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Comparative evaluation of change detection techniques based on multispectral images for measuring land cover dynamics of mango (*Mangifera indica* L.) in Malihabad, Lucknow (UP)

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Abstract

Change detection is a process of identifying and quantifying the differences between images of the same scene at different times and change detection in mango fruit crop is still a very challenging task. The major challenge of change detection in mango is discriminating between perennial fruit crops because many of these crops have similar reflectance profiles. Accurate change detection in the area of mango will help prepare a plan for Government agencies for area expansion and conservation planning. The main aim of this study was to determine the efficient change detection method for mango fruit crop among the most commonly used change detection methods. In this work, a comparative study was conducted using Landsat 8 OLI images of two different dates, *i.e.* 14 February 2015 and 25 February 2019, of the Malihabad mango region of Lucknow district. Four change detection methods, namely, Vegetation Index Differencing (VID), Log Ratio (LR), Principal Component Analysis (PCA), and Image Rationg (IR), were evaluated to detect the changes in mango crop area. To extract the mango regions, Soil Adjusted Vegetation Index (SAVI) images of 2015 and 2019 were calculated and further used to retrieve the VID, LR, PCA, and IR raster images. After that, these four raster images were thresholded to annotate the 'Positive change', 'Negative change', and 'No change' areas, and after that, to obtain the final change map, masking was applied to mask out the non-mango area. Change detection accuracy was calculated using ground truth data to assess performance. After conducting the comparative analysis of the accuracies of all four change detection methods, it was found that the highest change detection accuracy was achieved with the VID and PCA followed by LR and IR, respectively. PCA and VID methods provided higher accuracies, followed by LR to detect changes in mango crop area. It is due to these methods' capability to enhance the information for change detection.

Keywords: Accuracies, change detection, Landsat 8 OLI, mango, *Mangifera indica* L.*,* satellite images, vegetation

Introduction

India is the second largest producer of mango fruit (*Mangifera indica* L.) in the world and is a major fruit crop grown in India. Malihabad is the largest mango belt in Uttar Pradesh. Fruit crops are very important for improving land productivity and the economic condition of farmers by increasing income, generating employment and providing nutritional security. Information on the status of crop area change must be known for better crop management and to bring more area under fruit crops (Verma *et al.*, 2019). Several studies were focused on annual crops such as sugarcane, and seasonal crops such as wheat and paddy crops, while relatively few studies could be found that investigated discriminating between perennial fruit crops such as mango and guava (Zhong *et al.,* 2011; Widiatmaka, 2016; Peña *et al.,* 2017). This task is challenging because many perennial crops have similar temporal reflectance profiles (Peña *et al.,* 2017) and can be addressed by i) using multi-temporal images, which allow classifiers to learn per-species phenology (Zhong *et al.,* 2011), ii) using multitemporal images taken at anniversary or near anniversary dates and iii) by selecting the timing of images when there are no or little competing crops (Brinkhoff *et al.,* 2020).

The state of an entity or phenomenon changes with time and identifying the difference between the states at different times is known as change detection (Singh, 1989). Usually, change detection involves the use of multi-temporal images to quantitatively analyze the temporal effects of a particular phenomenon (Lu *et al*., 2004). Among all the changes, the trend of land use change caused by a human is regarded as one of the most significant factors for global changes in the environment (Shivakrishna *et al.,* 2021). The most commonly used satellite images are Landsat 8 Operational Land Imager (OLI), Linear Imaging Self-Scanning Sensor-4 (LISS-4), and Satellite Pour l'Observation de la Terre (SPOT), etc., which were used for various change detection applications (Lu *et al*., 2004). To detect accurate and efficient changes in land cover, the most commonly used change detection methods are Vegetation Image Differencing (VID), Principal Component Analysis (PCA), and post-classification comparison (Lu *et al*., 2004). Other methods are- Image Ratioing (IR), Log Ratio (LR), Mean Ratio (MR), *etc*. VID, IR and LR are pixel-based but PCA is a transformation-based change detection algorithm (Minu and Shetty, 2015).

Vegetation index differencing (VID) is a pixel-based change detection method where the first first-date vegetation index (VI) image is subtracted from the second-date VI images (Ahmed *et al*., 2016a). This method is applied in areas of vegetation change

(Guerra *et al*., 1998; Lyon *et al*., 1998), forest canopy change (Nelson 1983), etc. The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used vegetation indices for change detection in vegetation/biomass. But, it is observed that SAVI is more suitable for change detection in mango crops as this vegetation index reduces the background brightness effect on the image, reflected by soil exposed between canopies. Image rationing is a quick method for detecting changes. This method takes the pixel-by-pixel ratio of two images of different dates of the same place with one or more bands in an image (Singh, 1989). This method was used for land-use mapping and change detection (Prakash and Gupta, 1998). PCA is a very good method for change detection and dimensionality reduction. It has been applied for Land-cover change (Kwarteng and Chavez 1998), deforestation (Collins and Woodcock 1996), etc.

The present work aims to evaluate the relative performance of some of the most popular change detection methods for the detection of change in a perennial fruit crop, mango. In the literature, it was observed that most of the change detection techniques are useful to detect the changes in land cover areas, but detecting the changes in mango fruit crop is still challenging. As a result, an attempt was made in this paper to compare the existing change detection techniques for mango fruit crops, and to discover detection accuracy of PCA and VID, and possibility of developing an automatic change detection technique by using the combination of PCA and Log Ratio, along with the optimal threshold value, to make it adaptive and efficient change area mapping.

Materials and methods

Study Area: This study was conducted in Malihabad tehsil of Lucknow district in Uttar Pradesh, India. Malihabad is located in the west-north part of the Lucknow region, between the parallels of 26°51'34.70" and 27°10'11.61" N latitude and 80°32'6.79" and 81°4'24.01" E longitude. It is the largest mango belt of UP. Mango plantations are one of the main income sources of this region as mangoes are supplied to other parts of the country and exported to many neighbouring countries. False Color Composite (FCC) image of Malihabad was created by assigning bands combination of SWIR1, NIR and Green (*i.e.* band 6, 5, and 3) as Red, Green and Blue, respectively. In the FCC image, purple represents urban area/ bare earth and blackish green is dense vegetation, including mango orchards. Agricultural fields appear as vibrant green (Fig. 1).

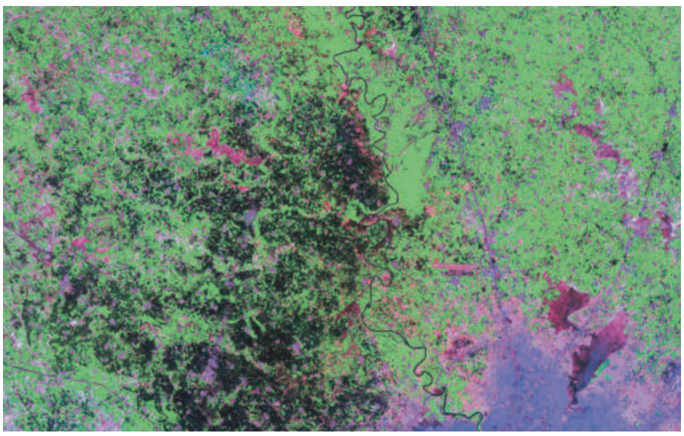

Fig.1. FCC image of Malihabad

Satellite Data: For this study, Landsat 8 OLI images were used. The satellite image source is 'USGS' and images are freely available for download through the USGS Earth Explorer web portal. Landsat 8 OLI images were considered in the present study due to their good spatial resolution (nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9, one Panchromatic band with 15 meters and two thermal bands with 100 meters resolution, each), and availability of long time series imageries with a temporal resolution of 16 days. Satellite images from 14 February 2015 and 25 February 2019 were used for this study (Table 1). A total 60 numbers of ground truth samples were used for evaluation purposes. The field data were collected with field visits and with the help of Google Earth from different mango orchards present in the study area.

Table 1. Details of Landsat 8 OLI images used for the study

Acquisition date	Data ID	Resolution (m)
14-02-2015	LC08_L1TP_144041_20150214_20170413_01_T1	30
25-02-2019	LC08_L1TP_144041_20190225_20190309_01_T1	30

Source: USGS

Theoretical background

Pre-processing of Landsat-8 Images: Out of various pre-processing steps for change detection, the most important steps are - multitemporal image registration, radiometric and atmospheric corrections (Lu, 2004). Radiometric calibrations convert digital numbers to surface reflectance or radiance values and correct pixel value errors. It improves the quality of satellite images by reducing the spectral noise and is required for quantitative analysis of multi-temporal images. Landsat images are already geo-referenced at the Universal Transverse Mercator projection system (zone: 44° N, datum: WGS–84). These images covering the Malihabad region were pre-processed by performing the Radiometric Calibration (Verma *et al.,* 2020), and were atmospherically corrected to remove the atmospheric effect from it to determine the true surface reflectance values. Digital Numbers (DNs) were converted to surface reflectance for quantitative analyses of multi-temporal images. This study considered Near-Infrared (NIR) and Red band images (Fig. 2).

It is a well-known fact that healthy vegetation actively absorbs red light and reflects near-infrared light, which means healthy vegetations have a lot of chlorophyll that actively absorbs red light and reflects NIR. But, from NIR and Red band images, it is very difficult to detect the changes. Therefore, there is a need to calculate the vegetation indices by using these two band images. Hence, the SAVI index image was used to determine the mango crop area changes.

Soil Adjusted Vegetation Index (SAVI): SAVI is computed from NIR and RED bands (Huete, 1988) of preprocessed images as follows:

$$SAVI = \frac{(\rho_{NIR} - \rho_R)*(1+L)}{(\rho_{NIR} + \rho_R + L)} \quad (1)$$

P_{NIR} and ρ_R are the reflectance values of the Near-Iinfrared (NIR) and Red bands, respectively, and L is the soil brightness correction factor. The value of L varies by the amount or cover of green vegetation. Generally, an L=0.5 works well in most situations. SAVI images are derived using eq. (1) for the years 2015 and 2019 (Fig. 3).

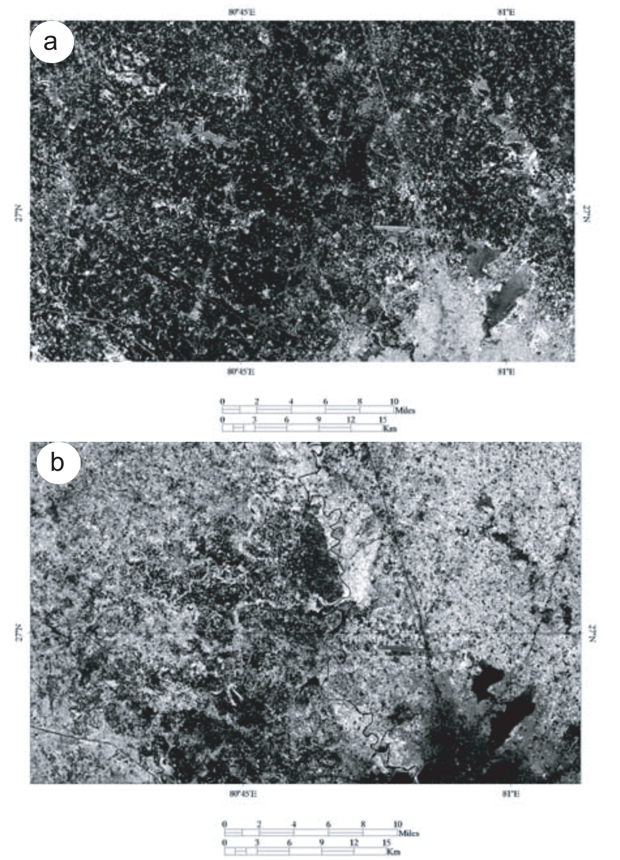

Fig.2. Pre-processed images of Malihabad of year 2015 (a) Red and (b) NIR bands

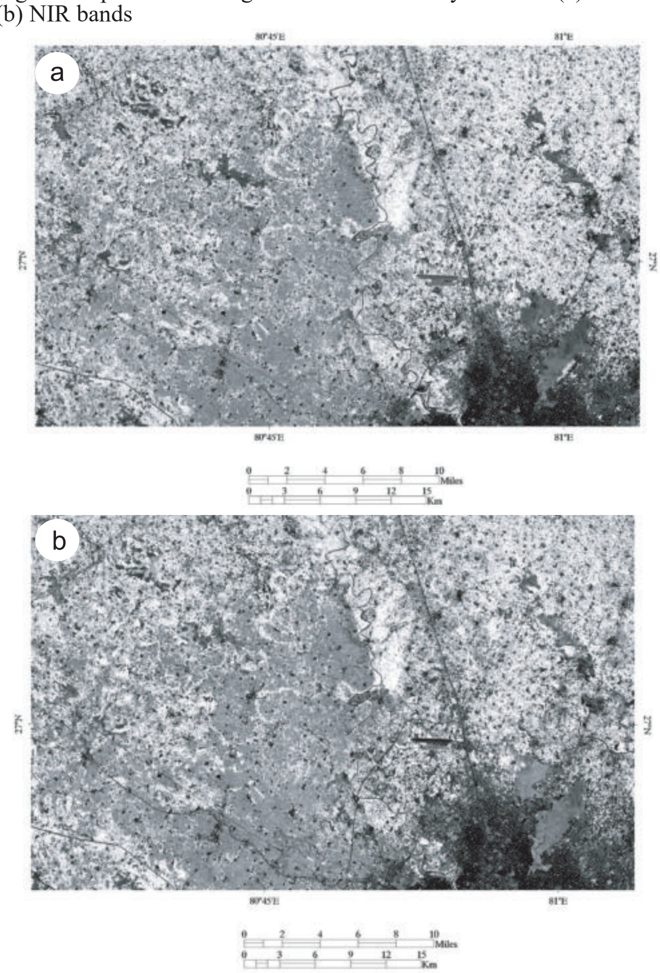

Fig.3. SAVI images, (a) SAVI image of 2015 and (b) SAVI image of 2019.

A gap exists between canopies in several mango orchards that expose background soil. The brightness reflected by soil has an adverse effect on the quality of the image. SAVI minimizes the background soil brightness effect on satellite images. Due to it, SAVI was used as a vegetation index to evaluate change detection methods.

Change detection methods: Some of the most commonly used methods of change detection are Image Differencing (Singh, 1986), Vegetation Index Differencing (Nelson, 1983; Singh, 1986), Image Ratioing (Nelson, 1983), Principal Component Analysis (Hussain *et al*., 2013), and Log Ratio (Dekker, 1998; Bovolo *et al*., 2013). In this research work, four change detection methods: VID, PCA, IR and LR were evaluated to detect changes in the mango fruit crop area. For accuracy assessment of change detection methods Percent Correct Classification (PCC) (Richard *et al*., 2005), Kappa Coefficient (KC) (Fung. and LeDrew, 1988), and F1-Score (Zhou *et al*., 2000) were calculated and critically analyzed.

Image thresholding: An image is segmented using Image thresholding, a method to create a binary image from a raster image. Image thresholding (density slicing) technique was used to identify the positive/negative change and no-change categories from four transformed images produced by PCA, VID, IR and LR. The 'positive change' and' negative change' pixels represent an increase and decrease in the area of mango, respectively. Similarly, 'no change' pixels represent the area where the mango crop area was not changed. In these transformed images, pixels of 'negative' and 'positive changes' are located at the left and right tails of the histograms, respectively. The pixels of no-change are distributed around the mean (Jensen and Toll, 1982). To acquire quantitative information about the areas of land-cover changes, thresholding (or density slicing) is applied to the transformed data to separate the change and no-change pixels (Fung and LeDrew, 1988).

The threshold levels can be determined as a standard deviation from the mean or chosen interactively with various thresholds until optimum ones are identified. Mean and standard deviation values for each change data were calculated. Threshold values of ± N * standard deviations from the mean were iteratively selected to separate the change from no-change pixels and the detailed process for optimizing the N value is described in the literature (Ahmed *et al.*, 2016b; Fung and Ledrew, 1988). In this paper, it was found that N = 0.60 is satisfactory for calculating the thresholds.

The methodology used for change detection implementation: Change detection in the urban and agriculture field is quite a simple task, but it is quite challenging in the case of mango crop. Landsat-8 images of two different dates are considered to analyze the changes in mango areas. The flow chart illustrates the steps followed in evaluating the performance of the change detection methods to detect the changes in the area of the mango fruit crop (Fig. 4).

LANDSAT 8 OLI satellite images of years 2015 and 2019 covering the Malihabad region were taken to evaluate the accuracy of change detection methods. Both images were pre-processed for radiometric and atmospheric correction. These pre-processed images were used to derive SAVI images, which were used as input to the VID, IR, LR and PCA change detection methods to derive the change maps. Change maps were classified using thresholding in the form of three classes: ' positive change', 'negative change' and 'no change' and then accuracy assessment was carried out using the PCC, Kappa Coefficient, and F1-score parameters.

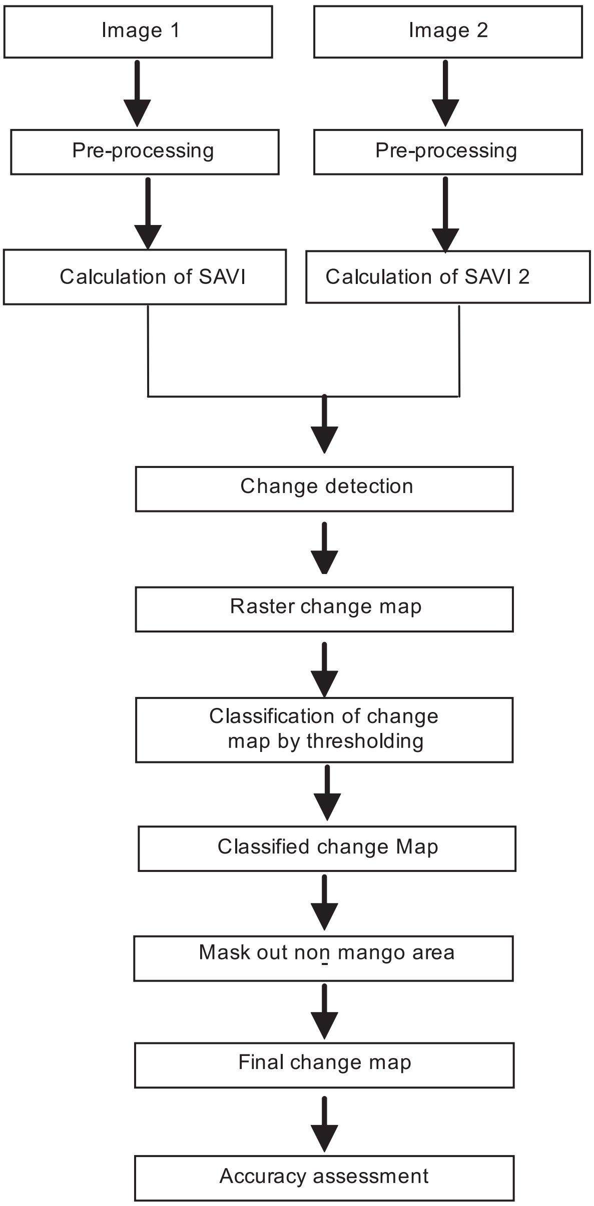

Fig.4. Flowchart showing the steps followed in the evaluation of change detection methods

Results and discussion

Change detection through PCA: To detect the changes in the mango fruit crop, PCA images were derived by layer stacking of SAVI 1 (*i.e.* 2015 image) and SAVI 2 (*i.e.* 2019 image) images. Standardized PCA was computed using a correlation matrix. In the present case, there were two input images; therefore, two principal components, *viz.,* PC1 and PC2, were generated due to PCA (Fig. 5). Principal Component 2 (PC2) was used for change detection by thresholding-based classification. The PC2 raster image was classified using thresholding as mentioned under the heading 'Thresholding images'.

Change detection by Vegetation Index Differencing (VID): SAVI 1 image was subtracted from SAVI 2 to produce a difference image (Fig. 6(a)). This image was thresholded to estimate the change in the area of the mango crop (Fig. 6(b)), which was found to be a positive change of 643 ha.

Change detection by Image Ratioing (IR): Image ratioing was calculated by using SAVI 1 and SAVI 2, respectively (Fig. 7 (a)), which was further thresholded to derive the change map (Fig. 7(b)).

The change in the area of mango was calculated using a change map and it was found that there is a positive change of 82.91 ha in the mango area, which seems to be very low.

Change detection by Log ratio (LR): Log Ratio was calculated by taking the natural logarithm of SAVI 2 to SAVI1 ratio. The Log Ratio raster image was derived and thresholded to retrieve the change map (Fig. 8).

The change in the area of the mango crop was calculated using a change map and it was found that there was a positive change of 1014 ha.

Accuracy assessment: All three accuracies as discussed under the heading **'**Change detection methods' were computed using classified change maps derived by using VID, IR, LR, and PCA methods. For this purpose, 60 ground truth samples were collected using field visits and Google Earth. The accuracies of different change detection methods were calculated (Table 2).

The result revealed that VID and PCA, both methods have the same accuracy measures, which are the highest followed by Log Ratio, but the IR method gave the Kappa coefficient as 0.1667, which is too low (Table 2). The change map revealed that IR failed to capture negative change. Therefore, it can be concluded that IR is the worst-performing change detection method for the present case.

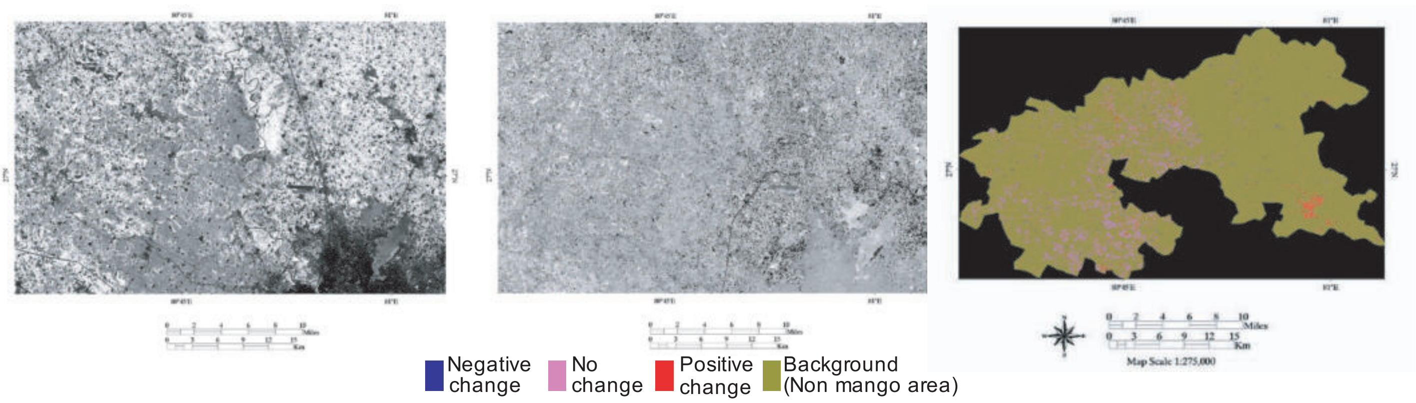

Fig. 5. PCA images (left) PC 1 (middle) PC 2 (right) Classified PC 2 change map

Some of the other latest studies compared traditional Change detection methods and have found that PCA is the best-performing method for change detection, even for some different land cover types. In this aspect, in a comparative study of four changes detection algorithms viz., Image Regression, Mean Ratio, Image Differencing and Log Ratio, it was found that the output of the log ratio method has been affected less with speckle noise (Sharma

Table 2. Accuracies of different change detection methods

Change detection method	KC	PCC	F1-Score
Vegetation Index Differencing (VID)	0.8787	0.953125	0.955224
Image Ratioing(IR)	0.1667	0.875	0.933333
Log Ratio(LR)	0.7672	0.949153	0.955224
PCA	0.8787	0.953125	0.955224

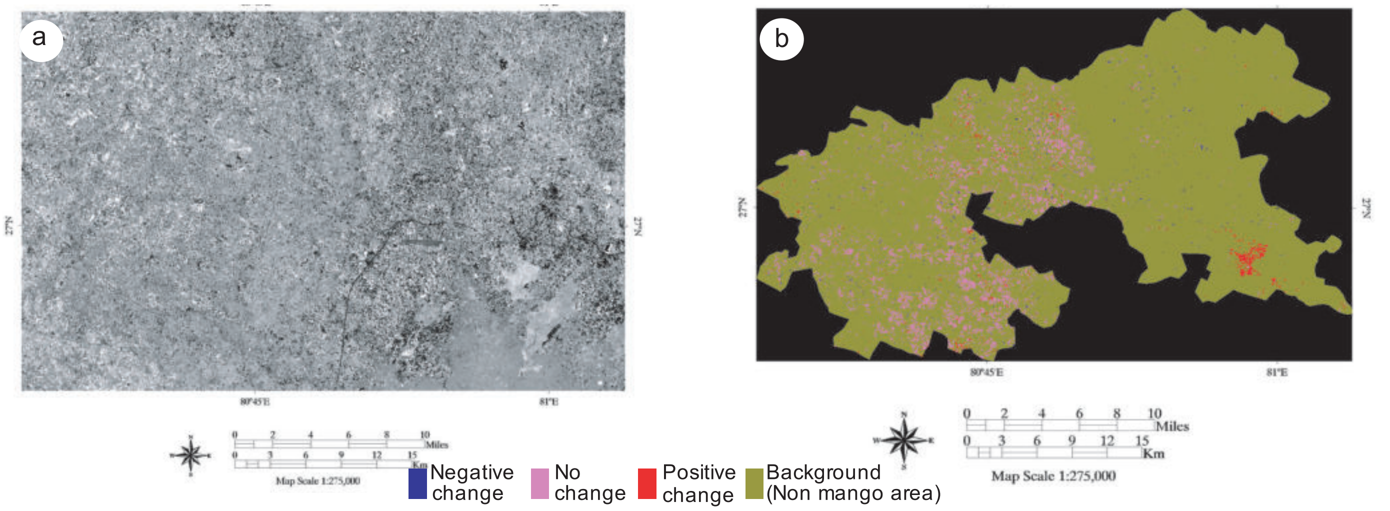

Fig. 6. Vegetation Image differencing Images (Left) VID image (Right) Classified VID change map

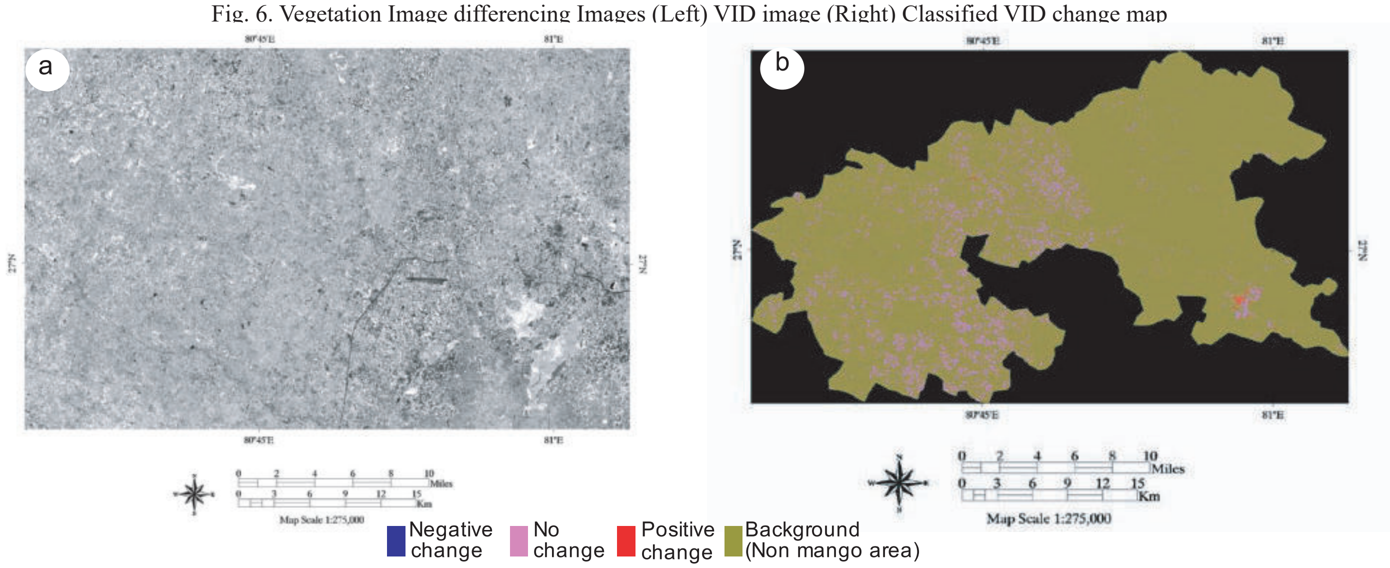

Fig. 7. Image Ratioing (Left) Image change image, (Right) Classified Image Ratio change map

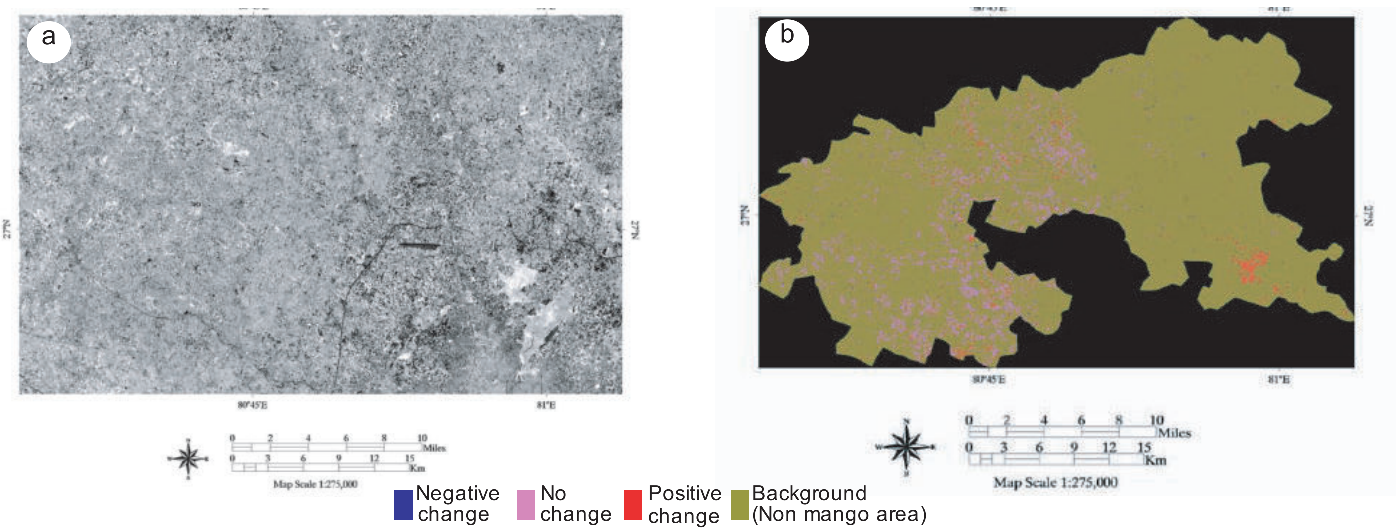

Fig. 8. Log Ratio images: (Left) Log Ratio image (Right) Log ratio change map

and Gulati, 2017). Further, it was also found that the Log Ratio method offers the highest accuracy and kappa coefficient. In another study, the researchers tried to find the most suitable technique for change detection using VHR satellite images to apply for change detection and they evaluated five change detection algorithms and found that the PCA provided the highest accuracy (Farrag *et al*., 2020).

In light of the results received in the present study, it has been observed that the problem with change detection is that it is quite difficult to get a good-quality near-anniversary image. In the future, an automatic change detection technique may be developed using the combination of PCA and Log ratio and the optimal threshold value to make it adaptive.

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