends, with the lowest NDFI values occurring in April. These seasonal dynamics improve the accuracy of training sample classification.

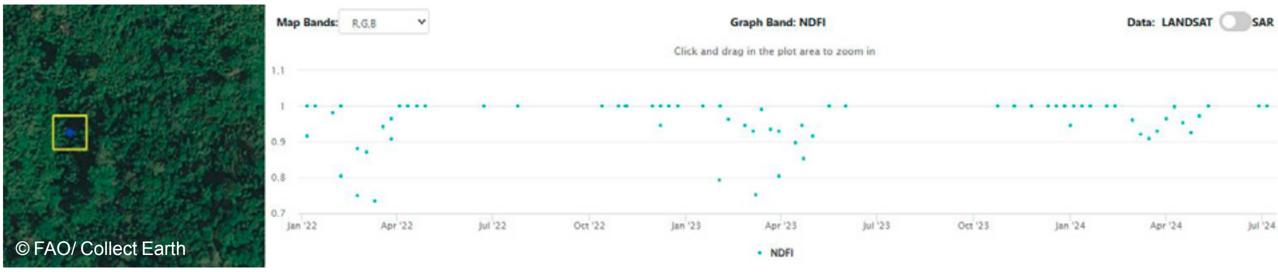
Overall, CEO played a crucial role in both visual data analysis and time-series examination, contributing to the creation of more accurate maps of bamboo distribution.

Figure 11. Evergreen forest sample visualization example in Collect Earth Online



Note: Google Earth Pro high-resolution satellite image (left), and NDFI time series (right).
Sources: Authors' own elaboration made in CEO (https://www.collect.earth).

Figure 12. Bamboo sample visualization example in Collect Earth Online



Note: Google Earth Pro high-resolution satellite image (left), and NDFI time series (right).
Sources: Authors' own elaboration made in CEO (https://www.collect.earth).

Feature importance and contribution

The importance of different variables in bamboo classification varies across Myanmar, Thailand, and the Chittagong Division of Bangladesh, as illustrated in the variable feature importance graphics (Figure 16, Figure 20 and Figure 24). Despite regional differences, several key features consistently play a critical role across all study areas.

Dominance of time-series features

Time-series features are the most influential variables in bamboo classification across all three regions, contributing between 36 and 49 percent of the total feature importance (Figure 13 and Figure 14). They are particularly significant in Bangladesh (48.9 percent), followed by Thailand (42.5 percent) and Myanmar (38.7 percent) (Figure 17, Figure 21 and Figure 25). These findings highlight the importance of capturing temporal dynamics and seasonal variations for accurate classification.

The top 20 feature importance heatmaps (Figure 18, Figure 21 and Figure 26) show that time-series metrics, such as NDFI phase and amplitude, frequently rank among the highest. In Myanmar, they hold the top two positions (Figure 18). In Thailand, key features include also SWIR1 and EVI amplitudes (Figure 26), while in Bangladesh, Red-edge3 and SWIR2 phases are most important (Figure 22).

Role of spectral features

Spectral features are the second most important category, contributing 16–21 percent of total importance across the regions (Figure 13, Figure 14 and Figure 15). Thailand shows the highest reliance on spectral features (21.3 percent, Figure 27), followed by Myanmar (20.2 percent, Figure 17) and Bangladesh (16.6 percent, Figure 22).

Optical bands, such as SWIR1 and SWIR2 in Myanmar and Bangladesh, contribute insights into chlorophyll content, leaf structure, and moisture levels.

Influence of topographic and geographic features

Topographic and geographic features also play a key role in bamboo classification across all three countries (Figure 13, Figure 14 and Figure 15). Feature importance distribution box plots (Figure 19, Figure 23 and Figure 24) confirm their consistent relevance.

Elevation is the most significant individual topographic variable and appears as the top feature in all regions (Figure 18, Figure 22 and Figure 26), reflecting its influence on bamboo distribution due to species preferences for specific elevation ranges. Geographical coordinates, longitude and latitude, are among the top three features in all countries, underscoring bamboo's strong spatial distribution patterns.

Contribution of vegetation indices

Vegetation indices account for 11–17 percent of the total feature importance (Figure 13 and Figure 14), with Bangladesh showing the highest dependence (16.7 percent), followed by Myanmar (15.6 percent) and Thailand (11.3 percent) (Figure 21, Figure 17 and Figure 25).

The top 20 feature importance heatmaps (Figure 18, Figure 22 and Figure 26) highlight the key roles of indices such as EVI, NDFI, MTCI, Land Surface Water Index (LSWI), and BI. These indices contribute both as individual bands and through their temporal characteristics (phase and amplitude). For example, BI ranks sixth in Myanmar and Thailand, while NDFI ranks fifth in Bangladesh. These results emphasize the value of using multiple indices to capture a range of biological and structural attributes specific to regional bamboo species and environments.

Textural and radar features

Textural features derived from GLCM analysis (for example, gray contrast, inverse difference moment [IDM]) contribute 5–7.4 percent to feature importance. Myanmar shows the highest reliance on texture (7.4 percent), followed by Thailand (6.7 percent) and Bangladesh (5 percent) (Figure 17, Figure 25 and Figure 21). This is likely due to distinctive canopy structures in Myanmar that enhance the usefulness of textural analysis.

Gray contrast ranks fourth and inverse difference moment ranks eighth in Myanmar’s feature list (Figure 18), and while these features and others also appear in Thailand and Bangladesh, they rank lower (Figure 26 and Figure 22). Textural metrics help identify spatial and structural canopy patterns that distinguish bamboo from other vegetation.

Similarly, radar (synthetic aperture radar [SAR]) features contribute 3–8 percent to classification, with Myanmar again showing the highest dependence (8 percent), followed by Thailand (4.9 percent) and Bangladesh (3.2 percent) (Figure 17, Figure 26 and Figure 21). This suggests that bamboo in Myanmar exhibits distinctive radar backscatter characteristics compared to other vegetation.

While radar data shows limited value to distinguish bamboo in Bangladesh, VH and VV polarization features appear in the top rankings for Myanmar and Thailand, indicating that microwave interactions with bamboo structure provide valuable classification information (Figure 18 and Figure 26).

Limited role of tree height data

Tree height data does not appear among the top 20 features in any region (Figure 18, Figure 22 and Figure 26), suggesting a weak correlation with bamboo distribution. This may be due to the temporal mismatch between the 2020 tree height dataset and the 2024 classification, as well as changes in vegetation cover due to regrowth, harvesting or environmental shifts.

Conclusion of feature contribution

Bamboo classification is influenced by a combination of spectral, temporal, topographic, textural, and radar features, with region-specific variations necessitating tailored classification models. The feature category values heatmap (Figure 14) and feature category importance graph (Figure 13) reveal that Myanmar and Thailand share similar feature importance distributions, while Bangladesh exhibits a unique pattern with stronger reliance on time-series data.

The consistent dominance of time-series features across all regions highlights the critical role of temporal and seasonal patterns in bamboo mapping. To enhance classification accuracy in diverse ecological contexts, a region-specific approach integrating time series, spectral, topographic, and geographic features is recommended, as illustrated in the feature category radar comparison (Figure 15).

Figure 13. Feature category importance (in percentage) by country

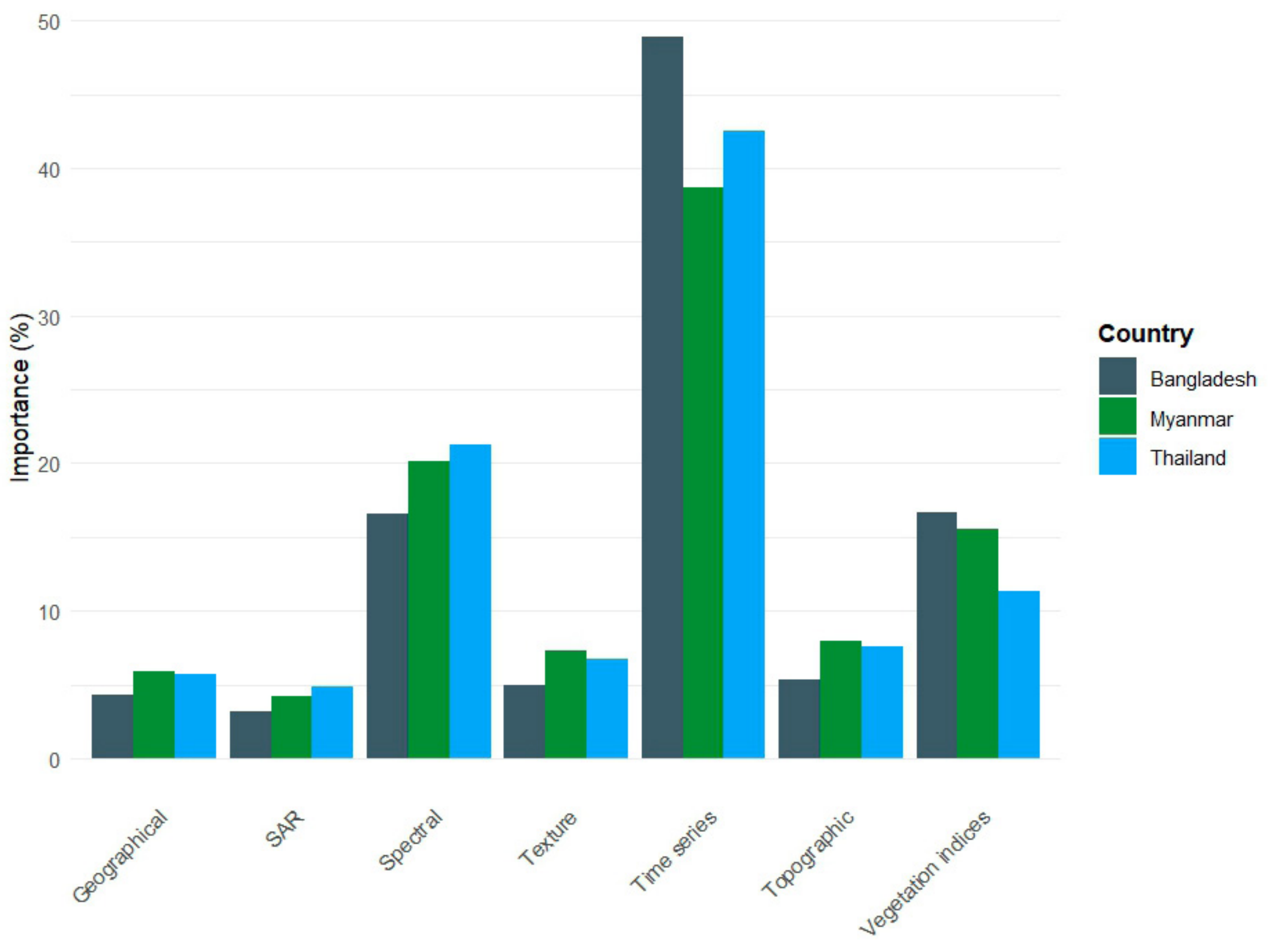


Figure 14. Feature category values and importance (heatmap) by country

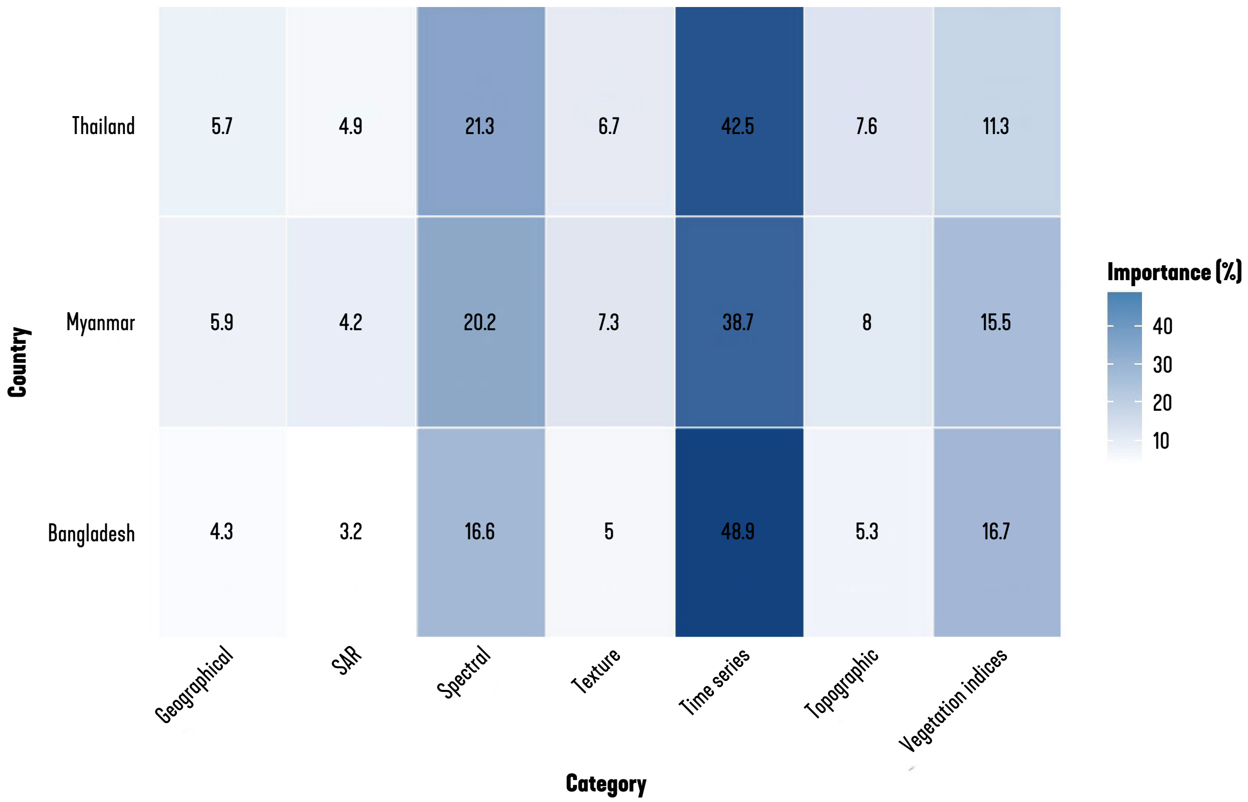


Figure 15. Feature category radar comparison by country

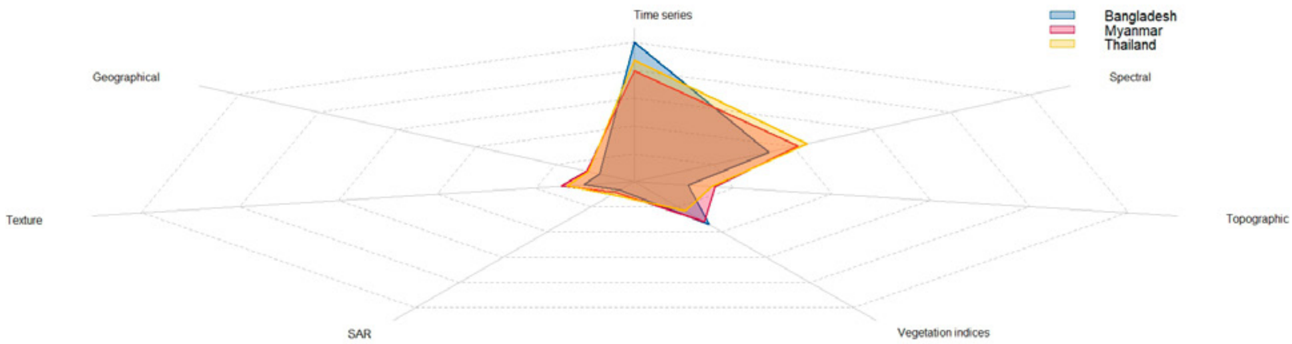


Figure 16. Feature importance for all variables for Myanmar

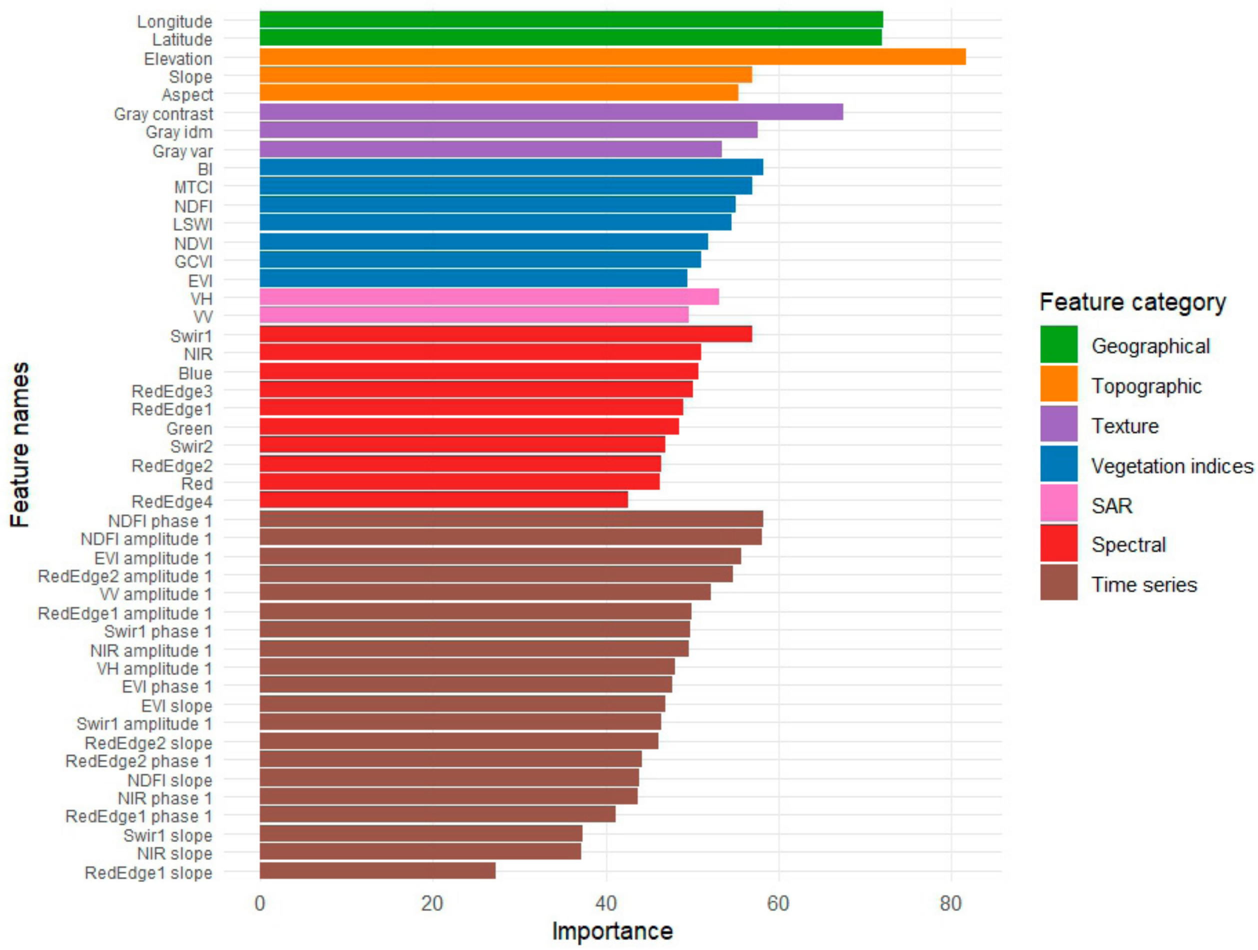


Figure 17. Feature importance distribution percentage across categories in Myanmar

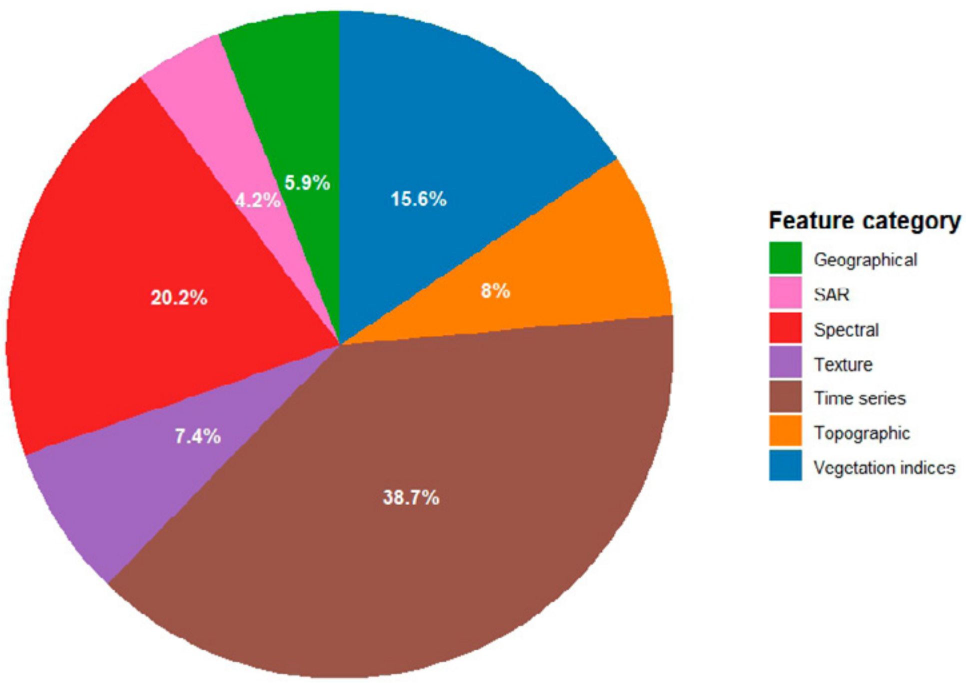


Figure 18. Top 20 feature importance heatmap for Myanmar

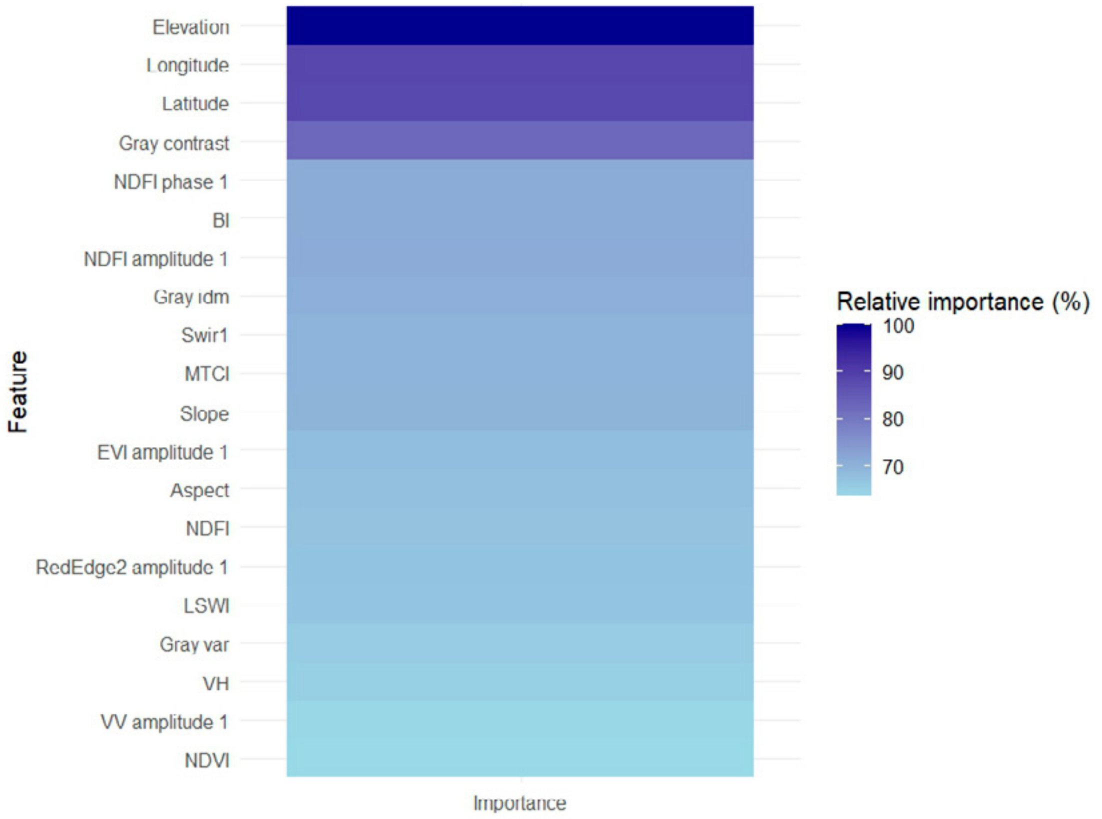


Figure 19. Feature importance distribution across categories in Myanmar

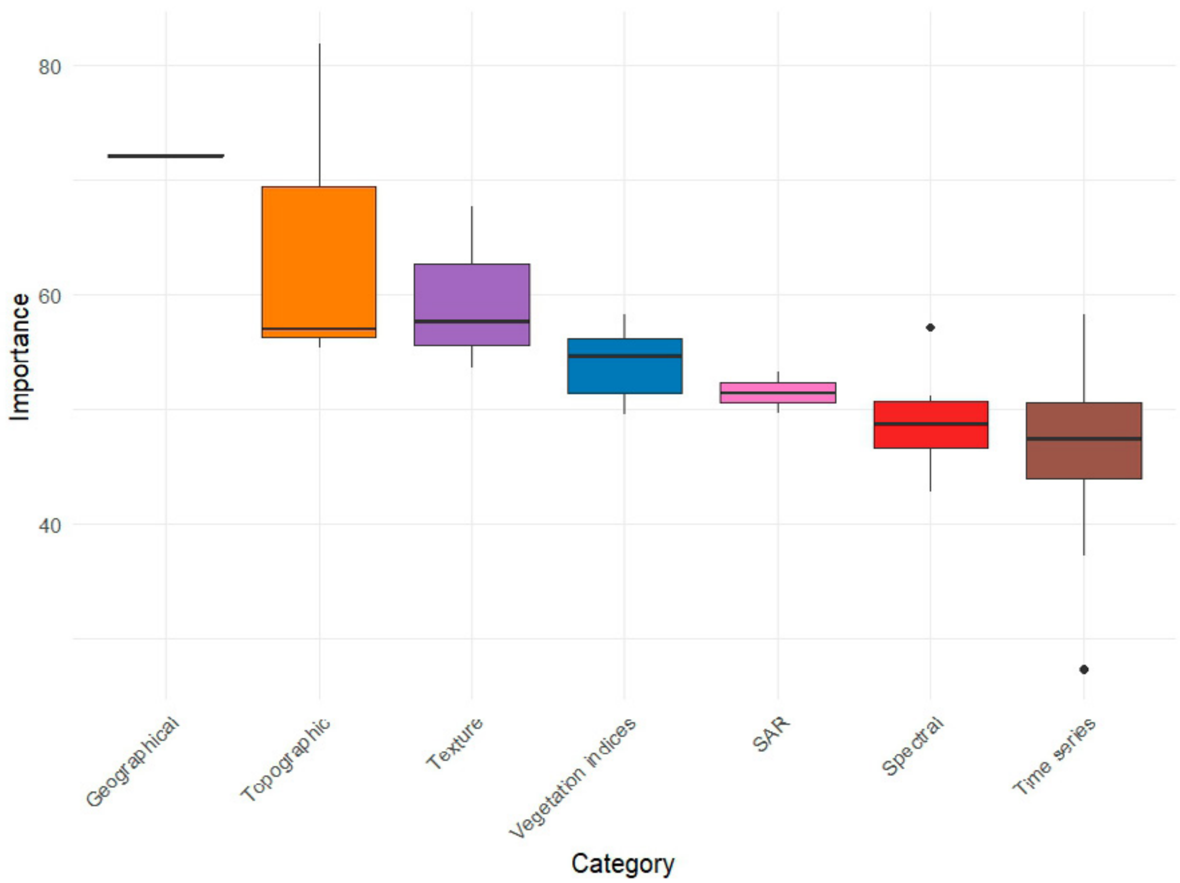


Figure 20. Feature importance for all variables for Chittagong Division

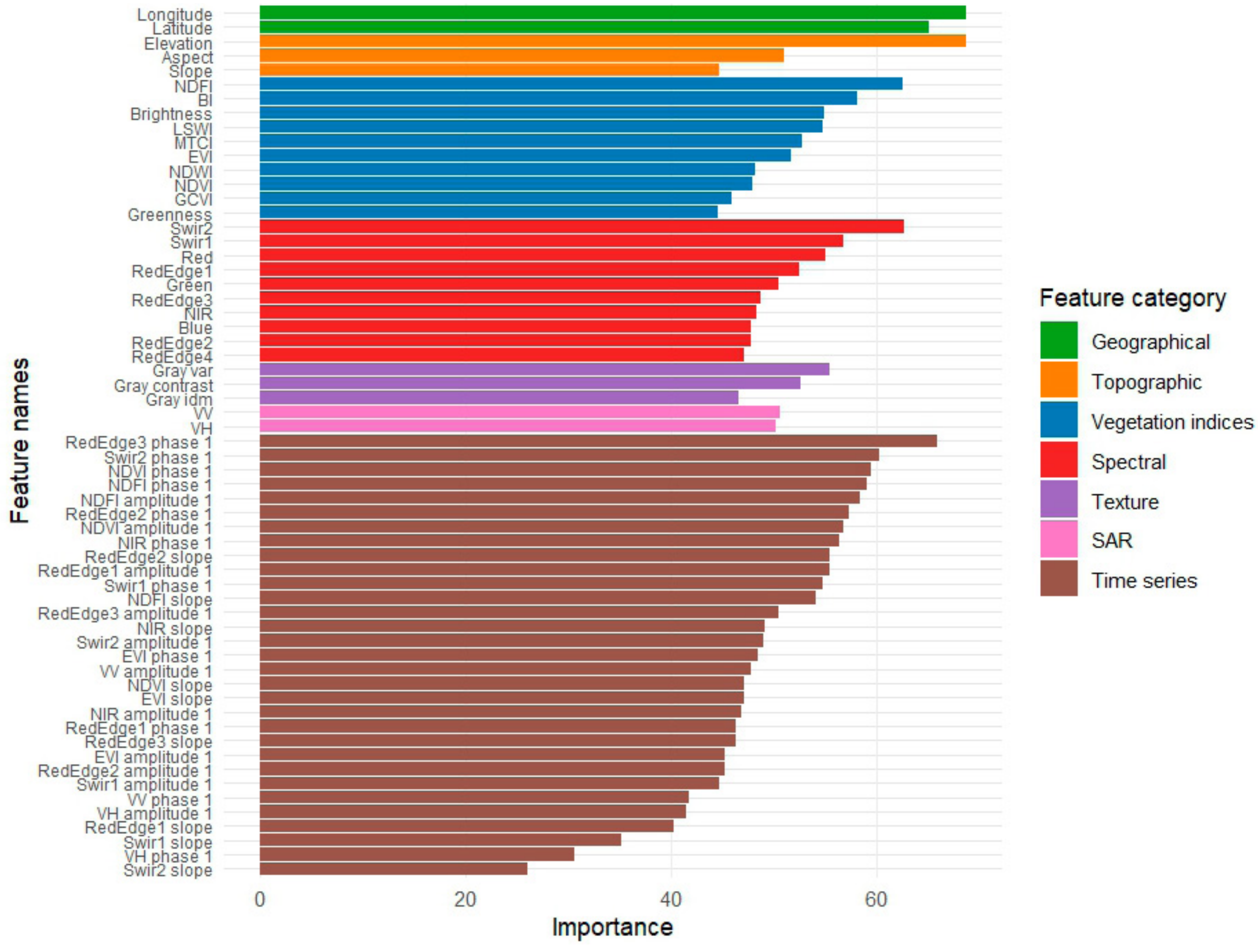


Figure 21. Feature importance distribution percentage across categories in Chittagong Division

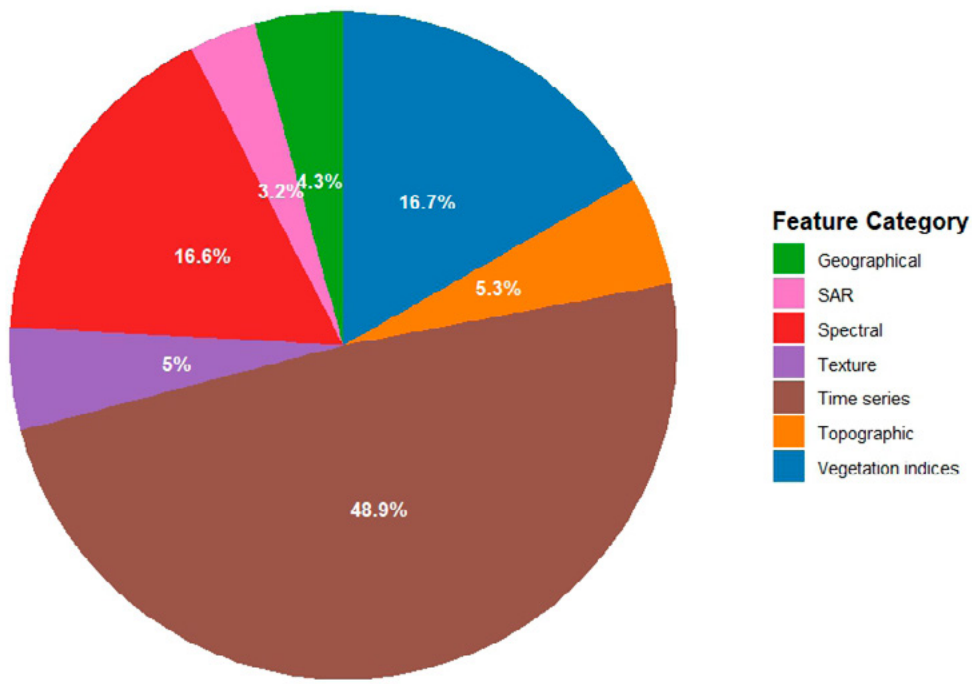


Figure 22. Top 20 feature importance heatmap for Chittagong Division

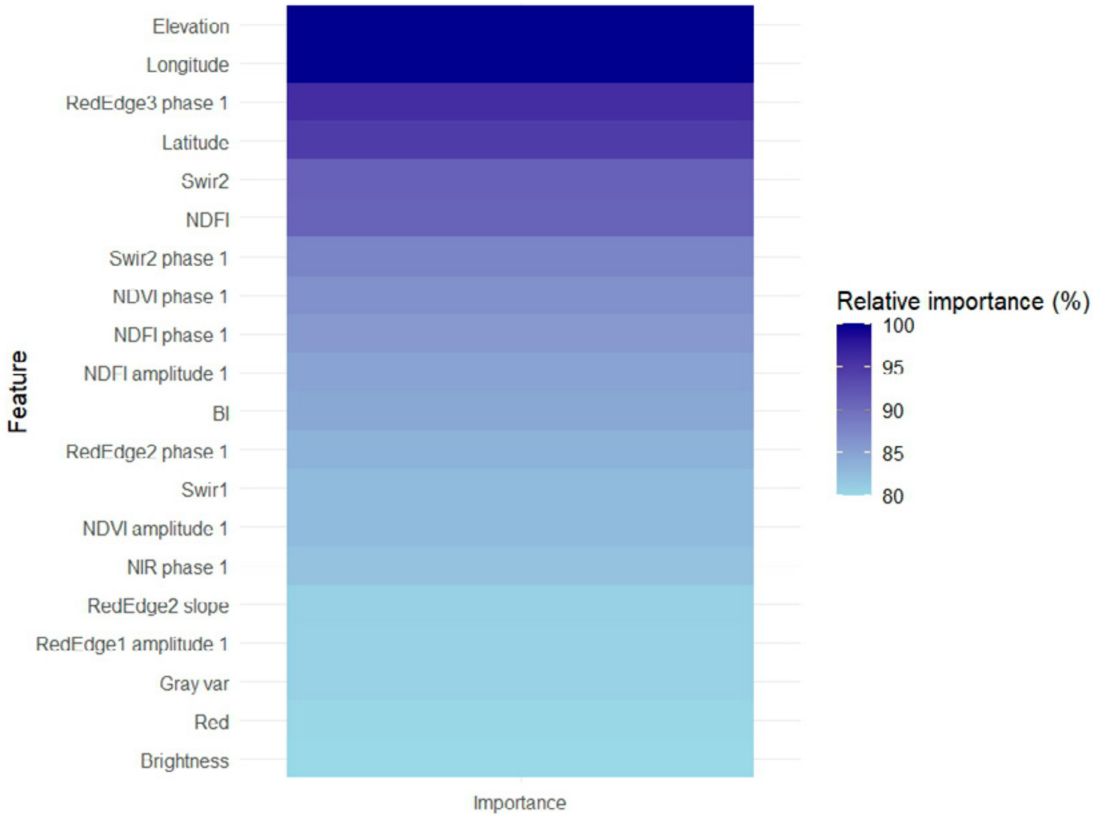


Figure 23. Feature importance distribution across categories in Chittagong Division

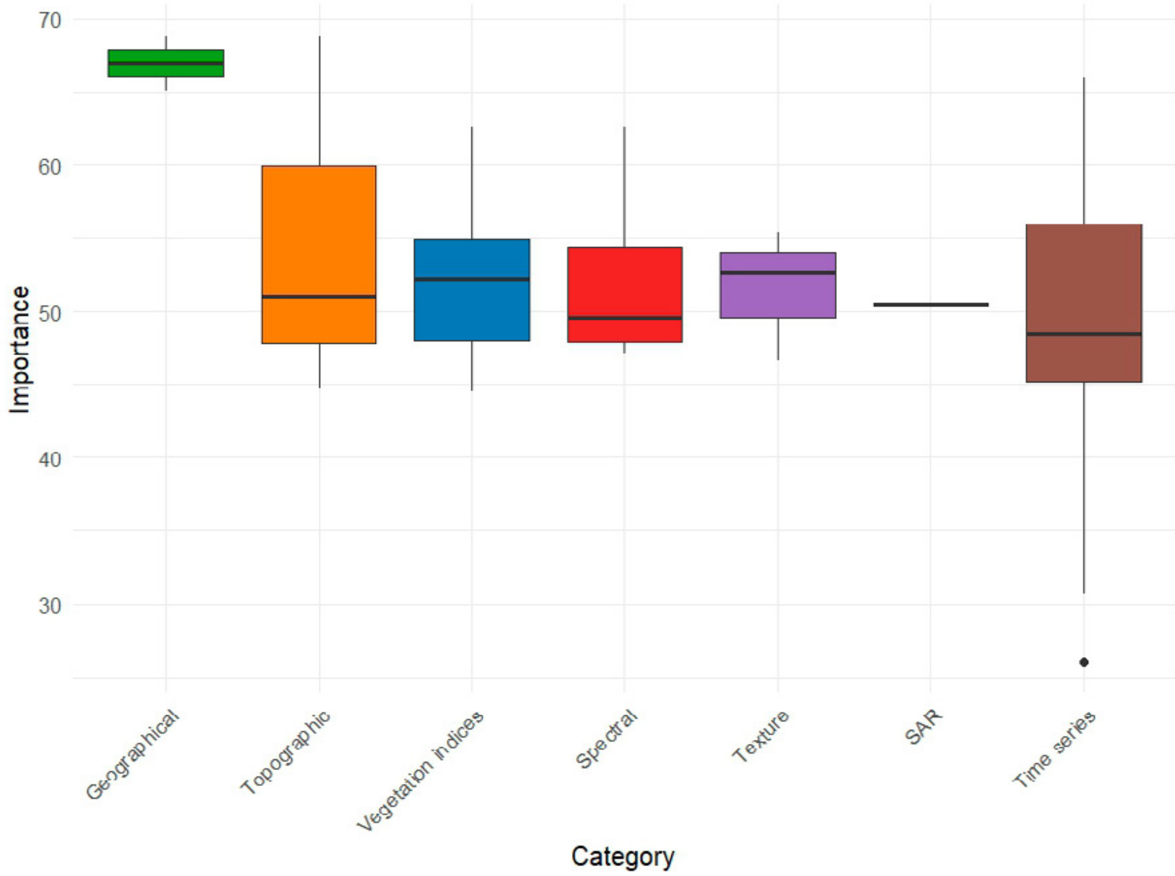


Figure 24. Feature importance for all variables for Thailand

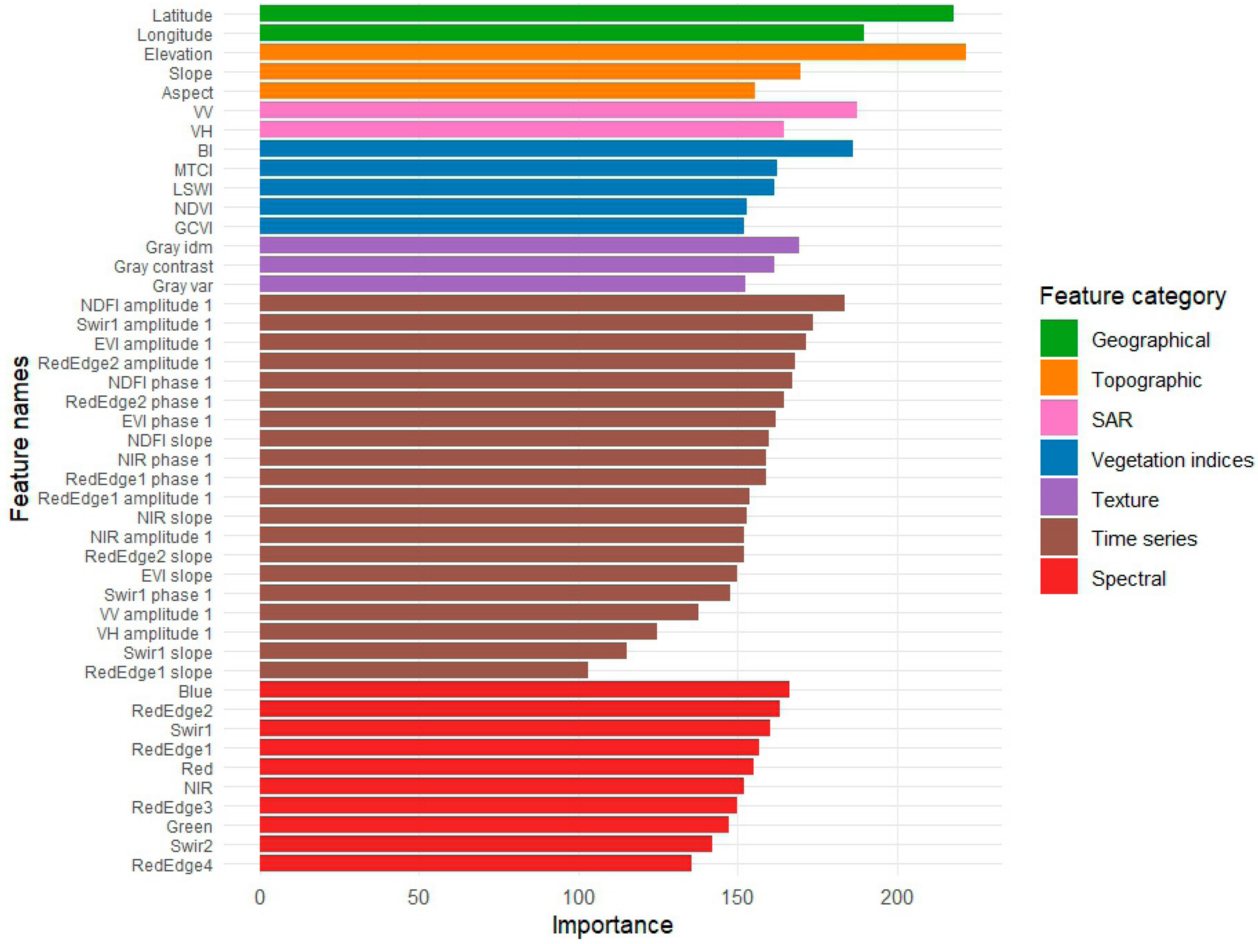


Figure 25. Feature importance distribution percentage across categories in Thailand

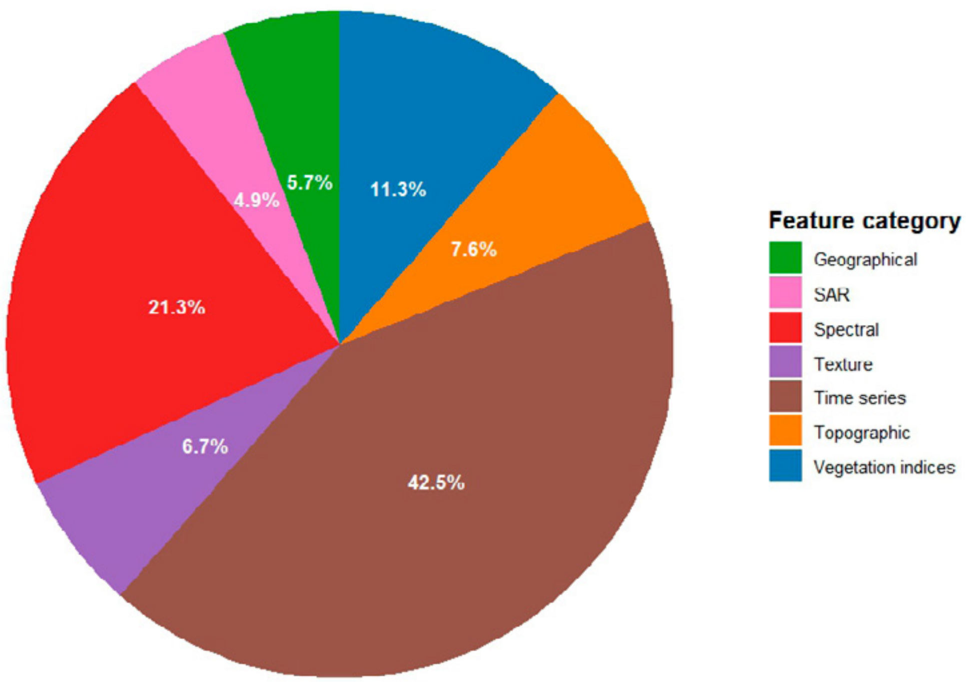


Figure 26. Top 20 feature importance heatmap for Thailand

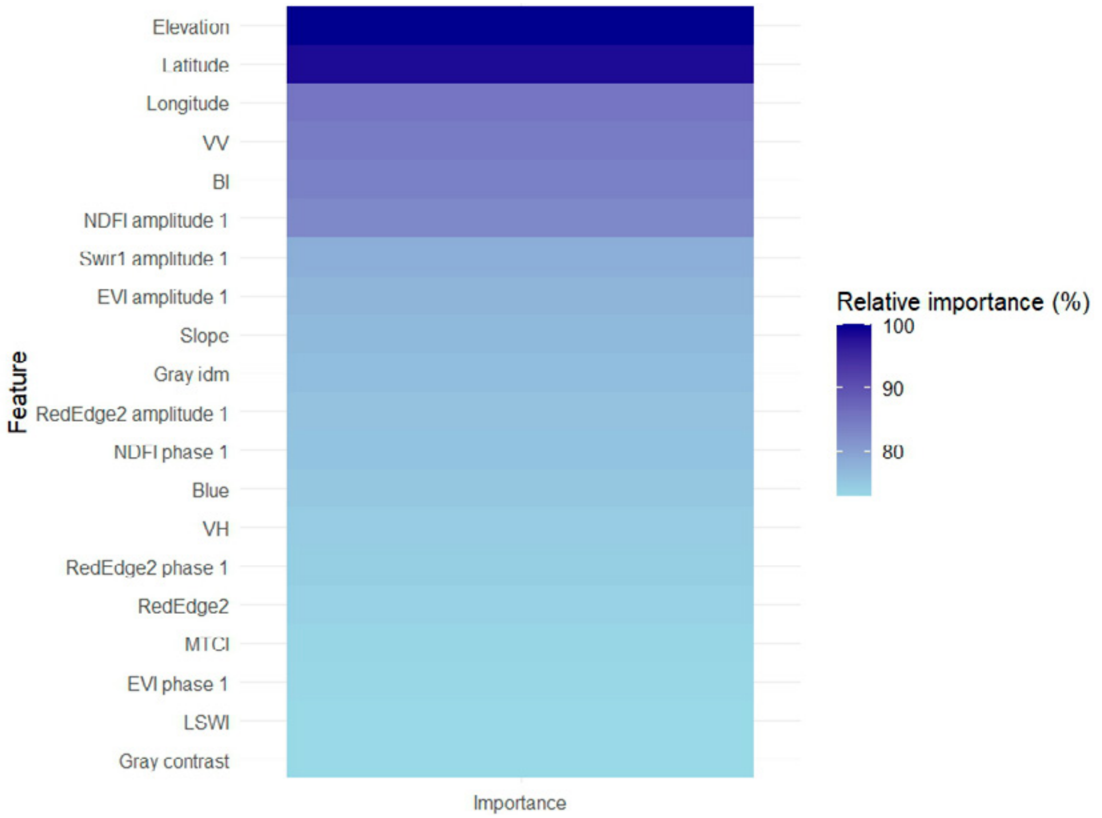
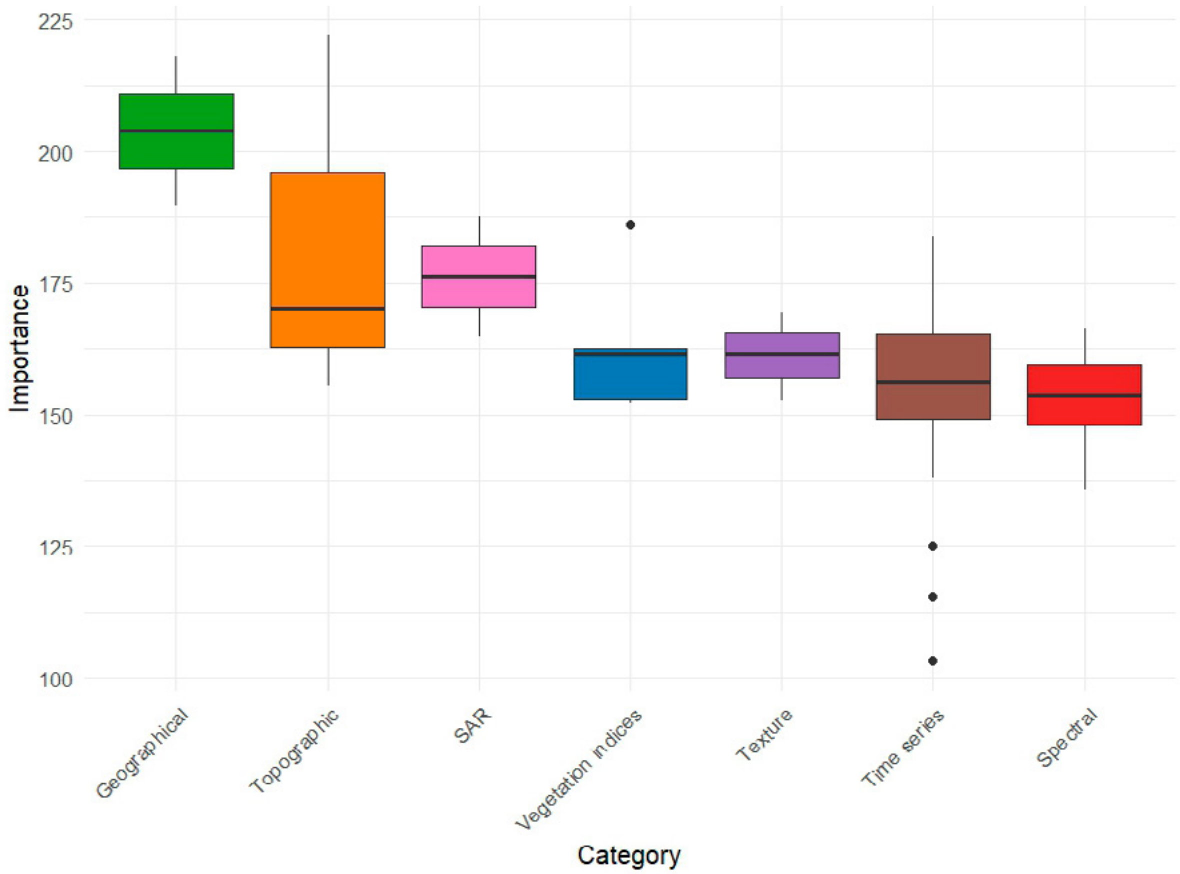


Figure 27. Feature importance distribution across categories in Thailand



Topological and geographical distribution

Bamboo thrives on moderate slopes of 8–17 degrees, at mid-elevations between 300 and 750 m, and in regions with intermediate rainfall ranging from 2 000 to 3 000 mm. These conditions provide well-drained soils, adequate moisture, and a favourable climate, creating an optimal environment for bamboo growth.

While bamboo prefers moderate ecological conditions, it also exhibits resilience in less-than-ideal environments. It can tolerate steeper slopes of 17–33 degrees and lower rainfall levels of 1 000–2 000 mm, demonstrating its adaptability where other plants may struggle.

While aggregated data indicates that bamboo is rarely found in extreme conditions, very steep slopes, high altitudes above 800 m, and areas with excessive or minimal rainfall, country-specific results show bamboo presence also in the low-elevation zones in the context of the agroforestry system in village areas, especially in Bangladesh.

Accuracy assessment

It is very important to provide a quantitative estimate of the accuracy of the classification model. The accuracy assessment process involves dividing the training samples into two random subsets: 70 percent for training the model and 30 percent for validation. This makes it easy to compare the predicted classifications to the actual values in the validation dataset. The accuracy of the model is measured using the confusion matrix (Stehman, 1997), from which several key metrics can be calculated:

- Overall accuracy: The percentage of samples correctly classified for all classes.
- Producer’s accuracy: Evaluates the ability of the model to predict each class, using omission errors.
- Consumer’s accuracy (reliability): Measures the reliability of the classification for each class, using commission errors.
- Kappa coefficient: Evaluates the agreement between the model's classification and the actual data, including the chance agreement.

These metrics together provide a holistic assessment of the model's performance to ensure that the classification results are not only accurate but also understandable. The bamboo extent map was validated with a 50 percent threshold; Figure 17 shows the confusion matrix used to further analyse the classification results.

The results for **Myanmar** (Table 2) indicate – when using 3 175 reference samples for the non-bamboo class – that 3 085 were correctly classified as such, while 90 were misclassified as the bamboo class. Similarly, when using 1 747 reference samples for the bamboo class, 1 566 were correctly identified, and 181 were incorrectly classified as non-bamboo. The overall accuracy of the classification is 94.49 percent (Table 5), which indicates that the model is rather accurate in its predictions. In terms of consumer’s accuracy or user’s accuracy, which is the proportion of times a predicted class is correct, the model achieved 94.45 percent for the non-bamboo class and 94.56 percent for the bamboo class, which is a good level of reliability in classification. On the other hand, the producer’s accuracy – the percentage of how well actual reference data were classified – was 97.16 percent for the non-bamboo class and 89.63 percent for the bamboo class, which suggests that the model does a fair job of capturing both classes with low omission errors. The kappa coefficient of 0.88 suggests a good agreement between the predicted and actual classifications after correcting for chance agreement.

Table 2. Confusion matrix for Myanmar

	Classification samples				Producer's accuracy
		Non-bamboo	Bamboo	Total (predicted)	
Reference samples	Non-bamboo	3 085	90	3 175	97.16%
	Bamboo	181	1 566	1 747	89.63%
	Total (actual)	3 266	1 656	4 922	
Consumer's accuracy or user's accuracy		94.45%	94.56%		

In the **Chittagong Division** (Table 3), the confusion matrix results show that out of 3 276 reference samples for non-bamboo, 3 228 were correctly classified, and 48 were wrongly assigned to the bamboo class. Similarly, from the 1 124 reference samples for bamboo, 994 were correctly identified and 130 were wrongly assigned to non-bamboo. The overall accuracy of the classification was 95.95 percent (Table 5), which is a good performance. The consumer's accuracy, which is the reliability of the predicted classes, was 96.13 percent for the non-bamboo class and 95.39 percent for the bamboo class, which means that most of the predicted values were accurate in relation to the reference data. The producer's accuracy, which is the rate at which reference data were classified, was 98.53 percent for the non-bamboo class and 88.43 percent for the bamboo class. The kappa coefficient of 0.89 indicates a good agreement between the actual data and the classification results.

Table 3. Confusion matrix for Chittagong Division (Bangladesh)

	Classification samples				Producer's accuracy
		Non-bamboo	Bamboo	Total (predicted)	
Reference samples	Non-bamboo	3 228	48	3 276	98.53%
	Bamboo	130	994	1 124	88.43%
	Total (actual)	3 358	1 042	4 400	
Consumer's accuracy or user's accuracy		96.12%	95.39%		

In **Thailand** (Table 4), the measures of accuracy from the confusion matrix reveal that from the 3 097 reference samples of non-bamboo, 2 873 were correctly assigned while 224 were misclassified to bamboo. For instance, from the 1 876 reference samples of bamboo, 1 659 were properly assigned while 217 were assigned to non-bamboo. The overall accuracy of the classification was 91.16 percent (Table 5). The consumer's accuracy, or the reliability of the predicted classes, was 92.97 percent for the non-bamboo class and 88.1 percent for the bamboo class, which means that most of the predicted values were accurate, as compared to the reference data. The producer's accuracy, the rate at which reference data were classified, was 92.76 percent for the non-bamboo class and 88.43 percent for the bamboo class. The kappa coefficient of 0.81 suggests that there is a good agreement between the actual data and the classification results.

Table 4. Confusion matrix for Thailand

	Classification samples				Producer's accuracy
		Non-bamboo	Bamboo	Total (predicted)	
Reference samples	Non-bamboo	2 873	224	3 097	92.76%
	Bamboo	181	1 659	1 876	88.10%
	Total (actual)	3 054	1 883	4 973	
Consumer's accuracy or user's accuracy		92.97%	88.1%		

Table 5. Overall accuracy and kappa coefficient values for the study areas

	Myanmar	Bangladesh	Thailand
Overall accuracy (%)	94.49	95.95	91.16
Kappa coefficient	0.88	0.89	0.81

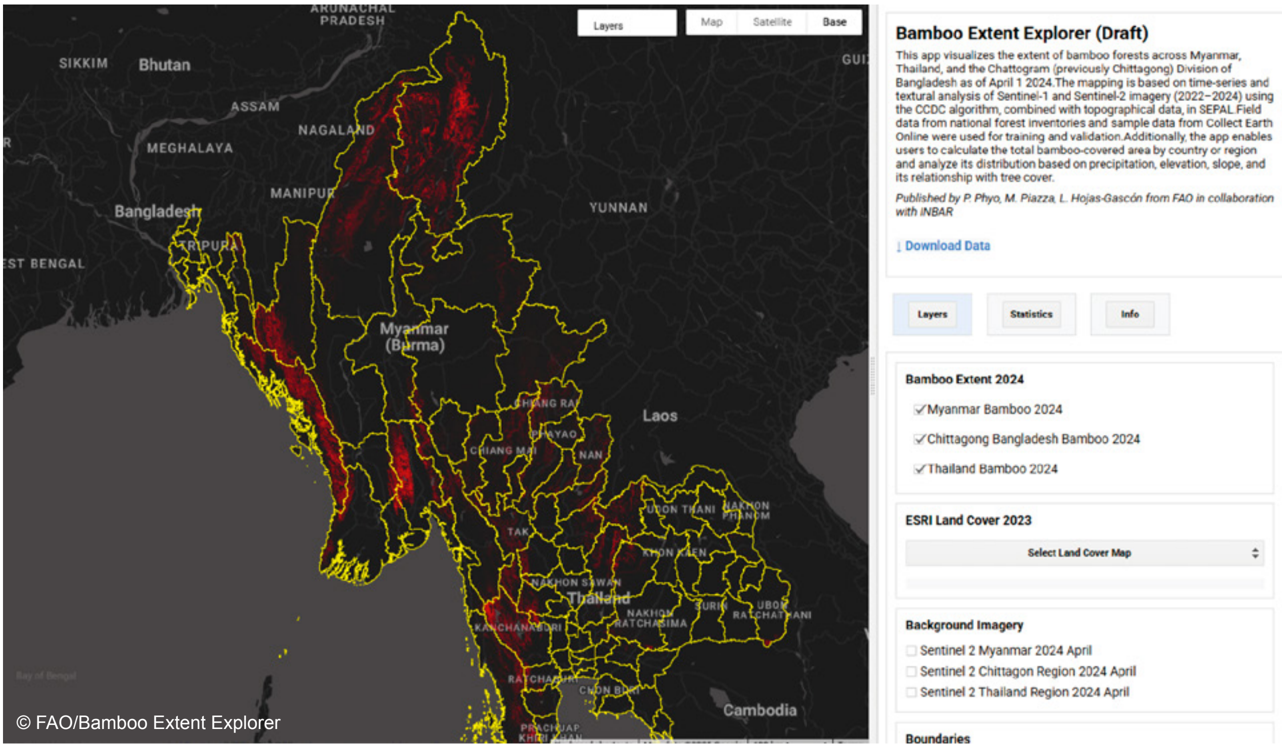
Bamboo Web Portal

The Bamboo Extent Explorer is a web application designed to provide easy access to information on bamboo distribution in Southeast Asia, developed as part of this study. It runs on GEE, integrating satellite imagery, land cover data, and geospatial analysis tools to help users explore bamboo coverage, generate statistical insights, and provide feedback (see view in Figure 28).

Key features include:

- Bamboo extent datasets: View detailed maps of bamboo coverage for 2024.
- ESRI land cover and Sentinel-2 imagery: Access high-resolution satellite imagery and land classification data.
- Interactive layers: Toggle layers on and off to visualize bamboo extent, adjust the base map, and view administrative boundaries.
- Statistical insights: Explore bamboo distribution across regions and environmental factors using bar and pie charts. Compare bamboo and tree cover with detailed breakdowns by region, province, or district.
- User-feedback section: Share comments and findings through a built-in feedback form, contributing to data accuracy, improved mapping methods, and regular updates.[4]

Figure 28. Bamboo Extent Explorer showing the bamboo extent of 2024 for Myanmar, Chittagong (Bangladesh), and Thailand

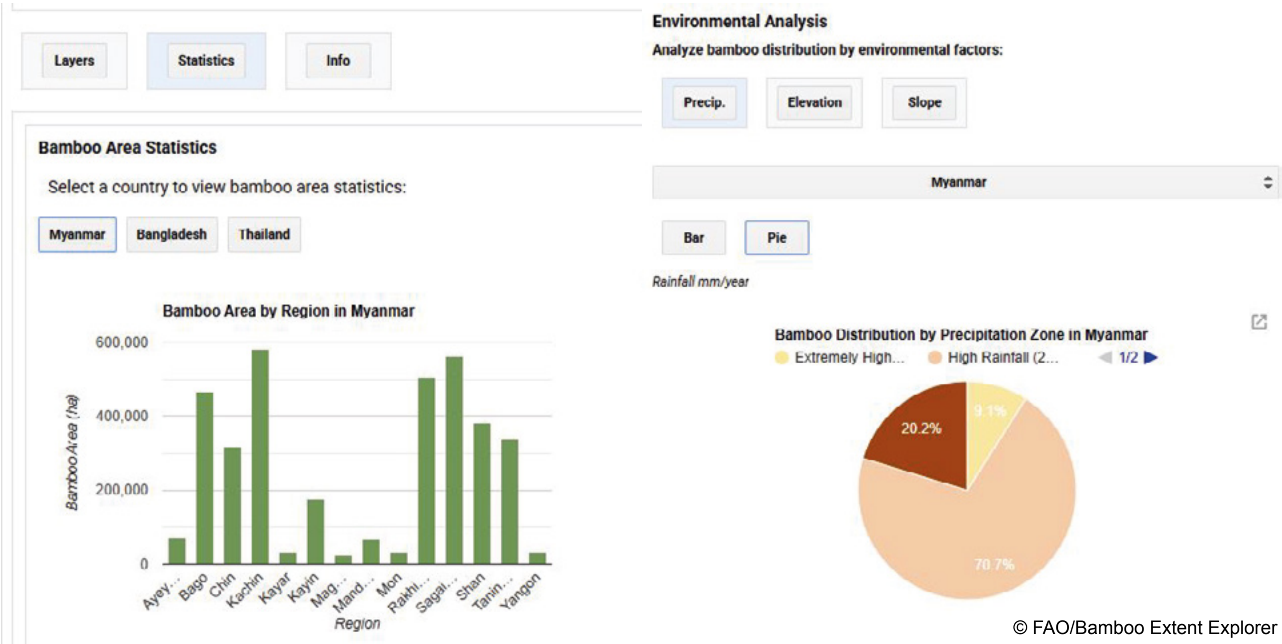


Note: Refer to the disclaimer on p. ii for the names and boundaries used in these maps.

Source: Authors' own elaboration made in Bamboo Extent Explorer (https://ee-bamboo.projects.earthengine.app/view/bamboo-extent-explorer).

[4] For more information, see https://ee-bamboo.projects.earthengine.app/view/bamboo-extent-explorer

Figure 29. Bamboo area by region and bamboo distribution by precipitation zone in Myanmar



Source: Authors' own elaboration made in Bamboo Extent Explorer (https://ee-bamboo.projects.earthengine.app/view/bamboo-extent-explorer).

Achievements

This study has produced the first large-scale bamboo extent map of Southeast Asia using a remote-sensing approach. By filling a critical knowledge gap on bamboo distribution, it establishes a baseline for future studies. The map covers Myanmar, Thailand, and the Chittagong Division of Bangladesh; its methodology is easily replicable, allowing for extension to other regions and countries.

The approach leverages the advanced capabilities of cloud-based platforms such as SEPAL and GEE. It integrates complex time-series analysis, multisensor spectral and temporal information, vegetation indices, and texture features to accurately classify bamboo across diverse landscapes and ecological contexts – all without requiring advanced technical expertise. SEPAL's user-friendly graphical interface enables complex geospatial analysis, including CCDC, without the need for programming skills.

A multisource data approach was used to enhance classification accuracy and minimize errors. This included Sentinel-1 and Sentinel-2 imagery, global canopy height datasets, and digital elevation model (DEM) data, ensuring a robust representation of both spectral and structural characteristics of bamboo.

Furthermore, phenological metrics – such as amplitude, phase and slope – derived from indices like EVI and NDFI, helped capture seasonal growth dynamics. This differentiation was crucial for distinguishing bamboo from other vegetation types in heterogeneous landscapes.

To improve training data reliability, a collaborative sample collection was conducted using CEO, combining visual interpretation with time-series analysis. This method enhanced the comprehensiveness of training datasets by automating the generation of non-bamboo categories using GEE, while allowing for manual collection of bamboo-specific samples in CEO.

The bamboo mapping methodology proved highly efficient and accurate, achieving an overall accuracy of 90–93 percent and kappa coefficients of 0.80–0.83 in the study areas. These metrics underscore the reliability and robustness of the approach in ecologically diverse and complex terrains.

Additionally, the bamboo extent maps and the Bamboo Web Portal developed in this study serve as valuable tools for stakeholders, including researchers, policymakers and land managers. These resources support evidence-based conservation planning, sustainable land management, and economic development.

This study fills critical data gaps and provides an accessible, replicable, and innovative method for future bamboo resource assessments. However, ongoing validation and adaptation to a wider range of regions and ecological conditions will be essential for its continued success.

Limitations

This study was primarily designed to assess bamboo coverage but does not differentiate between bamboo species.

The current methodology relies heavily on satellite data, which does not fully capture the ecological and spectral variability of bamboo species. In Myanmar and Bangladesh, the NFI has established only a limited number of bamboo sample plots, while Thailand relied exclusively on satellite-derived training data. This dependence introduces subjectivity and limits the robustness of the assessment.

To improve classification accuracy and enable species-level identification, future efforts should prioritize targeted field data collection for bamboo. Incorporating ground-based sampling would enhance model reliability and support more consistent results across diverse ecological zones. Comprehensive field validation is also essential for a more accurate evaluation of model performance.

Additionally, although the methodology has been applied across various regions, the results vary due to ecological differences and species-specific characteristics. Further validation in diverse environments is essential to assess the reliability and adaptability of this approach.

Another limitation is the computational cost of processing large datasets for time-series analysis, particularly at a 10 m spatial resolution. To optimize efficiency, a 20 m resolution was used, balancing computational feasibility with spatial detail. However, this may have reduced the ability to detect smaller bamboo patches. Moreover, some bamboo species with unique phenological traits may have been overlooked if they did not align with the general patterns identified in the analysis.

These challenges can be addressed through a combination of field data collection, expanded validation efforts, and improved computational resources. Despite these limitations, the use of medium-resolution (20 m) data remains suitable for country-level analysis, ensuring the methodology's applicability across diverse ecological zones.

Implications for bamboo management

Effective bamboo management requires strategies tailored to its ecological preferences and adaptability. While this study provides a valuable foundation for understanding bamboo distribution, management recommendations could be based on general bamboo characteristics rather than species-specific data due to limitations in species identification.

The correlation analysis highlighted bamboo's ecological preferences across different environmental conditions. For conservation and restoration efforts, priority should be given to regions with optimal slopes, elevations and rainfall to support sustainable bamboo growth.

Bamboo's climate adaptability makes it a valuable tool in combating land degradation and drought, particularly in semi-arid regions. Its resilience positions it as a key species in desertification control and sustainable land management.

Additionally, bamboo's extensive root system enables it to thrive on steep slopes, making it effective in preventing landslides and soil erosion. In erosion-prone areas, bamboo can be strategically utilized for soil stabilization, further emphasizing its role in landscape restoration.

This dual function – as both an ecological engineer and a climate-resilient species – reinforces bamboo's importance in ecological restoration and sustainable land use across diverse environments.

Conclusions

This study successfully developed a scalable and user-friendly method for mapping bamboo distribution across Southeast Asia. By addressing challenges such as cloud cover and spectral similarity of different vegetation types using freely available satellite data and advanced open-source tools like SEPAL and GEE, the study employed time-series phenology analysis and collaborative training sample collection as innovative solutions.

The findings highlight bamboo's ecological and economic significance, particularly in middle-altitude, moderate-slope and semi-arid regions, reinforcing its potential as a climate-resilient species.

The bamboo distribution maps generated in this study serve as valuable tools for stakeholders, supporting evidence-based conservation planning, sustainable land management, and economic development.

However, while the methodology is scalable, its performance may vary by region, necessitating further validation to ensure accuracy and adaptability across diverse ecological contexts. To expand its impact across Southeast Asia, additional activities will be carried out in the Lao People's Democratic Republic and Cambodia.

Detailed country-specific reports accompany this study, presenting methodologies, results, and key findings, along with graphs, maps, and statistical summaries to aid interpretation. These documents also discuss the implications for bamboo resource management, sustainable land use, and conservation planning.

Finally, it is important to note that the boundaries, names and designations used on the maps do not imply any legal opinion by FAO regarding the status of territories, cities or their authorities. Quantitative information on bamboo and tree resources has been compiled based on carefully selected sources, methodologies and protocols identified by the authors.

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Figure 1, Figure 2 and Figure 3

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