IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.8, Issue.8, August 2020 E-ISSN: 2347-2693

A Comparative Analysis of Vegetation Radiometric Indices for Classification of Bambusa Tulda using Satellite Imagery

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DOI: https://doi.org/10.26438/ijcse/v8i8.6772 | Available online at: www.ijcseonline.org

Received: 19/Aug/2020, Accepted: 25/Aug/2020, Published: 31/Aug/2020

***Abstract*—**Bamboo trees are very common in almost every household of rural areas in Assam. Monitoring their expansion is useful for various environmentalists. Bamboo is in the path of becoming a great replacement for plastics. Hence, its preservation and monitoring are very important. Most of the existing works of tree identification are based on machine learning models, Convolutional Neural Network, UNet and Fully Convolutional deep learning models. Specific tree detection of coconut and palm trees has also been done using satellite images. Very few works have mapped bamboo regions using Sentinel products. Landsat and WorldView are the repeatedly used data for bamboo mapping and classification. The aim of this study is to provide a view to the ability of Sentinel imagery and vegetation indices for monitoring of Bambusa Tulda (Jati bamboo) during winter season. The study was carried out in Dimoria Development Block of Assam, India. The bamboo classification techniques using satellite products have been vigorously compared in this work. We have used Normalized Difference Vegetation Index, Stress Index and Bamboo Index to extract the features of Bambusa Tulda. The results show that Bamboo Index and Stress Index improves the bamboo classification result.

***Keywords*—**Satellite Imagery, Bamboo mapping, Sentinel, NDVI, BI, SI, Tree identification

I. INTRODUCTION

Currently, object detection from satellite imagery is in high demand. Machine learning algorithms like seed growing, circular hough transform, local maxima point detection, random forests are applicable in vegetation detection and mapping. Forest is the most important resource in the ecosystem. Tree attributes like treetops, their heights and counts are being measured time to time for forest analysis. Due to global warming a necessity arises to observe and monitor the trees and crop diversities [1, 2]. Satellite imagery has been serving this cause for easy identification of plant characteristics and distribution. The commonly used satellite images in this case is the World View imagery [1, 2, 3] followed by Sentinel [5] and QuickBird [6]. Over the years many classification algorithms have been tested for tree species detection using satellite imagery. Some important algorithms include Support Vector Machine, Maximum likelihood, Decision tree, seed growing, local maxima point detection and circular though transform [7]. The tree tops are assumed as bright spots or star shaped structures. These features can be identified by local maxima filters and non-maximum suppression. Template matching is another approach. Morphological operations like regional maxima are also applied. The peak regions can be highlighted as top hats but it results in repeated detections. Euclidean minimum distance filtering may be useful to avoid these repeated detections. If the distance is smaller than tree tops are known to be merged into one [2, 3, 8]. Nowadays, deep learning is in high demand. It is resistant to the cloud covered satellite imagery. In its maiden years, deep learning was used only for document recognition. It was the attempt of Krizhevsky et al. [9] that made the deep learning possible for image classification on large datasets. This created a path to the beginning of new deep learning techniques [10][32, 33]. Deep learning proves to be a more robust approach in forest resource monitoring. Convolutional Neural Network is popular in solving the problem of individual tree detection.

In this paper, we investigated the potentiality of vegetation indices in satellite imagery for bamboo classification. The main focus is to identify the bamboo species Bambusa Tulda. The objectives of the present work are:

- To analyse the bamboo coverage in Dimoria of Assam through vegetation indices and spectral reflectance of satellite data.
- To check if classification is possible when bamboo index is used as an input feature to the random forest classifier.
- To compare our results with the existing works.

This paper consists of total five sections. The first section gives a basic introduction to the tree species detection using satellite images. The various models and techniques used in the existing works are mentioned in Section II. Section III introduces our study region and data used. It also explains the flow of our research. Section IV compares our results against the existing works. Finally the paper is concluded in Section V.

II. RELATED WORK

In middle of the year 2018, Watanabe, Sumi and Ise [11] tried to detect the bamboo trees by chopping the Google Earth images and by using LeNet and Convolutional Neural Network. The results proved the capability of deep learning models to detect bamboo forests accurately. Zhao et al [12] used phenological classification and Random forest for the bamboo mapping in the three East African countries. Chen et al [13] effectively estimated the aboveground biomass of bamboo forests. Random forest based classification model along with the satellite feature variables like seasonal bamboo index showed excellent performance. The pattern of Moso bamboo's extension was analyzed through Marked correlation functions, Mark variogram functions and pair correlation [14]. Spectral temporal signatures of bamboo dominated regions were analyzed to identify bamboo regions and bamboo life cycles by Greig, Robertson and Lacerda [15]. Zhang et al [16] applied a complete phenological approach of bamboo classification with the involvement of Normalized Vegetation Index, Enhanced Vegetaion Index, Land Surface Water Index and Green Chlorophyll Vegetation Index. This work suggested that phenological classification gives accurate results in tropical regions. Machine learning and deep learning models was very helpful in identification of Lei bamboo from other forests. Dong et al [17] proposed a hybrid technique comprising of random forest and Convolutional Neural Network for bamboo forest mapping. It was proved that Convolutional Neural Network performed best to estimate Lei bamboo aboveground biomass with coefficient of correlation 0.943. Li et al [18] performed bamboo classification supported by different vegetation indices and spectral characteristics extracted from satellite imagery.

Table 1. Few recent works for bamboo classification using images

References	**Methodology**		
	Technique	***Merit***	***Demerit***
Watanabe, Sumi and Ise (2018)	Convolutional Neural Network And LeNet	High target accuracy	Less samples
Zhao et al. (2018)	Phenological classification	Better performance	Less training samples
Chen et al., (2018)	Phenological classification	High user and producer accuracy	Inconsistency of field dates and image acquisition
Zhang and Xue, (2018)	Phenological classification	High accuracy	Less training data
Greig, Robertson and Lacerda (2018)	Hybrid spectral-temporal model, MLC	Highly effective	Misclassification due to drop in EVI value
Zhang et al., (2019)	Phenological classification and Ranndom Forest	High discrimination accuracy	Presence of unintegrated bamboo features
Li et al., (2019)	Decision tree and vegetation indices	Accurate proposed bamboo index	Landsat can tract bamboo features easily
Dong et al., (2020a)	Convolutional Random forest	Rich in bamboo features	Takes more time
Dong et al., (2020b)	Convolutional Random forest	Superior performance	Less sensitive to
Juyal et al., (2020)	Machine Learning	Convolutional Random forest	Sensitive to parameter GLCM features

Most recently, Juyal et al [21] have classified five bamboo species namely Phyllostachys nigra, Bambusa vulgaris 'Striata', Dendrocalamus giganteu, Bambusa ventricosa, and Bambusa tulda using a modified Convolutional Neural Network and digital bamboo images. There are no available bamboo dataset for classification. It was evident from the recent studies that the best time to be able to differentiate bamboo from other vegetation is during mid summer and during December-February [17]. Bamboo species like Moso and Lei which are available in Japan, China and Taiwan have been mapped using satellite imagery [18-20]. All the recent works [21-24] on bamboo species (four or more bamboo species classes) classification have used digital images. Individual bamboo species identification from satellite imagery is still in an initial stage [21]. This motivated us to introduce a method to analyze and classify Bambusa Tulda using Sentinel-2 data and vegetation indices.

III. METHODOLOGY

This section presents a detailed discussion on the mapping of Bambusa Tulda followed in this study. The structure of our research carried out during winter season is shown in Figure 1.

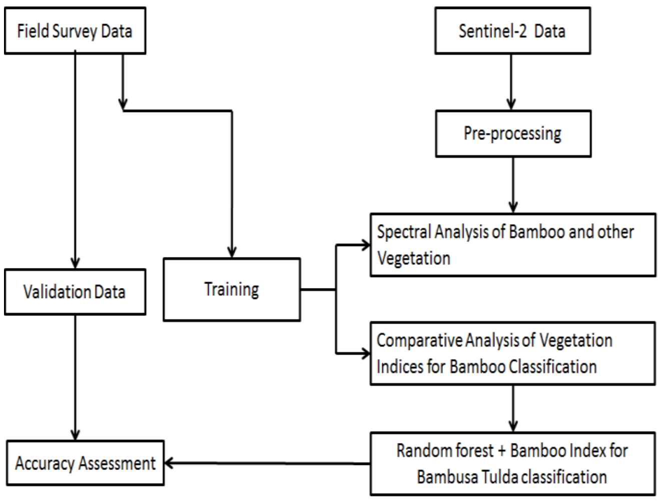


Figure 1. Framework for Bambusa Tulda classification

A. Study Area

Dimoria Development Block of Assam, India covering an area of 304.25 square kilometres was selected [25]. According to the Dimoria Block Register data of 2011, this block has a total population of 1,37,839. In order to explore the bamboo coverage in this block, two sub regions namely Senabar and Taloni were selected. The plain region (Senabar, Dimoria) and hilly region (Taloni, Dimoria) have an altitude of 70.5442177m and 70.60135m respectively. Bambusa Tulda (Jati Bamboo) is the most commonly available bamboo species in Dimoria. It is also called as spineless bamboo. This bamboo species appear as light green colored 'stretching stars' when seen from above.

B. Data Preparation

The fieldwork was carried out in the month of February 2020. A total of 15 large bamboo fields were visited. The coordinates of Bambusa Tulda in these fields were recorded as polygon features in Google Earth. Sentinel-2 Level 2A products containing 13 bands (Table 3) and field survey data were used in this comparative study. Sentinel-2 data were downloaded from the Copernicus Open Access Hub acquired on 17 January, 2020.

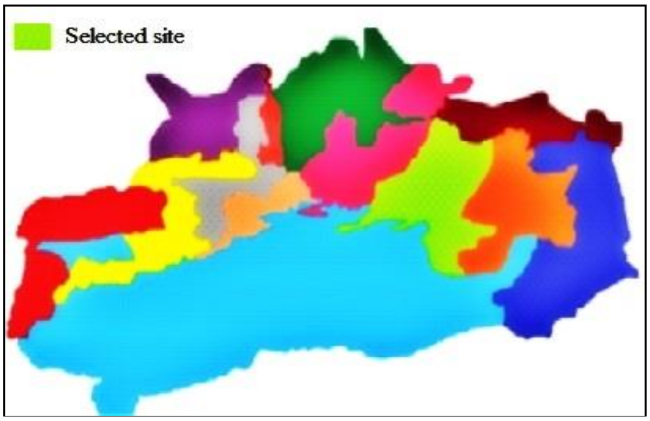
The pre-processing of Sentinel-2 data was performed in three steps. At first, the satellite image was clipped according to our study area. In the second step, bilinear resampling [26, 27] was applied to the created subset. The size of resampled product was defined according to band 2 of Sentinel data which has the highest resolution. Finally the resampled subset was projected to WGS 84/OTM zone 46N [18].

C. Spectral Analysis of Bamboo and other Forests

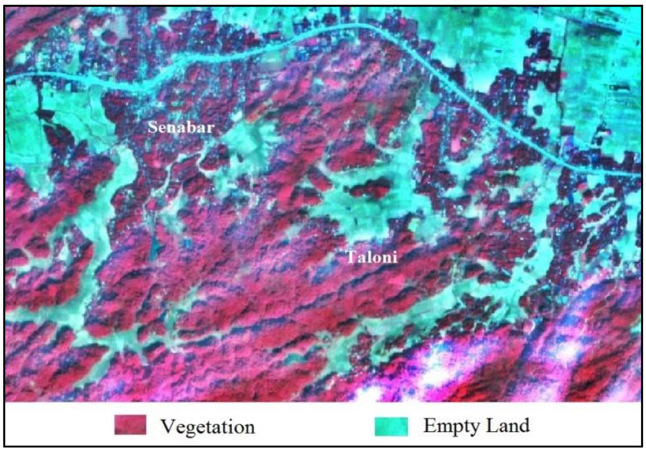
The spectral reflectance of plants gets extracted from their leaves' characteristics. This reflectance is controlled by water and photosynthetic pigments specially [28].

Table 2. Data used in this research

Satellite	**Characteristics of data**		
	Spatial resolution	***Location***	***Acquisition date***
Sentinel-2A	10m	Dimoria, Assam	17 January, 2020
Field Survey	-	Dimoria, Assam	February 2020



(a)



(b)

Figure 2. Study area. (a) Dimoria Development Block, Assam (b) False color composites of Sentinel-2 data, 17 January 2020.

In order to differentiate among the features of bamboo and other forests, spectral analysis was done. We selected bamboo (Bambusa Tulda), other natural forests and empty agriculture land for comparison. Mean values of spectral bands for each of these type was found and then spectral curves were obtained.

Table 3. Bands of Sentinel-2 used in the study

Band	**Characteristics of bands**		
	Resolution(m)	***Wavelength(nm)***	***Description***
B1	60	443	Ultra blue
B2	10	490	Blue
B3	10	560	Green
B4	10	665	Red
B5	20	705	Visible and near infrared
B6	20	740	Visible and near infrared
B7	20	783	Visible and near infrared
B8	10	842	Visible and near infrared
B8A	20	865	Visible and near infrared
B9	60	945	Short wave infrared
B11	20	1610	Short wave infrared
B12	20	2190	Short wave infrared

D. Mapping of Bambusa Tulda

The masking procedure [18] was implemented in order to achieve the bamboo forest classification. Normalized Difference Vegetation Index (NDVI) [28] was applied to differentiate the non-vegetation and vegetation regions during winter season. The pixels less than 0.5 or greater than 0.10001 were considered as non-vegetation types (empty land and roads). The pixels above or equal to 0.5 represented both bamboo and other forests. After this, Bamboo Index (BI) and Stress Index (SI) [29] were also analysed for this study. The approximate threshold in Bamboo Index was considered as 0.7 or 0.8. Thresholds in Stress Index were taken as 0.6 for vegetation class and 0.3 for non-vegetation class.

NDVI=(B8-B4)/(B8+B4) (1)

SI=(B8-B11) / (B8+B11) (2)

BI=(NDVI-SI) / (NDVI+SI) (3)

Random forest classifier [31] of 50 trees was applied to our method with Bamboo Index, Stress Index, NDVI and the bands of Sentinel-2 as feature variables. The validation points were obtained during field survey. Based on these validation points and visual interpretation, the resultant Bambusa Tulda map was compared.

IV. RESULTS

A. Spectral analysis of Bambusa Tulda and other Forests

The spectral reflectance of plants gets extracted from their leaves' characteristics. This reflectance is controlled by water and photosynthetic pigments specially [28]. In order to differentiate among the features of bamboo and other forests, spectral analysis was done.

Figure 3. Illustration of bamboo (Bambusa Tulda), its adjacent other forests and empty lands.

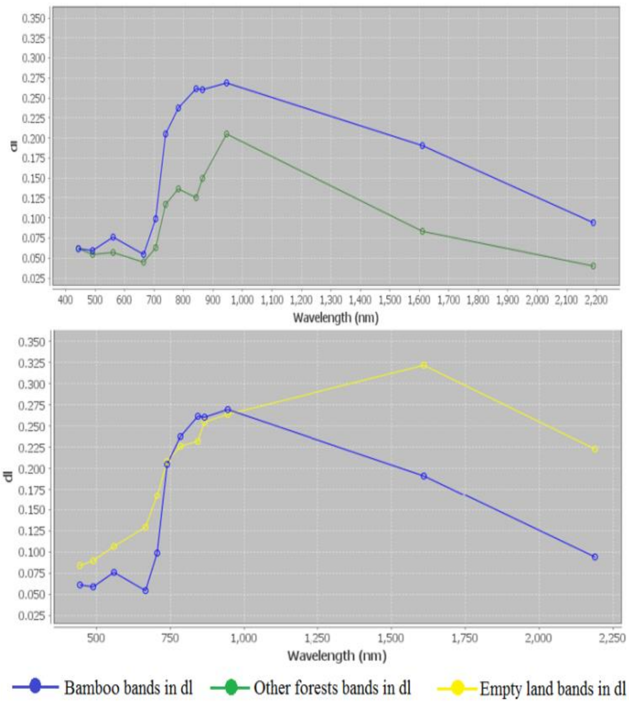


Figure 4. The comparative plot shows the spectral curves of bamboo, other forests and empty lands.

We selected Bambusa Tulda, other natural forests and empty land (Figure 3) for comparison. The spectral values of our selected bamboo species were found to be higher than the other forests types. There are points where the spectral reflectance tends to be identical in these three classes. Figure 4 shows that bamboo-growing areas can be spectrally differentiated using a combination of the different Sentinel bands.

B. Comparative Analysis of Different Indices

Normal bamboo Index range is between -79.1 to 175.6. Normalized Difference Vegetation Index (NDVI) ranges from 0.14 to 0.72. The non-vegetated areas are represented in dark green by NDVI (Figure 5a). Stress Index was mapped for evaluating the water content in the bamboo leaves. It is observed that Stress Index fluctuated between -0.21 to 0.26 (Figure 5d). It can be concluded from the Stress Index map that, bamboo has less water content. Bamboo Index experienced a coefficient of variation of 1.13 with a maximum error of 0.014. The coefficient of variation in the case of NDVI and SI were 0.196 and 0.9 respectively. Stress index and Bamboo index were processed as features through random forest classifier to map the Bambusa Tulda.

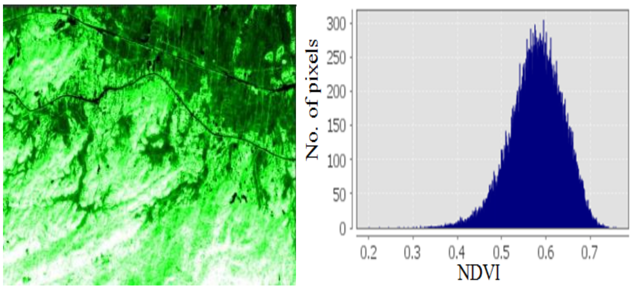
Wang et al. [30] used the Enhanced Vegetation Index which was lower in case of bamboo. Winter NDVI gave higher coefficient of determination which helped in visualizing the variation in bamboo coverage. Figure 5a shows the visual representation of NDVI estimation in our work. It is observed that the bamboo areas reflect more NDVI than other forest areas. Goswami, Tajo and Sarma [30] proposed a bamboo index which gave a cost effective result with kappa value of 0.79. In this study the bamboo species Bambusa Tulda was extracted by using the Sentinel-2 Level 2 datasets acquired during winter season in the study region. Extraction accuracies of Bambusa Tulda and other forests were 38.37% and 51.024% (Table 4) respectively. The resultant map of Bambusa Tulda (Figure 6) was overlayed with the ground truth map in Google Earth to find a good match.

V. CONCLUSION AND FUTURE SCOPE

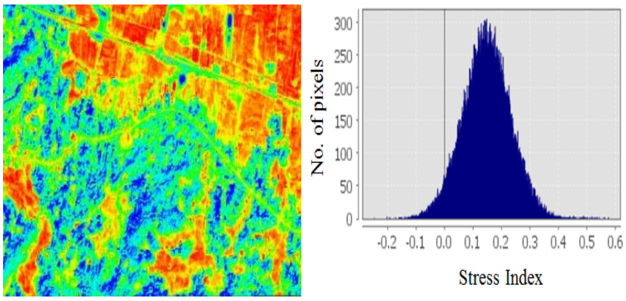
This study implemented and compared the competence of vegetation indices and spectral reflectances for the classification of Bambusa Tulda using Sentinel-2 data. Additionally including bamboo index and stress index as model inputs was very beneficial. With the winter season data the final classification map exhibited a total reasonable performance. The pattern of Bambusa Tulda is distinct. It is light green in color and the leaves come out in all directions starting from the centre. This information was utilised to collect the geographic coordinates of the areas containing Bambusa Tulda. Out of 13 bands of Sentinel-2 data, we have used only 12 bands. Feature variables like Normalized Vegetation Index, Stress index and Bamboo Index were used along with the satellite bands. The Random Forest Classifier was applied for classification purpose. This study will help in setting the foundation of bamboo mapping in the rural regions. As a future work, we plan to perform an enhanced comparative analysis of different non-parametric classifiers for classification of bamboo species other than Bambusa Tulda.

Table 4. Classification accuracy using Sentinel-2 data

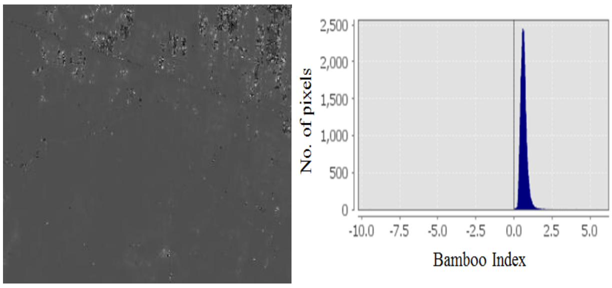
Class name	***Model accuracy***
Bambusa Tulda	38.37%
Other forests	49.49%
Empty land	13.16%



(a) NDVI map (b) Histogram for NDVI

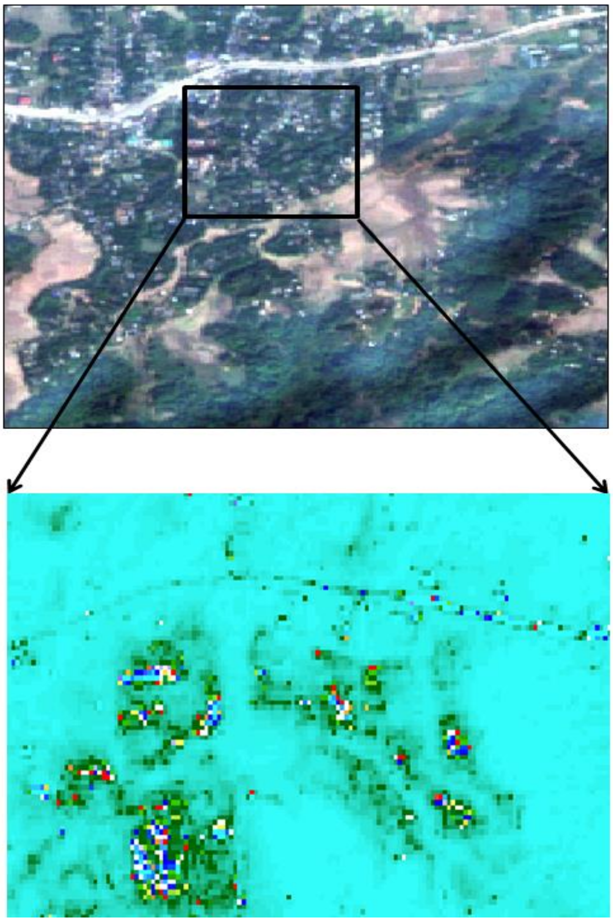


(c) Stress Index map (d) Histogram for Stress Index



(e) Bamboo Index map (f) Histogram for Bamboo Index

Figure 5. Comparative analysis of three vegetation indices. (a) and (b) Normalized Difference Vegetation Index (NDVI), (c) and (d) Stress Index (SI), (e) and (f) Bamboo Index (BI) during winter season.



(b)

Figure 6. The result of Bambusa Tulda classification. The Bambusa Tulda species are highlighted by red dots.

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