Impact of various Vegetation Indices on Mango orchard mapping using Object-Based Image Analysis

Steena Stephen*, Dipanwita Haldar, N.R. Patel
Indian Institute of Remote Sensing, Dehradun, 248001
*Email: steesaini@gmail.com

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Abstract: Mango farming is an important part of the Indian agriculture economy. Mapping of mango orchards is essential for monitoring mango plantations as well as its yield assessment. Object-based Image Analysis (OBIA) is a powerful image classification method which uses spatial and spectral information for image classification. This study assesses the impact of three vegetation indices; NDVI (Normalised Difference Vegetation Index), ReNDVI (Red Edge Normalised Difference Vegetation Index) and LSWI(Land Surface Water Index) on the accuracy of classification using object-based image analysis using Sentinel - 2 data. A temporal profile was generated to select the best possible dates for classification based on the maximum and minimum values of the index. LSWI gave the highest overall accuracy of the classification (89%) followed by ReNDVI (87%) and NDVI (86%).The study found that LSWI and ReNDVI have the potential for better mapping of Mango orchards and can be explored further to generate accurate Mango orchard maps.

Keywords: OBIA, NDVI, LSWI, ReNDVI, Mango Orchard, Sentinel 2

1. Introduction

Mango (*Mangifera indica L.*), the king of fruits is an important part of the Indian agriculture economy. India is the largest exporter of Mangoes in the world and the second-largest producer of fruits after China. Since growing mango is important for commercial farming, it is necessary to monitor the orchard for its yield and health. By assessing mango orchards for their yield, orchard management practices can be altered to get the required output from the trees. Mapping mango orchards is an important part of monitoring.

Studies have been carried out to map mango orchards using satellite and drone imagery. Drone imagery and machine vision have been used to map trees and to estimate yield (Liang et al., 2018). Laser scanning methods like airborne laser scanning (Wu et al., 2020) and terrestrial laser scanning methods have been used to map mango orchard canopies for better yield estimation. High spatial resolution imagery like Worldview 3 have also been explored for mango orchard mapping and yield estimation by using geometric and spectral data through ANN (Artificial Neural Network) (Rahman et al., 2018).
A study was conducted in 2014 which used high-resolution data for the generation of an inventory for orchards. For mango orchards, the parameters for classification were obtained through a temporal profile of orchard NDVI. The study identified further need for techniques that help in the delineation of orchards under wide spacing, diverse agro-horticultural systems and very young orchards (Hebbar et al., 2014). Another study conducted on the estimation of the area of orchards using pixel-based classification methods stated that the accuracy of classification reduces due to spectral mixing of Mango, Sapota trees and the presence of young orchards. Thus, a new method needs to be developed to solve the issue of spectral mixing of signatures from Mango trees and other crops (Chaudhari et al., 2019).Multi-temporal EVI data from MODIS was used to classify different LULC(Land Use Land Cover) features using object-based image analysis (OBIA). The study was performed with a single date image and a combination of multi-date imagery. It was found that the multi-date imagery gave better results compared to single date imagery (Gao et al., 2009).

Various studies indicate that traditional pixel-based classifiers don't use spatial information for classifying imagery making OBIA (Object-based image analysis) more efficient than these methods (Chandra et al., 2019; Blaschke et al., 2014). OBIA groups pixels in the form of image objects based on the spatial relationship with neighbouring pixels. Image segmentation is the most important part of classifying an image by OBIA (Baatz & Schape , 2000). After segmentation, the image is classified according to shape, size, spatial and spectral properties. Vegetation indices are calculated to enhance the contrast between vegetation and other features such as building and soil. This study assesses the impact of three vegetation indices; NDVI (Normalized Difference Vegetation Index), LSWI (Land Surface Water Index) and ReNDVI (Red Edge Normalized Difference Vegetation Index) on the accuracy of classification of mango orchards in level two classification using object-based image analysis.

2. Study area

Syana is a sub-district of Bulandshahr in Uttar Pradesh. The study area for the project is located at 28.626871° N, 78.060737° E and occupies an area of 756.237 Km^2 (Figure 1). The region receives a maximum rainfall of 782mm and the temperature ranges from 1.5° C to 44.5° C (Bhartariya, 2012). Syana lies in the mango producing belt of the country and is dominated by large clusters of mango orchards.

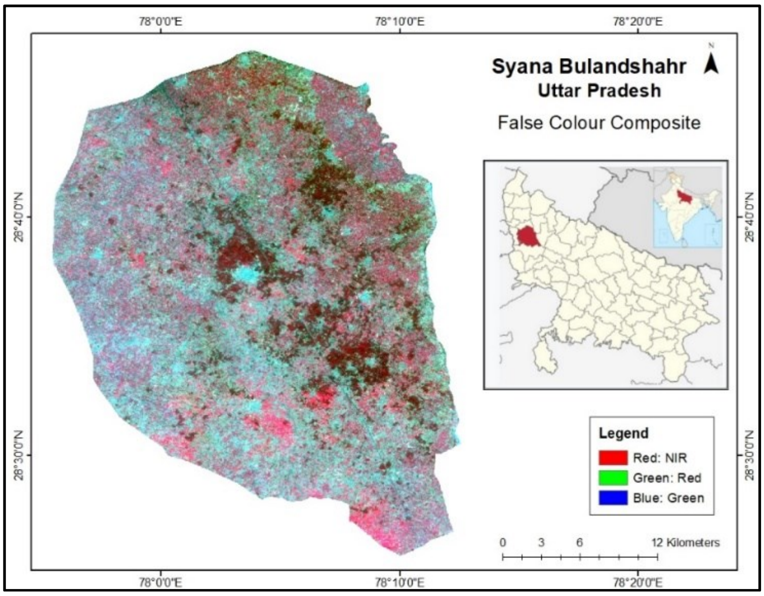

Figure 1. Study Area map

3. Methodology

The OBIA based methodology for level 2 classification is as mentioned below (Figure 2).

3.1 Satellite imagery

For the study, Sentinel 2 imagery has been used. Sentinel 2 satellite provides Multispectral data in 13 bands from visible, near-infrared and short-wave infrared through Multispectral Instrument (MSI) and has a temporal resolution of 5 days. The images were processed using google earth engine using 5 bands (Table 1).

3.2 Ground truth collection

The spatial location of Mango orchards was obtained through a survey carried out by Saha & Haldar (2021) from 2nd to 5th February 2021 in the study area. During this survey, a total of 96 points were collected corresponding to the satellite pass of 3rd February 2021. The mango orchards were found to be in the early inflorescence emergence stage during the survey.

Table 1. Bands used for the study

Band No	Name	Wavelength(µm)
3	Red	0.66
5	Red Edge	0.70
7	NIR	0.78
8A	Red Edge	0.86
11	SWIR	1.61

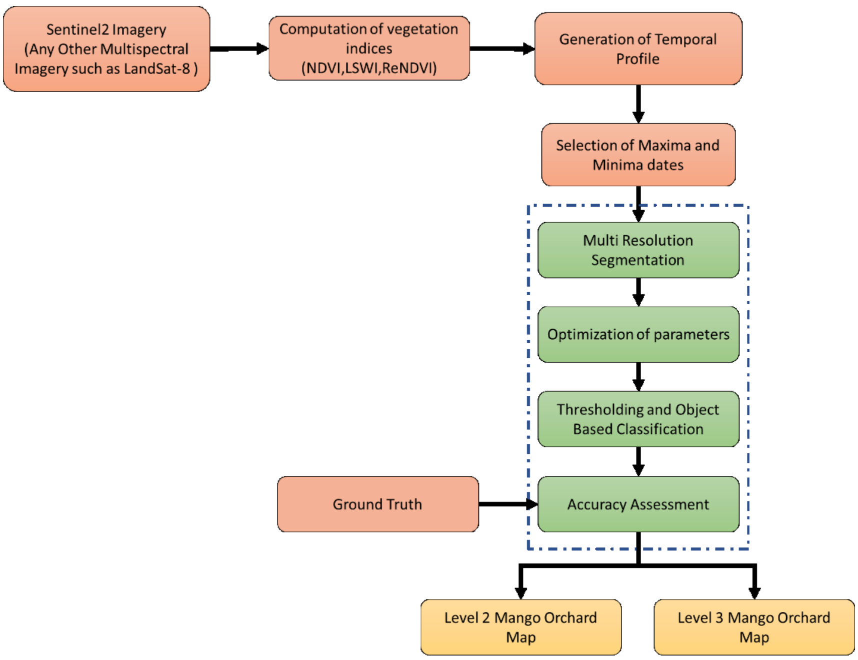

Figure 2. Methodology Flowchart

3.3 Vegetation indices generation
Vegetation indices combine the spectral reflectance of two or more wavelengths to highlight a particular property of vegetation. In this study, three indices were used: NDVI, LSWI and ReNDVI (Table 2.).

3.3.1 NDVI
Normalized Difference Vegetation Index is used to quantify vegetation by measuring the difference between NIR and red bands. This index is sensitive to vegetation cover, biomass, crop condition and density. NDVI has been used for classification of images into different land use and land cover classes (Clerici et al., 2012).

3.3.2 ReNDVI
Rededge Normalised Difference Index is the ratio between the red-edge band and the near-infrared band. It is a modification of the traditional NDVI and is used to monitor vegetation stress.

3.3.3 LSWI
Land Surface Water Index is calculated by using the shortwave infrared and near-infrared bands. This index is sensitive to the amount of moisture in vegetation and its soil background (Chandrasekar et al., 2010).This index has been used in the mapping of irrigated croplands and monitoring annual changes in irrigation(Xiang et al., 2020).

3.3 Temporal profile
By using the mango orchard and crop location coordinates collected during the ground truth survey and the vegetation indices, a temporal profile was generated from May 2020 to May 2021 using Google Earth Engine (GEE). Two age groups of mango orchards i.e old (>30yrs) and middle-aged (15 to 30 yrs) (Meena &Asrey, 2018) were chosen for the generation of the temporal profile due to the dominance of these age groups in the study area. Along with the two age groups of mango orchards, two crop types (wheat and sugarcane) grown in the region were also selected. The temporal profile was generated to observe separability between the features and to select the best possible dates for classification. The dates were then stacked for classification (Hebbar et al 2014*)*.

3.4 Classification
In OBIA, image segmentation is the first step for classification of an image. For this study, multiresolution segmentation was carried out. After segmentation, the image objects were classified using the threshold obtained from the temporal profile. Assign class algorithm, a knowledge-based classifier was used for classification. The images were classified into five classes; building, mango orchard, crop, fallow and waterbody.

3.5 Accuracy assessment
After classification, accuracy assessment was carried out using the ground truth samples collected from the field. An error matrix was generated and kappa coefficient was calculated.

4. Results

Using the Sentinel 2 imagery, vegetation indices were calculated (Table 2). A temporal profile was generated for each index illustrated below.

Temporal profiles were generated using the vegetation index values. The indices consisted of peak and troughs due to changes in seasons and the phenological cycle of the crops and mango orchards. The dips in the curves of mango orchards indicate the dormant and the flowering stages. The peaks in the temporal profiles indicate the vegetative stage.

The temporal profiles of NDVI and ReNDVI (Figure 3&4) have a similar pattern due to the use of similar band ranges (B4, B5, B8) for the computation of NDVI and ReNDVI. The graphs also indicate that the class separability is highest in the temporal profile of LSWI (Figure 5) compared to ReNDVI and NDVI. The maximum value of NDVI for the middle-aged orchard class was obtained on 3rd Feb2021 and the minimum value of NDVI was obtained on 5th Dec 2020. In case of ReNDVI, the maximum value was obtained on 18th June 2020 and minimum value was obtained on 5th Dec 2020. The temporal profile of LSWI shows maximum and minimum value on 01st Oct20 and 5th Dec20 respectively.

In the case of all the three vegetation indices, a combination of images obtained during the dormant stage and the peak vegetative stage have performed the best. After the generation of temporal profile, the images were classified and accuracy assessment was carried out using the ground truth collected. Error matrices for each index was generated to observe the effect of index on the accuracy of classification.

Table 2. Vegetation Indices used for the study

Index	Formula	Sentinel2 Bands used	Range
NDVI (Sellers, 2007)	(NIR-Red)/ (NIR+ Red)	(B8-B4)/(B8+B4)	-1 to 1
ReNDVI (Gitelson &Merzlyak, 1994)	(NIR-Red Edge) / (NIR +Red Edge)	(B8-B5)/(B8+B5)	-1 to 1
LSWI (Wong et al., 2019)	(NIR -SWIR) / (NIR +SWIR)	(B8A-B11)/(B8A+B11)	-1 to 1

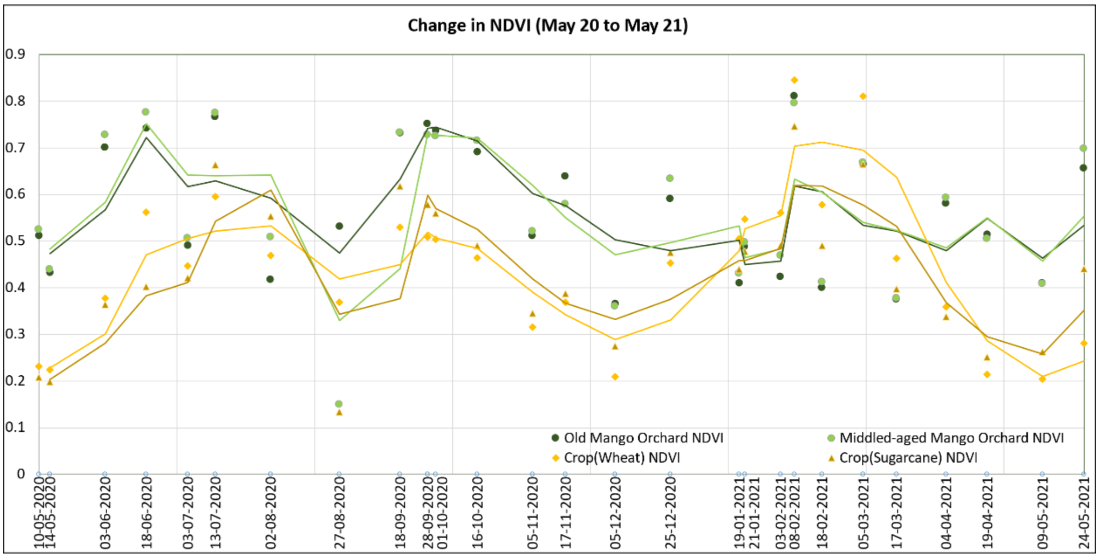

Figure 3. Temporal profile of NDVI from May 2020 to May 2021

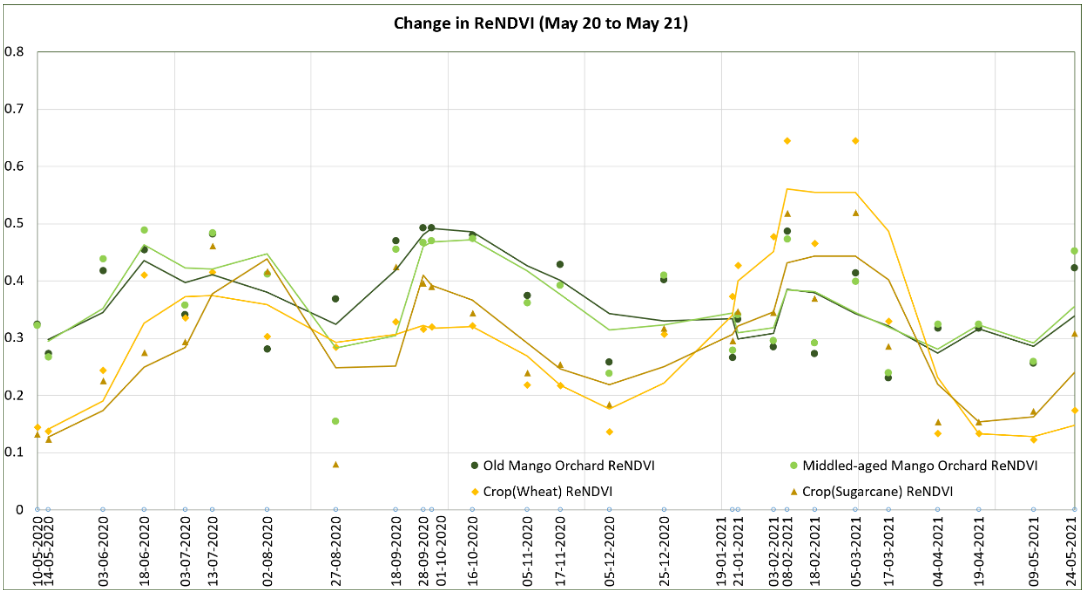

Figure 4. Temporal profile of ReNDVI from May 2020 to May 2021

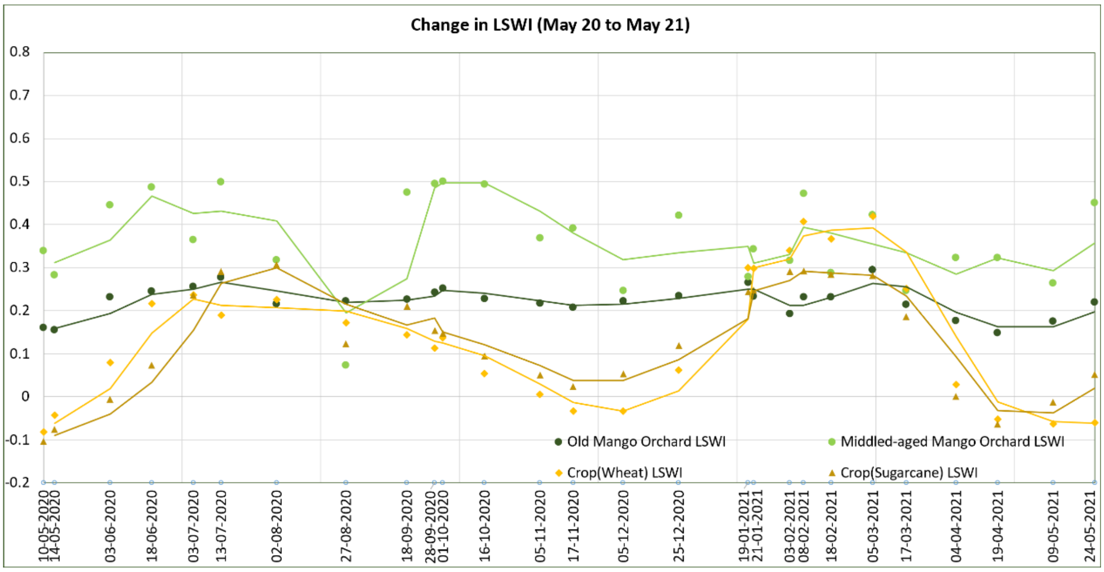

Figure 5. Temporal profile of LSWI from May 2020 to May 2021

Maps were generated (Figure 6, 7 & 8) after carrying out the classification and accuracy assessment. The image was classified into five major classes; building, mango orchard, crop, fallow and waterbody.

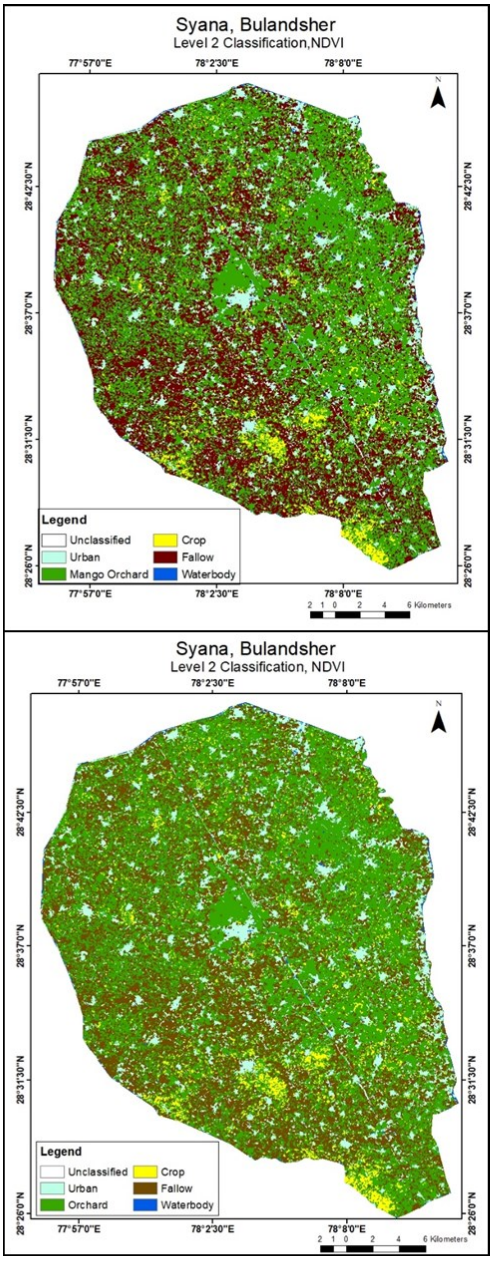

Figure 6. Classified image using NDVI stack of 3rd Feb21 and 5th Dec20

The accuracy assessment after classification (Table 3) revealed that the LSWI stack (Table 4) performed the best with an overall accuracy of 89% and a kappa coefficient of 0.86. NDVI (Table5) achieved an overall accuracy of 86% and a kappa coefficient of 0.83. This result is almost similar to the result of the Mango orchard classification carried out by Hebbar et al (2014). ReNDVI (Table 6) gave classification accuracy of 87% and a kappa coefficient of 0.84. The user and producer accuracy for the orchard class was the highest for ReNDVI, followed by LSWI and NDVI.

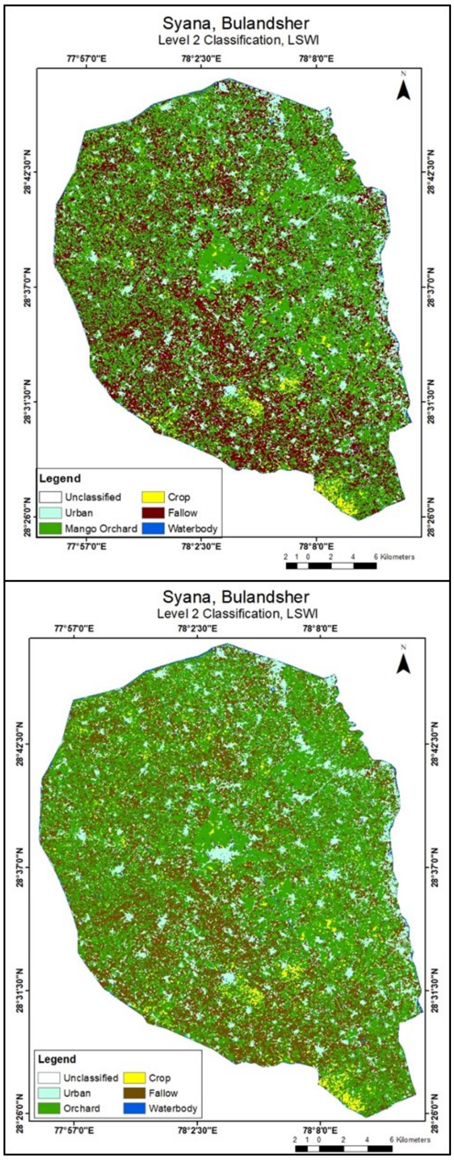

Figure 7. Classified image using LSWI stack of 1st Oct20 and 5th Dec20

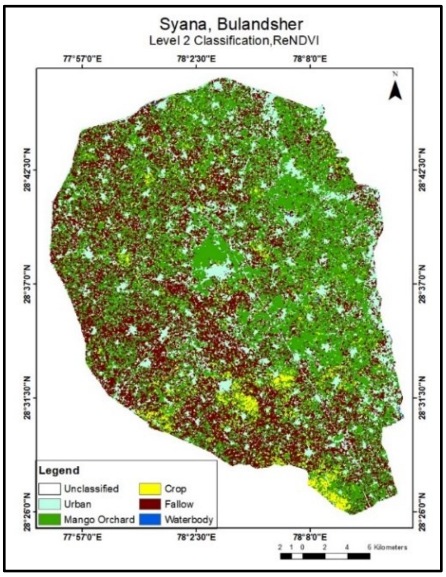

Figure 8. Classified image using ReNDVI stack of 18th June 20

Table 3. Comparison of results obtained of NDVI, ReNDVI and LSWI

Index	Overall Accuracy (%)	KIA	Mango Orchard User Accuracy	Mango Orchard Producer Accuracy
NDVI	86	0.83	0.65	1
ReNDVI	87	0.84	0.80	0.98
LSWI	89	0.86	0.78	0.96

Table 4. Classification carried out using LSWI stack; Overall accuracy: 89% Kappa Index Agreement: 0.86

	Urban	Mango Orchard	Crop	Fallow	Waterbody	Sum	User Accuracy
Urban	101	0	0	10	0	111	0.91
Mango Orchard	2	54	10	1	2	69	0.78
Crop	0	2	84	0	3	89	0.94
Fallow	1	0	1	89	0	91	0.97
Waterbody	2	0	4	2	42	50	0.84
Unclassified	3	0	0	0	0	3	
Sum	109	56	99	102	47		
Producer Accuracy	0.92	0.96	0.84	0.87	0.89		

Table 5. Classification carried out using NDVI stack; Overall accuracy: 86% Kappa Index Agreement: 0.83

	Urban	Mango Orchard	Crop	Fallow	Waterbody	Sum	User's Accuracy
Urban	97	0	0	4	7	108	0.89
Mango Orchard	0	42	12	6	4	64	0.65
Crop	0	0	85	0	0	85	1
Fallow	0	0	0	84	18	102	0.82
Waterbody	1	0	0	1	49	51	0.96
Unclassified	1	0	0	0	1	2	
Sum	99	42	97	95	79		
Producer Accuracy	0.97	1	0.87	0.88	0.62		

Table 6. Classification carried out using ReNDVI stack; Overall accuracy: 87% Kappa Index Agreement: 0.84

	Urban	Mango Orchard	Crop	Fallow	Waterbody	Sum	User's Accuracy
Urban	93	0	0	14	10	111	0.81
Mango Orchard	1	51	9	2	0	63	0.80
Crop	0	1	81	0	0	81	0.98
Fallow	0	0	0	84	7	91	0.92
Waterbody	0	0	0	0	44	51	0.86
Unclassified	0	0	0	0	0	0	
Sum	94	52	90	100	61		
Producer Accuracy	0.95	0.98	0.8	0.84	0.72		

5. Conclusions

In the previous studies, NDVI has been used to map Mango orchards (Hebbar et al., 2014). As NDVI saturates in dense canopy crops, a new approach has been made to study the effect of red edge and SWIR based indices on the accuracy of Mango orchard mapping. The study was carried out to map Mango orchards using three different vegetation indices and object-based classification. Two-day stacks were generated based on the maximum and minimum value of the vegetation index obtained from the temporal profile of the index. Out of the three indices, LSWI gave the best overall accuracy. The best user and producer accuracy for orchard class was given by ReNDVI. Therefore, ReNDVI and LSWI hold the best potential for mapping of mango orchards and can be explored further to improve classification and mapping. One of the possible future applications of this method could be mapping mango orchards based on their age groups. This methodology can be further improved by considering the textural variation amongst the mango orchard class.

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