ABSTRACT Change detection (CD) is the process of detecting changes from multi-temporal satellite images that have undergone spatial changes due to natural phenomena and/or human-induced activities. Mango is a major fruit crop in India, but detection of changes in mango crops remains a challenging task because the reason that many perennial crops have similar reflectance profiles. Therefore, a potent change detection technique is required for different applications such as the rate of deforestation, urban developments, damage evaluation, and resource monitoring. Compared to annual and seasonal crops, relatively few studies have been conducted on change detection in perennial fruit crops. In this study, a novel log ratio change detection technique (i.e., LR-PCA) is developed using the fusion of log-ratio (LR) and principal component analysis (PCA) images derived from bi-temporal soil adjusted vegetation index (SAVI) images to extract meaningful information and detect temporal changes in the mango fruit crop areas with high change detection accuracy. The proposed approach comprised two steps: (1) SAVI images from 2015 and 2019 were used to retrieve the log-ratio (LR) and principal component (PC) images, respectively, and both the images were fused by applying the pixel-by-pixel fusion approach. (2) Fused images were classified into three classes: “positive change”, “no change”, and “negative change” using a derived threshold value. The results show that the LR-PCA method of change detection yields a high change detection accuracy of 92% in comparison with the other change detection methods viz. vegetation image differencing, image ratioing, PCA, and log-ratio. To validate the adaptability of the proposed algorithm, experiments with two sets of bi-temporal SAVI indices images belonging to the Sitapur district of Uttar Pradesh State determine that the proposed change detection method performs well as compared to the existing individual methods for detection of changes in mango fruit crop. The proposed method is expected to be useful for detecting changes in the area of perennial crops. In the future, an accurate and efficient change detection analysis may be helpful for developing a real-time mango fruit crop monitoring system at the national level.

INDEX TERMS Landsat 8 OLI, change detection, log ratio, principal component analysis, mango crop.
changes to the Earth’s environment; therefore, there is a real need to develop an improved change detection technique to identify where and when these changes occur [2]. The changes that occur on the earth’s surface can be either natural or man-made, where natural changes are caused by changes in seasonal and/or annual climatic conditions, and these changes are commonly reflected by changes in land cover. Change detection is the process of identifying differences in the state of an object or phenomenon by observing them at different times [3]. Normally, change detection involves the use of multi-temporal images to quantitatively analyze the temporal effects of a particular phenomenon [4]. To better manage land use by discerning human interactions with natural phenomena, timely and accurate change detection needs to be employed. Among changes, the trend of land-use change caused by humans is regarded as one of the most significant factors affecting global changes in the environment [5]. Timely and accurate change detection of Earth’s surface features provides a basis for a better understanding of the interactions between human and natural phenomena to better manage land cover.

Many satellites images-based change detection methods have been proposed to detect the changed information, and these methods can be divided into two components: supervised and unsupervised algorithms [8], [9]. In a study, Landsat satellite time series data were used for the automatic mapping of the planting year for tree crops in California [10]. Landsat-5 TM images are used for the detection of changes in the area of coconut in the Klang, located in Selangor, Malaysia [11]. Due to the benefits of repetitive data acquisition in form of a digital format suitable for computer processing, satellite images, such as Landsat 8 Operational Land Imager (OLI), Radar and Advanced Very High-Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) and Satellite Pour l’Observation de la Terre (SPOT), etc., have become the major data sources for different change detection applications [4]. Landsat 8 OLI, MODIS, AVHRR, SPOT, LISS, and Cartosat are some of the important optical satellite images, which generate images of the Earth over relatively large areas and images are useful in the production of vegetation maps or to estimate vegetation parameters. The advantage is that these satellites provide long time-series data, while the disadvantage is that optical images get easily affected by cloud cover. Many change detection techniques have been developed recently; the most used change detection methods are image differencing (ID), principal component analysis (PCA), and post-classification comparison [4], while other methods are image ratioing (IR), log ratio (LR), image regression (IR), and change vector analysis (CVA). The important usage of different change detection methods is monitoring environmental changes and land use –land cover change detection.

PCA based change detection methods have been mostly used for multi-temporal, multispectral or panchromatic images [2], [3], [6]. Then, a classification step is necessary to decide whether the pixels are ‘change’ pixels or ‘no change’ pixels. In order to take this decision, many techniques are proposed, the simplest and the more used among them is the application of the thresholding method. Good performances are obtained in separating the changed pixels from the unchanged ones using principal component 2 (PC2). It is reported that the application of PCA results in two or more principal components, the first principal component i.e. principal component (PC1) contains most of the information that is common in both images. This way, the first principal component is almost similar to both input images while the second principal component i.e., PC2 provides information that is not shared by the pair of images [2].

In a study, researchers had evaluated the performance of four change detection algorithms viz., image regression, mean ratio, image differencing, and log ratio, and concluded that the output of the log ratio method has been affected less by speckle noise [12]. This is because of its ability to convert multiplicative speckle noise into additive. Further, they found that the log ratio method offers the highest accuracy and kappa coefficient value. Reference [13] has developed a remote sensing image change detection method based on a multi-scale geometric analysis fusion and fuzzy local information C-means clustering (FLICM) model. They used difference image (DI) calculated by the log-ratio operator (LR) and mean ratio operator (MR), respectively; the fused difference image generated by non-sub sampled contourlet transform (NSCT) fusion, and the final change detection map computed by (FLICM) model. In one of our previous studies, four change detection methods viz., vegetation index differencing, PCA, LR, and image ratioing are evaluated for changes in mango fruit crop areas. It is found that both PCA and vegetation index differencing performed best, and log ratio also performed reasonably well [14]. The goal of the present work is to propose a method that can automatically detect a real change and improve the quality of change detection in multi-date images.

II. STUDY AREA AND SATELLITE DATA USED

A. STUDY AREA

This study is conducted on Lucknow district images. Lucknow is almost centrally located in the Uttar Pradesh state of India. It is located between the parallels of 26°30’ and 27° 10’ N latitude and 80° 34’ and 81° 12’ E longitude. It is surrounded by the district Sitapur in the north, Barabanki district in the east, Rae Bareli in the south, Hardoi in the north-west and Unnao in the south-west. Sitapur and Unnao
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III. THEORETICAL BACKGROUND

A. PRE-PROCESSING OF LANDSAT 8 OLI IMAGES

Out of various pre-processing steps for change detection that includes multi-temporal image registration, radiometric calibration and atmospheric corrections [15]. Radiometric calibrations convert digital numbers to surface reflectance or radiance values and also correct the pixel value errors. It improves the quality of satellite images by reducing the noise and is much 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 cover the Lucknow district and are pre-processed by performing the Radiometric Calibration [16]. The atmospheric conditions, such as Sun zenith angle, solar radiance, cloud, haze, ice and atmospheric scattering, at different acquisition dates of the images, influence spectral signatures for the same invariant objects. Therefore, it is required to process the raw data into surface reflectance using a proper atmospheric calibration method [15], [17].

There are several methods such as relative calibration, dark-object subtraction to complex model-based calibration have been developed for radiometric and atmospheric correction [18]–[20]. The dark-object subtraction approach is commonly used in practice because it is strictly an image-based procedure and corrected for the effects caused by sun zenith angle, solar radiance, and atmospheric scattering [16], [20], [21], [36], [37]. The atmospheric conditions at the different acquisition dates influence spectral signatures for the same invariant objects. Therefore, conversion from raw data to surface reflectance using a proper atmospheric calibration method is needed [17], [18], [22], [38]. Pre-processed Red and NIR bands images are shown in Fig. 4, where multi-temporal images covering the Lucknow region are atmospherically corrected to remove the atmospheric effect from it to determine the true surface reflectance values. From Fig. 4, it is observed that individual NIR and Red bands images are not capable to detect the changes in mango areas. Hence, NIR and Red images are used to calculate the SAVI image.

B. SOIL ADJUSTED VEGETATION INDEX (SAVI) IMAGE

In several mango orchards, there exists a gap between canopies that exposes background soil. The brightness reflected by soil has an adverse effect on the quality of the image. Soil Adjusted Vegetation Index (SAVI) minimizes the background soil brightness effect on satellite images. Due to it, SAVI has been used as a vegetation Index for the development of change detection methods.

SAVI is computed from NIR and RED band images as follows:

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

where, $\rho_{NIR}$ is the reflectance value of the NIR band, $\rho_R$ is the reflectance of the red band, 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 [23].

C. CHANGE DETECTION METHODS
Change detection is the process of identifying divergences in the state of an object or phenomenon by observing it at different times. Some of the most used methods of change detection are vegetation index differencing (VID) [24], [25], image ratioing (IR) [24], [26], principal component analysis (PCA) [6], and log ratio [27], [36]. In this paper, four change detection methods have been evaluated: vegetation index differencing (VID), principal component analysis (PCA), image ratioing (IR), and log ratio (LR) to detect the changes in the Mango fruit crop. The details of these methods are given below:

1) IMAGE RATIOING (IR)
It is the ratio of two registered images of different dates, on a band-by-band basis. In the changed areas, the IR values will be greater than 1 or less than 1 depending on the nature of the changes between the two dates of the images.

$$IR = \frac{I_1}{I_2}$$

where, $I_1$ and $I_2$ are the images of time 1 and time 2.

2) VEGETATION INDEX DIFFERENCING (VID)
Vegetation index differencing (VID) is calculated by the subtraction of two registered vegetation index imageries, pixel by pixel.

$$VID = I_1 - I_2$$

where, $I_1$ and $I_2$ are the vegetation index images of time 1 and time 2.

3) LOG RATIO (LR)
It is a special case of image ratio. Considering the multiplicative nature of speckle noise, the log ratio method is proposed and widely used in the change detection of satellite images because logarithmic transformation can not only transform multiplicative noise into additive noise but also compress the value range of the ratio method [28], [29].

$$LR = \ln \left( \frac{I_2}{I_1} \right) = \ln (I_2) - \ln (I_1)$$

where, ln denotes natural logarithm, $I_1$ and $I_2$ are the SAVI images of time 1 and time 2.

4) PRINCIPAL COMPONENT ANALYSIS (PCA)
Principal component analysis (PCA) is a data transformation method, which is a very powerful method for processing multidimensional data, and it is used for information extraction in multi-temporal satellite images [2]. This multivariate analysis technique is used to reduce the number of spectral components to fewer principal components accounting for the most variance in the original multispectral images by projecting the images along with new non-correlated axes [3], [7], [38]. This method reduces data redundancy by transforming multivariate data into a new set of components with the assumption that areas of change are not highly correlated [30]. PCA can be computed in two ways viz. standardized and unstandardized PCA. If a PCA is computed using a correlation matrix, then it is called standardized PCA. Furthermore, if a PCA is computed using a covariance matrix then it is called an unstandardized PCA. For multi-spectral satellite images, the standardized PCA is reported to be better than the unstandardized PCA because in the former case, it has an improved signal-to-noise ratio (SNR) as compared to the latter one for the same data set [31], [32].

In the present study, standardized PCA is used to enhance the features of the Mango crop fruit areas. For transferring data to an uncorrelated set, a Covariance or Correlation matrix is used. Then sort the resulting matrices consisting of Eigenvectors in descending order. Most of the data variation is expressed by the first principal component. The next largest amount of variation is defined by the succeeding principal component, and this is orthogonal/ independent to the principal component that precedes it. The main advantage of PCA is that it reduces the redundancy of data [33], [37], [39]–[43]. However, the disadvantage of PCA-based change detection is that it cannot provide complete change information but requires the threshold of the image to identify the changes that occurred in the area.

D. FUSION OF LR AND PC2 IMAGES
LR and PC2 images are integrated using the algebraic sum method. Images derived by two change detection methods are fused to increase the accuracy/performance of the resultant change image derived by two change detection methods. The pixel-level fusion integrates the pixel value contained in source images into a single fused image. In the present case, pixel-based fusion is applied by summing up the pixel value of LR and PC2 images as shown in ‘(5)’:

$$I = LR + PC2$$

where, I is the resultant fused image, LR is the log ratio image and PC2 is the principal component 2 image.

E. IMAGE THRESHOLDING
For classifying LR-PC2 fused image as change and no change pixels, thresholds are computed as follows:

By using the mean value ($\mu$) and standard deviation ($\sigma$) of LR-PC2 fused image as proposed in the following equations:

$$T_0 = \mu - N * \sigma$$
$$T_1 = \mu + N * \sigma$$

where, ‘$N$’ is a factor that can be optimized manually. The value of ‘$N$’ is initialized with 0.1 and increased by the interval of 0.1 till it reaches 1.0 and the value of ‘$N$’ is selected as the optimum for which the optimum accuracy measures are found. $T_0$ and $T_1$ are used to determine ‘+ve change’, ‘no
developing a Decision Tree Classification with decision rule: If $0.3093 \leq \text{SA} \leq 0.35$ then ‘Mango crop’ else ‘non-mango crop area’. This decision rule is based on one of our studies in which a Decision Tree Classification is developed for classifying land cover into seven classes including the mango crop [16]. Once the image is classified, the pixel value of the mango crop class is set to one to make this area transparent and for other areas, pixel values are set to zero. When the mask image is overlaid on the thresholded image, the final image will show only the mango crop area and all other areas become background/unclassified with the color black. This process creates a mask image with the mango area transparent and other areas turned off.

After the raster image is thresholded to determine the ‘Positive change’, ‘Negative change’ and ‘No change’ areas, to obtain the final change map, a mask with pixel value ‘0’ is applied to mask out the non-mango area, and thereafter change detection accuracies are calculated by using ground truth data.

G. ACCURACY ASSESSMENT
Two important accuracy assessment parameters are computed using a change map. These are change detection accuracy (CDA) and false alarm rate (FAR).

Suppose class A is a positive class and class B is a negative class. The key terms of the confusion matrix are as follows:
- True positive (TP): Predicting positive class as positive
- False positive (FP): Predicting negative class as positive
- True negative (TN): Predicting negative class as negative
- False negative (FN): Predicting positive class as negative

Accuracy assessment parameters are computed using TP, FP, FN, and TN. These are given below:

1) CHANGE DETECTION ACCURACY (CDA)
The Change Detection accuracy is calculated by adding the number of correctly classified values (TP and TN) and dividing by the total number of values.

$$ CDA = \frac{TP + TN}{TP + FP + TN + FN} $$

2) FALSE ALARM RATE (FAR)
It is the ratio between the number of negative events wrongly categorized as positive (false positives) and the total number of actual negative events (regardless of classification).

$$ FAR = \frac{FP}{TN + TP} $$

IV. MODEL DEVELOPMENT AND IMPLEMENTATION
A. DEVELOPMENT OF LR-PCA BASED CHANGE DETECTION TECHNIQUE
Even though in our previous study, it was found that PCA and LR performed reasonably well for change detection in the area under the mango crop, however, there is a need to further improve the change detection accuracy. Therefore, an attempt has been made to develop an improved method by applying

F. MASKING OF THE NON-MANGO AREA
SAVI image of 2019 is converted as a mask image for retaining only mango crop area and discarding non-mango crop area from the classified map. For this purpose, the SAVI image is classified for mango and non-mango classes by

change’, and ‘—ve change’ pixels. The image pixel values that are in between $T_0$ and $T_1$ represent the ‘no change’ area, and pixel values less than $T_0$ represent ‘−ve’ change’. Similarly, the pixel values greater than $T_1$ represent ‘+ve change’. It can easily be understood by plotting the histogram of the fused raster image i.e., LR-PC2 as shown in Fig. 2. A histogram provides a method for the determination of the threshold. In general, a good threshold can be selected if the histogram peaks are tall, narrow, symmetric, and separated by deep valleys. Image regions with uniform intensity give rise to strong peaks in the histogram. The histogram in Fig. 2 is depicting a method to select ‘no change’, ‘Positive change’ and ‘Negative change’ pixels for thresholding the raster image as shown in Fig. 2.

A threshold value will vary in different regions, different times, and different images. The threshold value border of ‘change’ and ‘no change’ pixels is often chosen from the histogram of the ratio image [34]. Log ratio is found useful and easy to interpret because of the simplicity of the approach. But the important part of the histogram-based thresholding approach is the definition of thresholds indicating change [35]. Once the values of both thresholds are determined, the decision rules for three different classes ‘positive change’, ‘no change’, and ‘negative change’ can easily be framed as follows:

If pixel value $\leq T_0$ then pixel class = Negative change
If $T_0 < \text{pixel value} < T_1$ then pixel class = No change
If pixel value $\geq T_1$ then pixel class = Positive change

By using the above decision rules, the LR-PC2 image can easily be classified in Negative change, No change, and Positive change classes.

FIGURE 2. Histogram of digital fused image LR-PC2.
the fusion of LR and PCA images. The complete flowchart of the proposed change detection technique is shown in Fig. 3.

In this paper, Landsat 8 OLI images of two different dates (i.e. 14 Feb, 2015 and 25 Feb, 2019) have been taken for the development of the LR-PCA fusion based change detection algorithm. Both the images are pre-processed by applying radiometric normalization, and atmospheric correction. Pre-processed images are used to compute the SAVI images, which are further used to retrieve the PCA and LR images. Firstly, the PCA method has been used to test the quality and limitations of this approach. Secondly, the LR method has been applied for enhancing the quality of the change detection. Finally, to get more accurate information, a change detection method by fusing LR and PC2 of PCA images has been proposed that is better performing than applying just one of the classical PCA or LR techniques.

B. PRE-PROCESSING OF LANDSAT-8 OLI IMAGES

Both Landsat 8 OLI multi-temporal images are radiometrically and atmospherically corrected. Digital numbers (DN) are converted to surface reflectance for quantitative analysis of multi-temporal images. Red and NIR bands of pre-processed images are shown in Fig. 4(a) and 4(b).

Healthy vegetation actively absorbs red light and reflects near-infrared light. It means healthy vegetation has a lot of chlorophyll, and 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 SAVI image by using these two bands’ images.

C. SAVI IMAGES

SAVI images are computed using pre-processed and atmospherically corrected Red and NIR images of the Lucknow region using “(1)” for the years 2015 (i.e., Image-1) and 2019 (i.e. Image-2). Computed images are retrieved as SAVI-1 from 2015 and SAVI-2 from 2019 and retrieved images are shown in Fig. 5(a) and 5(b).

D. LOG RATIO AND PCA IMAGES

Log ratio image is calculated by using SAVI-1 and SAVI-2 images denoted by $I_1$ and $I_2$, respectively by using “(4)”. Similarly, standardized PCA is computed using a correlation matrix. SAVI-1 and SAVI-2 images are layer stacked and PCA is applied on layer stacked images. The output of this process are two principal components images namely, PC1 and PC2. After obtaining these two Principal components images, it is observed that the PC1 image is not suitable for change detection as described in the “Introduction” section. Therefore, the PC2 image is used for fusion with the LR image. These images are shown in Fig. 6(a) and 6(b).
E. FUSION OF LR AND PC2 IMAGES

It is observed that LR and PC2 images are not individually capable to detect the changes in Mango Fruit crop areas. Therefore, there is a need to fuse both the images by using the algebraic sum method as given in “(3)”. The resultant fused image is shown in Fig. 7.

From Fig. 7, it can be seen that the fused image is quite smooth. Here area with bright color corresponds to positive change, the area with dark color corresponds to negative change and the area with color between these two represents no change. But through visual interpretation accurate changes cannot be identified. Therefore, for accurate classification of a fused image to obtain the change pixels histogram based thresholding is used.

F. CLASSIFICATION OF LR-PC2 IMAGE THROUGH HISTOGRAM BASED THRESHOLDING

Histogram provides a method for the determination of the threshold to classify the taken image into two or more classes. The detailed procedure of histogram-based thresholding is described in the “Image Thresholding” section. For thresholding of raster change images, the color density slicing method is used in which it slices the images in the form of classes where the minimum and maximum values for each class are assigned along with the color of the class. This process is repeated for ‘no change’, ‘negative change’, and ‘positive change’ classes, and obtained classified image is shown in Fig. 8, in which red color represents ‘positive change’, blue color ‘negative change’, and white color ‘no change’ pixels.

The mean and standard deviation of all the pixel values of the fused image shown in Fig. 7 are calculated and found to be $-0.030814$ and $0.385613$, respectively. The values of thresholds i.e. $T_0$ and $T_1$ are retrieved for $N = 0.60$ by using “(6)” and “(7)” as given below:

$$T_0 = \mu - N\sigma = -0.030814 - 0.6*0.385613 = -0.26218$$

$$T_1 = \mu + N\sigma = -0.030814 + 0.6*0.385613 = 0.200554$$

The values of these two thresholds i.e., $T_0$ and $T_1$ are used for thresholding the fused LR-PC2 image by color density slicing or by applying the decision rules discussed in detail under ‘Section E’.

The main objective of this paper is to detect the change in the mango fruit crop only. Therefore, other areas are required to be masked.

G. MASKING OF NON MANGO AREA

Masking is performed on the classified LR-PC image shown in Fig. 8, to mask out the areas which do not belong to the mango crop.

Hence, a masked image is prepared using a classified image (i.e. Fig. 9) to segregate the mango and non-mango areas. Pixels belonging to the mango class are marked as ‘1’; however, all other pixels are marked as ‘0’ as shown in Fig. 10. All non-mango areas are masked with pixel value ‘0’ to exclude this area from consideration in change detection. This mask image is applied on the change map to mask out
non-mango areas, and the retrieved binary image is shown in Fig. 11.

V. RESULTS AND DISCUSSION
Accurate and efficient detection of changes in mango crop areas is still a very challenging task. In this regard, after masking the mango and non-mango areas as shown in Fig. 10, the next task is to detect the actual changes in mango crop areas only. Therefore, from the change map masked for non-mango areas, the outside area of the Lucknow region is discarded by creating the masked image using a shape file. The final change map of the mango crop of Lucknow is shown in Fig. 11, where blue color represents the “–ve change”, red color represents “+ve change”, pink color represents “no change” and green color represents the background or non-mango areas.

From the final change map of the Lucknow region, it is observed that the total positive change is 1368.45 ha and the negative change is 366.21 ha. It has also been observed that maximum change occurred in the Mall-Kakori-Malihabad famous mango belt of Lucknow.

A. ACCURACY ASSESSMENT OF CHANGED AREA
Accuracy assessment has been carried out by assessing the change detection accuracy (CDA) and false alarm rate (FAR), which are computed by using the “(8)” and “(9)”, respectively. These accuracy values were statistically analysed to determine the optimum value of ‘N’. For the optimum value of ‘N’, CDA should be highest and FAR should be lowest. The initial value of N is taken as 0.10 for thresholding and the value of N is increased at the interval 0.10 till it reaches 1, the obtained values of CDA and FAR are shown in Table 2.

From Table 2, it is observed that S. No.1 to 5 showed low CDA and high FAR value, therefore the performance of these cases is not suitable for change detection. Similarly, in the case of S. No. 7 to 10, CDA is lower and FAR is higher, hence, these cases are also not suitable. Further, S. No. 6 has

| S. No. | N   | CDA (%) | FAR    |
|--------|-----|---------|--------|
| 1      | 0.1 | 91.071  | 0.060  |
| 2      | 0.2 | 91.071  | 0.060  |
| 3      | 0.3 | 91.429  | 0.057  |
| 4      | 0.4 | 91.579  | 0.075  |
| 5      | 0.5 | 91.111  | 0.049  |
| 6      | 0.6 | **92.308** | **0.037** |
| 7      | 0.7 | 91.045  | 0.087  |
| 8      | 0.8 | 90.741  | 0.100  |
| 9      | 0.9 | 88.889  | 0.125  |
| 10     | 1.0 | 89.189  | 0.100  |
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FIGURE 12. CDA (%) values of change map vs N values.

FIGURE 13. FAR (%) values of change map vs N values.

In this paper, a rigorous analysis has been carried out and varied the value of ‘N’ from 0.1 to 1.0 at the step of 0.1. CDA and FAR for different values of ‘N’ is shown in Fig. 12 and Fig. 13, and it is observed that CDA increases, while FAR is decreasing with the increasing value of N. CDA stops increasing at a particular value of N.

From Fig. 12 and 13, it is observed that maximum CDA and minimum FAR, which are desirable, for all the data sets are obtained at N = 0.60.

B. ANALYSIS FOR FINDING THE OPTIMUM VALUE OF N

Curve fitting as shown in Fig. 14 and 15 has been applied to obtain the relation between CDA and N, and FAR and N, respectively. The best-fitted relations are obtained as given in “(8)” and “(11)”, where the relatively good R² values are obtained with a 95% confidence level which indicates that obtained relationship is acceptable.

Cubic polynomial regression fitted for CDA as shown in Fig. 14, the regression equation for CDA is retrieved as follows:

\[ CDA(\%) = y_0 + ax - bx^2 - cx^3 \]  \hspace{1cm} (10)

where, \( y_0 = 90.5632; a = 3.7922; b = -1.2979; c = -4.3170 \) and \( x = N \).

Substituting the values of all constants/variables of “(10),” the final equation to calculate CDA is as follows:

\[ CDA(\%) = 90.5632 + 3.792N - 1.2979N^2 - 4.3170N^3 \]  \hspace{1cm} (11)

The R² value of the regression equation is 0.79.

Cubic polynomial regression is fitted for FAR as shown in Fig. 15, the regression equation for FAR is found as follows:

\[ FAR = y_0 + ax + bx^2 + cx^3 \]  \hspace{1cm} (12)

where, \( y_0 = 0.0847; a = -0.2238; b = 0.4433 \) and \( c = -0.1897 \) and \( x = N \).
Substituting the values of all constants/variables in \((12)\), the final equation to calculate FAR is:

\[
\text{FAR} = 0.0847 - 0.2238N + 0.4433N^2 - 0.1897N^3 \quad (13)
\]

The \(R^2\) value of regression is 0.64.

To determine the overall goodness of fit for the mathematical Equations \((9)\) and \((11)\), Shapiro–Wilk (SW) test is applied to the 5% significance level. The attained SW values and their corresponding p-values are shown in Table 3. The obtained p-values are greater than the 0.05 (5% significance level). The critical value for 10 numbers of samples for a 5% significance level is 0.842. From Table 3, it is observed that the obtained SW value is greater than the critical value and the p-value is greater than the 5% significance level, it specifies that the obtained relationship for CDA and FAR is highly significant. Therefore, from the results of Table 2, it is concluded that out of accuracy measurement parameters, the accuracy of the change map of mango crop derived by LR-PCA is optimum for \(N = 0.60\).

C. COMPARATIVE EVALUATION OF ACCURACIES OF CHANGE DETECTION METHODS

CDA and FAR accuracies have been calculated for four change maps by using field data and shown in Table 4. Change images derived by using IR, VID, LR, PCA and LR-PCA methods for change under mango crop area during 2015-19 in Lucknow district at optimum accuracies have been shown in Fig. 11 and obtained change image is shown in Fig. 16(a) to 16(d). Here it is to mention that for LR-PCA, the CDA and FAR values are taken from Table 2, which is derived from the change image shown in Fig.11.
From Table 4, it is evident that change detection accuracy and false alarm rate of the LR-PCA method are highest i.e., 0.923 and 0.031, respectively followed by the PCA method which has CDA and FAR values of 0.918 and 0.033.

Similarly, the LR method ranked third with CDA and FAR values of 0.917 and 0.040, respectively followed by the VID method with CDA and FAR values of 0.916 and 0.053. For the IR method, CDA and FAR values are 0.913 and 0.091, respectively.

From Table 4, it is concluded that the IR method produced the worst accuracies and the LR-PCA change detection method produced the best accuracies among all five change detection methods. Hence, it is observed that the proposed LR-PCA fusion-based method may be applied to other study areas for the optimum value of N as 0.60.

D. VALIDATION OF PROPOSED ALGORITHM

For validation of the proposed LR-PCA based change detection algorithm, the steps discussed in previous sections are applied to the images of the Sitapur district, which are subsets of Image-1 and Image-2 to detect the changes in Mango crop areas only. The steps used to validate the proposed LR-PCA fusion-based technique are as follows:

(1) Landsat 8 OLI images of the years 2015 and 2019 are cropped for the Sitapur district.
(2) The above images are pre-processed and atmospherically corrected.
(3) After that, SAVI images are computed for the years 2015 and 2019, which are further used to compute the Log Ratio and PCA images.
(4) LR and PC2 images are fused and the LR-PC2 fused image is used for change detection purposes and it is thresholded using N =0.60 to obtain the “−ve change”, “+ve change”, “no change” pixels.
(5) In classified image non-mango areas are masked, image is smoothened, and a final change map is generated.

LR-PCA fused image of Sitapur district is shown in Fig.17, which is further used to detect the changes in mango crop areas.

For change detection using LR-PCA image, threshold values are calculated using $N = 0.60$ in “6” and “7”. Mean ($\mu$) and standard deviation ($\sigma$) of the pixel values of this image are determined as 0.066872 and 0.529180, respectively.

$$T_0 = \mu - N\sigma = 0.066872 - 0.60 \times 0.529180 = -0.2506$$

$$T_1 = \mu + N\sigma = 0.066872 + 0.60 \times 0.529180 = 0.38438$$

Sitapur district image is thresholded by using the values of $T_0$ and $T_1$. The pixels of the image with a value less than the value of $T_0$, are classified as ‘negative change’. The pixels with a value between $T_0$ and $T_1$ are classified as ‘no change’ pixels. Similarly, the pixels with a value greater than
TABLE 4. Comparison of accuracies of different change detection methods.

| S.N. | Log Ratio(LR) | Image Ratio(LR) | Vegetation Index Differencing (VID) | Principal Component Analysis (PCA) | LR-PCA |
|------|---------------|-----------------|------------------------------------|-----------------------------------|--------|
|      | CDA | FAR | CDA | FAR | CDA | FAR | CDA | FAR | CDA | FAR | CDA | FAR | CDA | FAR |
| 0.1  | 0.914 | 0.038 | 0.913 | 0.091 | 0.911 | 0.068 | 0.892 | 0.121 | 0.911 | 0.060 |
| 0.2  | 0.913 | 0.039 | 0.903 | 0.100 | 0.916 | 0.053 | 0.907 | 0.089 | 0.911 | 0.060 |
| 0.3  | 0.913 | 0.039 | 0.889 | 0.111 | 0.906 | 0.060 | 0.914 | 0.074 | 0.914 | 0.057 |
| 0.4  | 0.909 | 0.098 | 0.857 | 0.143 | 0.911 | 0.065 | 0.913 | 0.077 | 0.916 | 0.075 |
| 0.5  | 0.910 | 0.087 | 0.800 | 0.150 | 0.909 | 0.063 | 0.909 | 0.089 | 0.911 | 0.049 |
| 0.6  | 0.909 | 0.074 | 0.750 | 0.182 | 0.896 | 0.074 | 0.918 | 0.033 | 0.923 | 0.031 |
| 0.7  | 0.917 | 0.040 | 0.786 | 0.154 | 0.895 | 0.070 | 0.902 | 0.107 | 0.910 | 0.087 |
| 0.8  | 0.909 | 0.039 | 0.813 | 0.143 | 0.875 | 0.095 | 0.886 | 0.115 | 0.907 | 0.100 |
| 0.9  | 0.900 | 0.048 | 0.769 | 0.182 | 0.912 | 0.083 | 0.857 | 0.154 | 0.889 | 0.125 |
| 1.0  | 0.903 | 0.041 | 0.786 | 0.172 | 0.852 | 0.200 | 0.882 | 0.120 | 0.892 | 0.100 |

the value of $T_1$ are classified as ‘positive change’ pixels. Further, masking is performed to mask out the non-mango areas. In the last step, the Shape file of the Sitapur district is used to remove the outside boundary area. The change image of the Sitapur mango crop area is shown in Fig. 18.

From the final change map of the Sitapur district shown in Fig. 18, it is observed that the total positive change area is 3417.84 ha and the negative change area is 2538.0 ha. The positive change in mango crop area derived from the LR-PCA method agreed with the difference in mango areas in the years 2015 and 2019, which suggests that the proposed LR-PCA based change detection technique works quite effectively and efficiently. In future, LR-PCA based change detection algorithm may be used on other optical sensor images for effective Mango crop monitoring.

VI. CONCLUSION
Presently, satellite images are a very important source of information for multi-temporal change detection. The advantage of multi-spectral images from all types of satellite images is that it characterizes the earth’s surface in different bands and each band provides useful information. In this work, a methodology based on the fusion of LR and PCA allows for detecting changes from multi-temporal satellite images. Using this method change map of the mango crop is derived and change detection accuracies are computed using ground truth data. From the results of the accuracy assessment of change detection in the area under mango crop for Lucknow, it is found that determining the optimal value of ‘N’ for computing a suitable threshold value is quite a time taking and difficult task. The methodology discussed in this paper has been applied satisfactorily to detect the changes between bi-temporal images. The value of $N = 0.60$ is found to be optimum for deriving threshold values and segmenting LR-PCA images for the detection of change in mango crop area. In future, a developed change detection approach may be useful to develop a Mango fruit crop monitoring system for effective and efficient mango fruit crop monitoring.

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