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The interactive effects of human disturbances and biological invasion on tropical moist deciduous forest

(熱帯湿潤落葉樹林における人為攪乱と生物学的侵入の相互効果)

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Abstract

Invasive alien plant species (IAPs) are species that are introduced to an area outside its natural range mostly by human activities, and then spread aggressively, causing ecological and/or economic harm. IAPs threat biodiversity through the degradation of habitats and ecosystems. IAPs poses a risk of deteriorating natural ecosystems and often accelerated by human-induced disturbances. Among IAPs, *Acacia auriculiformis* C. Cunn. ex Benth., is widespread throughout Bhawal National Park (50.2 km²) in Bangladesh, a protected area recognized for its high biodiversity. *A. auriculiformis* is an evergreen species, whereas the native species, particularly the dominant tree, *Shorea robusta* Gaertner f, are deciduous.

Detecting the distribution characteristics of invasive species is prerequisite for controlling biological invasion. To detect the distribution, firstly, I investigated the effects of disturbances and biological invasion on tropical moist deciduous forests, using satellite imagery and machine learning. The invasive species were detected by seasonal variations of vegetation indices (VIs) using multispectral image classification. Using Sentinel-2A data (10 m resolution) across four seasons (winter, summer, monsoon, and autumn) in 2022 and 2023, six common VIs were calculated: normalized difference VI (NDVI), enhanced VI (EVI), green chlorophyll index (GCI), green-red VI (GRVI), soil-adjusted VI (SAVI), and atmospherically resistant VI (ARVI). The results indicated that NDVI, GRVI and GCI in winter were effective for extracting *A. auriculiformis*, while ARVI, NDVI and GCI were effective in summer. All VIs for each season were used along with a composited multi-season image to map *A. auriculiformis*. Field observations from 2022 were used to train and validate the classification. The binary and multi-class classification with Random Forest (RF) applied to multi-season imagery achieved an overall accuracy (OA) of 71.1% with a kappa coefficient (κ) of 0.59 and 76.8% with κ of 0.71. The integration of VIs and elevation (DEM, 12.5 m resolution) into the RF classification improved performance, yielding an OA of 90% ($\kappa = 0.88$) in winter and 83% ($\kappa = 0.80$) in multi-season. The variations in VIs between invasive and native vegetation suggested that integrating multiple VIs with phenology and topography enhanced the efficiency of invasive species detection, particularly when the invasive species exhibited distinct phenological patterns and elevation preferences to native vegetation, offering broader understanding of invasive species dynamics and their biological interaction with native vegetation.

Phenological differences derived from multispectral remotely sensed (RS) data were analyzed to map the invasive species distribution. The temporal profiles of three VIs: NDVI,

GRVI and ARVI were used to examine the spectral response of invasive *A. auriculiformis*, dominant native *S. robusta* forest and Mixed vegetation using Sentinel-2A images from 2022 to 2023. Analysis of temporal VI profiles identified two distinct phenological periods: senescence and green, characterizing plant phenological patterns. VIs from each phenological period were processed by the median composite method in Google Earth Engine. Phenological spectral features-based VIs were derived from these composited datasets and subsequently used to generate a new feature image encapsulating spectral characteristics from both the green and senescence periods. This facilitated comprehensive spectral differentiation of *A. auriculiformis* from native vegetation. Images generated by phenological spectral features-based VIs were incorporated into three classification algorithms: RF, Support Vector Machine (SVM) and Classification and Regression Tree (CART) to compare classification. The classifications were trained and validated using ground truth data from field observations in 2022. Among the classifiers, RF showed the highest OA of 87% ($\kappa = 0.83$). The results indicated that composited image incorporating phenological spectral features enhances spectral separability of invasive species from coexisting vegetation. By capturing spectral reflectance variations, this approach improved accuracy of classification. The phenological spectral features-based VIs provides a clear idea of spectral separability among species in ecosystem. The findings highlighted the efficiency of phenological spectral features into species detection, support forest conservation efforts and control invasive species.

MaxEnt was used in conjunction with RS data, environmental parameters and human-influenced variables to identify factors shaping the distribution of *A. auriculiformis*. The incorporation of spectral variables as factors improved model accuracy, with MaxEnt achieving an area under the curve (AUC) of 0.936, indicating an expansion in the potential distribution range of the species. The jackknife test showed that human-influenced factors, distance from settlement (31.3%), population density (17.2%) and distance from road (5.7%) were contributors to predicting the distribution range. NDVI in winter played a key role in detecting the presence of *A. auriculiformis*, contributing 24.3%. Additional factors influencing its spread included precipitation (5.3%) and soil nitrogen (6.2%). The human-induced disturbance factor, distance from settlement was evaluated as the most significant factor in terms of percent contribution (36.4%), permutation contribution (31.3%) and larger drop on training gain. An area of 3.6 km² was identified as having high suitability for *A. auriculiformis* distribution, indicated the risk zone. Human-induced disturbances were found in accelerating the spread of invasive species. Moreover, integrating RS data

into MaxEnt model facilitates the development of proactive management strategies to detect early stages of invasion.

This study presents an approach by integrating seasonal RS data, VIs and topography to detect *A. auriculiformis*. The phenological patterns and MaxEnt model revealed key environmental factors that affected ecological traits, suitable habitats and high-risk invasion zones. The link between human disturbances and spread was evident from distribution patterns showing higher *A. auriculiformis* presence in areas with intense human activity. This method offers generality in detecting invasive species and understanding invasion dynamics across ecosystems and supports strategies for biodiversity conservation and sustainable forest management with a global perspective.

General Introduction

Invasive alien plant species (IAPs) pose a global threat to biodiversity by causing habitat and ecosystem degradation (Pyšek et al., 2012). IAPs impact native ecosystems by outcompeting the native species (Simberloff, 2000), leading to their extinction (Dueñas et al., 2021). IAPs, registered in IUCN Red List, contribute 25% of plant extinctions (Rai, 2022). Plantation is one of the ways to restore biodiversity in degraded areas. For plantation, fast-growing and wide-adaptive species are often selected because these species show high productivity and economic benefits. Such species are often exotic and therefore, exotic species become biologically invasive and often invade disturbed habitats (Dodet and Collet, 2012). The invasive behavior of IAPs depends on both species traits and environmental factors, with disturbances, such as land use changes, especially forestry and accessibility practices that disrupt soil often increasing further spread (Cesar et al., 2017). Disturbance, a natural or human-induced disruption of ecosystems, often facilitates invasion by fast-growing plantation tree species (Dodet and Collet, 2012). Nowadays, *Acacia auriculiformis* C. Cunn. Ex Benth., an evergreen fabaceous species, native in Australia becomes common in Bhawal National Park (50.2 km²), Bangladesh, originating from plantation (Foster-Turley et al., 2016; Rangra et al., 2019). The perception and management of *Acacias* are different in the respective regions, depending on management practices influenced by environments and disturbances (Richardson et al., 2011). To manage *A. auriculiformis*, the first step of an effective management strategy is that *A. auriculiformis* should be detected and mapped.

Remote sensing (RS) is effective to map, detect and monitor invasive plants across large regions (Nandasena et al., 2023). Plants with unique spectral, textural and phenological characteristics are suitable for RS applications (Bradley, 2014). Vegetation indices (VIs), driven by photosynthetic activity, capture leaf phenology, enabling the distinction between evergreen and deciduous forests during defoliation period (Grabska et al., 2020; Melaas et al., 2016). I applied normalized difference vegetation index (NDVI) (Tucker, 1979), enhanced vegetation index (EVI) and soil-adjusted vegetation index (SAVI) (Zeng et al., 2022), green-red vegetation index (GRVI) (Shishir et al., 2020), green chlorophyll index (GCI) (Nadjla et al., 2022), and atmospherically resistant vegetation index (ARVI) (Xue and Su, 2017) to detect invasive species from the native vegetation. VIs increasing with plant greenness distinguishes vegetation classes through a combination of two or more wavelengths, such as blue, red and near-infrared, because of differences in

photosynthesis among species and seasons (Shishir and Tsuyuzaki, 2018). I examined the seasonal fluctuations of selected six VIs to distinguish *A. auriculiformis* from native vegetation. Each of the chosen VIs offers distinct advantages in detecting invasive species through spectral differences across seasons. Seasonal Sentinel-2A (10 m resolution) images from 2022 and 2023 (winter, summer, monsoon, and autumn) were selected from the Google Earth Engine (GEE) catalog and combined to generate a multi-season composite. Digital elevation model (DEM) was used to extract elevation data (12.5 m resolution). All images were stored, shared and processed within the GEE platform (Gorelick et al., 2017). Ground truth data were obtained in 2022 on 614 points in various land use classes. The collected points were used to train and validate classification. Machine learning classifier Decision Tree (DT) and Random Forest (RF) were applied to detect *A. auriculiformis* from native vegetation and classification of vegetation classes. In a specific season, RF detected *A. auriculiformis* well when multiple VIs and elevation data were integrated.

Phenological variations among tree species are an indicator for distinguishing invasive species from native vegetation through spectral reflectance captured in satellite images (Bradley, 2014). Vegetation phenology, defined as the study of seasonal cycle in plant growth and development, is influenced by changes, including greening, maturing, shedding leaves and bud dormancy. These species-specific changes allow to classify vegetation classes (Huang et al., 2025; Li et al., 2022). Time-series images were used for mapping invasive species, due to increase in classification accuracy (Kollert et al., 2021). In this study, the phenological spectral difference between *A. auriculiformis* and native deciduous forests during specific phenological periods were examined and an index was developed to increase spectral separability using time-series RS data. Multiple phenological periods were found by constructing temporal profiles of multiple VIs. The ability of identified phenological spectral features were tested on RF, Support Vector Machine (SVM), and Classification and Regression Tree (CART) to discriminate invasive species from deciduous forests. The study developed a phenological spectral features-based index (PVI), assessed spectral separability for *A. auriculiformis*, and applied machine learning classifiers for its distribution mapping. The study advanced phenological spectral features-based RS techniques in *A. auriculiformis* detection in tropical moist deciduous forest. It offered a robust approach that strengthens the global efforts to monitor and map invasive species to manage biological invasion.

Mapping and predicting the spread of *A. auriculiformis* are crucial for controlling *A. auriculiformis* at regional scale. Maximum Entropy (MaxEnt) was conducted after the

detection of *A. auriculiformis* distribution to predict its potential range based on the environmental factors that influence its spread. While the initial detection focused on identifying areas where *A. auriculiformis* is currently present, the MaxEnt model uses these locations along with environmental factors, e.g., climatic, physiographic and land use to assess the suitability of other areas for the species. MaxEnt was effective for predicting potential sites for *A. auriculiformis* plantation and identifying key environmental factors influencing its distribution (Moreno-Amat et al., 2015). Human-induced disturbances like land use changes were found in accelerating the spread of invasive species. Human activities change ecological niches, defined as the range of environmental conditions that allow a species to survive, thereby favor the growth and persistence of invasive plants by altering the frequency and intensity of disturbances (Manier et al., 2014). Because RS supports to detect biological invasions by mapping the spread of IAPs at various scales (Rocchini et al., 2015), RS data were combined with MaxEnt to detect and predict the distribution of *A. auriculiformis*. MaxEnt detected sites for transplantation and showed that human-induced disturbances were key factors in managing the invasive plants. These areas are at high risk of invasion. The results not only can advance local management strategies but also contribute to the global efforts in an era of rapid environmental and societal change.

In this study, the term ‘interactive’ refers to the combined influence of phenological features, VIs, topography, and environmental factors in detecting and mapping invasive species. These factors were not studied separately but together, using models like MaxEnt to understand how they jointly affect distribution patterns.

Integrating the phenological traits, elevation, human-induced disturbances and environmental factors into RS and species distribution models added new insights to the approach by enhancing the detection of invasive species and improving predictions of how various activities and conditions impact ecologically sensitive areas. This integrated approach not only can support effective conservation and management strategies by identifying key areas for restoration, protection and targeted control efforts in the protected areas but also promote generality by applying the method across diverse ecosystems. This approach contributed to a broader understanding of invasive species dynamics, aiding in the development of globally relevant strategies for biodiversity conservation and ecological resilience.

Study site

The study site was Bhawal National Park (24°01'N, 90°20'E), located 40 km north to Dhaka, Bangladesh (**Figure 0-1**). The park (50.2 km²) was designated as a protected area (IUCN Management Category IV) in 1982. The native forest belongs to a tropical moist deciduous forest (Toma et al., 2022) and dominated by deciduous *Shorea robusta* Gaertner f. (Kabir and Ahmed, 2005). Field observations in 2022 confirmed that the cohabitants were *Tectona grandis* L.f. (deciduous), *Terminalia belerica* (Gaertn.) Roxb. (deciduous), *Swietenia mahagoni* (L.) Jacq. (evergreen), *Terminalia arjuna* (Roxb.) Wight et Arn. (evergreen), *Mangifera indica* L. (evergreen), *Butea monosperma* (Lam.) Taub. (deciduous), *Terminalia chebula* Retz. (deciduous), *Elaeocarpus floribundus* Bl. (evergreen), *Eucalyptus camaldulensis* Dehnh. (evergreen, invasive), *A. auriculiformis*, etc. The park consists of the National Forest Park Range and the Bhawal Forest Range (Masum et al., 2016). The topography is dating back to the Pleistocene epoch, elevated 10 to 15 m above the surrounding floodplains, with nutrient-poor and slightly acidic soil types (Islam et al., 2014; Rahman et al., 2010a). Mean annual temperature is 25.6°C with an annual rainfall of 2214 mm in the study site (Karim et al., 2023). The study site has a warm, humid climate with distinct seasonal variations in rainfall, moderately warm temperature and high humidity. It experiences four seasons: a dry winter from December to February, a hot pre-monsoon summer from with high temperature from March to May, a wet monsoon with the highest rainfall from June to September, and a post-monsoon autumn from October to November (Islam et al., 2014; Shahid, 2010). More than 75% of the rainfall occurs here in the monsoon season (Khan et al., 2019). Vegetation phenology is affected by the seasonal changes in rainfall that affect plant growth, including greening, maturing, and senescence (Huang et al., 2025). Growing season/greenness is marked from June to November as vegetation attains its peak in the time of highest rainfall (Islam et al., 2021). Senescence (leaf-shedding) of native deciduous forests occurs in dry winter season (Costa et al., 2014; Singh et al., 2020).

Bhawal National Park, once abundant in biodiversity, is now experiencing biodiversity decline due to intense human activities such as encroachment, the creation of settlements and industries, the planting of invasive species, illegal logging, and agricultural expansion (Alauddin et al., 2020; Masum et al., 2016). The protected areas are at risk because of biological invasions due to human disturbances and the spread of invasive species (Bhatta et al., 2024). The monoculture with the fast-growing exotic species are practiced within the forest area by the Forest Department of Bangladesh (Alauddin et al., 2020). However, the

initiatives disrupted the plant and animal diversities in the forest (Hasan and Bahauddin, 2014).

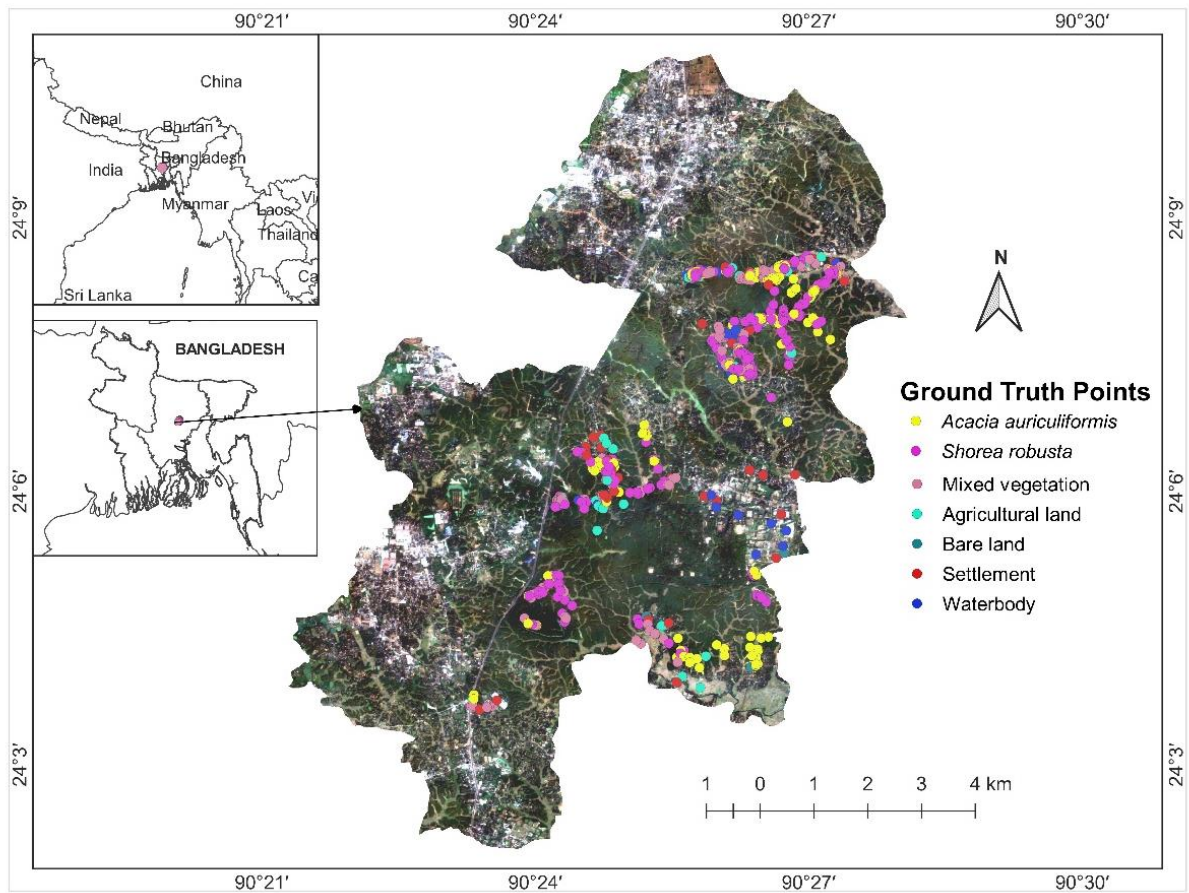


Figure 0-1. Ground truth point locations (indicated by circles) within the study site are displayed on Sentinel-2A imagery captured during the winter season, spanning December 1, 2022, to March 15, 2023. The circles are color-coded to represent different land use classes. Coordinates for these locations were recorded using a portable GPS. The upper left corner of the figure shows the geographical context, highlighting the study sites in Southwest Asia (top) and Bangladesh (bottom).

During the 20th century, Bangladesh introduced the fast-growing Australian evergreen tree *A. auriculiformis* (Fabaceae), reflecting its longstanding practice of incorporating species from various regions (Mukul et al., 2021). *A. auriculiformis* explained 26% of the forest areas in the park (Rahman et al., 2010b). This is a nitrogen fixing species and becomes 30 m in height and 30 cm in diameter at breast height in mature stage (Zerkout et al., 2021). *A. auriculiformis* flourishes in warm climates with temperatures from 12°C to 34°C and in humid areas with 1000 to 4500 mm of annual rainfall (Heringer et al., 2019).

A. auriculiformis often displaces indigenous forest vegetation and other local wild flora,

as they lack edible fruits or nectar to support wildlife (Rahman et al., 2010a). *Acacia* species have been planted globally and are most extensively spread across ecosystems and ecologically impactful due to their long-lived and easily dispersed seeds, disturbance-triggered germination, ability to resist water stress and flexible symbiosis with nitrogen-fixing bacteria (Hui et al., 2014). *A. auriculiformis* has specific functional traits from native deciduous vegetation, i.e., fast-growth and high competition ability (Maitre et al., 2011), due to its deep roots that absorbs more nutrients, long-lasting leaves that saves energy, and nitrogen-fixing ability, which together support its fast-growth and dominance over native species (Morris et al., 2011). Moreover, native deciduous forests are sensitive to invasive *A. auriculiformis* due to phenological differences, which promote invasiveness (Lediuk et al., 2014). The phenological differences, such as extended leaf phenology, allow it to gain a competitive advantage over native species and affect communities by using nutrients first, blocking sunlight, avoiding pests, and disrupting native plant interactions (Smith, 2013).

Land use classes were recorded from field observations during winter season (leaf-off period) in March 2022 and use the sampling points as ground truth data (**Table 0-1**). The coordinates on each point were measured by a portable Global Positioning System (Garmin Rino 750; Garmin Corporation, Taipei, Taiwan). At each ground truth point, key ecological parameters, including phenological stage, topographical factors, land use were recorded to support interpretation of vegetation structure and spectral variability, thereby enhancing classification accuracy.

The field observations occurred during the leaf-off period, and deciduous forests such as *S. robusta* showed reduced canopy cover (visually estimated at 20–40%) due to seasonal leaf-fall. In contrast, *A. auriculiformis* and other native evergreen species maintained dense canopy cover (>60%). This phenological contrast enhanced spectral separability among vegetation classes. The satellite image acquisition was aligned with field observations timing to ensure consistency in phenological conditions, further improving classification accuracy.

Table 0-1: The summary of collected ground truth points of various vegetation classes through field observations from the study site.

Feature	Name	Phenology	Sample no.	Elevation	Phenological stage	Land use class
Invasive alien plants	<i>A. auriculiformis</i>	evergreen	129	low to high (12m ~)	Leaf flush to mature (evergreen phase)	plantation/ agroforestry
Dominant tree	<i>S. robusta</i>	deciduous	215	high (>19m)	leaf fall	natural/ protected area
Mixed vegetation	cohabitant deciduous and evergreen plants	mixed	145	mid to high (16m ~)	mixed stages	natural/ disturbed forest
Agricultural land		seasons-dependent	58	varied	planted or harvest stage	cultivated
Non-vegetation	Waterbodies, bare land, buildings, roads	not applicable	67	varied	not applicable	not applicable

During field observations, the dominant species *S. robusta* was observed to be in a declining state (Rahman et al., 2010b), while *A. auriculiformis* was planted throughout the forests, predominantly near human-made structures (**Figure 0-2**).

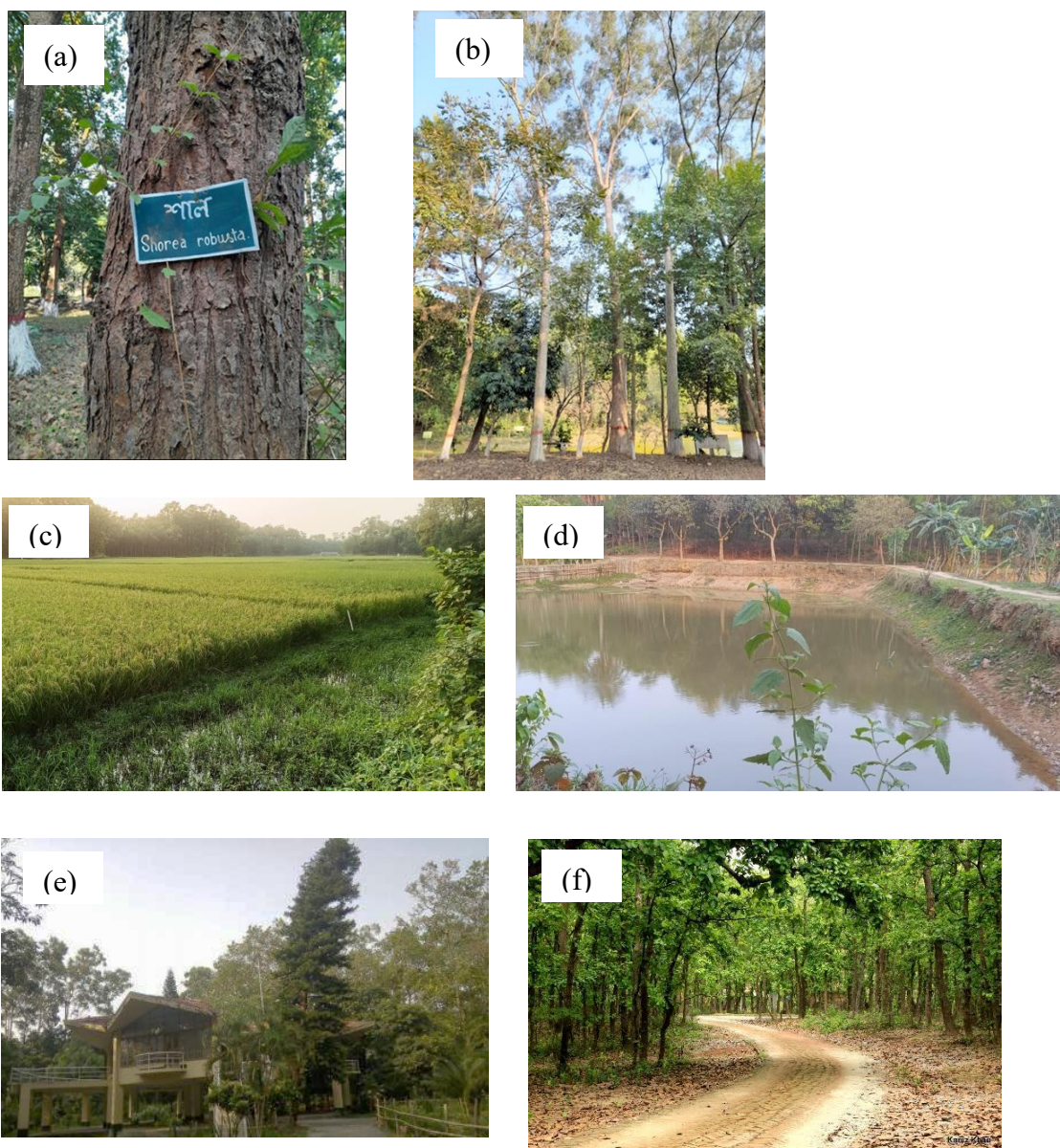


Figure 0-2. (a) *S. robusta* (b) *A. auriculiformis* (c) Agricultural land (d) Water body (e) Human-made structure, and (f) road inside the forest.

(Source: field observations 2022)

Chapter 1

Detecting biologically invasive species by phenology and topography in tropical moist deciduous forests at satellite remote sensing scale

1.1. Introduction

Invasive alien plant species (IAPs) threaten biodiversity worldwide through habitat and ecosystem degradation (Pyšek et al., 2012). IAPs are responsible for 25% plant extinctions globally (Dudley et al., 2008; Rai, 2022). Numerous IAPs were introduced into Bangladesh, particularly during the British colonial period in the late 19th century, to increase timber productivity with fast-growing trees (Mukul et al., 2020). In the 20th century, Australian trees, represented by *Eucalyptus* and *Acacia*, were introduced for afforestation on degraded lands (Rahman and Roy, 2014). Currently, *Acacia auriculiformis* C. Cunn. ex Benth., an evergreen invasive tree, is widespread in protected areas, including national parks in Bangladesh (Foster-Turley et al., 2016). This species shows phenological differences from native deciduous trees, allowing for the detection of invasive species through spectral differences and seasonal changes in vegetation indices (VIs) using remote sensing (Bradley, 2014).

Remote sensing (hereafter RS) is a tool for mapping, identifying, and monitoring the distribution of forests (Nandasena et al., 2023). Evergreen forests are distinguished from deciduous forests by VIs during defoliation (Grabska et al., 2020; Liu et al., 2023). RS identifies invasive shrubs in deciduous forest understories because these shrubs shed their leaves earlier than native deciduous shrubs (Resasco et al., 2007). This technique is applied to monitor leaf phenology between invasive shrubs and native trees in deciduous forests (Wilfong et al., 2009). Since VIs are affected by photosynthetic activities, leaf phenology is detected by VIs (Melaas et al., 2016).

The normalized difference vegetation index (NDVI) evaluates various vegetation characteristics, e.g. vegetation class, plant activity, and productivity (Tucker, 1979). However, NDVI accuracy is reduced by atmospheric, edaphic, and topographic interferences (Shishir and Tsuyuzaki, 2018). To mitigate these effects, alternative VIs, i.e., enhanced vegetation index (EVI), soil-adjusted Vegetation Index (SAVI) (Huete, 1988; Zeng et al., 2022), green-red vegetation index (GRVI) (Shishir et al., 2020), green

chlorophyll index (GCI) and atmospherically resistant vegetation index (ARVI) (Nadjla et al., 2022; Xue and Su, 2017) were often used.

Decision Tree (DT) was used for classifying vegetation classes due to their training capability and result interpretation (Peña-Barragán et al., 2011). However, DT tends to overfit training data (Prajwala, 2015), Random Forest (RF) was employed for the image classification. RF is an ensemble learning method widely used for land cover classification with multispectral and hyperspectral images, offering high accuracy and robustness to noise compared to single classifiers (Rebelo et al., 2021; Rodriguez-Galiano et al., 2012).

RF is efficient for processing RS data (Eugenio et al., 2021; Silva et al., 2023), including detecting invasive species (Belgiu and Drăguț, 2016; Lawrence and Ripple, 2000). RF is suitable for detecting vegetation and land use for spatiotemporally auto-correlated data (Masemola et al., 2020). Since the biological invasions often show spatiotemporal correlation (Mistro et al., 2012), this classifier was applied.

Topographic features, such as elevation, play a crucial role in mapping processes (Albert and Ammar, 2021). The digital elevation model (DEM) was used to analyze the effects of elevation on the distribution of invasive and native species with VIs (Saadat et al., 2008). *A. auriculiformis* was immigrated from plantations to natural forests dominated by *Shorea robusta* Gaertner f. in the Bhawal National Park, Bangladesh (Rahman et al., 2010b). This area is suitable for analyzing the effectiveness of identifying and mapping of IAPs by multispectral RS data due to the temporal changes in the surface reflectance of *A. auriculiformis* and native vegetation. This study examined: (1) the detection of evergreen *A. auriculiformis* considering the phenology of vegetation classes and (2) the detection of *A. auriculiformis* by integrating multiple VIs with elevation under an RF algorithm in a particular season.

1.2. Materials and Methods

1.2.1. Study site and species

The study site, Bhawal National Park (50.2 km²), is located 40 km north to Dhaka, capital city of Bangladesh (24°01' N, 90°20' E) (**Figure 1-1**). Designated as a protected area (IUCN Management Category IV) in 1982, the park includes the Bhawal Forest Range and the National Park Forest Range, along with seven forest beats, that is the smallest forest management units (Masum et al., 2016). The park is a raised platform from the Pleistocene

Epoch, elevated at 10 to 15 m above the neighboring floodplains (Islam et al., 2014). It is classified as a tropical moist deciduous forest (Toma et al., 2022), dominated by the endangered, deciduous tree, *S. robusta* Gaertner f. (Kabir and Ahmed, 2005). Protecting *S. robusta* forests was a key reason for the park designation (Rahman et al., 2010a). *S. robusta* forms the forest canopy, covering 25% to 75% of the area (Rahman and Vacik, 2010), with densities exceeding 4000 stems/ha in every forest beats (Mondol et al., 2021). Field observations in 2022 identified the cohabitants including *Tectona grandis* L.f., *Terminalia belerica* (Gaertn.) Roxb., *Swietenia mahagoni* (L.) Jacq., *Terminalia arjuna* (Roxb.) Wight et Arn., *Mangifera indica* L. and *Elaeocarpus floribundus* Bl. *Eucalyptus camaldulensis* Dehnh., *A. auriculiformis*, etc. Agricultural activities have replaced some forested areas over several decades (Alauddin et al., 2020; Rahman et al., 2010b). The climate is warm and humid (Islam et al., 2014), with a mean annual temperature of 25.6°C and annual precipitation of 2214 mm (Karim et al., 2023). The region experiences four seasons: winter (dry season, December to February), summer (pre-monsoon warm, March to May), monsoon (highest rainfall, June to September), and autumn (post-monsoon, October to November) (Shahid, 2010).

The national park has been affected by human impacts, driven by its accessibility from Dhaka, rapid population growth, and ongoing industrialization (Alam et al., 2022). *A. auriculiformis*, a fast-growing species, has been planted in 26% of the forest area in the national park as a part of a plantation program by the Bangladesh Government (Rahman et al., 2010b). *A. auriculiformis* is broadly established in the study site (Rangra et al., 2019). This species reaches 30 m in height and 30 cm in diameter at breast height when mature and it grows rapidly even in nutrient-poor habitats due to its nitrogen-fixing ability (Zerkout et al., 2021).

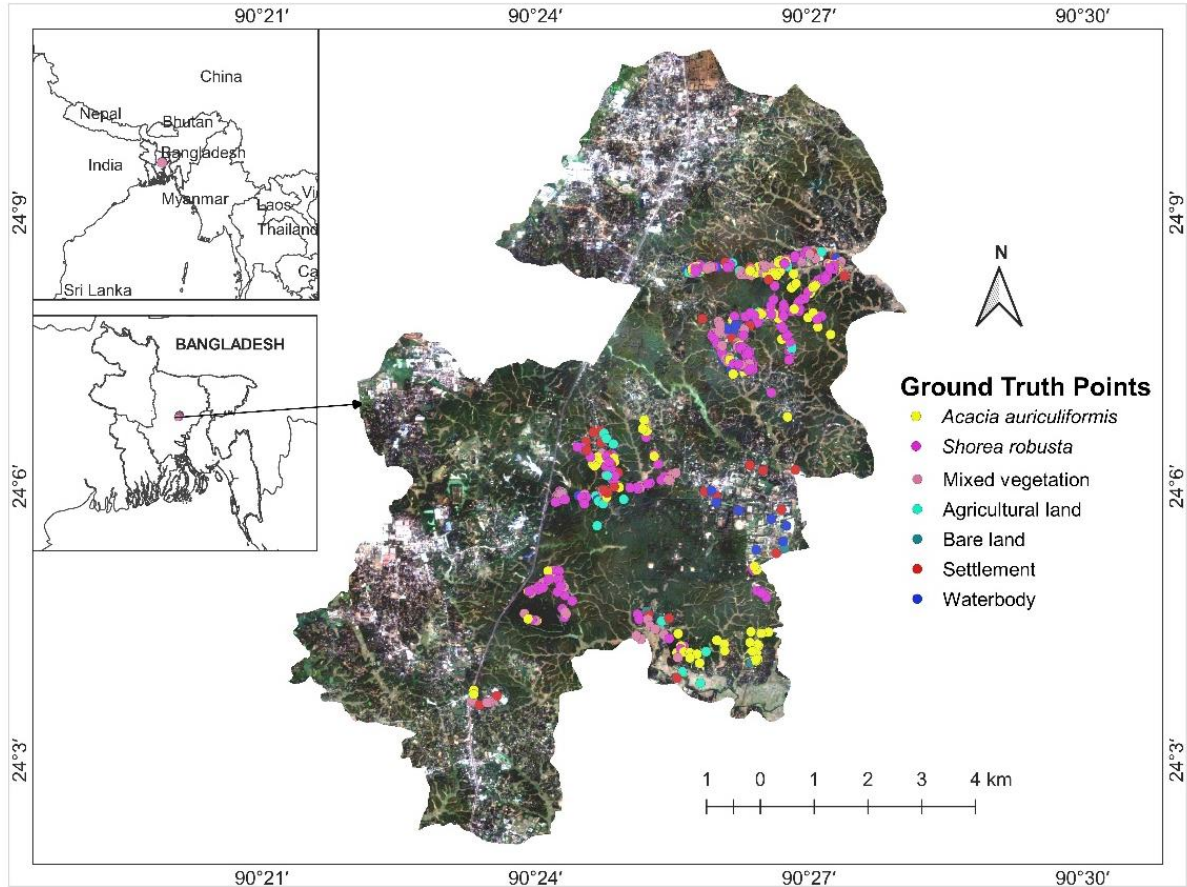


Figure 1-1. The locations of ground truth points (color-coded circles) in the study site displayed on Sentinel-2A images taken during winter (December 1, 2022, to March 15, 2023). Different circles show different land use classes. Coordinates were determined by a portable GPS. The upper left corner of the figure shows the study site location in Southwest Asia (top) and Bangladesh (bottom).

1.2.2. Datasets and image processing

By Google Earth Engine (GEE) catalog, cloud-free data was obtained from Sentinel-2A (European Space Agency Copernicus) to map *A. auriculiformis* and other land use classes. The multispectral instrument on Sentinel-2A captures atmospheric reflectance data, which are processed into surface reflectance without requiring further atmospheric corrections. Sentinel-2A images have 13 spectral bands with resolutions of 10, 20 and 60 m, available at approximately 5-day intervals. Sentinel-2A is advantageous for vegetation classification due to its four specific bands (5, 6, 7, and 8A) in the red region (Rebelo et al., 2021). The 10 m resolution bands, Blue, Green, Red, and near-infrared (NIR) were combined for VIs across seasons for vegetation classification.

The multispectral images were acquired across four seasons in 2022 and 2023, as each season provides distinct spectral and phenological signals essential for distinguishing vegetation classes. For each season (winter, summer, monsoon, and autumn), composited images were generated by integrating data captured at different times within each season. These seasonal composite images were then aggregated to create a multi-season image representing data from all seasons.

Elevation data was obtained from a DEM provided by the Advanced Land Observing Satellite, with a 12.5 m spatial resolution. All image data were stored, shared and processed in the GEE platform (Gorelick et al., 2017).

1.2.3. Field data collection

Sampling points used as ground truth data for land use classes were set after defoliation in March 2022, excluding inaccessible locations. The numbers of points were 129 for *A. auriculiformis*, 215 for *S. robusta*, 145 for Mixed vegetation and 59 for Agricultural lands. Coordinates for each point were measured by a portable GPS (Garmin Rino 750; Garmin Corporation, Taipei, Taiwan). The *A. auriculiformis* were separated into patches to assess their invasiveness by evaluating their spread and impact. I recorded 67 points without vegetation, i.e., bare lands, water bodies and man-made structures (buildings and roads) as non-vegetation class. In total, five classes were recorded. These points were used to train and validate the classification.

1.2.4. Vegetation indices (VIs)

To distinguish *A. auriculiformis* from native forests, I examined the seasonal fluctuations of six VIs:

- (1) Normalized Difference Vegetation Index (NDVI) = $(\text{NIR} - \text{red}) / (\text{NIR} + \text{red})$ (Tucker, 1979).
- (2) Green-Red Vegetation Index (GRVI) = $(\text{green} - \text{red}) / (\text{green} + \text{red})$ (Yin et al., 2022), uses green wavelengths instead of NIR in the equation of NDVI. It is enabled to detect dense vegetation, particularly, on forest canopy (Shishir and Tsuyuzaki, 2018).
- (3) Enhanced Vegetation Index (EVI) = $G \times (\text{NIR} - \text{red}) / (\text{NIR} + C1 \times \text{red} - C2 \times \text{blue} + L)$, where L is canopy background adjustment, and C1 and C2 area aerosol resistance terms (Huete et al., 2002). EVI can estimate biomass by weakening the noises of canopy

background signal from atmospheric interferences (Johnson et al., 2016).

- (4) Soil-Adjusted Vegetation Index (SAVI) = $(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED} + L) \times 1 \times L$, where L is a factor that considers soil brightness and atmospheric conditions, with a default of 0.5 (Huete, 1988).
- (5) Green Chlorophyll Index (GCI) = $(\text{NIR}/\text{G}) - 1$ (Kumar et al., 2018). GCI estimates chlorophyll content of leaves that indicates vegetation health, making GCI useful to monitor seasonal impacts, as chlorophyll in stressed plants (Nadjla et al., 2022).
- (6) Atmospherically Resistant Vegetation Index (ARVI) = $[\text{NIR} - (2 \times \text{RED}) + \text{BLUE}] / [\text{NIR} + (2 \times \text{RED}) + \text{BLUE}]$, designed to reduce atmospheric moisture interference, in particular, in tropical regions (Kureel et al., 2022).

The *A. auriculiformis* was detected in GEE by the six VIs in each season. All indices increase with increasing vegetation and range from -1 to 1, except GCI. The differences were compared between the vegetation classes in each season. A pair-wise *t*-test was used to investigate the differences in mean between vegetation classes (Mishra et al., 2019).

1.2.5. Performance evaluation and accuracy assessment of RF and DT

The DT and RF classifiers were applied to categorize vegetation classes using six VIs across seasons, splitting the dataset into 70:30 for training and validation, which increased the accuracy of the classification (Adelabu et al., 2015). The performance of DT was evaluated by confusion matrices and kappa coefficient (κ) in R version 4.3.2 (R Core Team (2023)).

RF classification was performed on each season and multi-season images in GEE using ground truth data. RF involves two parameters, *mtry* the number of variables at each split and *ntree*, the number of nodes in the clustering tree (Breiman, 2001; Masemola et al., 2020). I set *mtry* to 3 and *ntree* to 20. RF classification was conducted separately for each season, incorporating elevation data and VIs with multispectral composited images. The accuracy of RF classification was evaluated by confusion matrices and the kappa coefficient (κ) coefficient (Aji et al., 2023). The κ was calculated for each season to assess the accuracy (Kuplich, 2006). The selection of training and validation points improves overall accuracy of the classification (Ma et al., 2015). The seasonal differences were investigated using winter image as a benchmark, focusing on the period when deciduous trees lose their leaves.

All satellite images were classified in two steps. First, binary classification was performed to determine the presence or absence of *A. auriculiformis*, distinguishing between areas dominated by *A. auriculiformis* and others land use classes. This step facilitated rapid detection of invasion edges and areas at risk. Next, a more detailed multi-class classification was applied by adjusting non-*A. auriculiformis* classes into ecologically relevant land use classes: *S. robusta*, Mixed vegetation, Agricultural land, and the non-vegetation. The Mixed vegetation refers to forests consisting of evergreen and deciduous, excluding *A. auriculiformis* and *S. robusta*, providing critical insights into the composition and structure of native ecosystems. Multiple VIs and elevation from DEM were analyzed to detect *A. auriculiformis* accurately.

1.3. Results

1.3.1. The detection of *A. auriculiformis*: binary and multi-class image classifications on multi-season image

The binary and multi-class classification detected *A. auriculiformis* well using RF with multispectral reflectance (**Figure 1-2**), although differences in accuracy between them were confirmed. The performance of both the classifications was evaluated from the confusion matrices. For binary classification, the image was classified into two classes: *A. auriculiformis* and others. The overall accuracy (OA) was 71.1% with a κ of 0.59, demonstrating the separability of *A. auriculiformis* from others. The producer accuracy (PA) for *A. auriculiformis* was 90.8% and user accuracy (UA) was 35.4%. The lower UA suggested a high rate of commission error, due to spectral similarities with other evergreen species during phenological periods.

In contrast, the multi-class classification classifying five classes: *A. auriculiformis*, *S. robusta*, Mixed vegetation, Agricultural land, and non-vegetation improved classification accuracy. This approach achieved a higher OA of 76.8% (κ of 0.71). For *A. auriculiformis*, PA increased to 92.1%, while UA improved to 64.2%, suggesting a reduction in false positive and better separation from ecologically similar classes. These results showed that *A. auriculiformis* were effectively detected from native vegetation by capturing distinct reflectance at specific times of the year.

Misclassification in the binary approach was noticed which was mostly associated with Mixed vegetation (**Figure 1-2**), likely due to the evergreen *A. auriculiformis*. Spectral

similarities during the growing season led to confusion between *A. auriculiformis* and *S. robusta*. The multi-class classification enhanced accuracy by reducing misclassification of *A. auriculiformis* with native vegetation classes.

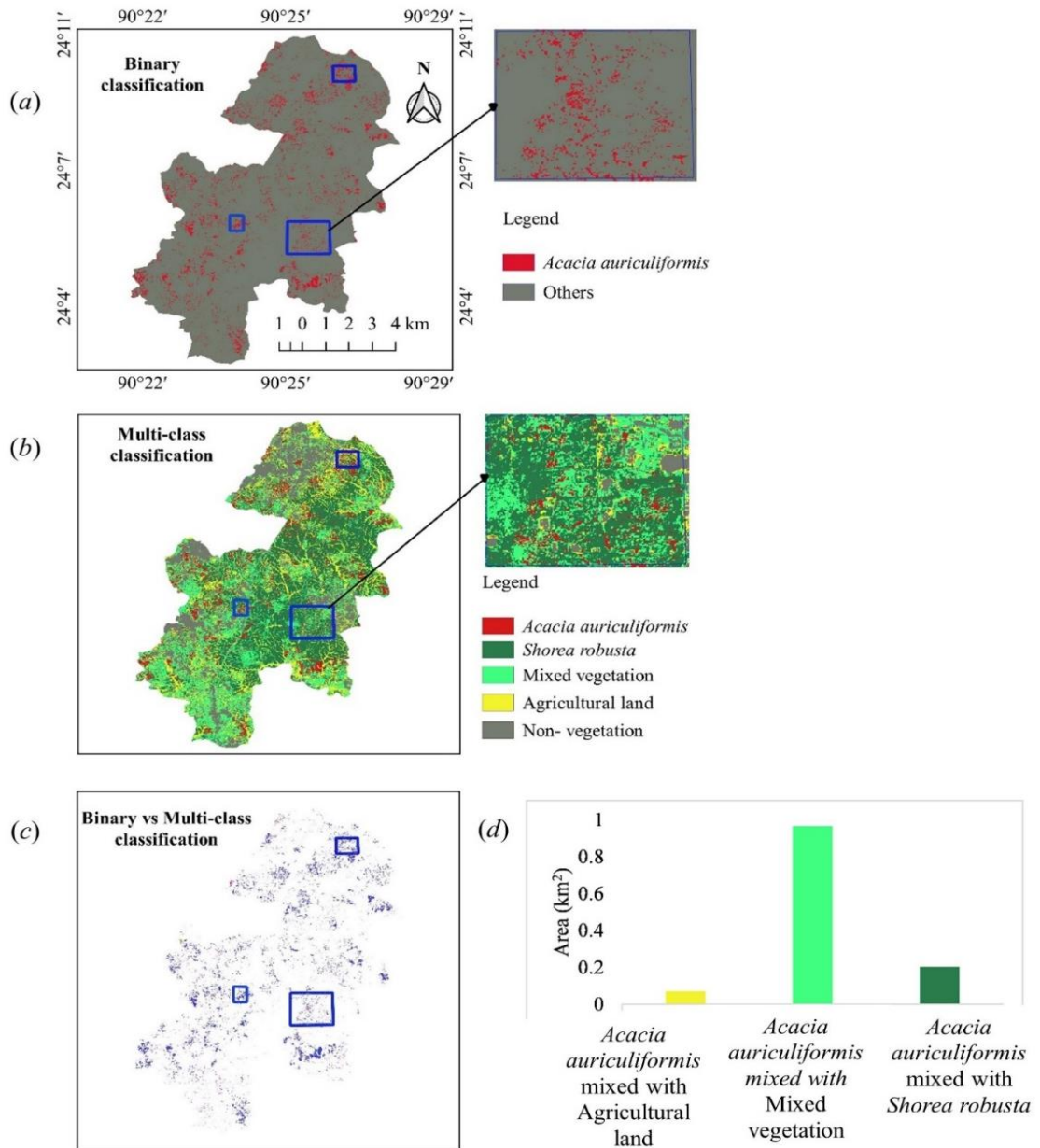


Figure 1-2. (a) Distribution of *A. auriculiformis* estimated by binary classification and (b) multi-class classification with magnified views. The magnified plots indicated by blue boxes in (a) and (b) indicate where dense vegetation occurs. (c) *A. auriculiformis*-Mixed vegetation by Binary classification (blue color areas indicate misclassification and blue boxes indicate areas with large misclassification) and (d) misclassified areas.

1.3.2. Seasonal surface reflection of VIs in vegetation classes

Fluctuations in VIs were observed among classes across seasons (**Figure 1-3**). Green contrasts between evergreen and deciduous forests were evident from late winter to early summer.

Among the six examined VIs, GCI was higher for *A. auriculiformis* in both winter (mean = 3.03) and summer (3.52) compared to other vegetation classes (t -test, $p < 0.01$). The NDVI of *A. auriculiformis* varied little seasonally and remained at peak in all seasons among the vegetation classes. In contrast, *S. robusta* forest varied seasonally and showed lower NDVI in winter, remaining low until early summer. This seasonal defoliation of deciduous forests allowed the classification of evergreen *A. auriculiformis* in winter. In summer, *A. auriculiformis* exhibited higher and more stable NDVI, facilitating detection in both winter and summer. In autumn, the peak NDVI across all vegetation classes (> 0.75) complicated classification, except for Agricultural land which had a low NDVI (0.67) (t -test, $p < 0.01$).

GRVI was observed lower in winter and summer than in monsoon and autumn. *A. auriculiformis* showed higher GRVI (0.08) in winter, aiding its detection (t -test, $p < 0.01$). However, increased GRVI during monsoon and autumn caused overlaps among vegetation classes, hindering separation of *A. auriculiformis*. GRVI distinctly identified Agricultural land in summer (0.07).

EVI of *A. auriculiformis* fluctuated seasonally, that ranged from 0.31 to 0.48. The average EVI in winter was 0.34, separating *A. auriculiformis* from Mixed vegetation (0.30) and Agricultural land (0.29) but not from *S. robusta* (0.33). In summer, EVI was lower for three vegetation classes (0.28 on *S. robusta*, 0.29 on Mixed vegetation and 0.31 on *A. auriculiformis*) than on Agricultural land (0.39). EVI showed small fluctuations in *A. auriculiformis*, *S. robusta* and Mixed vegetation during all seasons and did not clearly separate *A. auriculiformis* (**Figure 1-3**).

SAVI for the evergreen *A. auriculiformis* fluctuated from 0.27 in winter to 0.44 in autumn (**Figure 1-3**). SAVI separated Agricultural land (0.39) from *A. auriculiformis* (0.33) in summer (t -test, $p < 0.01$). Deciduous forests had lower SAVI in winter (0.31) and summer (0.30) than in monsoon (0.42) (t -test, $p < 0.01$). *S. robusta* forest had a SAVI of 0.31 in winter, while Mixed vegetation had 0.29. *A. auriculiformis* had a SAVI of 0.32 in winter, allowing it to be separated from Mixed vegetation.

A. auriculiformis showed ARVI of 0.77 in monsoon and autumn. The seasonal fluctuations of ARVI distinguished *A. auriculiformis* from *S. robusta* and Mixed vegetation, particularly in summer (t -test, $p < 0.01$). In summer, *A. auriculiformis* had an ARVI of 0.42, separated it from remaining classes. ARVI in Agricultural land averaged 0.39 in winter, 0.49 in summer and 0.61 in autumn, differentiated the class from vegetation classes. *A. auriculiformis* were not distinguished from *S. robusta* and Mixed vegetation during winter, monsoon and autumn.

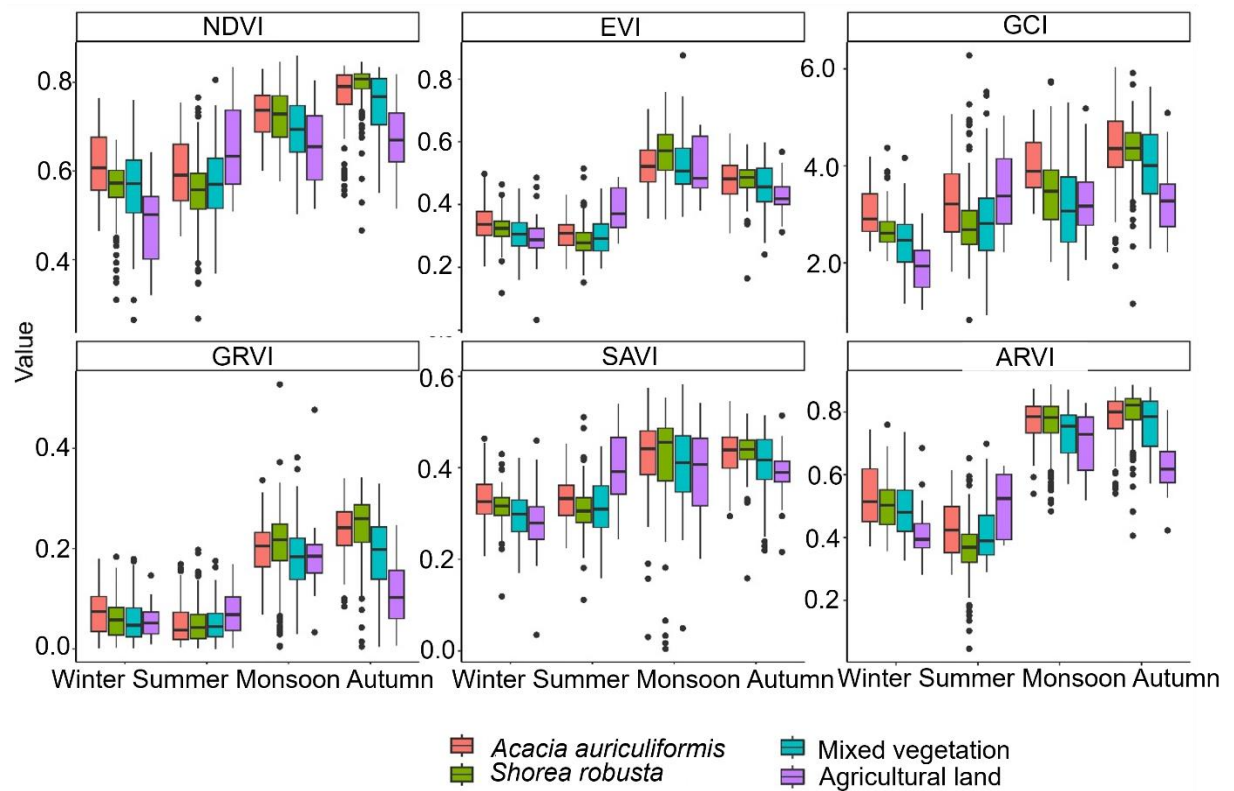


Figure 1-3. The seasonal fluctuations of NDVI, EVI, SAVI, GCI, ARVI, and GRVI in *A. auriculiformis*, *S. robusta*, Mixed vegetation and Agricultural land, shown with box-whisker plots. The box represents the first and third quartiles, with bold lines indicating median. The horizontal lines show the minimum and maximum values within the normal data range (first quartile minus $1.5 \times$ interquartile distance to third quartile plus $1.5 \times$ interquartile distance). Outliers are shown as open circles.

In **Figure 1-4**, *A. auriculiformis* showed higher VIs than *S. robusta*. The magnitude of the VIs reflected the degree of difference between *A. auriculiformis* and *S. robusta*. NDVI, GCI and GRVI effectively distinguished *A. auriculiformis* (t -value = 3.36-6.51, $p < 0.01$) in winter. In summer, ARVI showed differences between *A. auriculiformis* and *S. robusta* with high variations. These two species were separated in both winter and summer with NDVI, ARVI, GRVI, and GCI. The results indicated that seasonal measurements of VIs were effective for extracting *A. auriculiformis*.

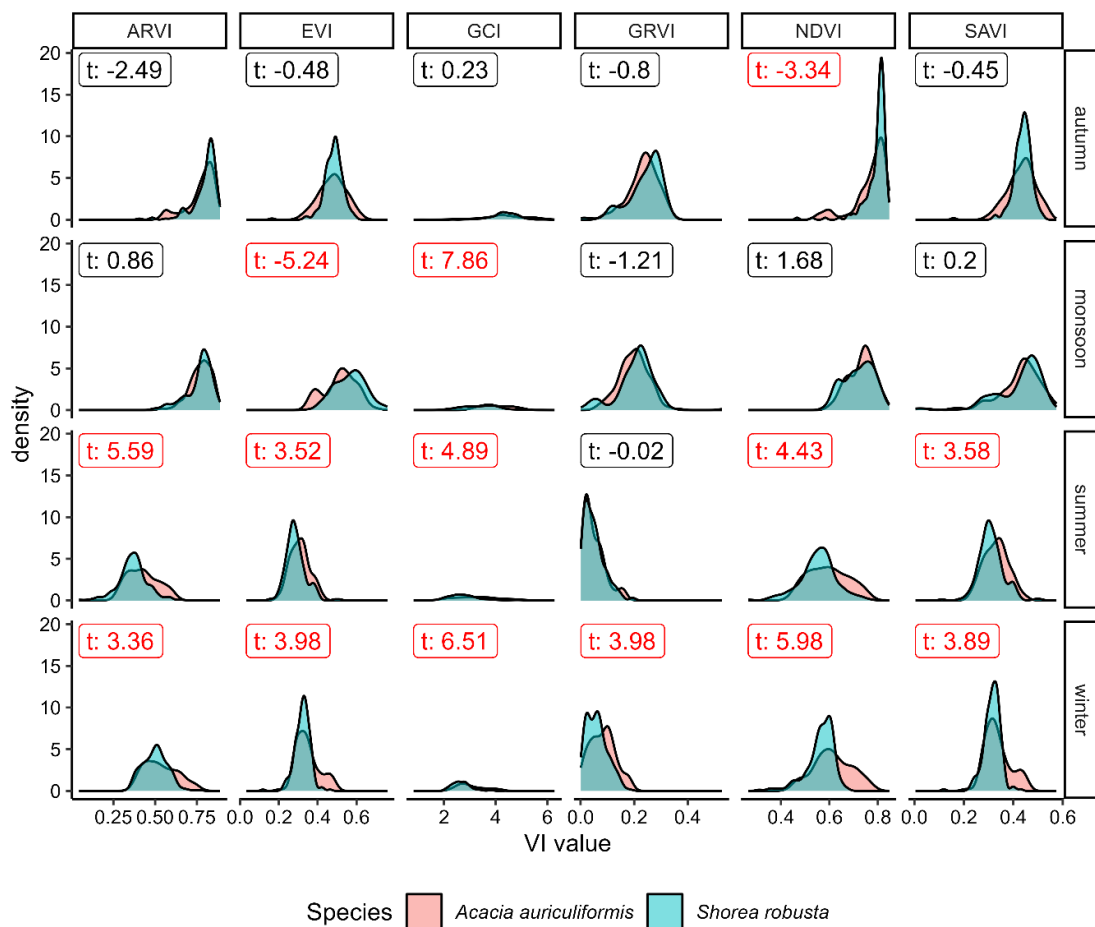


Figure 1-4. Distribution of VIs (columns) in four seasons (rows) for *A. auriculiformis* (invasive vegetation) and *S. robusta* (native vegetation). The t -values are shown on each panel. The y-axis shows the probability density. When VIs between *A. auriculiformis* and *S. robusta* are significantly different at $p < 0.01$ (t -test), the t -values are highlighted in red. For details on the other classes, see in the text.

1.3.3. Discriminating *A. auriculiformis* from native vegetation using DT

In winter, DT separated *S. robusta* from Mixed vegetation by GCI (< 2.00) (**Figure 1-5**). NDVI distinguished Agricultural land from Mixed vegetation (> 0.44). Elevation (< 18) separated Mixed vegetation from *S. robusta*. When GCI was > 3.20 , *A. auriculiformis* was separated from Mixed vegetation. *A. auriculiformis* was distinguished from *S. robusta* when NDVI was > 0.63 . The combination of elevation and ARVI extracted *S. robusta* when elevation and ARVI were < 19 and < 0.50 , respectively. GRVI detected *A. auriculiformis* when $GRVI \geq 0.09$. DT showed OA of 65% ($\kappa = 0.5$) in winter. When applied to summer, monsoon and autumn, OA was 67% ($\kappa = 0.52$), 72% ($\kappa = 0.59$) and 69% ($\kappa = 0.54$).

Elevation affected accuracy, with DT showing lower accuracy in winter than in the other seasons. The threshold in **Figure 1-5** using VIs and elevation can be applied to other areas after adjusting them with local conditions and data.

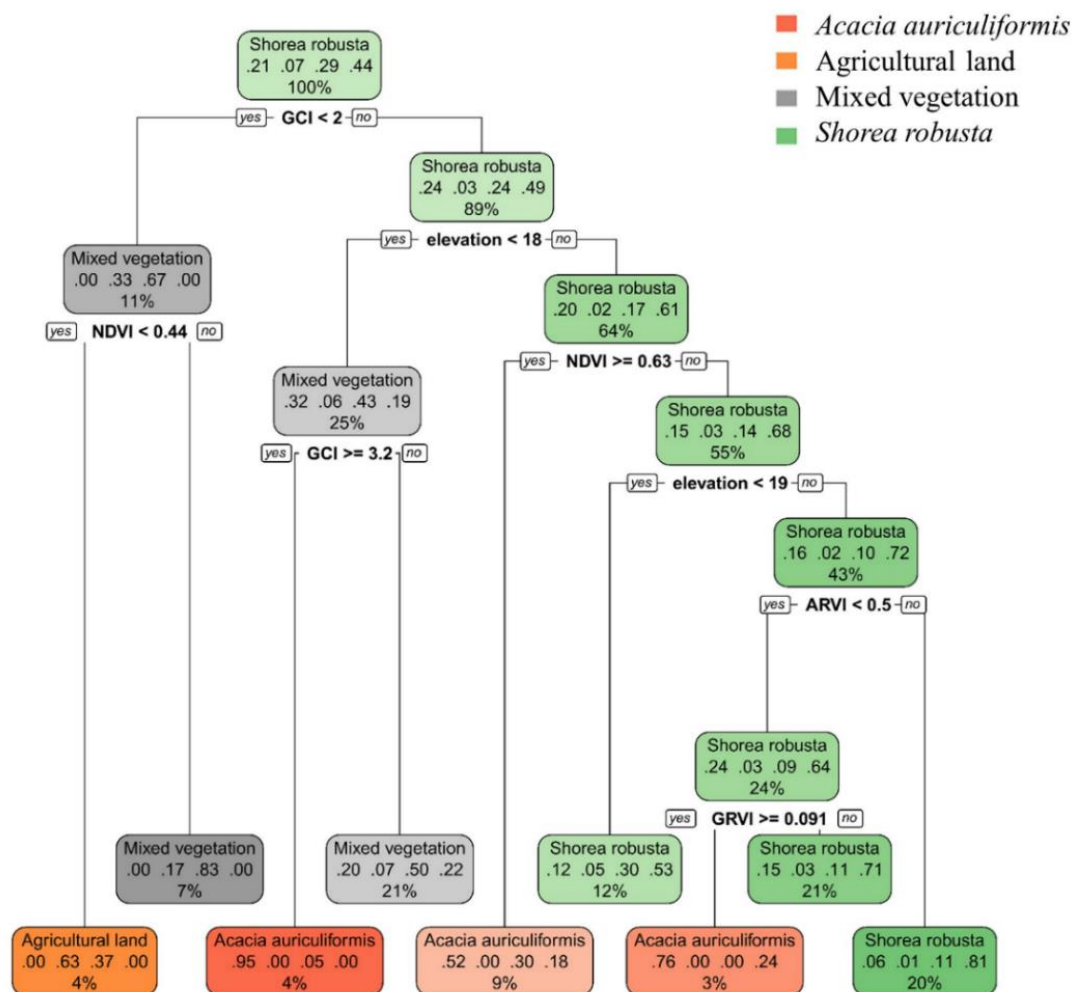


Figure 1-5. DT classification of vegetation classes in winter. DT utilized a combination of VIs and elevation as predictors for the classification. For details on the other seasons, see in the text.

1.3.4. A. auriculiformis detection by multispectral composited seasons and multi-season image classification by RF

The spectral reflectance and seasonal fluctuations in VIs were used to distinguish IAP from native vegetation using multi-class image classification approach with RF (**Figure 1-6**). RF produced the highest OA of 90% ($\kappa = 0.88$) in winter due to distinct spectral characteristics among classes. In summer, OA was 86% ($\kappa = 0.85$). Similar spectral characteristics during monsoon and autumn resulted in lower OA of 73% ($\kappa = 0.69$) in autumn and OA of 76% ($\kappa = 0.71$) in monsoon. Combining multispectral reflectance data from all seasons as a multi-season image improved classification compared to specific seasons (monsoon and autumn), with an OA of 83% ($\kappa = 0.80$). Although lower than the accuracies for winter and summer, it was higher than those for autumn and monsoon. These results demonstrated that multi-season data enhanced vegetation mapping by capturing diverse phenological variations; however distinct seasonal spectral characteristics captured by VIs achieved higher accuracy in specific seasons to classify *A. auriculiformis* and others.

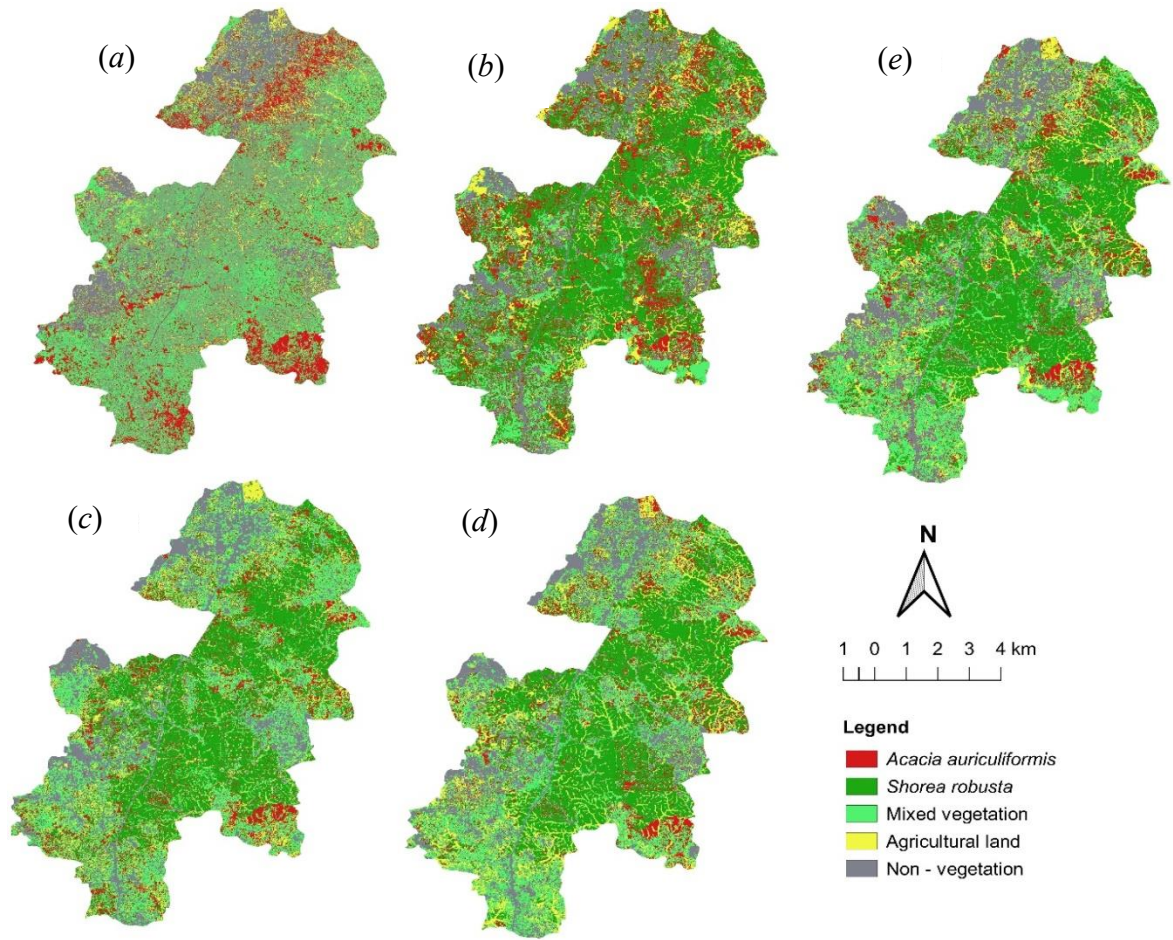


Figure 1-6. RF generated classification maps in winter (a), summer (b), monsoon (c) and autumn (d) with multi-season (e).

1.3.5. Classification accuracy with different model combinations on seasons and multi-season images

The classification accuracies obtained by RF were enhanced when reflectance data of multispectral images (MSI), VIs and elevation were combined (**Figure 1-7**). The OA of classifications were 73%, 76%, 86% and 90% in autumn, monsoon, summer, and winter. The κ was 0.69 in autumn, 0.71 in monsoon, 0.85 in summer, and 0.88 in winter, showing the highest OA in winter when the deciduous trees were defoliated. The OA of multi-season improved to 83% with $\kappa = 0.81$, compared to OA of 76.8% with $\kappa = 0.71$ without combination. Employing GEE, RF was trained using spectral data, VIs and elevation. When NDVI was combined with classification, the accuracy was 82% in winter ($\kappa = 0.78$), 83% in summer ($\kappa = 0.81$), 65% in monsoon ($\kappa = 0.57$), 63% in autumn ($\kappa = 0.56$), and 77.8% in multi-season ($\kappa = 0.72$). When elevation was added in the model, the accuracy increased to

88% in winter ($\kappa=0.86$), 82% in summer ($\kappa=0.79$), 65% in monsoon ($\kappa=0.57$), 65% in autumn ($\kappa=0.58$), and 79% in multi-season ($\kappa=0.79$). These results indicated that elevation played a significant role in classification.

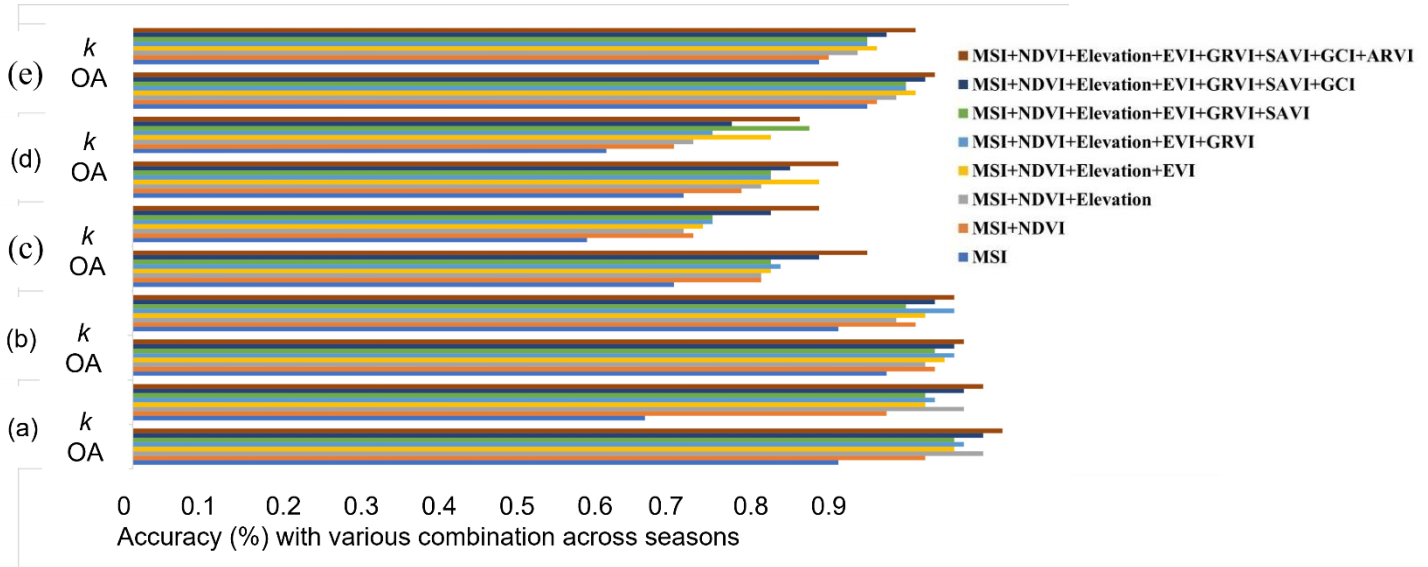


Figure 1-7. Overall accuracy (OA) and κ on the vegetation classification conducted by RF on (a) winter, (b) summer, (c) monsoon, (d) autumn, and (e) multi-season with various model combinations.

When all the VIs and elevation combined with multispectral reflectance data, OA reached a maximum of 90% in winter ($\kappa=0.88$), 86% in summer ($\kappa=0.85$), 76% in monsoon ($\kappa=0.71$), 73% in autumn ($\kappa=0.69$), and 83% in multi-season ($\kappa=0.81$). High accuracy in winter and summer highlighted the ability of VIs to capture key phenological traits with specific spectral bands, while multi-season data enhanced accuracy by reducing spectral similarities. These results indicated that elevation affected the distribution of vegetation classes, even with a difference of only 10 to 15 m.

1.4. Discussion

1.4.1. Assessing the better strategy: binary vs multi-class

The binary classification required fewer samples for supervised training but sometimes increased misclassification. Adjusting subclasses from multi-class classification reduced this misclassification (Zhao and Qin, 2022). In multi-class classification, four vegetation classes and one non-vegetation class were extracted by spectral reflectance from different seasons and multi-season images. By considering multiple classes, the multi-class approach produced higher accuracy. The classification accuracy was linked to spectral differences between species, reflecting the actual distribution of vegetation classes (Ferreira et al., 2016). However, the clear distinction between Agricultural land and other vegetation classes facilitated the differentiation of *A. auriculiformis* in multi-class classification.

1.4.2. Seasonality of VIs: advantages and disadvantages

Unique seasonal patterns in the spectral reflectance were observed, particularly on GRVI, GCI and NDVI in winter and on NDVI, ARVI and GCI in summer. In monsoon and autumn, vegetation classes were not well-classified, likely due to dense vegetation growing.

GCI effectively detected *A. auriculiformis* in winter and summer by highlighting persistent green vegetation. GCI is sensitive to chlorophyll content (Sun et al., 2024), accurately detecting phenological differences (Nadjla et al., 2022).

Similarly, NDVI was higher for *A. auriculiformis* in winter and summer than for the native deciduous forests. Evergreen trees show leaf shedding in early summer but flush leaves earlier than deciduous trees (Negi, 2006), allowing *A. auriculiformis* detection by NDVI in these seasons.

GRVI detected *A. auriculiformis* only in winter, indicating its limited year-round applicability. However, GRVI effectively identified plant phenology and separated dense vegetation (Nagai et al., 2012). In summer, *A. auriculiformis* were extracted by high ARVI, distinguishing them from *S. robusta* and Mixed vegetation. ARVI also distinguished *A. auriculiformis* from Agricultural land, although ARVI on Agricultural land was higher than that on *A. auriculiformis*, reflecting high productivity (Idol et al., 2017).

Winter and summer VIs (NDVI, GRVI, GCI, and ARVI) played key roles in distinguishing deciduous and evergreen vegetation by capturing phenological differences. Using seasonal fluctuations of multiple VIs provides valuable insights for monitoring the temporal dynamics of invasive species.

1.4.3. Effectiveness of combination of VIs and elevation

The combination of multiple VIs with elevation increased the accuracy of land use and land cover classification. The differences in VIs were linked to the spectral behavior of the evergreen and deciduous species throughout the seasons, as well as to the images derived from red and NIR bands of Sentinel-2A (Masemola et al., 2020). In winter and summer, the deciduous vegetation is exposed due to leaf-off in the study site, and the analysis of VIs demonstrated a clear distinction between *A. auriculiformis* and native vegetation. The combined use of all VIs and elevation highlighted the importance of selecting VIs for the classification because spectral values capture phenological traits (Caparros-Santiago et al., 2021).

Elevation, as a topographic feature, determined vegetation distribution, including *A. auriculiformis*, even with small elevation differences (Liu et al., 2019). Therefore, elevation should be examined even if the topography is flat.

1.4.4. Assessment of RF classification

The accuracy of classification was low in winter when DT was employed with multiple VIs and elevation. Higher accuracy was observed during monsoon due to the higher spectral reflectance of trees. In winter, vegetation class reflection was insufficient for tree classification (Wu et al., 2017). DT leads the high classification accuracy when the training data are sufficient (Friedl and Brodley, 1997).

Using RF with VIs and DEM, detection of *A. auriculiformis* was highest in winter and lowest in autumn. High OA observed in winter, summer and multi-season images indicated well-characterized phenological differences among tree species. The multispectral image classification effectively classified vegetation. VIs improved target species identification by refining spectral signatures, distinguishing *A. auriculiformis* from remaining classes (Anuar et al., 2022). The elevation data improved classification with geomorphologic attributes (Zhu and Liu, 2014). Dense vegetation during monsoon and autumn complicated class differentiation. The study showed that VIs focusing on key phenological traits enhanced accuracy in specific seasons. This approach highlighted the effectiveness of RF classification using phenological data and the integration of spectral, VIs and elevation for vegetation mapping.

1.5. Conclusion

Seasonal variations in VIs helped to identify the optimal periods for acquiring RS imagery, enhancing mapping accuracy by distinguishing invasive plants from natives. Fluctuations in VIs were observed in winter and summer, reflecting leaf phenology. The study showcased the effectiveness of multispectral images, VIs and elevation using the GEE platform across seasons to identify *A. auriculiformis* within Bhawal National Park. NDVI, GRVI and GCI extracted evergreen invasive *A. auriculiformis* effectively from native deciduous forests in winter, due to phenological differences (Bradley, 2014). ARVI, NDVI and GCI also detected *A. auriculiformis* in summer. RF classification in two steps showed comparable performance. Composited datasets from all seasons improved identification, as seasonal variations in spectral reflectance at various wavelengths increased invasive species detection (Holland and Aplin, 2013). However, specific seasons captured the species phenological traits more effectively. One limitation is the use of VIs derived only from Sentinel-2A imagery with a resolution of 10 m. Integrating fine-resolution data generally improves identification. Nevertheless, this research established a precise method of detecting and monitoring the spread of invasive plants by RS and machine learning. This contributes to the understanding of effective conservation strategies and supports global efforts in combating biological invasions at a large scale.

Chapter 2

Applicability of phenological spectral features to map invasive plants in tropical moist deciduous forests

2.1. Introduction

Invasive plants harm biodiversity and the environments by disrupting native vegetation and habitats (Tian et al., 2020). The detection of the spread of invasive species is essential for ecosystem and biodiversity conservation (Bhaveshkumar et al., 2024). Remote sensing (RS) is effective in mapping invasive species, using phenological informations from multi-temporal image data (Xu et al., 2021). Phenological variations have been recognized as a key indicator for detecting invasive species from the native vegetation (Bradley, 2014). Vegetation phenology refers to the seasonal changes in plant growth, including greening, maturing, shedding leaves, and dormancy that varies by species and aids in distinguishing vegetation classes (Huang et al., 2025). Phenological information increases tree species mapping accuracy, as different species have unique phenological patterns, and their spectral characteristics during leafless or senescence improve species identification (Li et al., 2022). Time-series images of Sentinel-2A (10 m resolution) obtained from Google Earth Engine (GEE) catalogue were used for mapping invasive species, because time-series images have proven to be more effective in mapping tree species (Kollert et al., 2021). *A. auriculiformis* C. Cunn. ex Benth., an evergreen invasive tree, is widely spread across Bhawal National Park, a protected area in Bangladesh and expand in warm, humid climates (Foster-Turley et al., 2016; Heringer et al., 2019). The forest class of the area belongs to a tropical moist deciduous forest (Toma et al., 2022). The park is now experiencing drastic land use changes that led to habitat fragmentation (Alauddin et al., 2020), and this fragmentation is linked to the spread of IAPs, as landscape disturbance influences invasion dynamics (Dodet and Collet, 2012).

In this study, the phenological spectral difference between *A. auriculiformis* and the coexisting native deciduous forests during specific phenological periods were examined and an index was proposed to increase spectral separability using time-series RS data. The multiple phenological periods were observed by constructing temporal profiles using multiple vegetation indices (VIs). The ability of phenological spectral features was tested on Random Forest (RF), Support Vector Machine (SVM) and the Classification and

Regression Tree (CART) to discriminate invasive species from the native deciduous forests. RF uses decision tree-based framework, because it is used for classifying invasive species (Bhaveshkumar et al., 2024). SVM requires limited training data and prevents overfitting, which improves classification (Grabska et al., 2020). CART is convenient to use with a large training dataset (Arasumani et al., 2021). All image classification was conducted using GEE platform. While **Chapter 1** demonstrated how seasonal VIs with topography supported classification strategies, this chapter focuses on developing phenology-specific indices to refine spectral separability based on growth cycles.

The objective of the study is to (1) develop phenological spectral features-based index (PVI) by compositing images from key phenological periods, (2) calculate spectral separability index (SI) for *A. auriculiformis* separation and (3) apply multiple machine learning classifiers for mapping the distribution of *A. auriculiformis*.

2.2. Data and Methods

2.2.1. Study site

The study was conducted in Bhawal National Park, located 40 km north to Dhaka, the capital city of Bangladesh (24°01'N, 90°20'E) (**Figure 2-1**). The park covers 50.2 km² and is designated as a protected area by IUCN Management Category IV in 1982. It is classified as a tropical moist deciduous forest (Toma et al., 2022), dominated by endangered, deciduous tree, *S. robusta* Gaertner f. (Kabir and Ahmed, 2005). The climate is warm and humid (Islam et al., 2014) with seasonal variations where dry season observed in February to until mid-April and a wet rainy season from June to October (Shahid, 2010). Growing season/greenness is marked from June to November as vegetation attains its peak in the time of highest rainfall (Islam et al., 2021), while senescence (leaf-shedding) of native deciduous forests occurs in dry winter season (Costa et al., 2014). The area experiences a mean annual temperature of 25.6°C and annual precipitation of 2214 mm (Karim et al., 2023). *A. auriculiformis* (Fabaceae), a fast-growing evergreen species, has been planted across 26% of the forest area in the national park as a part of a plantation program by the Forest Department of Bangladesh and grows broadly in the site (Rahman et al., 2010b; Rangra et al., 2019). This species grows up to 30 m in height and attains a diameter of 30 cm at breast height at maturity, and its rapid growth even in nutrient-poor soils is supported by its nitrogen-fixing ability (Zerkout et al., 2021).

Sampling points used as ground truth for land use classes were recorded after defoliation in March 2022, excluding inaccessible locations. Coordinates for each point were measured by a portable Global Positioning System (Garmin Rino 750; Garmin Corporation, Taipei, Taiwan). These points were used to train and validate the classification.

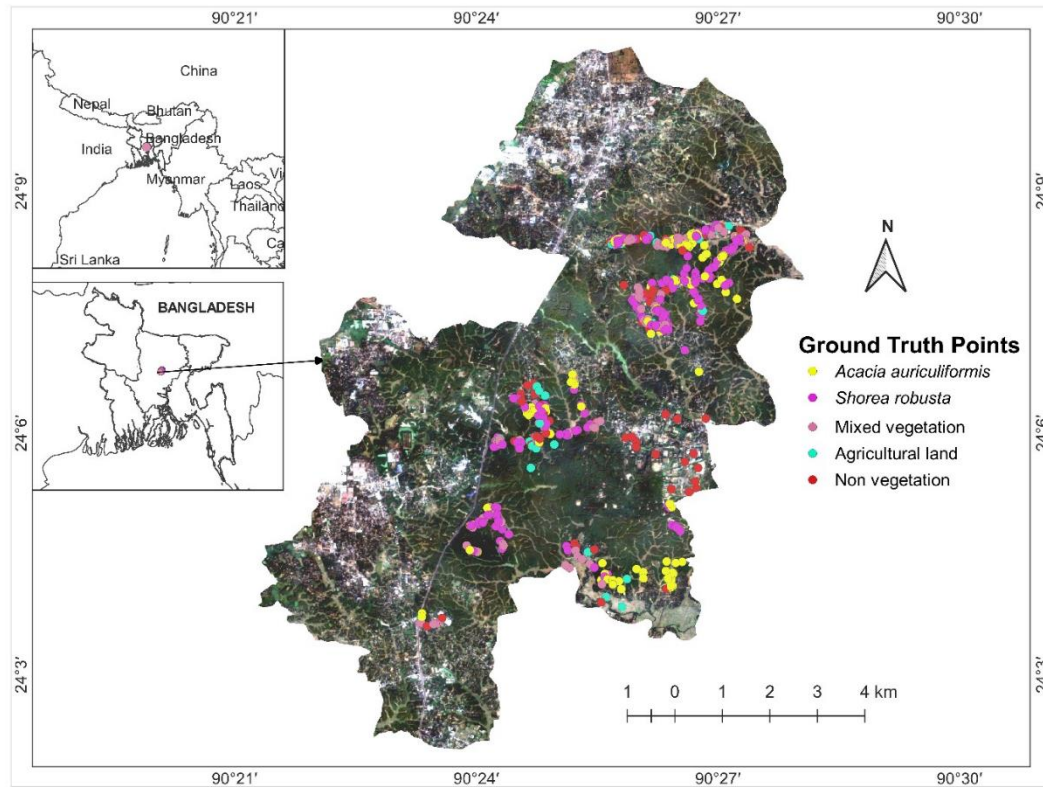


Figure 2-1. The ground truth points (color-coded circles) recorded by a portable GPS are mapped on Sentinel-2A images taken during winter (December 1, 2022, to March 15, 2023). Different colored circles show different land use classes. The upper left corner of the figure shows the study site location in Southwest Asia (top) and Bangladesh (bottom).

2.2.2. Datasets

The Sentinel-2A Multispectral Instrument (MSI) was used within GEE platform to map invasive species through time-series analysis. Sentinel-2A MSI captures 13 spectral bands: visible and near-infrared (NIR) at 10 m, red edge and shortwave infrared (SWIR) at 20 m, and atmospheric bands at 60 m spatial resolution. Surface reflectance indices derived from Sentinel-2A were used, offering data for monitoring vegetation dynamics. All available data from December 2022 to November 2023 (covering all seasons) were filtered on GEE for temporal analysis. Composite images containing phenological information were generated from the datasets.

Reference data were recorded throughout the study sites of various forest cover classes. The data were collected in March 2022 to train and validate the output. The sampling points were recorded by a portable GPS (Garmin Rino 750; Garmin Corporation, Taipei, Taiwan) and converted them into shape files in ArcGIS 10.8. To analyze their phenological spectral features, three classes of forest cover (*S. robusta*, *A. auriculiformis* and Mixed vegetation) were made based on the field data.

2.2.3. The phenological spectral feature analysis

2.2.3.1. Cloud masking

The cloudy pixel was removed to filter Sentinel-2A images in the study site by cloud mask function on GEE. The function was performed using 10th and 11th bits of QA60 bitmask band that contains cloud mask information (Wang et al., 2021). The images with less than 5% cloud cover were used for the analysis.

2.2.3.2. Identifying key phenological periods

The spectral signatures of the three identified classes using all the data on selected years were used. The temporal profiles of three spectral vegetation indices (VIs) were calculated based on the green, blue, red, and NIR bands of Sentinel-2A and identified the phenological periods of vegetation classes. The VIs used in this study are as follows:

- i. Normalized Difference Vegetation Index (NDVI)

$$= (\text{NIR} - \text{red}) / (\text{NIR} + \text{red})$$
, where NIR is near-infrared (Tucker, 1979). NDVI is useful for measuring vegetation health; related to green cover and biomass (Sapkota et al., 2025).
- ii. Green-Red Vegetation Index (GRVI)

$$= (\text{green} - \text{red}) / (\text{green} + \text{red})$$
, to detect dense vegetation, especially the forest canopy (Shishir and Tsuyuzaki, 2018).
- iii. Atmospherically Resistant Vegetation Index (ARVI)

$$= [\text{NIR} - (2 \times \text{RED}) + \text{BLUE}] / [\text{NIR} + (2 \times \text{RED}) + \text{BLUE}]$$
, to reduce the interferences of atmospheric moisture, particularly in tropical regions affected by ash from slash-and-burn agriculture (Kureel et al., 2022).

After analyzing the temporal profile of VIs, two phenological periods were determined: senescence period from February to April and green period from June to November. The senescence period represents the aging stage of plants that signifies their

deterioration, while green period is when plants are actively growing, represents healthy vegetation (Caswell and Salguero-Gómez, 2013). Evergreen *A. auriculiformis* showed different phenological patterns compared to native deciduous forests. *A. auriculiformis* trees maintained high VI throughout the year (**Figure 2-2**), while deciduous forests showed low VI during the senescence periods. All species showed high VIs during the green period.

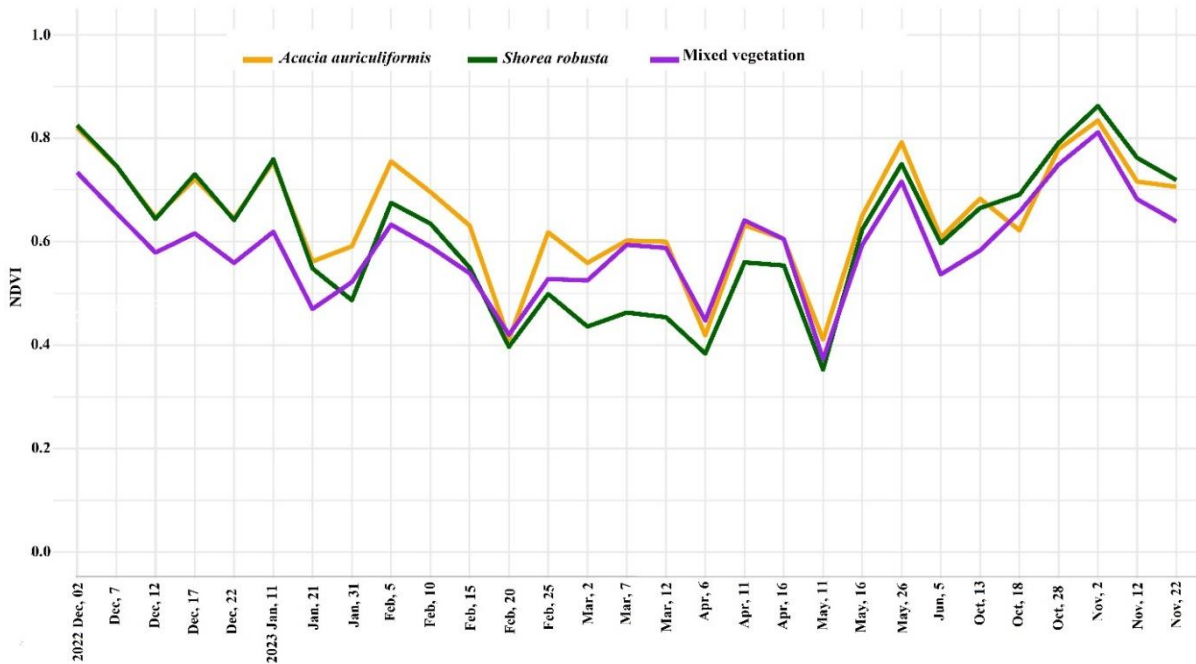


Figure 2-2. Temporal profile of NDVI corresponding to *A. auriculiformis*, *S. robusta* and Mixed vegetation

2.2.3.3. Phenological features based image composition

From each VIs, two distinct seasonal composite images were generated to capture the phenological variability: VI in senescence period (seVI) and VI in green period (grVI). The seVIs and grVIs indicated spectral reflectance differences calculated from the training samples of *A. auriculiformis*, *S. robusta* and Mixed vegetation. The seVI comprised seNDVI, seGRVI and seARVI, while the grVI comprised grNDVI, grGRVI and grARVI, corresponding to the senescence and peak greenness periods, respectively. These composite processes minimized spatial phenological variation (Tian et al., 2020).

A new composite image was created by combining the grVIs and seVIs into a single composite vegetation index (CVI) by the median pixel of each period. Finally, from CVIs,

the phenological spectral feature-based indices (PVI) were calculated for each VI: namely PNDVI, PGRVI and PARVI. These VIs were designed to reflect seasonal changes in vegetation by capturing the variations in spectral signals. The following two equations (Bhaveshkumar et al., 2024; Xu et al., 2021) were used:

- i. $CVI = seVI + gVI$
- ii. $PVI = CVI / (CVI_{max} - CVI_{min})$, where CVI_{max} and CVI_{min} indicate maximum and minimum of calculated CVIs, respectively.

The generated images offered a standard approach for capturing phenological characteristics of plants species (Tian et al., 2020). The inter-class variabilities for spectral separability of *A. auriculiformis* from *S. robusta* and Mixed vegetation were calculated by separability index (SI). SI was calculated by following equation (Xu et al., 2021):

$$SI_{aj} = \Delta_{interaj} / \Delta_{intraaj} = (\mu_a - \mu_j) / 1.96 \times (\sigma_a + \sigma_j),$$

where SI_{aj} referred to the SI between *A. auriculiformis* and one of the other two classes (denoted as *a* and *j* respectively). μ and σ denoted mean VI and standard deviation of PVI, respectively, for classes *a* and *j*. Higher SI indicated higher separability between classes.

2.2.4. Mapping invasive *A. auriculiformis* distribution

Using phenological differences among vegetation classes, pixel-based image classification was applied using RF, SVM and CART. PNDVI, PGRVI and PARVI were added into image classification on RF, SVM, and CART. RF is an ensemble method for land cover classification using multispectral and hyperspectral images, offering higher accuracy and noise robustness than single classifiers (Rebelo et al., 2021). SVM is a supervised classification method that separates data into classes using an optimal decision boundary with the help of training data (Kaul and Raina, 2022). CART creates DT by splitting data at a point and cutting unnecessary parts to reduce overfitting (Bhaveshkumar et al., 2024). The accuracy of the classifications was assessed using a set of ground truth points recorded from the field observations with confusion metrices and kappa coefficients (κ) (Aji et al., 2023; Kuplich, 2006).

2.3. Results

2.3.1. Analysis of time series of different indices

The temporal profile of each VIs showed distinct phenological features of *A. auriculiformis* from the native species (**Figure 2-3**). *S. robusta* exhibited a seasonal cycle, with peaking VIs in green period and declining in senescence period. In contrast, *A. auriculiformis* maintained constantly higher VIs throughout the year with less seasonal fluctuation, due to evergreen. The Mixed vegetation showed intermediate VIs due to the mixture of deciduous and evergreen trees.

NDVI for the green period reached up to 0.83 for *A. auriculiformis*, 0.84 for *S. robusta* and 0.81 for the Mixed vegetation. NDVI in senescence was 0.35 to 0.67 for *S. robusta* and Mixed vegetation, while it was higher for *A. auriculiformis* from 0.45 to 0.77.

The temporal profile of GRVI showed higher for *A. auriculiformis* in senescence than *S. robusta* and Mixed vegetation. The ARVI profile was stable for *A. auriculiformis* in the senescence.

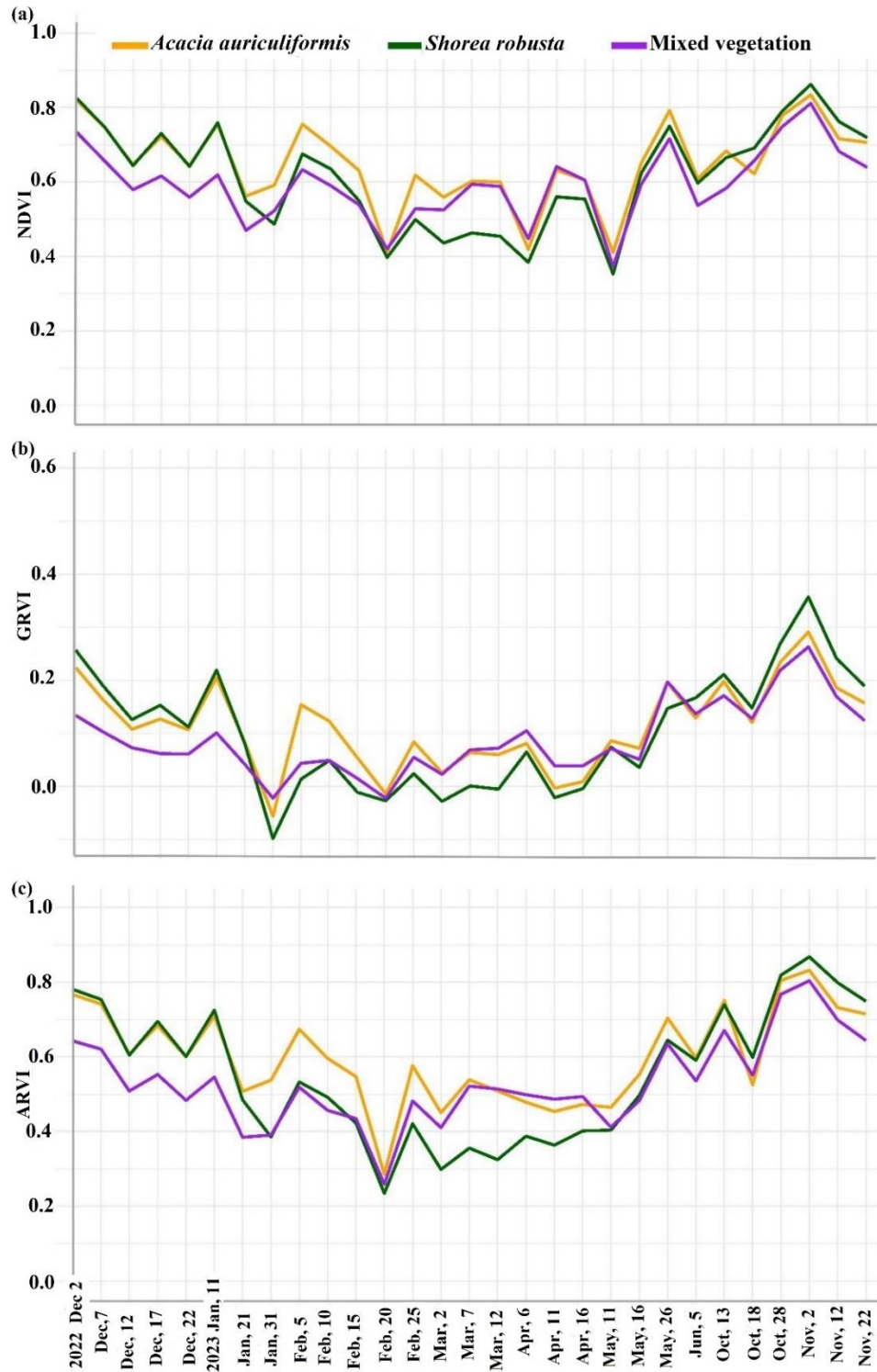


Figure 2-3. Temporal profile for different VIs for year 2022 to 2023: (a) NDVI, (b) GRVI and (c) ARVI

2.3.2. Separability analysis

seVIs indicated differences in spectral reflectance among vegetation classes in senescence period (**Figure 2-4**). The three distinct curves were obtained by spectral patterns among the classes. *S. robusta* showed a sharp peak around 0.53 to 0.56, indicating homogeneously and moderately green vegetation. Mixed vegetation displayed a broader distribution centered around 0.50 to 0.53, reflecting moderate greenness with variability. *A. auriculiformis* has a flatter, more spread-out curve with a peak around 0.58 to 0.60, suggesting higher and more variable greenness during senescence compared to *S. robusta* and Mixed vegetation. The result demonstrated that seVIs was effective in separating *A. auriculiformis* from the native vegetation during the senescence period.

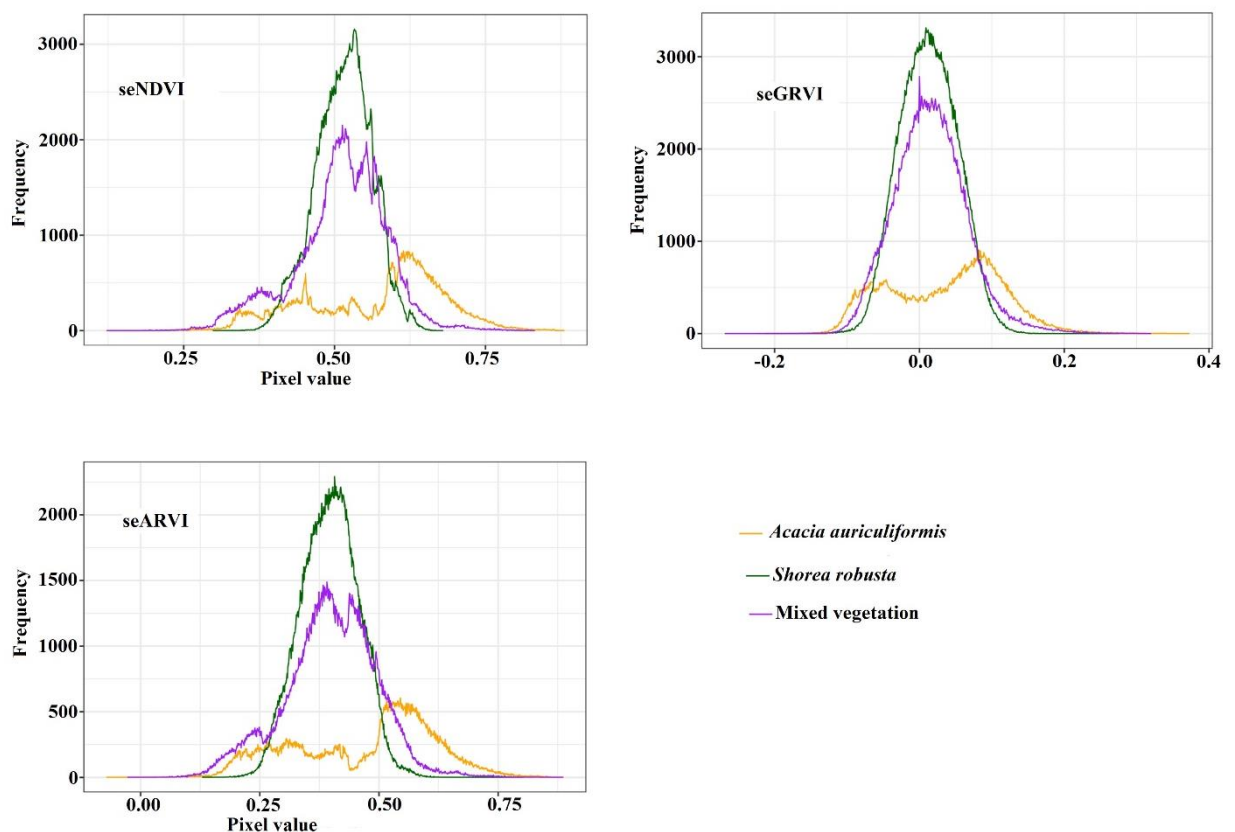


Figure 2-4. Frequency curves of VIs in senescence period (seNDVI, seGRVI and seARVI)

The frequency curves of VIs in the green period (grNDVI, grGRVI and grARVI) showed the changes in frequency and pixel values for each class (**Figure 2-5**). The range of grVIs of *A. auriculiformis* had a large overlap with *S. robusta* and Mixed vegetation

classes, indicated the higher vegetation greenness made *A. auriculiformis* detection difficult. However, the frequency curves showed potential overlap in pixel values for inter-class separability, resulting in mixed pixel values and decreased classification accuracy.

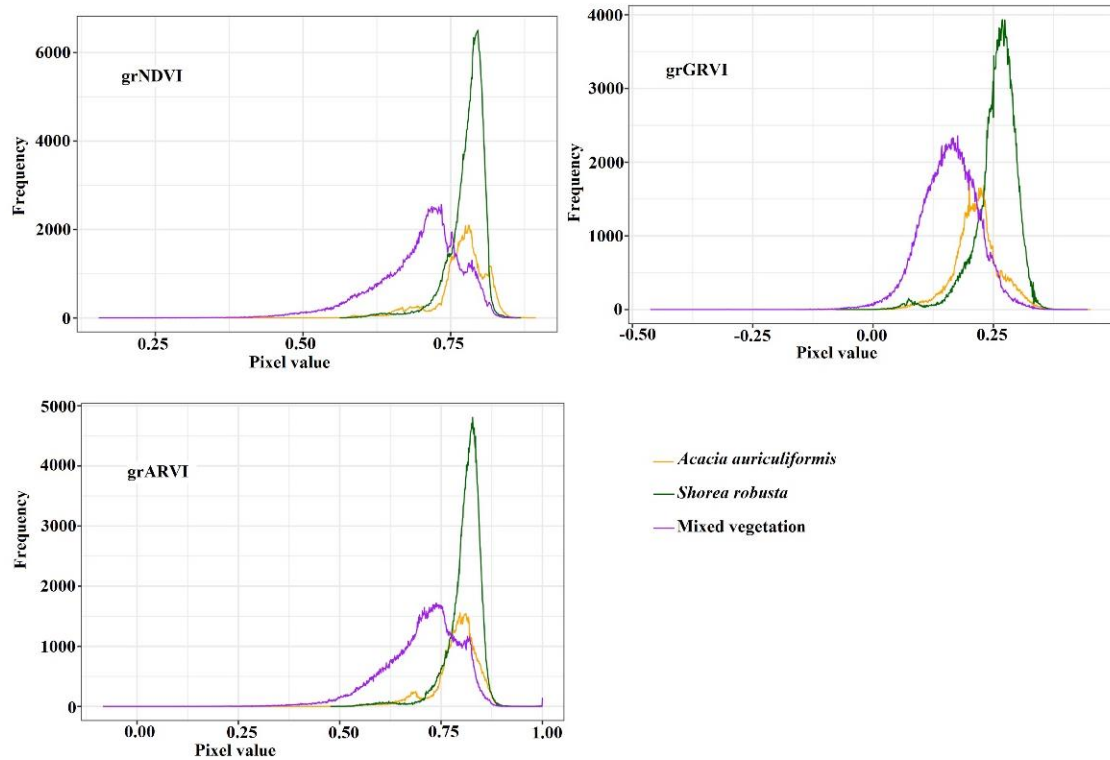


Figure 2-5. Frequency curves of VIs in green period (grNDVI, grGRVI and grARVI)

PVIs reduced the greenness overlap in grVIS and seVIs. The frequency curve of PNDVI and PARVI showed effectiveness in inter-class variabilities among classes by neutralizing peak greenness during the green and senescence periods (**Figure 2-6**). For example, in PNDVI, *A. auriculiformis* presented a flatter distribution with higher pixel value, peaking near 0.59. *S. robusta* exhibited a sharp, narrow peak around 0.55, reflecting spectral consistency. Mixed vegetation showed intermediate variability. The inter-class variability, particularly in the range of 0.50 to 0.63, supported effective differentiation of *A. auriculiformis* from *S. robusta* and Mixed vegetation using pixel thresholding in PNDVI. The results indicated that *A. auriculiformis* had distinctly higher PVI values, especially during the senescence and transitional times, compared to *S. robusta* and Mixed vegetation. These consistent spectral differences enabled clear separation based on PVI.

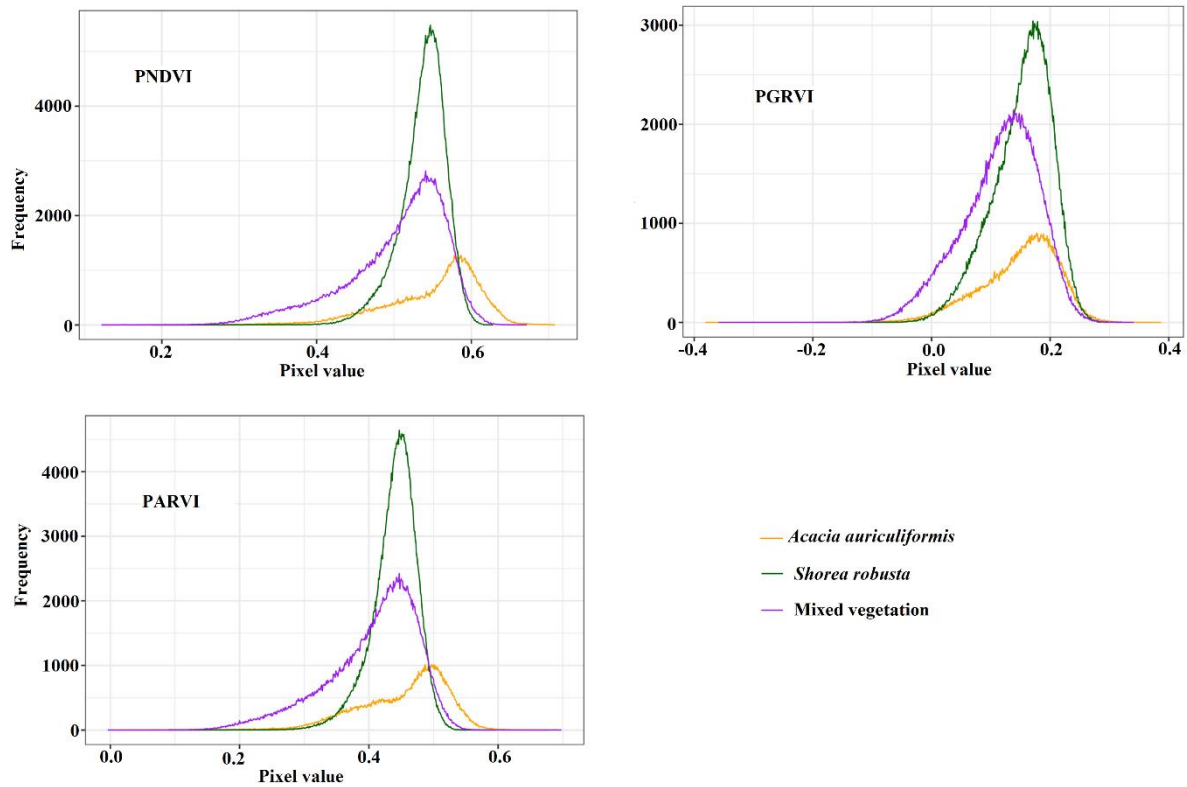


Figure 2-6. Frequency curves of PVI indices (PNDVI, PGRVI and PARVI)

Figure 2-7 shows the spectral separability (SI) value of seVIs, grVIs and PVI indices. The seVIs achieved higher separability index (SI) values ($SI > 0.25$) compared to PVI indices and grVIs when distinguishing *A. auriculiformis* from both *S. robusta* and Mixed vegetation. In contrast, grVIs yielded the lowest SI values ($SI < 0.03$), indicating that *A. auriculiformis* is more spectrally distinct during the senescence period than in the green period. Among all indices, PARVI exhibited the highest separability, with an SI of 0.41 in distinguishing *A. auriculiformis* from *S. robusta* and 0.18 from Mixed vegetation. This result demonstrated PARVI and seARVI were the most effective indices for capturing phenological contrasts and maximizing class separability during senescence.

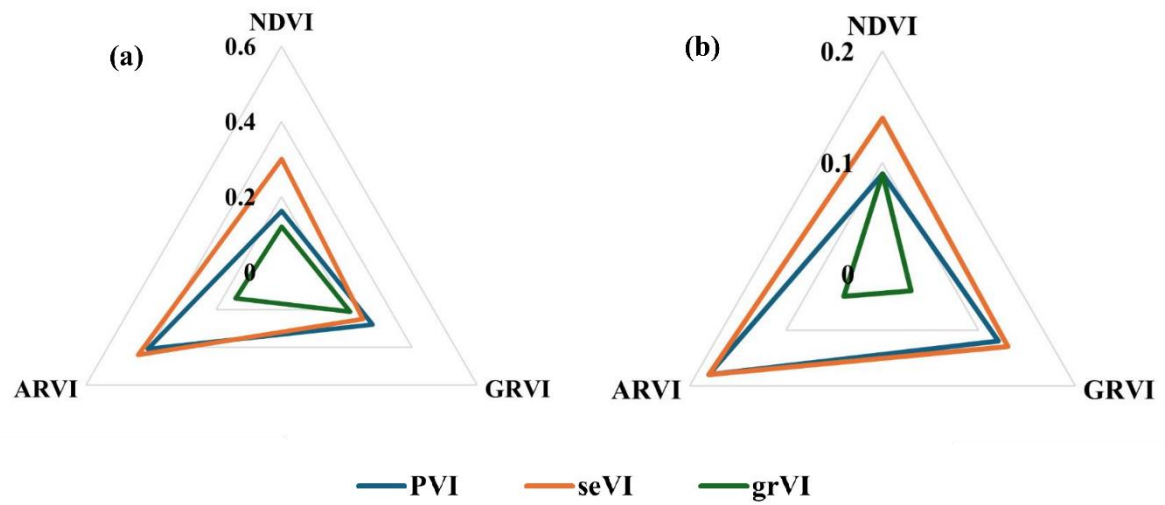


Figure 2-7. SI value of the VIs between different classes: (a) *A. auriculiformis* vs *S. robusta* and (b) *A. auriculiformis* vs Mixed vegetation

2.3.3. Classification performance evaluation

Supervised classification using RF, SVM and CART based on the PVIs effectively mapped the distribution of *A. auriculiformis* in the study site (**Figure 2-8**). The mapping showed that machine learning algorithms assisted distinguishing invasive species from the native vegetation and land cover classes. Due to spectral similarities observed among vegetation classes, this study aimed to evaluate the efficiency of each classifier in using phenological spectral characteristics to improve class separability.

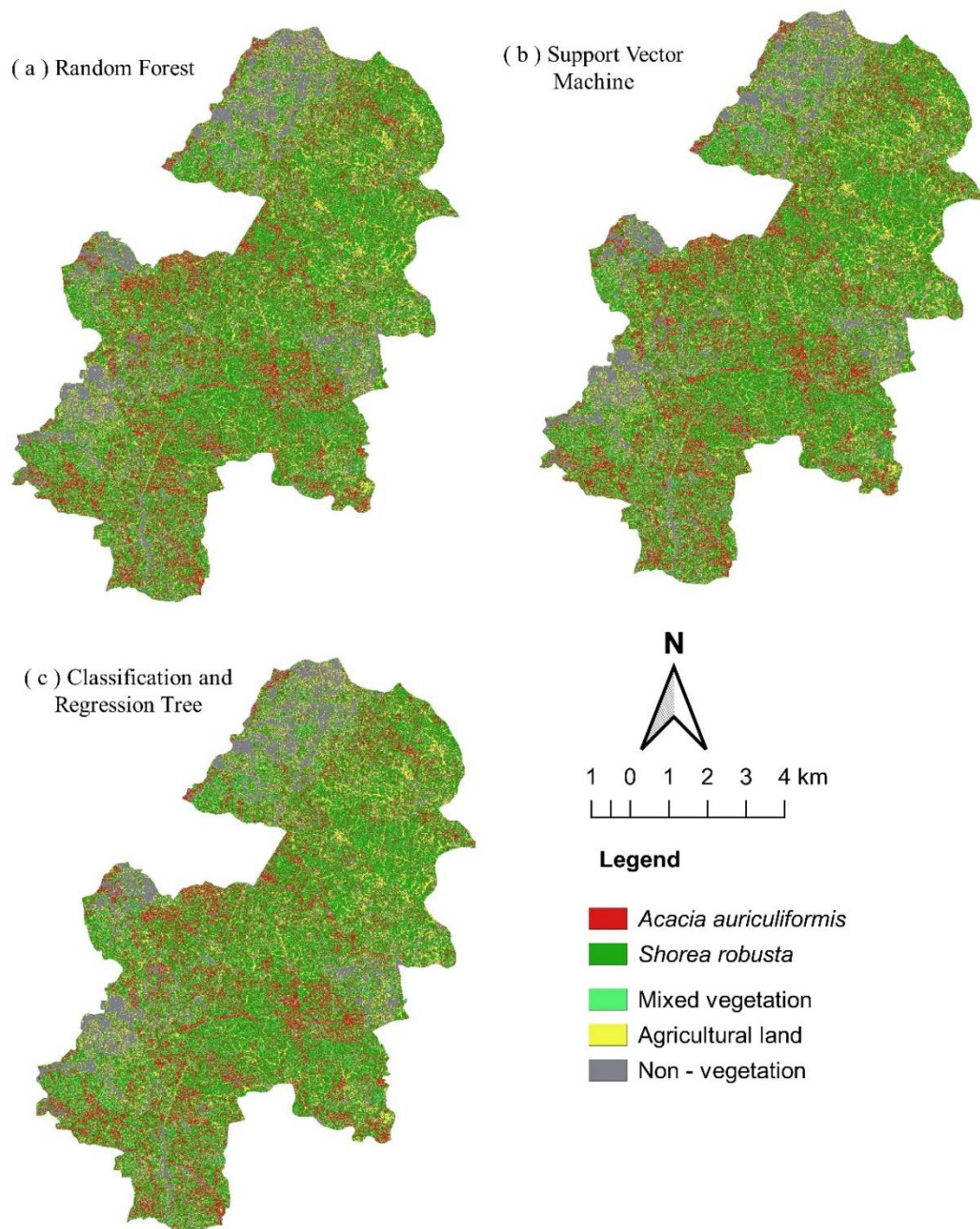


Figure 2-8. Separation and distribution of *A. auriculiformis* from vegetation and land cover classes using different algorithms: (a) RF, (b) SVM and (c) CART.

Among the three tested classification models, RF achieved the highest accuracy (overall accuracy, OA = 87%) with κ of 0.83, demonstrating its effectiveness to detect *A. auriculiformis*. SVM followed with an OA of 82% with κ of 0.78, while CART exhibited the lowest performance (OA = 63% with a κ of 0.42). Therefore, RF was the most effective for mapping *A. auriculiformis* due to its ability to operate high-dimensional spectral data.

RF can capture complex patterns of spectral overlapping between invasive and native vegetation in certain phenological periods. In addition, incorporating phenological spectral features across phenological periods improved classification accuracy. The enhanced inter-class spectral separability reduced the misclassification and improved *A. auriculiformis* discrimination from vegetation classes. Selecting the classifier and leveraging phenological spectral characteristics were important for invasive species mapping.

2.4. Discussion

2.4.1. Usefulness of phenological spectral features

A phenological composite incorporating senescence and green periods in VIs was examined by the spectral separability on vegetation classes. The method maximized the inter-class separability by identifying and combining phenological characteristics in the vegetation classes. The time-series images obtained from multiple phenological periods improved the spectral separability of invasive species, because these images cover all seasons and key growth stages, aiding classify vegetation classes (Tian et al., 2020). Also, the phenological changes in VIs improved mapping accuracy by highlighting unique spectral patterns on each species (Li et al., 2022). The utilization of these attributes had proven to be effective in enhancing spectral separability because of specific phenological pattern of species (Fang et al., 2020).

Two important phenological periods were identified to separate *A. auriculiformis* from other vegetation classes. The phenological periods examined from the time-series analysis effectively captured the key seasonal traits essential for detecting *A. auriculiformis* without redundancy because time series data is able to capture differences in surface reflectance related to phenological variation among vegetation classes (Hu et al., 2019). NDVI, GRVI and ARVI characterized the phenological spectral characteristics that developed PVIs. PVIs facilitated the inter-class separability by combining the phenological features from each vegetation class. Because the seVIs represented the green pixels in the senescence period, evergreen *A. auriculiformis* set it apart from native deciduous forests. In contrast, grVIs did not contribute to separate vegetation classes as trees were in their growing stage with dense canopy. During the green period, high biomass of all tree species led to mixed pixel structures (Khare et al., 2018). The seVIs were quick and effective because the leaf-off season created a strong spectral contrast between evergreen and deciduous species, making

their detection easier based on phenological difference (Bradley, 2014). However, seVIs were season-specific, depending on the timing of image acquisition. PVIs, the composite of senescence and green periods, facilitated the discrimination of *A. auriculiformis* by capturing its spectral reflectance in both phenological periods. PVI effectively traced plants growth cycles and phenological differences, making it valuable for vegetation mapping (Bhaveshkumar et al., 2024; Xu et al., 2021). The main advantage of PVI was its ability to generalize across time by compositing distinct phenological periods, therefore improved mapping accuracy for large-scale and long-term vegetation monitoring (Tian et al., 2020). Though PVI reduced misclassification, it may introduce complexity during processing multi-temporal data compared to using single-season indices like seVIs. However, seVIs are simple and performed well in senescence season but may be less effective at other times. PVI, though more complex, improved class separation and performed across seasons by using multi-temporal data (**Figure 2-7**).

SI indicated the potentiality of each VIs in enhancing inter-class spectral separability of *A. auriculiformis* from *S. robusta* and Mixed vegetation. Spectral separability increased when the phenological spectral features were added (Li et al., 2022). PARVI reached the highest separability that effectively improved the classification accuracy. The senescence period helped the most in enhancing separability between *A. auriculiformis* from *S. robusta*, along with Mixed vegetation class. The separation of *A. auriculiformis* was notified by considering the variation of plant phenological traits (**Figure 2-6**). Therefore, in this study it was effective to combine two phenological periods to separate invasive species.

2.4.2. Classification with the phenological spectral features

The phenological spectral feature-based VIs were applied to evaluate the performance improvement of RF, SVM, and CART in invasive species mapping in a protected area. The separability of PVIs can be explained by high spatial and temporal resolution of satellite images and composition technique. Machine learning algorithms relies on various features, e.g., field data, spectral, textural, and geometric features for classification, with classifier selection played a key role in accuracy (Bhaveshkumar et al., 2024). The freely accessible Sentinel-2A images with high spatial and temporal resolution were used for classification. The training data set was developed from field observations and used in classifications to classify land cover and vegetation classes for invasive species detection. The training dataset was carefully chosen, as it is essential for phenology-based feature selection and classification (Hu et al., 2019). The accuracy of all three classifiers considerably varied

when their performance was considered in classifying vegetation using their phenological features. In our study, RF outperformed SVM and CART classifiers, and produced highest OA and κ . The performance of RF indicated PVIs with image composition technique captured the greenest stage from both phenological stages, enhancing inter-class separability among vegetation classes. This was due to the performance of RF in land cover classification, especially in detecting invasive species within diverse vegetation (Belgiu and Drăguț, 2016; Rebelo et al., 2021). The senescence was observed in the deciduous forests started from late February to mid-March, while *A. auriculiformis* also experienced senescence but began leaf flushing earlier. This clear difference was detected using dense satellite time-series data, which helped to extract clearer spectral signatures of vegetation. The high accuracy of RF to detect *A. auriculiformis* using phenology-based VIs highlighted the value of considering phenological differences in invasive species mapping.

The distinct phenological differences were explored between *A. auriculiformis* and deciduous forests, with spectral separation improved by PVIs and seVIs. Since each vegetation class follows a unique growth rhythm and phenological pattern (Xu et al., 2021), these indices prove useful for classification.

2.5. Conclusion

This study demonstrated the effectiveness of indices derived by phenological spectral features for detecting and mapping an invasive species, *A. auriculiformis*, from the natives. Using VIs during both green and senescent periods, spectral separability was maximized. The senescence period proved to be most effective in distinguishing *A. auriculiformis* from other vegetation classes. The PVIs minimized the influence of greenness during the peak growing season, enhancing spectral separation. PARVI and seARVI were the most reliable indices for detecting *A. auriculiformis*, capturing subtle spectral variations in vegetation.

Incorporating phenological attributes improved the performance of machine learning classifiers, RF in this study, for mapping *A. auriculiformis* distribution. The use of high-resolution spatial and temporal time-series data differentiated invasive species from native vegetation, particularly during the senescence period. These findings can help ecologists and forest managers by showing when and how to detect invasive species accurately. This improved understanding supports and strengthens the global efforts to monitor and map invasive species to manage biological invasion more effectively.

Chapter 3

Remote Sensing-MaxEnt framework for monitoring and predicting the spread of invasive *Acacia auriculiformis* in a protected area

3.1. Introduction

Tree plantation is a strategy for mitigating degraded ecosystems after deforestation that leads to the loss of biodiversity and ecosystem functions (Lee et al., 2005). Fast-growing non-native trees, such as *Pinus*, *Acacia* and *Eucalyptus*, are often used for reforestation by transplantation and often invade disturbed habitats (Dodet and Collet, 2012). Transplanted invasive alien plant species (IAPs) alter both transplanted habitats and natural ecosystems (Makobe et al., 2024; Simberloff, 2000), leading to the extinction of endemic plant species (Dueñas et al., 2021). IAPs caused the extinction of 25% of plant species globally (IUCN, 2017). To protect endemic species, protected conservation areas (PAs) are essential for limiting the spread of IAPs (Bhatta et al., 2024). However, afforestation by IAPs has been performed in the Bhawal National Park, a protected area in Bangladesh, to reforest the area promptly (Rahman et al., 2010b). *S. robusta* Gaertner f., a native, deciduous, dominant tree, has been assigned as a least concern (LC) in the Red List (IUCN, 2017). The endemic forests, consisting of *S. robusta*, in the park have been threatened, mostly due to the spread of *A. auriculiformis* A. Cunn. ex Benth (Fabaceae) from the plantation (Masum et al., 2016; Rahman et al., 2010a).

Many alien species have traits that help them to invade new areas successfully (Dodet and Collet, 2012). The spread of IAPs is largely influenced by the combination of species-specific traits and environmental factors, particularly soil-disturbing disturbances like land use change, forestry, and increased accessibility (Cesar et al., 2017). Incorporating the anthropogenic viewpoint is crucial (Adionyi et al., 2024), as human-induced disturbances, e.g., land use changes accelerate the spread of non-native species, shaping their distribution pattern (Warziniack et al., 2021). Once established in these fragmented areas, non-native species migrate from human modified areas into natural forests using roads and other linear corridors for dispersal (Lázaro-Lobo et al., 2021). The detection of IAPs is desirable at the initial stages of invasion, because early detection promotes the prediction of potential sites for transplantation and invasion (Chiou et al., 2016; Santillan et al., 2021). Mapping the distribution of IAPs reveals introduction pathways, secondary spread patterns and invasion

prone land use class (Szymura et al., 2023). The Maximum Entropy species distribution model (hereafter MaxEnt) has been widely used to predict potential and initial distributions of IAPs (West et al., 2016), with an advantage that this model does not require absence data (Ma and Sun, 2018). Distribution of IAPs often lacks absence data (Václavík and Meentemeyer, 2009). MaxEnt investigates the relationships between species distribution and environmental factors (Moreno-Amat et al., 2015). This model has not been examined to afforestation well (Santillan et al., 2021), even though the immigration source of IAPs often originates from afforestation due to their fast-growth nature.

Mapping and predicting the spread of IAPs are the primary steps for controlling *A. auriculiformis* on a regional scale. The perception and management of *Acacias* are different around the world, with management practices influenced by environmental factors and disturbance patterns (Richardson et al., 2011). Predicting where invasive species may spread helps planners take quick action, manage risks and plan for long-term control (Bushi et al., 2023). Remote Sensing (RS) data was integrated with MaxEnt because RS is effective for detecting and mapping the distribution of IAPs at regional scale (Halmy et al., 2019; Rocchini et al., 2015), particularly at the initial invasion stages (Bradley, 2014). This study used RS data related to the phenology of plant species for the better understanding of habitat characteristics (Cord et al., 2014; Pettorelli et al., 2005). To examine the phenology on the modelling, I added vegetation indices (VIs) which are common RS indicators of vegetation dynamics (Schwager and Berg, 2021). Recent studies showed adding VIs in distribution model enhanced the habitat model performance (Wen et al., 2015). Therefore, this study combined RS with MaxEnt to detect and predict the distribution of *A. auriculiformis*, while determining the most relevant set of factors driving its distribution.

The major objectives were: (1) detect the current distribution of *A. auriculiformis*, (2) identify key environmental factors affecting the distribution and (3) evaluate the efficiency of RS with MaxEnt. This integrated framework can guide ecosystem conservations by prioritizing the management and monitoring of invasive species and offer valuable tools for ecological models to combat biological invasion.

3.2. Data and materials

3.2.1. Study site related to invasive species

Bangladesh has 17 national parks (Alauddin et al., 2020). Of them, Bhawal National Park (50.2 m²) was selected for the study, because of the large area and high biodiversity that is reduced by human-induced disturbances, including biological invasion (**Figure 3-1**). The transplantation of *A. auriculiformis* has been primarily conducted by the government lead plantation program and partly by illegal logging (Alauddin et. al., 2020; Masum et al., 2016). The park is a designated protected area (IUCN management category IV), located to 40 km north of Dhaka, the capital city of Bangladesh (24°01'N, 90°20'E) (**Figure 3-1**). The natural vegetation of this region is classified into tropical moist deciduous forest (Masum et al., 2016). The mean annual temperature is 25.6°C and annual precipitation is 2214 mm in this region (Karim et al., 2023). The topography in the forest area varies from 10 to 15 m above the surrounding floodplains (Islam et al., 2014). The predominant soil type ranges from red laterite to Pleistocene clay, with a clay content of 70% (Roy et al., 2024).

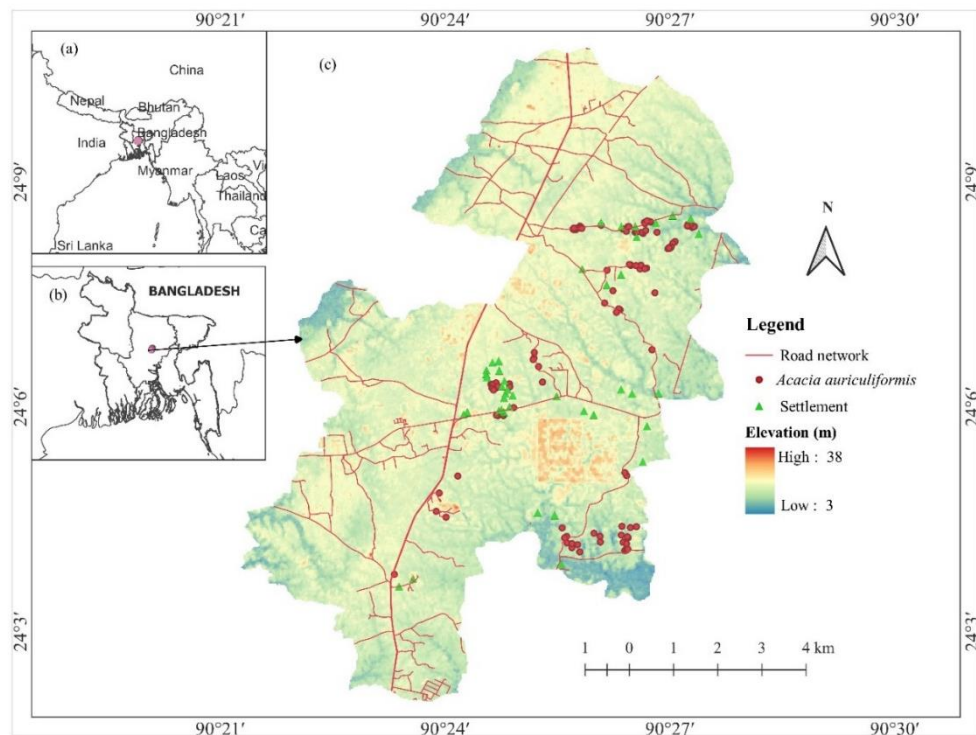


Figure 3-1. Topography of Bhawal National Park showing with the locations of *A. auriculiformis* (red circles) and settlement (green triangle) recorded in the field observations. The coordinates of the locations are determined by a portable GPS. The locations of the study site in Southwest Asia (top) and Bangladesh (bottom) are shown in the upper left corner of the figure. The road network of the area is also shown.

The Forest Department of Bangladesh practices exotic monocultures by the fast-growing exotic species, including *A. auriculiformis*, with a rotation period of 10 to 12 years in the park (Alauddin et al., 2020; Haque et al., 2021). *A. auriculiformis* has been planted in 26% of *S. robusta* forests by governmental led plantation program (Rahman et al., 2010b). Nowadays, *A. auriculiformis*, a nitrogen- fixing and evergreen tree, is commonly found in the protected area (Foster-Turley et al., 2016; Rangra et al., 2019). *A. auriculiformis* frequently outcompetes native flora and offers little support to wildlife, as it lacks edible fruits or nectar (Rahman et al., 2010a). Long-lived and easily dispersed seeds, disturbance-induced germination, water stress resistance ability, and flexible nitrogen-fixing symbiosis aid its easy spreading and impact the ecology (Hui et al., 2014). The tree grows up to 30 m in height and 30 cm in diameter at breast height when mature (Zerkout et al., 2021). *A. auriculiformis* thrives in warm climate with temperatures between 12°C and 34°C and humid environments with annual rainfall between 1000 mm and 4500 mm (Heringer et al., 2019). *A. auriculiformis* absorbs more nutrients with its deep roots, saves energy by its long-lasting leaves, and phenological difference, which together support its fast-growth and gain advantages of dominating native species (Morris et al., 2011; Smith, 2013).

3.2.2. Measurement of *A. auriculiformis* plantation

The distribution of *A. auriculiformis* was investigated by field observations in early March 2022. The presence of *A. auriculiformis* was recorded from 129 locations across study site. The forest patches, reflecting human-induced disturbances, were also chosen for handling MaxEnt for modeling the fragmented landscapes. The coordinates (latitude and longitude) on each location were marked by a portable GPS (Garmin Rino 750; Garmin Corporation, Taipei, Taiwan).

3.2.3. Measurement of environmental factors

To detect environmental determinants on *A. auriculiformis* distribution, eleven factors were examined by MaxEnt: annual precipitation (mm, hereafter, precipitation) and annual mean temperature (°C , temperature) as climatic factors obtained from the Terra Climate image collection, elevation (m) as topographic factor from the Advanced Land Observing Satellite (ALOS) digital elevation model (DEM, 12.5 m resolution) and organic carbon (OC, g/kg),

pH and nitrogen (N, g/kg) as soil chemistry factors from Open Land Maps. These data were accessed and handled through the Google Earth Engine (GEE) cloud computing platform and clipped to fit the study site (Gorelick et al., 2017).

To examine the effects of human activities, population density (/km²), distance from the nearest road (m, distance from road) and distance from nearest settlement (m, distance from settlement) were used. Population density was obtained from gridded population of the world (version 4) in 2020 with a resolution of 30 arc-second, approximately equivalent to 1 km grid cells through GEE. All types of human-made structures, such as household, educational institutes, shops, industries etc. were included as settlement. The locations of settlement were recorded during field observations and the distance from settlement was calculated using Sentinel-2A images (10 m resolution). Based on the digitization, distance from road were calculated. Euclidean distance from road and settlement to the surrounding areas were calculated using the Spatial Analyst tool in ArcMap 10.8.

VI was added to improve accuracy by capturing unique spectral features of tropical environments and reducing the atmospheric influence. Normalized Difference Vegetation Index (NDVI) and Green-Red Vegetation Index (GRVI) were calculated using composite images obtained in winter season (December to early March 2022) from Sentinel-2A (10 m resolution) from GEE:

- i. $NDVI = (NIR - red) / (NIR + red)$ (Tucker, 1979)
- ii. $GRVI = (green - red) / (green + red)$ (Yin et al., 2022)

The range of VIs is -1 to 1. The dissimilarities in the spectral reflectance were observed in winter between evergreen and deciduous vegetation due to the defoliation of deciduous trees. NDVI detects various forest by reflecting seasonal changes in leaf phenology (Jiang et al., 2014), while GRVI extracts dense and green vegetation (Shishir et al., 2020). These VIs helped the model to accurately detect the presence of *A. auriculiformis* by enhancing its discriminatory power.

To harmonize environmental layers with varying spatial resolutions, all the layers were resampled to a uniform resolution of 10 m using the bilinear resample technique in ArcGIS 10.8 and reprojected to WGS84 coordinate system. The resampling method ensures data consistency (Li et al., 2025) and also, matches their geographic extent (Padalia et al., 2014). Since all environmental factors were obtained by raster format, these data were converted to vector format prior to input into MaxEnt. Because spatial autocorrelations among the

environmental factors led overestimation of the predicted distribution (Zhang et al., 2019), the Pearson correlation coefficients (r) were calculated among the environmental factors and the autocorrelated factors ($r > 0.7$) were removed (Xu et al., 2019). Nine factors remained in the model, precipitation, temperature, elevation, distance from road, distance from settlement, population density, NDVI in winter, soil nitrogen and soil organic carbon.

3.2.4. Model evaluation

The nine environmental factors were ran on MaxEnt (version 3.4.1) (Phillips et al., 2006). I selected 75% of the sample data randomly as the training set, while the remaining 25% was used as testing set (Zhang et al., 2018b). Model calibration and robustness were performed by the area under the curve (AUC), ranging from 0 to 1, of the receiver operating characteristic (ROC) along a jackknife randomization test (Zhang et al., 2019).

The AUC evaluates the ability of model to accurately rank the likelihood of presence (sensitivity) vs absence (specificity) by comparing observed and predicted target species distributions (Mkungo et al., 2023). When AUC exceeds 0.90, the model performance is precise (Yi et al., 2016). The jackknife test assesses the contribution of each factor to the distribution (Liu, et al., 2019). The impact of environmental factors was evaluated by the percent contribution, permutation importance and the drop in training gain when each factor was removed. The percent contribution indicated the contribution of each factor to species distribution, permutation importance showed the reliance of model on that factor and the drop in training gain reflected the unique ecological information the factor provides about habitat preferences of the species (Wang et al., 2020). A response curve (RC) was generated to examine the distributional relationships between the target species and environmental factors (Abolmaali et al., 2018).

Maxent predicted the probability of presence, showing the habitat suitability for the target species. The habitat suitability was classified, ranging from 0 to 1, into five classes at 0.2 intervals: optimal (0.8-1.0), high (0.6-0.8), moderate (0.40-0.6), marginal (0.2-0.4), and poor (0.0-0.2) (Santillan et al., 2021).

3.3. Results

3.3.1. Environmental factors affecting *A. auriculiformis* distribution

MaxEnt showed that, in the park, 7.2% of area (3.6 km²) was optimal for the establishment of *A. auriculiformis*, followed by 10.8% (5.4 km²) of high suitability and 20.3% (10.2 km²) of moderate suitability (**Figure 3-2**). The range of suitable habitats was clustered in regions where the most land transformation and disturbance activities occurred. The results showed that suitable habitats were in areas affected by human activities.

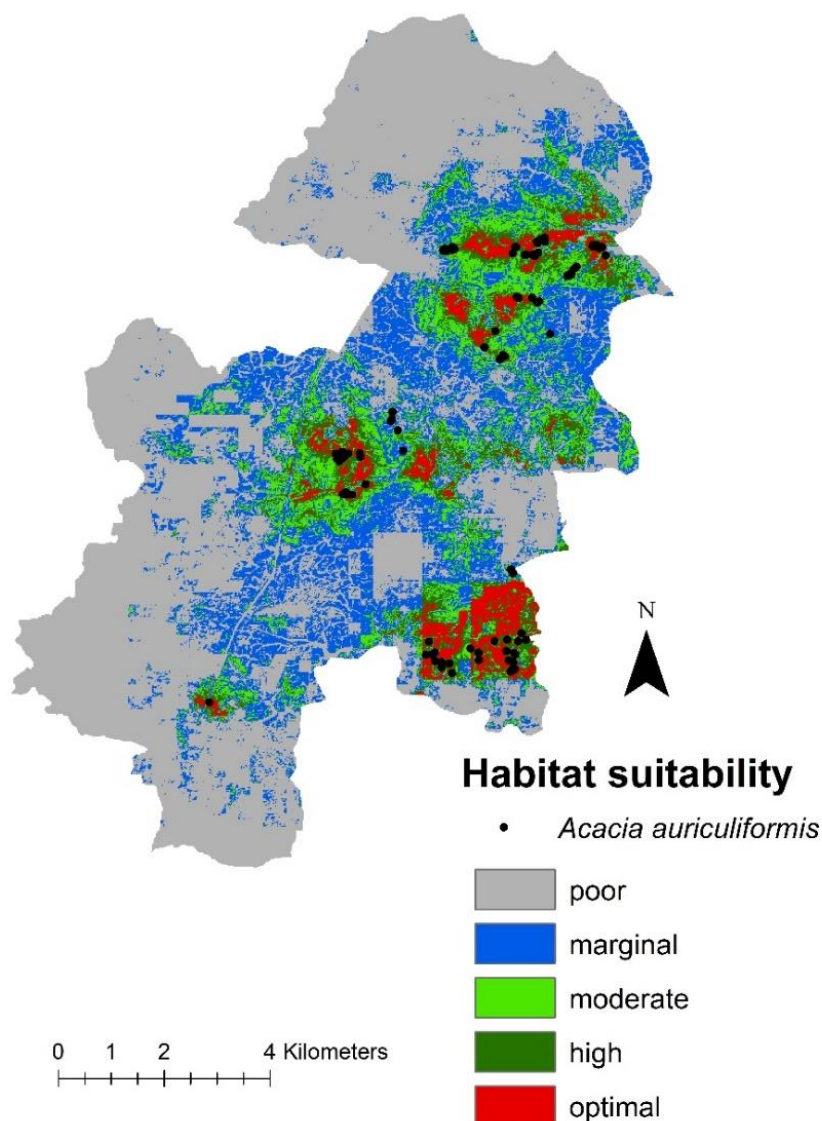


Figure 3-2. The potential habitats for *A. auriculiformis* trees in the Bhawal National Park, predicted by MaxEnt

The jackknife test was applied to determine the important environmental factors for *A. auriculiformis* distribution (**Figure 3-3**). The jackknife test showed that distance from settlement explained 31.3% of *A. auriculiformis* distribution, followed by NDVI in winter that explained 24.3%, population density (17.2%), N (6.2%), and distance from road (5.7%). The precipitation and temperature explained 5.3% and 2.1% of distribution, respectively. OC contributed 6.1%. Elevation showed the lowest contribution, 1.9%.

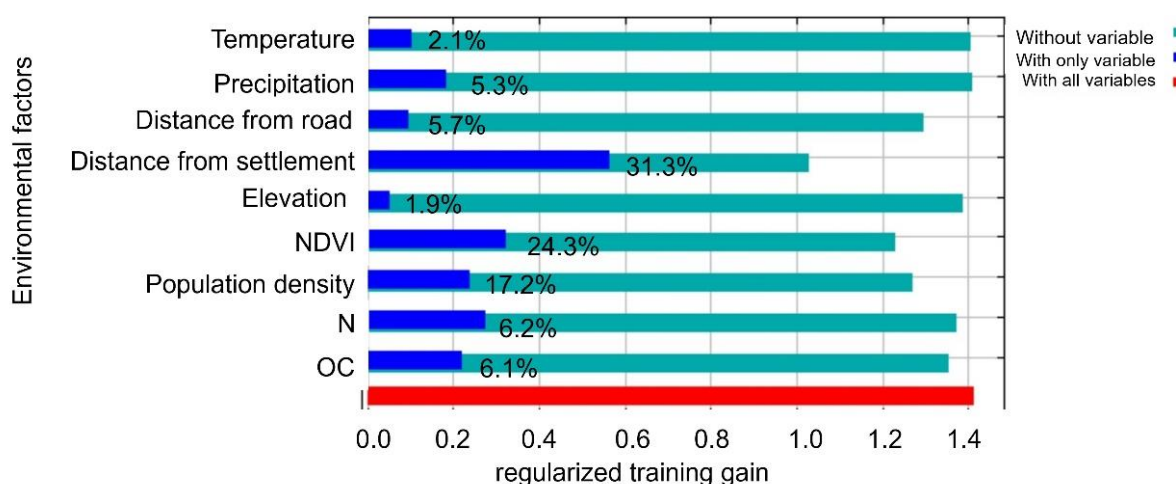


Figure 3-3. Contribution of factors to the distribution of *A. auriculiformis* predicted by MaxEnt, examined by jackknife randomization test. The regularized training gain describes how better the Maxent distribution fits the presence data compared to the assumption of uniform distribution. The dark blue bars indicate the gain from each factor in isolation, the light blue bars indicate the gain lost by removing the single factor from the full model, and the red bar indicates the gain from using all the factors.

The impact of environmental factors in the distribution was evaluated based on their percent contribution, permutation importance, and the drop in training gain (**Figure 3-4**). The human-induced disturbance factors, distance from settlement had higher intensity in terms of percent contribution (36.4%), permutation contribution (31.3%), and larger value in the drop in train gain. The human population density and distance from road also had disturbance intensity with percent contribution of 17% and 8.2% and permutation contribution of 17.2% and 5.7% respectively, with larger drop in gain. The results indicated that human disturbance factors contain information that was distinct and not shared by other factors, highlighting its unique role in predicting the distribution of *A. auriculiformis*. The NDVI, precipitation and soil nitrogen showed significant information.

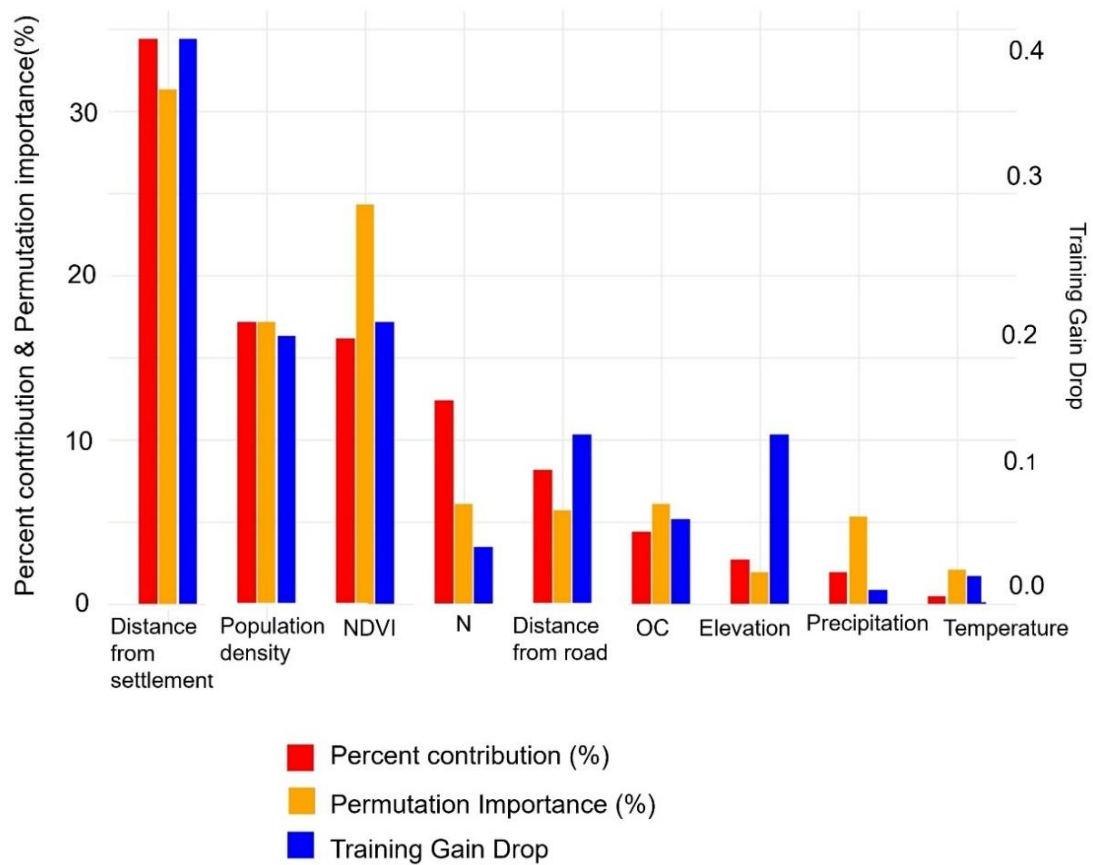


Figure 3-4. The importance of environmental factors to the distribution model evaluated by percent contribution, permutation importance, and drop in training gain without the variable.

The RC of environmental factors indicated that two distance factors, settlement and road, created favorable conditions for growth of *A. auriculiformis* (**Figure 3-4**), showing that this species had not immigrated largely to unpopulated areas. The RC of distance from settlement and road showed that the highest probability of presence occurred within 1000 m from the settlements and within 500 m from the roads. The RC of winter NDVI showed that, as NDVI increases, the probability of *A. auriculiformis* presence increased. As an evergreen species, it thrived with more green vegetation when deciduous species underwent foliage, making winter NDVI a reliable indicator of its distribution. The RC of population density showed the presence of invasive plants declined with increasing population density, as land use changes became more intense.

Of the climatic factors, *A. auriculiformis* established more with higher precipitation (Figure 3-4). Soil OC showed peak along with the concentration gradient, showing that optimal OC was present for the establishment of *A. auriculiformis*. Soil N and temperature affected the distribution of *A. auriculiformis* distribution less.

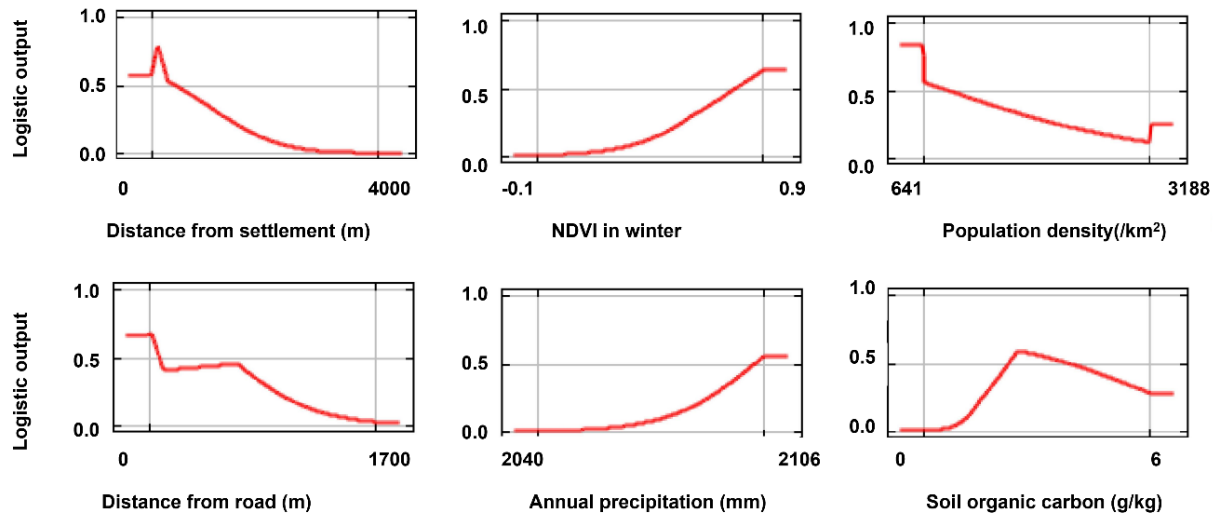


Figure 3-5. Response curves for probability of presence with most contributed factors for *A. auriculiformis* distribution

3.3.2. MaxEnt model performance

The AUC in the ROC curve in MaxEnt was 0.934 for training run and 0.898 for test run (Figure 3-6), indicating that the model performed well. The results showed that the model detected *A. auriculiformis* presence and spread effectively. This high AUC reflected that MaxEnt was robust in identifying the environmental conditions that *A. auriculiformis* favored.

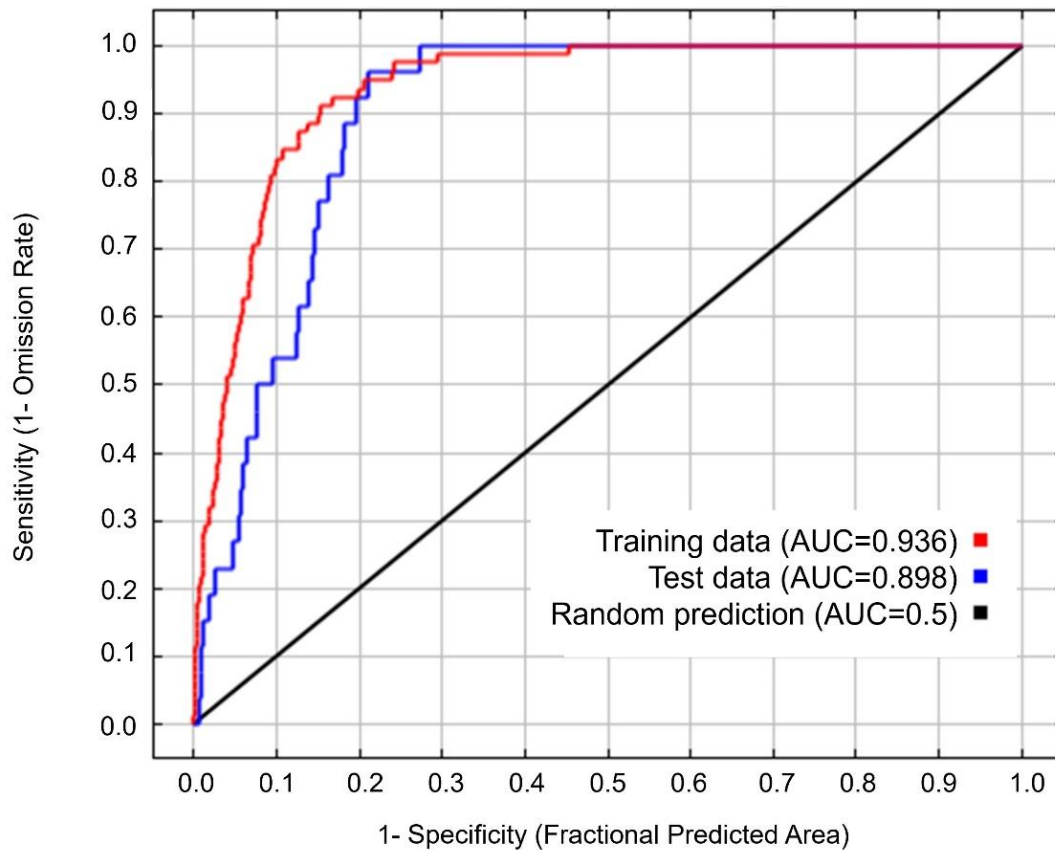


Figure 3-6. The AUCs for predicting the potential *A. auriculiformis* distribution by MaxEnt. The red lines show the fit of the model to the training data. The blue lines indicate the fit of the model to the testing data.

3.4. Discussion

3.4.1. Distribution of *A. auriculiformis*

The tropical moist deciduous covers 4.7% of forest area in Bangladesh and is unevenly distributed in the country (Rahman et al., 2010b). Bhawal National Park is in the central deciduous forest of Bangladesh, where 75% of the forest cover has been lost in the last two decades due to intense human activity, and only 10% area is now protected to conserve the forest and its biodiversity (Masum et al., 2016). The MaxEnt analysis was done only within the protected area (50.2 km²) to keep the results accurate because this area has diverse vegetation and the land is mostly fragmented outside the park due to human activities and there is less vegetation cover which makes the environment very different. Since the study focused on finding invasive species early to protect native plants, working inside the park

made it easier to get clear and reliable results. If the area included land outside the park, the vegetation would be quite different, making the analysis harder. Staying inside the protected area gives better and more meaningful information about where invasive species might spread.

AUCs in MaxEnt confirmed the accurate mapping of *A. auriculiformis*, suggesting that the prediction and control of *A. auriculiformis* by MaxEnt are possible, based on the distribution of environmental factors (Václavík and Meentemeyer, 2009). The determinant related to human activities were influential to the model. The results suggested that the manipulation of human activities is related to establishment of *A. auriculiformis*. Human activities seem to modify dispersal pathways by reshaping niches and geographic barriers (Li et al., 2025). Settlements and roads provided a measure of disturbances that facilitated the expansion of invasive species by increasing accessibilities (Simpson et al., 2011). The road network should promote the spread of *A. auriculiformis*. IAPs often disperse along roads, as roads create disturbed areas and act as corridor that help in movement and spread (Dodet and Collet, 2012; Nath et al., 2019). The probability of *A. auriculiformis* presence decreased with increase in population density, although densely populated areas are more susceptible to distribution of invasive species (Tu et al., 2021). The study site experienced a remarkable changes in land use, i.e., urban expansion and agricultural intensification (Alauddin et al., 2020), which alter habitat suitability and reduce the *A. auriculiformis* presence. The results suggested that densely populated areas, despite having more settlements, have unsuitable habitats for *A. auriculiformis*, due to intense and frequent changes in land use. However, the study found that human-induced disturbances, i.e., land use changes promote invasive species spread by altering disturbance patterns (Manier et al., 2014).

NDVI in winter affected the distribution of *A. auriculiformis*, underscoring the effectiveness of VIs. By considering the distinct spectral signatures of *A. auriculiformis* from deciduous natives, high NDVI succeeded in detecting *A. auriculiformis* (Jiang et al., 2014). The results confirmed that *A. auriculiformis* had already been established in native forests and that NDVI effectively detected its presence in the park.

Although precipitation and temperature are determinants on plant distribution (Poorter and Nagel, 2000), these two factors affected less on distribution of *A. auriculiformis*. One reason is fluctuations of these climatic factors were small in the area examined. Although their individual contributions were small, these factors should be included in the model because climate and edaphic factors interact to shape species distribution (Taylor and

Kumar, 2013). Because *A. auriculiformis* is a nitrogen-fixer, the establishment of species is not affected largely by soil N and establishes even on N-poor habitats largely (Norisada et al., 2005).

3.4.2. Effectiveness of RS and MaxEnt for mapping *A. auriculiformis*

Combining VI from RS data and species occurrence data helped the model to locate areas at risk of invasion (Adionyi et al., 2024). I therefore considered winter season, characterized by defoliation of deciduous trees. NDVI showed the unique reflectance pattern of the plant species the model is trying to map (Schwager and Berg, 2021). In this study, the calculated winter NDVI obtained high contribution in MaxEnt and showed strong predictive power for mapping the distribution of *A. auriculiformis*. This is because winter NDVI captures spectral differences between evergreen and deciduous species (Sultana et al., 2025). Such season-specific phenological signals reflect underlying ecological variation, making winter NDVI a valuable predictor for invasive species distribution modeling (Wen et al., 2015).

Given the study's focus on current distribution, including winter NDVI in MaxEnt was appropriate as it highlighted phenological differences between evergreen invasive species and deciduous natives. Seasonal VIs from satellite imagery improved Maxent predictions by capturing dynamic vegetation pattern over time (Mahmoud et al., 2025). Thus, winter NDVI provided meaningful explanatory power in the detection-oriented context of the study and supported the ecological basis of the model.

While elevation affects tree cover and increases the accuracy of species distribution prediction (Ahmadi et al., 2023), the elevation did not affect the accuracy of prediction. Although elevation did not function significantly as a predictor due to the continuous land use changes observed in the study area, it is still a useful variable for assessing species distribution, as it influences the establishment of non-native species (Lázaro-Lobo et al., 2021). The *A. auriculiformis* distribution in this study was influenced highly by land use changes through plantation, settlement and other human disturbances. In the surveyed national park, finer scale factors, such as NDVI, affected the distribution of target tree species (Heshmati et al., 2019).

3.4.3. Implications for management planning

A. auriculiformis is already widespread in Bhawal National Park where human activities are high. Since planted non-native species often become invasive (Schutzenhofer et al., 2009), for planning suitable conservation strategies of native ecosystems, the dynamics of invasive species should be clarified (Saito and Tsuyuzaki, 2012). To promote the exclusion of IAPs, examining the potential distribution of IAPs is required at regional scale or larger (Foxcroft et al., 2017). To obtain the potential distribution, the current distribution should be censused carefully (Choudhury et al., 2016). Because MaxEnt only requires presence data, conducting a census is completed in a short time compared to a presence/absence census. Based on the prediction, effective strategies can be decided for monitoring to protect natural forests. In addition, MaxEnt is likely to apply the prevention of the establishment of IAPs based on the distribution prediction (El-Barougy et al., 2021). Habitat disturbance should be considered for IAP management (Cesar et al., 2017).

Of the nine environmental factors, human activities affected primarily the distribution of *A. auriculiformis*. Even in protected areas, including Bhawal National Park, human activities as a measure of disturbances were prime determinants on the establishment of IAPs (Shackleton et al., 2016). The probability of *A. auriculiformis* presence showed minimal variation across the examined ranges of temperature and soil N. This is likely due to the narrow range of the factors, which influenced less the distribution of *A. auriculiformis*. In regions with greater climatic and topographic diversity, these factors warrant more thorough investigation.

This study highlighted that invasive species are not always restricted to ecologically or climatically suitable habitats; rather, human disturbances enable their distribution even in unsuitable environments. By integrating human disturbances into the model, the study detected the role of human activities in invasion patterns and underscored the importance of managing human-induced disturbances and monitoring vegetation changes as key strategies for controlling invasive species spread and preserving native forest ecosystems.

3.5. Conclusion

Plant invasion is often promoted by exotic plantations. This chapter focused on the research effort on invasive plantation trees. This study explored the presence of invasive species with environmental factors. MaxEnt at large scale, examined by RS, predicted *A.*

auriculiformis distribution well. The result demonstrated that the park close to roads and settlements accelerated the expansion of *A. auriculiformis* due to disturbances. Using the phenological differences between evergreen and deciduous trees, winter NDVI detected *A. auriculiformis* distribution. MaxEnt and its associated models should be utilized to identify the potential areas for transplantation as well as ecological zones at risk to prevent further expansion. Integrating with remote sensing, MaxEnt is a frequently and rapidly updated, evidence-based planning tool.

Forest managers utilize MaxEnt to mitigate biological invasions by (1) understanding the ecological impact of *A. auriculiformis*, (2) monitoring the spread of *A. auriculiformis* and mapping invasion pathways over time. The study emphasized the need for disturbance-focused and long-term management strategies. The result can be used as a tool for the risk assessment of potential future invasion. However, although spatial details may be limited, the model offered valuable guidance for understanding regional invasion dynamics and informing large-scale management and conservation efforts as well as monitoring activities.

General Discussion

This study investigated seasonal RS data and species distribution modeling to improve the detection and mapping of *A. auriculiformis*, focusing on phenological dynamics within tropical moist deciduous forests. The detection of *A. auriculiformis* distribution was assessed by multiple VIs derived from seasonal satellite imagery (**Chapter 1**). The phenological spectral attributes of vegetation were examined by multiple VIs focusing on the phenological spectral features of the vegetation in different phenological periods (**Chapter 2**). While **Chapter 1** evaluated the use of multiple seasonal VIs and elevation for classifying *A. auriculiformis*, **Chapter 2** shifted focus on phenological spectral features. It examined whether integrating reflectance data from key growth stages: green and senescence improves classification. Unlike the broader strategy in **Chapter 1**, **Chapter 2** introduced composite indices (PVI, seVI) that captured phenology-based spectral distinctions to enhance species discrimination and refined detection methods. An additional analysis in **Chapter 2** was essential to build upon the findings of **Chapter 1** and to introduce methodological innovations (e.g., PVI, seVI) for future efforts in invasive species mapping. MaxEnt effectively predicted the potential distribution of *A. auriculiformis* when RS data were integrated. In addition, the model suggested that human-induced disturbances determined the spread of this species largely (**Chapter 3**). By incorporating ecological processes and human interference with advanced geospatial tools, it presented a comprehensive framework applicable across ecosystems, contributing to the development of informed strategies for global biodiversity conservation and ecosystem resilience.

Biologically invasive species detection using phenology and topography

The differentiation of *A. auriculiformis* in multi-class classification produced higher accuracy than the binary classification. The classification accuracy was linked to spectral differences between species, reflecting the distribution of vegetation classes (Ferreira et al., 2016). In binary classification, misclassification was often observed largely. The multi-class classification produced high accuracy by capturing the differentiation in the surface reflectance among the vegetation classes. Distinct patterns in the spectral reflectance were observed with GRVI, GCI and NDVI in winter and for NDVI, ARVI and GCI in summer. In monsoon and autumn, vegetation classes were not well-classified, probably due to dense vegetation. The integration of VIs with elevation underscores the critical role of selecting VIs for classification, as spectral measurements reflect phenological characteristics

(Caparros-Santiago et al., 2021). RF classification using VIs with DEM achieved highest accuracy in winter and summer, showing the effectiveness of integrating phenological, spectral and elevation data for mapping *A. auriculiformis*.

Applicability of phenological spectral feature-based indices

A composite image using VIs from both the senescence and green seasons was created to check if different plants are separated by the spectral attributes. Phenological features improves mapping accuracy by unique spectral distribution pattern on each species (Li et al., 2022). Two phenological periods, green and senescence, were integrated into VIs, NDVI, GRVI and ARVI, to increase separability of invasive species, with one of the composite indices, PVIs. Senescence in deciduous forests began in late February. However, *A. auriculiformis* started leaf flushing earlier, allowing clear spectral separation and high RF accuracy. Given that each vegetation class exhibits distinct growth rhythms and phenological patterns, these indices demonstrate their utility in classification (Xu et al., 2021). The originality of the study is linked in the application of phenology-based VIs, such as seVIs and PVIs, which effectively captured seasonal changes in surface reflectance. While seVIs used information from a single season, PVIs captured information across seasons. RF performed well when PVI was integrated, indicated analyzing the phenological features of each vegetation class before classification. The results suggested that phenology-based VIs can be considered ecologically meaningful for mapping invasive species into different ecosystems, particularly where species exhibit distinct seasonal patterns.

Monitoring the distribution of A. auriculiformis

The high AUC observed in MaxEnt showed the importance of developing a predictive understanding of its distribution to facilitate early detection for effective control of *A. auriculiformis* spreading (Václavík and Meentemeyer, 2009). The habitat of *A. auriculiformis* were increased by human activities, indicating that settlements and roads act as disturbances provide a measure of disturbances that facilitate the expansion of invasive species by increasing the accessibilities (Simpson et al., 2011). High winter NDVI detected the presence of *A. auriculiformis*, highlighting VIs in distinguishing it from deciduous forests (Jiang et al., 2014). Although climatic factors are often determinants on plant distribution (Poorter and Nagel, 2000), these factors affected less the distribution of *A. auriculiformis* due to the narrow variation of these environmental factors. The results

highlight that human-induced disturbances are major drivers of biological invasions, even within protected zones. The study presented methodological advancement by emphasizing seasonally enriched remote sensing data and context-specific human disturbance layers, offering a more comprehensive and ecologically relevant understanding of invasion dynamics.

This study demonstrated that combining seasonal RS, multiple VIs, topography, phenological features, and human disturbances provides an effective approach to detect *A. auriculiformis*, a major invasive species threatening tropical moist deciduous forests. Using MaxEnt, both suitable transplantation zones for reforestation high-risk invasion areas were identified, especially in regions affected by human disturbances that promote invasion spread. The results emphasized that biological invasions are closely linked to disturbance-induced changes in forest structure, which can disrupt ecological balance. However, the study has limitations, including moderate resolution datasets and possible uncertainties in the modelling process.

The new insight in this work is linked in integrating phenological data with environmental factors in modelling invasive species distribution in complex and seasonally dynamic ecosystems. This framework is particularly applicable to tropical and temperate forests, where seasonal variation in surface reflectance aided invasive species detection. Though its applicability may be limited in ecosystems with less seasonal variability or sparse vegetation biomes, such as tundra or taiga.

I concluded that integrating phenology, VIs, elevation, and the human-induced disturbances in RS and species distribution models enhanced the understanding of invasive species dynamics across diverse ecosystems and offered a valuable tool for guiding future management strategies and control efforts.

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References

- Abolmaali, S. M.-R., Tarkesh, M., and Bashari, H. (2018). MaxEnt modeling for predicting suitable habitats and identifying the effects of climate change on a threatened species, *Daphne mucronata*, in central Iran. *Ecological Informatics*, 43, 116–123. <https://doi.org/10.1016/j.ecoinf.2017.10.002>
- Adelabu, S., Mutanga, O., and Adam, E. (2015). Testing the reliability and stability of the internal accuracy assessment of random forest for classifying tree defoliation levels using different validation methods. *Geocarto International*, 30(7), 810–821. <https://doi.org/10.1080/10106049.2014.997303>
- Adionyi, L., Adero, N., Mutua, S., Korir, D., and Siljander, M. (2024). Habitat Suitability Modeling for the Invasive *Opuntia stricta* Using Remote Sensing and Maxent in Tsavo East National Park, Kenya. *Journal of Geography, Environment and Earth Science International*, 28(12), 1–18. <https://doi.org/10.9734/jgeesi/2024/v28i12845>
- Ahmadi, K., Mahmoodi, S., Pal, S. C., Saha, A., Chowdhuri, I., Nguyen, T. T., Jarvie, S., Szostak, M., Socha, J., and Thai, V. N. (2023). Improving species distribution models for dominant trees in climate data-poor forests using high-resolution remote sensing. *Ecological Modelling*, 475, 110190. <https://doi.org/10.1016/j.ecolmodel.2022.110190>
- Aji, M. A. P., Kamal, M., and Farda, N. M. (2023). Mangrove species mapping through phenological analysis using random forest algorithm on Google Earth Engine. *Remote Sensing Applications: Society and Environment*, 30, 100978. <https://doi.org/10.1016/j.rsase.2023.100978>
- Alam, H. E., Arafat, Md. Y., Ahmed, K. T., and Uddin, Md. N. (2022). Temporal Variation of Land Surface Temperature in Response to Changes in Vegetation Index of Bhawal National Park, Bangladesh. In I. Pal and S. Kolathayar (Eds.), *Sustainable Cities and Resilience* (Vol. 183, pp. 329–337). Springer Singapore. https://doi.org/10.1007/978-981-16-5543-2_27
- Alauddin, Md., Hossain, Md. N., Islam, Md. B., Islam, S., and Islam, Md. K. (2020). Management Strategies for Sustainable Forest Biodiversity Conservation in Protected Areas of Bangladesh: A Study of Bhawal National Park, Gazipur. *Grassroots Journal of Natural Resources*, 3(3), 56–72. <https://doi.org/10.33002/nr2581.6853.03035>
- Albert, G., and Ammar, S. (2021). Application of random forest classification and remotely sensed data in geological mapping on the Jebel Meloussi area (Tunisia). *Arabian Journal of Geosciences*, 14(21), 2240. <https://doi.org/10.1007/s12517-021-08509-x>
- Anuar, A. N., Jusoh, I., Suhaili, A., and Wisma Sumber Alam. (2022). Vegetation Indices

- of Acacia Mangium using Landsat 8 Operational Land Imager. *Journal of Sustainability Science and Management*, 17(4), 57–69. <https://doi.org/10.46754/jssm.2022.4.005>
- Belgiu, M., and Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>
- Bhatta, S., Hejda, M., and Pyšek, P. (2024). Impact of invasive plants on vegetation in protected areas of Nepal. *Biological Invasions*. <https://doi.org/10.1007/s10530-024-03408-0>
- Bhaveskumar, K. I., Sharma, L. K., and Verma, R. K. (2024). Applicability of phenological indices for mapping of understory invasive species using machine learning algorithms. *Biological Invasions*, 26(9), 2901–2921. <https://doi.org/10.1007/s10530-024-03361-y>
- Bradley, B. A. (2014). Remote detection of invasive plants: A review of spectral, textural and phenological approaches. *Biological Invasions*, 16(7), 1411–1425. <https://doi.org/10.1007/s10530-013-0578-9>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- Bushi, D., Mahato, R., Nimasow, O. D., and Nimasow, G. (2023). MaxEnt-based prediction of the potential invasion of Lantana camara L. under climate change scenarios in Arunachal Pradesh, India. *Acta Ecologica Sinica*, 43(4), 674–683. <https://doi.org/10.1016/j.chnaes.2022.08.004>
- Caparros-Santiago, J. A., Rodriguez-Galiano, V., and Dash, J. (2021). Land surface phenology as indicator of global terrestrial ecosystem dynamics: A systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 171, 330–347. <https://doi.org/10.1016/j.isprsjprs.2020.11.019>
- Caswell, H., and Salguero-Gómez, R. (2013). Age, stage and senescence in plants. *Journal of Ecology*, 101(3), 585–595. <https://doi.org/10.1111/1365-2745.12088>
- Cesar De Sa, N., Carvalho, S., Castro, P., Marchante, E., and Marchante, H. (2017). Using Landsat Time Series to Understand How Management and Disturbances Influence the Expansion of an Invasive Tree. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 10(7), 3243–3253. <https://doi.org/10.1109/JSTARS.2017.2673761>
- Choudhury, M. R., Deb, P., Singha, H., Chakdar, B., and Medhi, M. (2016). Predicting the

- probable distribution and threat of invasive *Mimosa diplotricha* Suavalle and *Mikania micrantha* Kunth in a protected tropical grassland. *Ecological Engineering*, 97, 23–31. <https://doi.org/10.1016/j.ecoleng.2016.07.018>
- Cord, A. F., Klein, D., Mora, F., and Dech, S. (2014). Comparing the suitability of classified land cover data and remote sensing variables for modeling distribution patterns of plants. *Ecological Modelling*, 272, 129–140. <https://doi.org/10.1016/j.ecolmodel.2013.09.011>
- Costa, T. C. E. C., Viana, J. H. M., and Ribeiro, J. L. (2014). Semideciduous Seasonal Forest Production of Leaves and Deciduousness in Function of the Water Balance, LAI, and NDVI. *International Journal of Ecology*, 2014, 1–15. <https://doi.org/10.1155/2014/923027>
- Dodet, M., and Collet, C. (2012). When should exotic forest plantation tree species be considered as an invasive threat and how should we treat them? *Biological Invasions*, 14(9), 1765–1778. <https://doi.org/10.1007/s10530-012-0202-4>
- Dudley, N., Andalusia (Spain), IUCN World Commission on Protected Areas, Fundación Biodiversidad, and IUCN--The World Conservation Union (Eds.). (2008). *Guidelines for applying protected area management categories*. IUCN.
- Dueñas, M.-A., Hemming, D. J., Roberts, A., and Diaz-Soltero, H. (2021). The threat of invasive species to IUCN-listed critically endangered species: A systematic review. *Global Ecology and Conservation*, 26, e01476. <https://doi.org/10.1016/j.gecco.2021.e01476>
- El-Barougy, R. F., Dakhil, M. A., Halmy, M. W., Gray, S. M., Abdelaal, M., Khedr, A.-H. A., and Bersier, L.-F. (2021). Invasion risk assessment using trait-environment and species distribution modelling techniques in an arid protected area: Towards conservation prioritization. *Ecological Indicators*, 129, 107951. <https://doi.org/10.1016/j.ecolind.2021.107951>
- Eugenio, F., Badin, T. L., Fernandes, P., Mallmann, C. L., Schons, C., Schuh, M. S., Soares Pereira, R., Fantinel, R. A., and Pereira Da Silva, S. D. (2021). Remotely Piloted Aircraft Systems (RPAS) and machine learning: A review in the context of forest science. *International Journal of Remote Sensing*, 42(21), 8207–8235. <https://doi.org/10.1080/01431161.2021.1975845>
- Fang, F., McNeil, B. E., Warner, T. A., Maxwell, A. E., Dahle, G. A., Eutsler, E., and Li, J. (2020). Discriminating tree species at different taxonomic levels using multi-temporal WorldView-3 imagery in Washington D.C., USA. *Remote Sensing of Environment*,

- 246, 111811. <https://doi.org/10.1016/j.rse.2020.111811>
- Ferreira, M. P., Zortea, M., Zanotta, D. C., Shimabukuro, Y. E., and De Souza Filho, C. R. (2016). Mapping tree species in tropical seasonal semi-deciduous forests with hyperspectral and multispectral data. *Remote Sensing of Environment*, 179, 66–78. <https://doi.org/10.1016/j.rse.2016.03.021>
- Foster-Turley, Rishiraj Das, Md. Kamrul Hasan, and Peerzadi Rumana Hossain. (2016). BANGLADESH TROPICAL FORESTS AND BIODIVERSITY ASSESSMENT. UNITED STATES FOREIGN ASSISTANCE ACT, SECTION 118/119 REPORT, USAID Bangladesh.
- Foxcroft, L. C., Pyšek, P., Richardson, D. M., Genovesi, P., and MacFadyen, S. (2017). Plant invasion science in protected areas: Progress and priorities. *Biological Invasions*, 19(5), 1353–1378. <https://doi.org/10.1007/s10530-016-1367-z>
- Friedl, M. A., and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, 61(3), 399–409. [https://doi.org/10.1016/S0034-4257\(97\)00049-7](https://doi.org/10.1016/S0034-4257(97)00049-7)
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Grabska, E., Frantz, D., and Ostapowicz, K. (2020). Evaluation of machine learning algorithms for forest stand species mapping using Sentinel-2 imagery and environmental data in the Polish Carpathians. *Remote Sensing of Environment*, 251, 112103. <https://doi.org/10.1016/j.rse.2020.112103>
- Hasan, E and Bahauddin, K.M. (2014). Community's Perception and Involvement in Co-management of Bhawal National Park, Bangladesh. *Journal of Natural Sciences Research*, 4(3), 60–67.
- Heringer, G., Bueno, M. L., Meira-Neto, J. A. A., Matos, F. A. R., and Neri, A. V. (2019). Can *Acacia mangium* and *Acacia auriculiformis* hinder restoration efforts in the Brazilian Atlantic Forest under current and future climate conditions? *Biological Invasions*, 21(9), 2949–2962. <https://doi.org/10.1007/s10530-019-02024-7>
- Heshmati, I., Khorasani, N., Shams-Esfandabad, B., and Riazi, B. (2019). Forthcoming risk of *Prosopis juliflora* global invasion triggered by climate change: Implications for environmental monitoring and risk assessment. *Environmental Monitoring and Assessment*, 191(2), 72. <https://doi.org/10.1007/s10661-018-7154-9>
- Holland, J., and Aplin, P. (2013). Super-resolution image analysis as a means of monitoring

- bracken (*Pteridium aquilinum*) distributions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 75, 48–63. <https://doi.org/10.1016/j.isprsjprs.2012.10.002>
- Hu, Q., Sulla-Menashe, D., Xu, B., Yin, H., Tang, H., Yang, P., and Wu, W. (2019). A phenology-based spectral and temporal feature selection method for crop mapping from satellite time series. *International Journal of Applied Earth Observation and Geoinformation*, 80, 218–229. <https://doi.org/10.1016/j.jag.2019.04.014>
- Huang, W., Fei, X., Yang, W., Wang, Z., Gao, Y., and Yan, H. (2025). A study on the classification of coastal wetland vegetation based on the Suaeda salsa index and its phenological characteristics. *Ecological Indicators*, 170, 113021. <https://doi.org/10.1016/j.ecolind.2024.113021>
- Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309. [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Huete, Didan, K., Miura, T., Rodriguez, E. P., Gao, X., and Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1–2), 195–213. [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2)
- Hui, C., Richardson, D. M., Visser, V., and Wilson, J. R. U. (2014). Macroecology meets invasion ecology: Performance of Australian acacias and eucalypts around the world revealed by features of their native ranges. *Biological Invasions*, 16(3), 565–576. <https://doi.org/10.1007/s10530-013-0599-4>
- Idol, T. W., Morales, R. M., Friday, J. B., and Scowcroft, P. G. (2017). Precommercial release thinning of potential *Acacia koa* crop trees increases stem and crown growth in dense, 8-year-old stands in Hawaii. *Forest Ecology and Management*, 392, 105–114. <https://doi.org/10.1016/j.foreco.2017.02.029>
- Islam, A. R. M. T., Islam, H. M. T., Shahid, S., Khatun, M. K., Ali, M. M., Rahman, M. S., Ibrahim, S. M., and Almoajel, A. M. (2021). Spatiotemporal nexus between vegetation change and extreme climatic indices and their possible causes of change. *Journal of Environmental Management*, 289, 112505. <https://doi.org/10.1016/j.jenvman.2021.112505>
- Islam, M. A. Haydar, M. I. Ali, D. Paul, M. L. Ali, and S. M. A. Islam. (2014). Background Gamma Radiation Mapping in Bangladesh: Radioactivity in the Surface Soil of ‘BhawalGahr’ Area of Gazipur. *IOSR Journal of Applied Physics (IOSR-JAP)*, 6(5 ver II), 53–61.
- Jiang, Y., Wang, T., De Bie, C. A. J. M., Skidmore, A. K., Liu, X., Song, S., Zhang, L.,

- Wang, J., and Shao, X. (2014). Satellite-derived vegetation indices contribute significantly to the prediction of epiphyllous liverworts. *Ecological Indicators*, 38, 72–80. <https://doi.org/10.1016/j.ecolind.2013.10.024>
- Johnson, M. D., Hsieh, W. W., Cannon, A. J., Davidson, A., and Bédard, F. (2016). Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods. *Agricultural and Forest Meteorology*, 218–219, 74–84. <https://doi.org/10.1016/j.agrformet.2015.11.003>
- Kabir, D. S., and Ahmed, A. Z. (2005). Wildlife Biodiversity in Bhawal National Park: Management Techniques and Drawbacks of Wildlife Management and Nature Conservation. *Our Nature*, 3(1), 83–90. <https://doi.org/10.3126/on.v3i1.340>
- Karim, Md. R., Mukul, S. A., Zahir, R. B., Saimun, S. R., and Arfin-Khan, M. A. S. (2023). The role of protected areas co-management in enhancing resistance and resilience of deciduous forest ecosystem to extreme climatic events in Bangladesh. *Journal of Environmental Management*, 326, 116800. <https://doi.org/10.1016/j.jenvman.2022.116800>
- Khan, M. H. R., Rahman, A., Luo, C., Kumar, S., Islam, G. M. A., and Hossain, M. A. (2019). Detection of changes and trends in climatic variables in Bangladesh during 1988–2017. *Heliyon*, 5(3), e01268. <https://doi.org/10.1016/j.heliyon.2019.e01268>
- Khare, S., Latifi, H., and Ghosh, S. K. (2018). Multi-scale assessment of invasive plant species diversity using Pléiades 1A, RapidEye and Landsat-8 data. *Geocarto International*, 33(7), 681–698. <https://doi.org/10.1080/10106049.2017.1289562>
- Kollert, A., Bremer, M., Löw, M., and Rutzinger, M. (2021). Exploring the potential of land surface phenology and seasonal cloud free composites of one year of Sentinel-2 imagery for tree species mapping in a mountainous region. *International Journal of Applied Earth Observation and Geoinformation*, 94, 102208. <https://doi.org/10.1016/j.jag.2020.102208>
- Kumar, V., Sharma, A., Bhardwaj, R., and Thukral, A. K. (2018). Comparison of different reflectance indices for vegetation analysis using Landsat-TM data. *Remote Sensing Applications: Society and Environment*, 12, 70–77. <https://doi.org/10.1016/j.rsase.2018.10.013>
- Kuplich, T. M. (2006). Classifying regenerating forest stages in Amazônia using remotely sensed images and a neural network. *Forest Ecology and Management*, 234(1–3), 1–9. <https://doi.org/10.1016/j.foreco.2006.05.066>
- Kureel, N., Sarup, J., Matin, S., Goswami, S., and Kureel, K. (2022). Modelling vegetation

- health and stress using hypersepctral remote sensing data. *Modeling Earth Systems and Environment*, 8(1), 733–748. <https://doi.org/10.1007/s40808-021-01113-8>
- Lawrence, R. L., and Ripple, W. J. (2000). FIFTEEN YEARS OF REVEGETATION OF MOUNT ST. HELENS: A LANDSCAPE-SCALE ANALYSIS. *Ecology*, 81(10), 2742–2752. [https://doi.org/10.1890/0012-9658\(2000\)081\[2742:FYOROM\]2.0.CO;2](https://doi.org/10.1890/0012-9658(2000)081[2742:FYOROM]2.0.CO;2)
- Lázaro-Lobo, A., Ramirez-Reyes, C., Lucardi, R. D., and Ervin, G. N. (2021). Multivariate analysis of invasive plant species distributions in southern US forests. *Landscape Ecology*, 36(12), 3539–3555. <https://doi.org/10.1007/s10980-021-01326-3>
- Le Maitre, D. C., Gaertner, M., Marchante, E., Ens, E., Holmes, P. M., Pauchard, A., O’Farrell, P. J., Rogers, A. M., Blanchard, R., Blignaut, J., and Richardson, D. M. (2011). Impacts of invasive Australian acacias: Implications for management and restoration. *Diversity and Distributions*, 17(5), 1015–1029. <https://doi.org/10.1111/j.1472-4642.2011.00816.x>
- Lediuk, K. D., Damascos, M. A., Puntieri, J. G., and Svriz, M. (2014). Differences in phenology and fruit characteristic between invasive and native woody species favor exotic species invasiveness. *Plant Ecology*, 215(12), 1455–1467. <https://doi.org/10.1007/s11258-014-0402-3>
- Lee, E. W. S., Hau, B. C. H., and Corlett, R. T. (2005). Natural regeneration in exotic tree plantations in Hong Kong, China. *Forest Ecology and Management*, 212(1–3), 358–366. <https://doi.org/10.1016/j.foreco.2005.03.057>
- Li, M., Sun, Y., Yang, Y., and Zhang, X. (2025). Impacts of Climate Change and Human Activity on the Habitat Distribution of *Metasequoia glyptostroboides*. *Ecology and Evolution*, 15(4), e71269. <https://doi.org/10.1002/ece3.71269>
- Li, X., Tian, J., Li, X., Wang, L., Gong, H., Shi, C., Nie, S., Zhu, L., Chen, B., Pan, Y., He, J., Ni, R., and Diao, C. (2022). Developing a sub-meter phenological spectral feature for mapping poplars and willows in urban environment. *ISPRS Journal of Photogrammetry and Remote Sensing*, 193, 77–89. <https://doi.org/10.1016/j.isprsjprs.2022.09.002>
- Liu, X., Frey, J., Munteanu, C., Still, N., and Koch, B. (2023). Mapping tree species diversity in temperate montane forests using Sentinel-1 and Sentinel-2 imagery and topography data. *Remote Sensing of Environment*, 292, 113576. <https://doi.org/10.1016/j.rse.2023.113576>
- Liu, Y., Gong, W., Xing, Y., Hu, X., and Gong, J. (2019). Estimation of the forest stand mean height and aboveground biomass in Northeast China using SAR Sentinel-1B,

- multispectral Sentinel-2A, and DEM imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 151, 277–289. <https://doi.org/10.1016/j.isprsjprs.2019.03.016>
- Liu, Y., Huang, P., Lin, F., Yang, W., Gaisberger, H., Christopher, K., and Zheng, Y. (2019). MaxEnt modelling for predicting the potential distribution of a near threatened rosewood species (*Dalbergia cultrata* Graham ex Benth). *Ecological Engineering*, 141, 105612. <https://doi.org/10.1016/j.ecoleng.2019.105612>
- Ma, L., Cheng, L., Li, M., Liu, Y., and Ma, X. (2015). Training set size, scale, and features in Geographic Object-Based Image Analysis of very high resolution unmanned aerial vehicle imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 102, 14–27. <https://doi.org/10.1016/j.isprsjprs.2014.12.026>
- Mahmoud, A. R., Farahat, E. A., Hassan, L. M., and Halmy, M. W. A. (2025). Remotely sensed data contribution in predicting the distribution of native Mediterranean species. *Scientific Reports*, 15(1), 12475. <https://doi.org/10.1038/s41598-025-94569-y>
- Manier, D. J., Aldridge, C. L., O'Donnell, M., and Schell, S. J. (2014). Human Infrastructure and Invasive Plant Occurrence Across Rangelands of Southwestern Wyoming, USA. *Rangeland Ecology & Management*, 67(2), 160–172. <https://doi.org/10.2111/REM-D-12-00056.1>
- Masemola, C., Cho, M. A., and Ramoelo, A. (2020). Sentinel-2 time series based optimal features and time window for mapping invasive Australian native Acacia species in KwaZulu Natal, South Africa. *International Journal of Applied Earth Observation and Geoinformation*, 93, 102207. <https://doi.org/10.1016/j.jag.2020.102207>
- Masum, K. M., Islam, M. N., Saha, N., Hasan, Md. Z., and Mansor, A. (2016). Assessment of land grabbing from protected forest areas of Bhawal National Park in Bangladesh. *Landscape Research*, 41(3), 330–343. <https://doi.org/10.1080/01426397.2015.1078456>
- Melaas, E. K., Sulla-Menashe, D., Gray, J. M., Black, T. A., Morin, T. H., Richardson, A. D., and Friedl, M. A. (2016). Multisite analysis of land surface phenology in North American temperate and boreal deciduous forests from Landsat. *Remote Sensing of Environment*, 186, 452–464. <https://doi.org/10.1016/j.rse.2016.09.014>
- Mishra, P., Singh, U., Pandey, C., Mishra, P., and Pandey, G. (2019). Application of student's t-test, analysis of variance, and covariance. *Annals of Cardiac Anaesthesia*, 22(4), 407. https://doi.org/10.4103/aca.ACA_94_19
- Mistro, D. C., Díaz Rodrigues, L. A., and Petrovskii, S. (2012). Spatiotemporal complexity of biological invasion in a space- and time-discrete predator–prey system with the

- strong Allee effect. *Ecological Complexity*, 9, 16–32.
<https://doi.org/10.1016/j.ecocom.2011.11.004>
- Mkungo, L., Odindi, J., Mutanga, O., and Matongera, T. N. (2023). Modelling landscape vulnerability to the Bracken fern (*Pteridium aquilinum*) invasion in a remnant urban Sandstone Sourveldt grassland ecosystem. *Scientific African*, 22, e01947.
<https://doi.org/10.1016/j.sciaf.2023.e01947>
- Mondol, Wadud, M.A, and Rahman, G.M.M. (2021). Tree and shrub diversity, composition and stand structure of Tropical Deciduous Sal Forests of Bangladesh. *International Journal of Agroforestry and Silviculture*, 9(8), 001–016.
- Moreno-Amat, E., Mateo, R. G., Nieto-Lugilde, D., Morueta-Holme, N., Svenning, J.-C., and García-Amorena, I. (2015). Impact of model complexity on cross-temporal transferability in Maxent species distribution models: An assessment using paleobotanical data. *Ecological Modelling*, 312, 308–317.
<https://doi.org/10.1016/j.ecolmodel.2015.05.035>
- Morris, T. L., Esler, K. J., Barger, N. N., Jacobs, S. M., and Cramer, M. D. (2011). Ecophysiological traits associated with the competitive ability of invasive Australian acacias. *Diversity and Distributions*, 17(5), 898–910. <https://doi.org/10.1111/j.1472-4642.2011.00802.x>
- Mukul, S. A., Arfin Khan, M. A. S., and Uddin, M. B. (2020). Identifying threats from invasive alien species in Bangladesh. *Global Ecology and Conservation*, 23, e01196.
<https://doi.org/10.1016/j.gecco.2020.e01196>
- Mukul, S. A., Arfin-Khan, M. A. S., and Uddin, M. B. (2021). Invasive Alien Species of Bangladesh. In T. Pullaiah and M. R. Ielmini (Eds.), *Invasive Alien Species* (1st ed., pp. 1–15). Wiley. <https://doi.org/10.1002/9781119607045.ch13>
- Nadjla, B., Assia, S., and Ahmed, Z. (2022). Contribution of spectral indices of chlorophyll (RECI and GCI) in the analysis of multi-temporal mutations of cultivated land in the Mostaganem plateau. *2022 7th International Conference on Image and Signal Processing and Their Applications (ISPA)*, 1–6.
<https://doi.org/10.1109/ISPA54004.2022.9786326>
- Nagai, S., Saitoh, T. M., Kobayashi, H., Ishihara, M., Suzuki, R., Motohka, T., Nasahara, K. N., and Muraoka, H. (2012). *In situ* examination of the relationship between various vegetation indices and canopy phenology in an evergreen coniferous forest, Japan. *International Journal of Remote Sensing*, 33(19), 6202–6214.
<https://doi.org/10.1080/01431161.2012.682660>

- Nandasena, W. D. K. V., Brabyn, L., and Serrao-Neumann, S. (2023). Monitoring invasive pines using remote sensing: A case study from Sri Lanka. *Environmental Monitoring and Assessment*, 195(2), 347. <https://doi.org/10.1007/s10661-023-10919-1>
- Nath, A., Sinha, A., Lahkar, B. P., and Brahma, N. (2019). In search of Aliens: Factors influencing the distribution of *Chromolaena odorata* L. and *Mikania micrantha* Kunth in the Terai grasslands of Manas National Park, India. *Ecological Engineering*, 131, 16–26. <https://doi.org/10.1016/j.ecoleng.2019.02.012>
- Negi, G. C. S. (2006). Leaf and bud demography and shoot growth in evergreen and deciduous trees of central Himalaya, India. *Trees*, 20(4), 416–429. <https://doi.org/10.1007/s00468-006-0056-4>
- Norisada, M., Hitsuma, G., Kuroda, K., Yamanoshita, T., Masumori, M., Tange, T., Yagi, H., Nuyim, T., Sasaki, S., and Kojima, K. (2005). *Acacia mangium* , a Nurse Tree Candidate for Reforestation on Degraded Sandy Soils in the Malay Peninsula. *Forest Science*, 51(5), 498–510. <https://doi.org/10.1093/forestscience/51.5.498>
- Padalia, H., Srivastava, V., and Kushwaha, S. P. S. (2014). Modeling potential invasion range of alien invasive species, *Hyptis suaveolens* (L.) Poit. in India: Comparison of MaxEnt and GARP. *Ecological Informatics*, 22, 36–43. <https://doi.org/10.1016/j.ecoinf.2014.04.002>
- Peña-Barragán, J. M., Ngugi, M. K., Plant, R. E., and Six, J. (2011). Object-based crop identification using multiple vegetation indices, textural features and crop phenology. *Remote Sensing of Environment*, 115(6), 1301–1316. <https://doi.org/10.1016/j.rse.2011.01.009>
- Pettorelli, N., Vik, J. O., Myrsetrud, A., Gaillard, J.-M., Tucker, C. J., and Stenseth, N. Chr. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, 20(9), 503–510. <https://doi.org/10.1016/j.tree.2005.05.011>
- Phillips, S. J., Anderson, R. P., and Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190(3–4), 231–259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Poorter, H., and Nagel, O. (2000). The role of biomass allocation in the growth response of plants to different levels of light, CO₂, nutrients and water: A quantitative review. *Functional Plant Biology*, 27(12), 1191. https://doi.org/10.1071/PP99173_CO
- Prajwala. (2015). A Comparative Study on Decision Tree and Random Forest Using R Tool. *IJARCCCE*, 196–199. <https://doi.org/10.17148/IJARCCCE.2015.4142>

- Pyšek, P., Jarošík, V., Hulme, P. E., Pergl, J., Hejda, M., Schaffner, U., and Vilà, M. (2012). A global assessment of invasive plant impacts on resident species, communities and ecosystems: The interaction of impact measures, invading species' traits and environment. *Global Change Biology*, 18(5), 1725–1737. <https://doi.org/10.1111/j.1365-2486.2011.02636.x>
- R Core Team (2023). (n.d.). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. version 4.3.2. <https://www.R-project.org/>.
- Rahman, M. M., and Vacik, H. (2010). Vegetation analysis and tree population structure of Sal (*Shorea robusta* C.F. Gaertn) forests: A case study from the Madhupur and Bhawal National Park in Bangladesh. In *National Parks: Vegetation, Wildlife and Threats* (pp. 193–206).
- Rahman, Md. H., and Roy, B. (2014). Population Structure and Curative Uses of Invasive Plants in and around the Protected Forests of Bangladesh: A Means of Utilization of Potential Invasive Species. *Journal of Ecosystems*, 2014, 1–14. <https://doi.org/10.1155/2014/249807>
- Rahman, Md. Motiur Rahman, and Mahbubul Alam. (2010a). Disappearing Forest Tree Species Diversity in Tropical Moist Deciduous Forest and Its Implications: A Case Study in the Madhupur Tract of Central Bangladesh. *Journal of Forest Science*, 26(3), 161–170.
- Rahman, Md. Motiur Rahman, Zhang Guogang, and Kazi Shakila Islam. (2010b). A review of the present threats to tropical moist deciduous Sal (*Shorea robusta*) forest ecosystem of central Bangladesh. *Tropical Conservation Science*, Vol. 3(1), 90–102.
- Rai, P. K. (2022). Environmental Degradation by Invasive Alien Plants in the Anthropocene: Challenges and Prospects for Sustainable Restoration. *Anthropocene Science*, 1(1), 5–28. <https://doi.org/10.1007/s44177-021-00004-y>
- Rangra, N., Samanta, S., and Pradhan, K. (2019). A comprehensive review on phytopharmacological investigations of *Acacia auriculiformis* A.Cunn. Ex Benth. *Asian Pacific Journal of Tropical Biomedicine*, 9(1), 1. <https://doi.org/10.4103/2221-1691.250263>
- Rebelo, A. J., Gokool, S., Holden, P. B., and New, M. G. (2021). Can Sentinel-2 be used to detect invasive alien trees and shrubs in Savanna and Grassland Biomes? *Remote Sensing Applications: Society and Environment*, 23, 100600. <https://doi.org/10.1016/j.rsase.2021.100600>

- Resasco, J., Hale, A. N., Henry, M. C., and Gorchov, D. L. (2007). Detecting an invasive shrub in a deciduous forest understory using late-fall Landsat sensor imagery. *International Journal of Remote Sensing*, 28(16), 3739–3745. <https://doi.org/10.1080/01431160701373721>
- Richardson, D. M., Carruthers, J., Hui, C., Impson, F. A. C., Miller, J. T., Robertson, M. P., Rouget, M., Le Roux, J. J., and Wilson, J. R. U. (2011). Human-mediated introductions of Australian acacias – a global experiment in biogeography. *Diversity and Distributions*, 17(5), 771–787. <https://doi.org/10.1111/j.1472-4642.2011.00824.x>
- Rocchini, D., Andreo, V., Förster, M., Garzon-Lopez, C. X., Gutierrez, A. P., Gillespie, T. W., Hauffe, H. C., He, K. S., Kleinschmit, B., Mairota, P., Marcantonio, M., Metz, M., Nagendra, H., Pareeth, S., Ponti, L., Ricotta, C., Rizzoli, A., Schaab, G., Zebisch, M., ... Neteler, M. (2015). Potential of remote sensing to predict species invasions: A modelling perspective. *Progress in Physical Geography: Earth and Environment*, 39(3), 283–309. <https://doi.org/10.1177/0309133315574659>
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., and Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93–104. <https://doi.org/10.1016/j.isprsjprs.2011.11.002>
- Saadat, H., Bonnell, R., Sharifi, F., Mehuys, G., Namdar, M., and Ale-Ebrahim, S. (2008). Landform classification from a digital elevation model and satellite imagery. *Geomorphology*, 100(3–4), 453–464. <https://doi.org/10.1016/j.geomorph.2008.01.011>
- Saito, T. I., and Tsuyuzaki, S. (2012). Response of riparian vegetation to the removal of the invasive forb, *Solidago gigantea*, and its litter layer. *Weed Biology and Management*, 12(2), 63–70. <https://doi.org/10.1111/j.1445-6664.2012.00436.x>
- Santillan, J. R., Gagula, A. C., and Makinano-Santillan, M. (2021). Machine Learning Approach for Tree Plantation Suitability Mapping. *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 6865–6868. <https://doi.org/10.1109/IGARSS47720.2021.9554792>
- Schutzenhofer, M. R., Valone, T. J., and Knight, T. M. (2009). Herbivory and population dynamics of invasive and native Lespedeza. *Oecologia*, 161(1), 57–66. <https://doi.org/10.1007/s00442-009-1354-5>
- Schwager, P., and Berg, C. (2021). Remote sensing variables improve species distribution models for alpine plant species. *Basic and Applied Ecology*, 54, 1–13.

<https://doi.org/10.1016/j.baae.2021.04.002>

- Shackleton, R. T., Le Maitre, D. C., Van Wilgen, B. W., and Richardson, D. M. (2016). Identifying barriers to effective management of widespread invasive alien trees: *Prosopis* species (mesquite) in South Africa as a case study. *Global Environmental Change*, 38, 183–194. <https://doi.org/10.1016/j.gloenvcha.2016.03.012>
- Shahid, S. (2010). Recent trends in the climate of Bangladesh. *Climate Research*, 42(3), 185–193. <https://doi.org/10.3354/cr00889>
- Shishir, S., Mollah, T. H., Tsuyuzaki, S., and Wada, N. (2020). Predicting the probable impact of climate change on the distribution of threatened *Shorea robusta* forest in Purbachal, Bangladesh. *Global Ecology and Conservation*, 24, e01250. <https://doi.org/10.1016/j.gecco.2020.e01250>
- Shishir, S., and Tsuyuzaki, S. (2018). Hierarchical classification of land use types using multiple vegetation indices to measure the effects of urbanization. *Environmental Monitoring and Assessment*, 190(6), 342. <https://doi.org/10.1007/s10661-018-6714-3>
- Silva, S. D. P., Eugenio, F. C., Fantinel, R. A., Amaral, L. D. P., Dos Santos, A. R., Mallmann, C. L., Dos Santos, F. D., Pereira, R. S., and Ruoso, R. (2023). Modeling and detection of invasive trees using UAV image and machine learning in a subtropical forest in Brazil. *Ecological Informatics*, 74, 101989. <https://doi.org/10.1016/j.ecoinf.2023.101989>
- Simberloff, D. (2000). Global climate change and introduced species in United States forests. *Science of The Total Environment*, 262(3), 253–261. [https://doi.org/10.1016/S0048-9697\(00\)00527-1](https://doi.org/10.1016/S0048-9697(00)00527-1)
- Simpson, Prots, B., and Vykhov, B. (2011). Modeling of the invasive plant distribution: Case study of Sosnowski's hogweed *Heracleum sosnowskyi* Manden. In the Ukrainian Carpathian Mts. *Journal of Biological Systems*, 3(1), 80–89.
- Singh, B., Jeganathan, C., and Rathore, V. S. (2020). Improved NDVI based proxy leaf-fall indicator to assess rainfall sensitivity of deciduousness in the central Indian forests through remote sensing. *Scientific Reports*, 10(1), 17638. <https://doi.org/10.1038/s41598-020-74563-2>
- Smith, L. M. (2013). Extended leaf phenology in deciduous forest invaders: Mechanisms of impact on native communities. *Journal of Vegetation Science*, 24(6), 979–987. <https://doi.org/10.1111/jvs.12087>
- Sultana, M., Tsuyuzaki, S., and Bhuiyan, Md. A. H. (2025). Detecting biologically invasive species by phenology and topography in tropical moist deciduous forests at satellite

- remote sensing scale. *International Journal of Remote Sensing*, 1–19. <https://doi.org/10.1080/01431161.2025.2474168>
- Sun, X., Zhou, Y., Jia, S., Shao, H., Liu, M., Tao, S., and Dai, X. (2024). Impacts of mining on vegetation phenology and sensitivity assessment of spectral vegetation indices to mining activities in arid/semi-arid areas. *Journal of Environmental Management*, 356, 120678. <https://doi.org/10.1016/j.jenvman.2024.120678>
- Taylor, S., and Kumar, L. (2013). Potential distribution of an invasive species under climate change scenarios using CLIMEX and soil drainage: A case study of *Lantana camara* L. in Queensland, Australia. *Journal of Environmental Management*, 114, 414–422. <https://doi.org/10.1016/j.jenvman.2012.10.039>
- Tian, J., Wang, L., Yin, D., Li, X., Diao, C., Gong, H., Shi, C., Menenti, M., Ge, Y., Nie, S., Ou, Y., Song, X., and Liu, X. (2020). Development of spectral-phenological features for deep learning to understand *Spartina alterniflora* invasion. *Remote Sensing of Environment*, 242, 111745. <https://doi.org/10.1016/j.rse.2020.111745>
- Toma, R. A., Rabby, M. F., Roni, R., and Rashid, M. S. (2022). Assessing the Efficiency of Classification Techniques Between SVM and ML for Detecting Land Transformation in Bhawal Sal Forest. In G. S. Bhunia, U. Chatterjee, K. C. Lalmalsawmzauva, and P. K. Shit (Eds.), *Anthropogeomorphology* (pp. 443–458). Springer International Publishing. https://doi.org/10.1007/978-3-030-77572-8_23
- Tu, W., Xiong, Q., Qiu, X., and Zhang, Y. (2021). Dynamics of invasive alien plant species in China under climate change scenarios. *Ecological Indicators*, 129, 107919. <https://doi.org/10.1016/j.ecolind.2021.107919>
- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Václavík, T., and Meentemeyer, R. K. (2009). Invasive species distribution modeling (iSDM): Are absence data and dispersal constraints needed to predict actual distributions? *Ecological Modelling*, 220(23), 3248–3258. <https://doi.org/10.1016/j.ecolmodel.2009.08.013>
- Wang, G., Wang, C., Guo, Z., Dai, L., Wu, Y., Liu, H., Li, Y., Chen, H., Zhang, Y., Zhao, Y., Cheng, H., Ma, T., and Xue, F. (2020). Integrating Maxent model and landscape ecology theory for studying spatiotemporal dynamics of habitat: Suggestions for conservation of endangered Red-crowned crane. *Ecological Indicators*, 116, 106472. <https://doi.org/10.1016/j.ecolind.2020.106472>

- Warziniack, T., Haight, R. G., Yemshanov, D., Apriesnig, J. L., Holmes, T. P., Countryman, A. M., Rothlisberger, J. D., and Haberland, C. (2021). Economics of Invasive Species. In T. M. Poland, T. Patel-Weynand, D. M. Finch, C. F. Miniati, D. C. Hayes, and V. M. Lopez (Eds.), *Invasive Species in Forests and Rangelands of the United States* (pp. 305–320). Springer International Publishing. https://doi.org/10.1007/978-3-030-45367-1_14
- Wen, L., Saintilan, N., Yang, X., Hunter, S., and Mawer, D. (2015). MODIS NDVI based metrics improve habitat suitability modelling in fragmented patchy floodplains. *Remote Sensing Applications: Society and Environment*, 1, 85–97. <https://doi.org/10.1016/j.rsase.2015.08.001>
- Wilfong, David L. Gorchov, and Mary C. Henry. (2009). Detecting an Invasive Shrub in Deciduous Forest Understories Using Remote Sensing. *Weed Science*, 512–520.
- Wu, Q., Zhong, R., Zhao, W., Fu, H., and Song, K. (2017). A comparison of pixel-based decision tree and object-based Support Vector Machine methods for land-cover classification based on aerial images and airborne lidar data. *International Journal of Remote Sensing*, 38(23), 7176–7195. <https://doi.org/10.1080/01431161.2017.1371864>
- Xu, D., Zhuo, Z., Wang, R., Ye, M., and Pu, B. (2019). Modeling the distribution of *Zanthoxylum armatum* in China with MaxEnt modeling. *Global Ecology and Conservation*, 19, e00691. <https://doi.org/10.1016/j.gecco.2019.e00691>
- Xu, R., Zhao, S., and Ke, Y. (2021). A Simple Phenology-Based Vegetation Index for Mapping Invasive *Spartina Alterniflora* Using Google Earth Engine. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 190–201. <https://doi.org/10.1109/JSTARS.2020.3038648>
- Xue, J., and Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, 2017, 1–17. <https://doi.org/10.1155/2017/1353691>
- Yang, L., Liu, N., Ren, H., and Wang, J. (2009). Facilitation by two exotic *Acacia*: *Acacia auriculiformis* and *Acacia mangium* as nurse plants in South China. *Forest Ecology and Management*, 257(8), 1786–1793. <https://doi.org/10.1016/j.foreco.2009.01.033>
- Yi, Y., Cheng, X., Yang, Z.-F., and Zhang, S.-H. (2016). Maxent modeling for predicting the potential distribution of endangered medicinal plant (*H. riparia* Lour) in Yunnan, China. *Ecological Engineering*, 92, 260–269. <https://doi.org/10.1016/j.ecoleng.2016.04.010>

- Yin, G., Verger, A., Descals, A., Filella, I., and Peñuelas, J. (2022). A Broadband Green-Red Vegetation Index for Monitoring Gross Primary Production Phenology. *Journal of Remote Sensing*, 2022, 2022/9764982. <https://doi.org/10.34133/2022/9764982>
- Zeng, J., Sun, Y., Cao, P., and Wang, H. (2022). A phenology-based vegetation index classification (PVC) algorithm for coastal salt marshes using Landsat 8 images. *International Journal of Applied Earth Observation and Geoinformation*, 110, 102776. <https://doi.org/10.1016/j.jag.2022.102776>
- Zerkout, Muskhazli Mustafa, Hishamuddin Omar, Mohd Hafiz Ibrahim, and Rusea Go. (2021). Acacia auriculiformis Cunn. Ex Benth As Phytoextraction Agent: A Growth Response, Physiological Tolerance and Lead Removal Capability Evaluation. *Jordan Journal of Biological Sciences*, 14(03), 423–431. <https://doi.org/10.54319/jjbs/140307>
- Zhang, K., Yao, L., Meng, J., and Tao, J. (2018b). Maxent modeling for predicting the potential geographical distribution of two peony species under climate change. *Science of The Total Environment*, 634, 1326–1334. <https://doi.org/10.1016/j.scitotenv.2018.04.112>
- Zhang, K., Zhang, Y., Zhou, C., Meng, J., Sun, J., Zhou, T., and Tao, J. (2019). Impact of climate factors on future distributions of Paeonia ostii across China estimated by MaxEnt. *Ecological Informatics*, 50, 62–67. <https://doi.org/10.1016/j.ecoinf.2019.01.004>
- Zhao, C., and Qin, C.-Z. (2022). Identifying large-area mangrove distribution based on remote sensing: A binary classification approach considering subclasses of non-mangroves. *International Journal of Applied Earth Observation and Geoinformation*, 108, 102750. <https://doi.org/10.1016/j.jag.2022.102750>
- Zhu, X., and Liu, D. (2014). Accurate mapping of forest types using dense seasonal Landsat time-series. *ISPRS Journal of Photogrammetry and Remote Sensing*, 96, 1–11. <https://doi.org/10.1016/j.isprsjprs.2014.06.012>

Appendices

Appendix A

Table A1-A2

Figure A1-A6

Table A-1: the wavelength bands of Sentinel-2A images

Band name	Description	Wavelength (nm)	Spatial resolution (m)
B2	Blue	496	10
B3	Green	560	10
B4	Red	665	10
B5	Red Edge 1	704	20
B6	Red Edge 2	740	20
B7	Red Edge 3	783	20
B8	Near Infrared (NIR)	835	10
B8A	Red Edge 4	864	20
B11	Shortwave Infrared-1 (SWIR 1)	1613	20
B12	Shortwave Infrared-1 (SWIR 2)	2202	20

Table A-2: Environmental variables for MaxEnt

No.	Environmental factors	unit	Source
1	Annual precipitation	mm	ImageCollection("IDAHO_EPSCOR/TERRACLIMATE") resolution: 4638.3 m
2	Annual mean temperature	⁰ C	ImageCollection("IDAHO_EPSCOR/TERRACLIMATE") resolution: 4638.3 m
3	Elevation	m	DEM from Advanced Land Observing Satellite (ALOS) resolution: 12.5 m
4	Soil pH		OpenLandMap/SOL/SOL_PH-H2O_USDA-4C1A2A_M/v02 resolution: 250 m
5	Soil nitrogen (N)	g/kg	projects/soilgrids-isric/nitrogen_mean resolution: 250 m
6	Organic carbon (OC)	g/kg	OpenLandMap/SOL/SOL_ORGANIC-CARBON_USDA-6A1C_M/v02; resolution: 250m
7	NDVI		Processed in Google Earth Engine
8	GRVI		Processed in Google Earth Engine
9	Distance from road	m	Digitized from Google Earth Pro and processed in ArcGIS
10	Distance from the settlement	m	Digitized from Google Earth Pro and processed in ArcGIS
11	Population density	(/km ²)	CIESIN/GPWv411/GPW_Population_Density resolution: 927.67 m

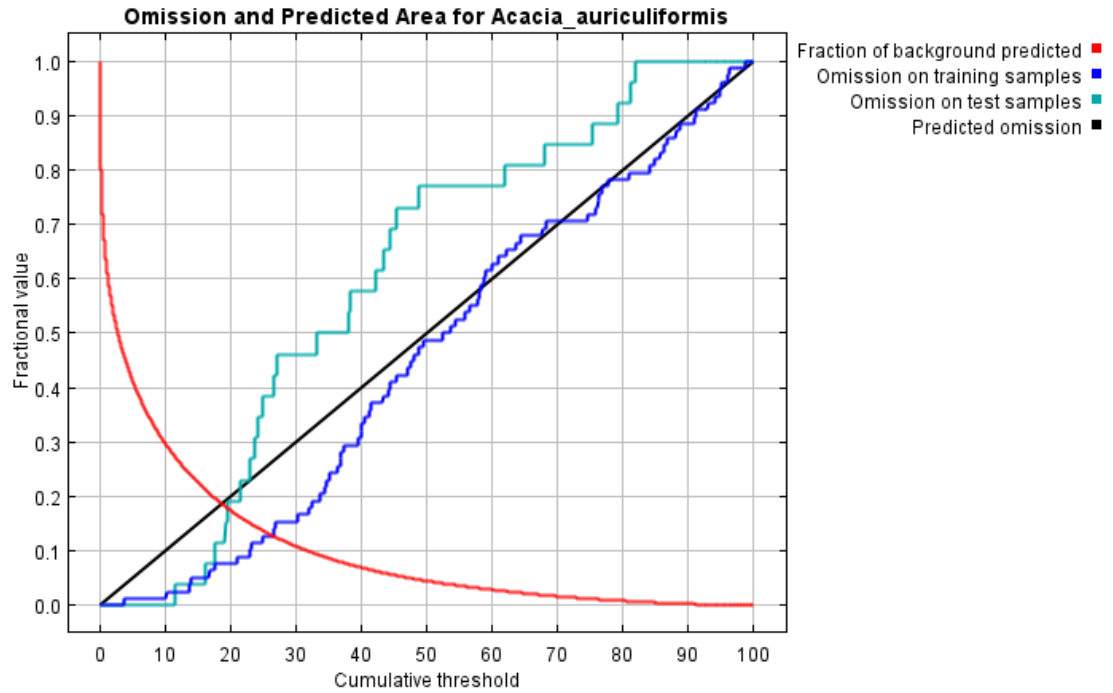


Figure A-1 The curve of omission rate and predicted area as a function of the cumulative threshold. The omission rate is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

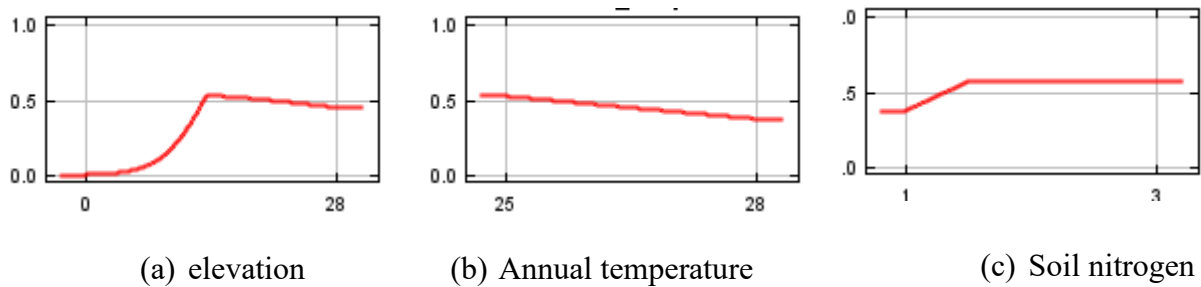


Figure A-2 The response curve of environmental variables with less contributions

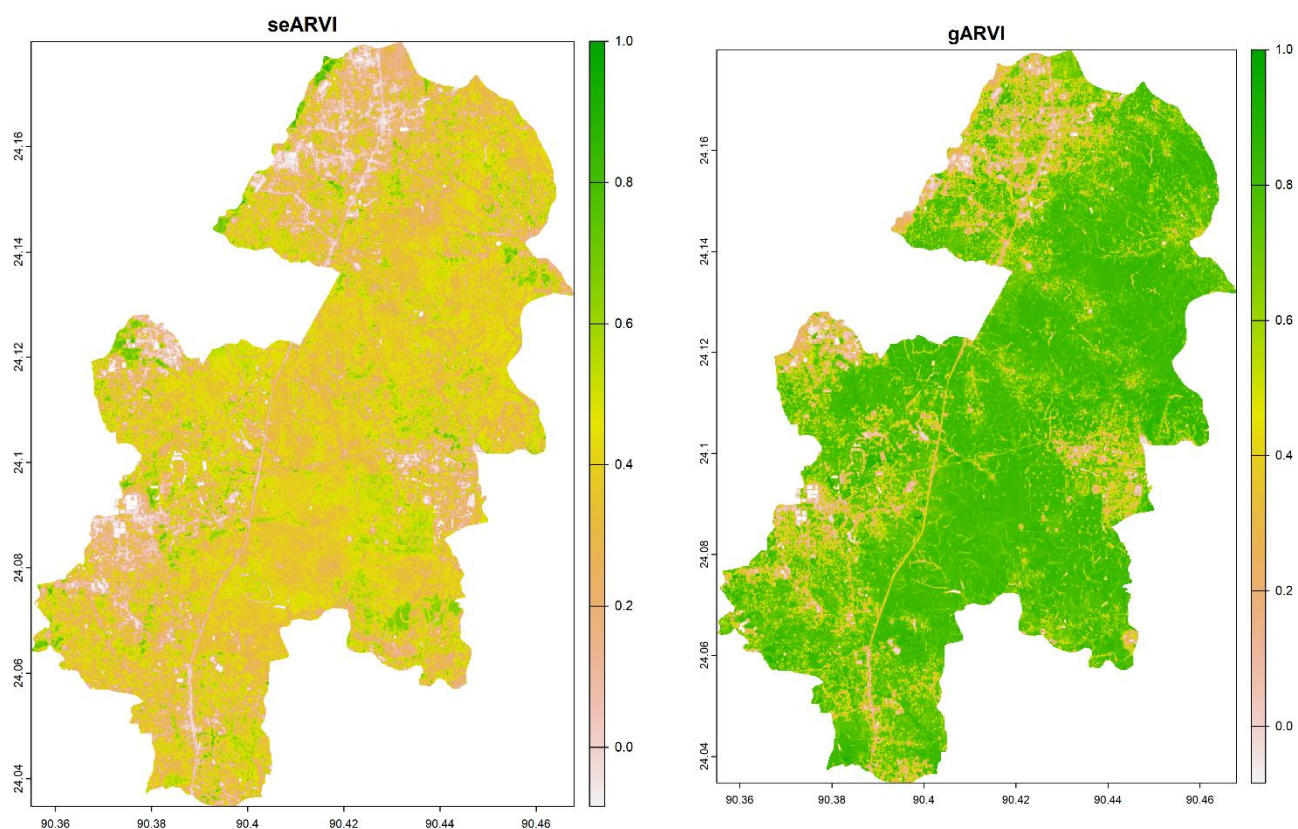


Figure A-3: composited images of seARVI and gARVI for creating frequency curves

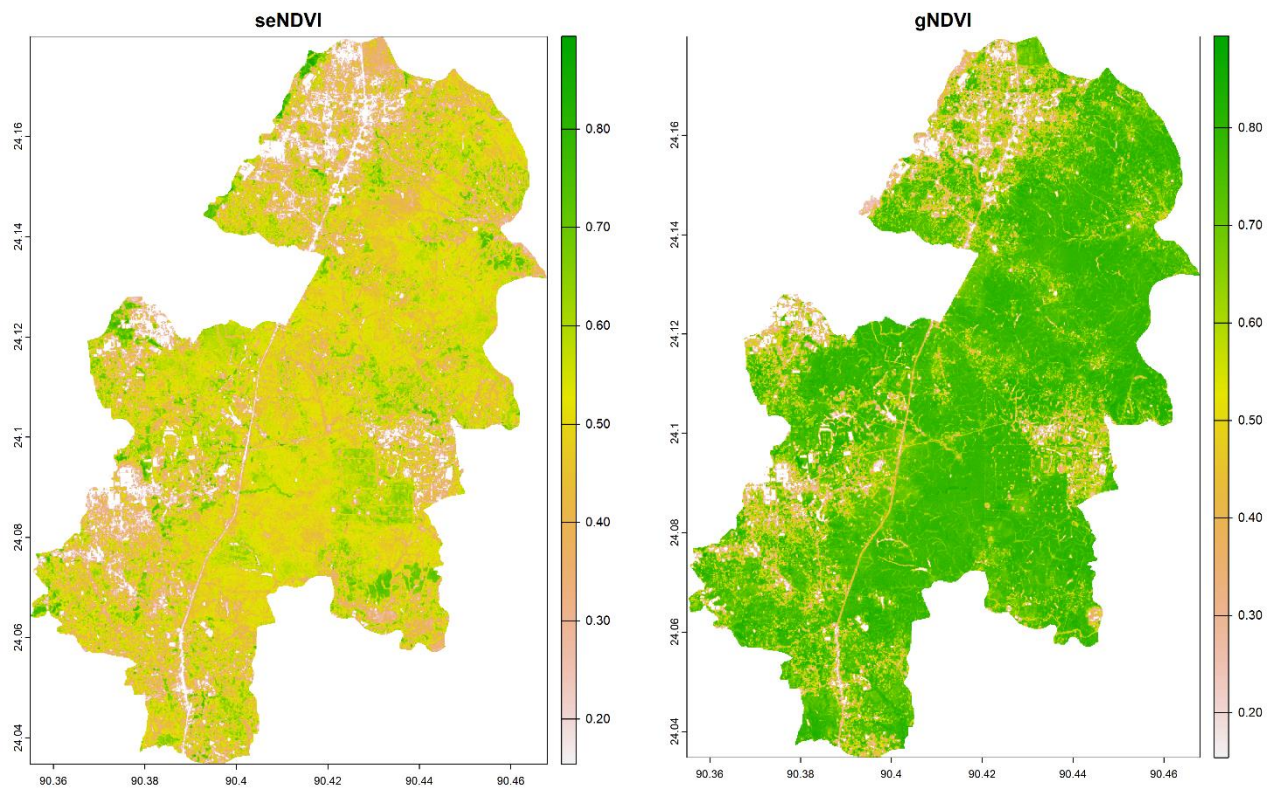


Figure A-4: composited images of seNDVI and gNDVI for creating frequency curves

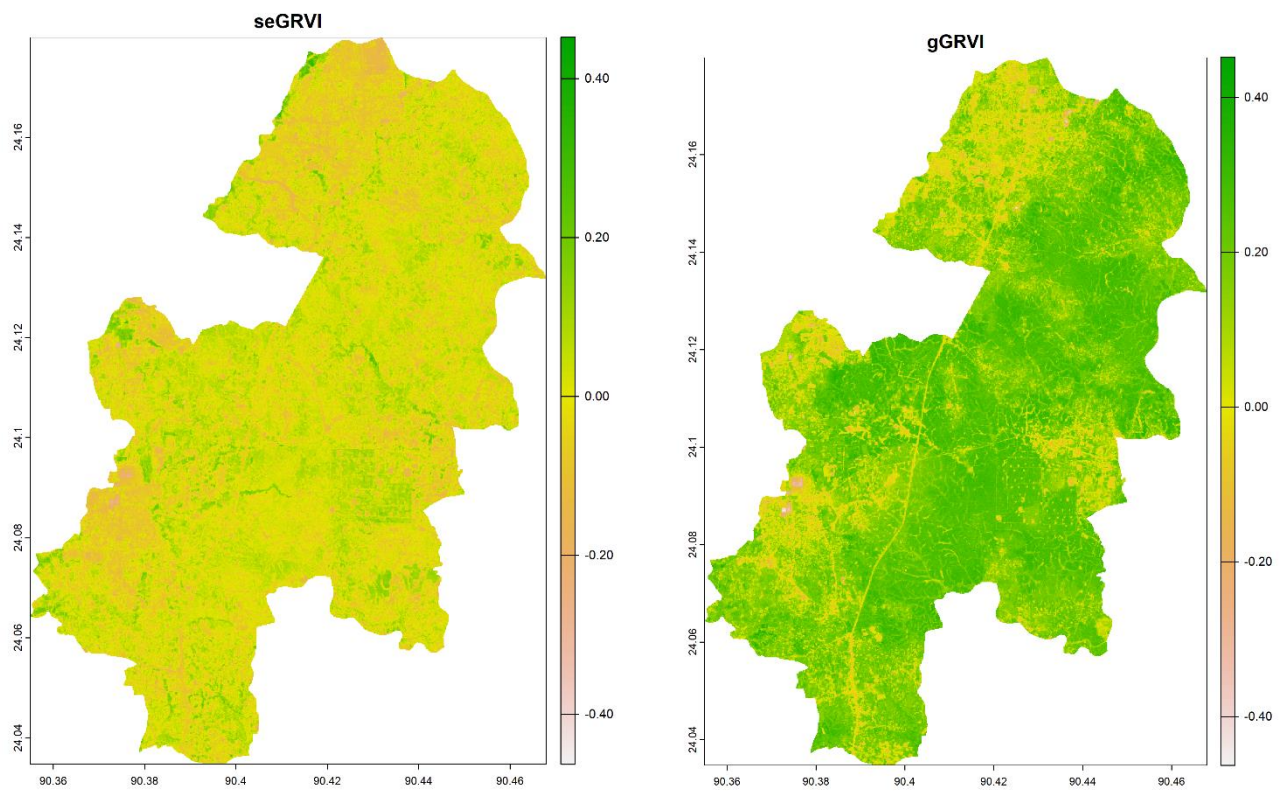


Figure A-5: composited images of seGRVI and gGRVI for creating frequency curve

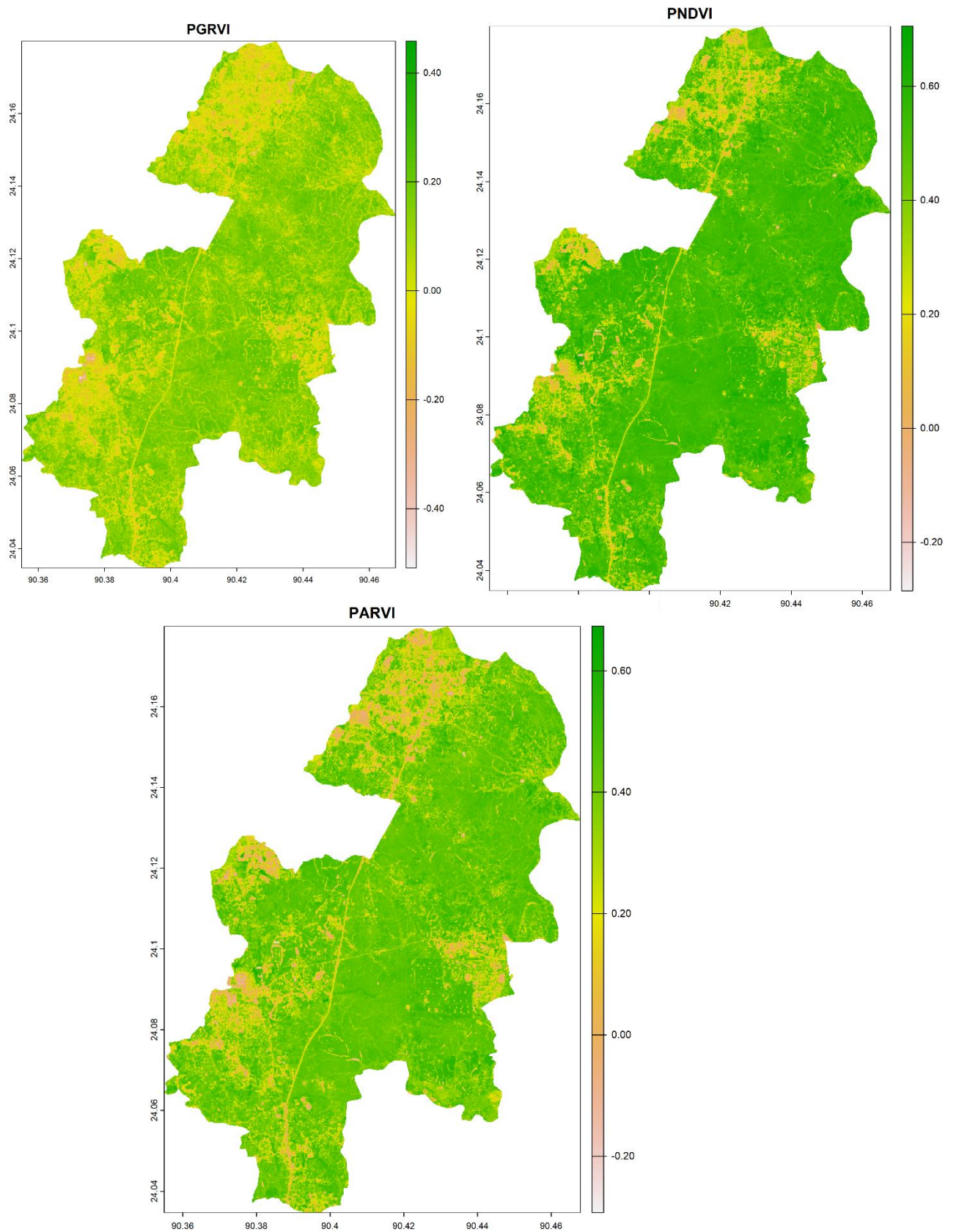


Figure A-6: composited images of PNDVI, PARVI and PGRVI for creating frequency curves