Fuzzy machine learning-based algorithms for mapping chickpea crop fields using sentinel-2 satellite data

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(Received on 1 August 2023; in final form 02 April 2024)

***DOI**: https://doi.org/10.58825/jog.2024.18.1.101*

Abstract: This study examined the Noise Clustering (NC) and Possibilistic C Means (PCM) classifiers, which classified and mapped the chickpea crop fields in the Nagaur district of Rajasthan using two distinct techniques for selecting training samples. Two training parameter approaches are "mean" and "individual sample as mean" which have been tested in this study. Two approaches have been attempted to decrease spectral information in processing temporal data. One is the Modified Soil Adjusted Vegetation Index 2 (MSAVI2), and the other is the Class-Based Sensor Independent Modified Soil Adjusted Vegetation Index-2 (CBSI-MSAVI2). The MMD (Mean Membership Difference) and RMSE (Root Mean Square Error) approaches were employed to measure accuracy. In order to demonstrate that the classifier successfully identifies classes, cluster validity (SSE) was also carried out, and the variance parameter was computed to handle heterogeneity among chickpea crop fields. To obtain RMSE results, Sentinel-2 satellite data was classified, whereas Planet scope satellite data was used as the reference data set.NC classifier applying ‘individual sample as mean’ on CBSI-MSAVI2 temporal indices gives the best result. RMSE, MMD, Variance, and SSE values for the NC classifier using ‘individual sample as mean’ on CBSI-MSAVI-2 temporal indices were 0.01802, 0.00046, 0.13077, and 5.10003, respectively for the m=1.1.

Keyword: Class-Based Sensor Independent-Modified Soil Adjusted Vegetation Index 2, Mean Membership Difference, Sentinel-2, temporal

1. Introduction

Chickpea is a significant pulse crop farmed and consumed throughout the world, particularly in Afro-Asian nations. The scientific name of Chickpea is Cicer arietinum. It is also one of the main pulse crops grown and consumed in India and is called Bengal gramme. India is the main producer of chickpeas, producing more than 75% of the entire global production (Merga et. al. 2019). Chickpeas are a significant Rabi crop typically planted in September through November and harvested in February through April. 90 to 120 days are needed to complete a crop. During the crop growing season, minimum and maximum temperature extremes ranged between 15.9°C to 25.7°C and 33.80°C to 36.57°C, respectively. In overcoming the nutritional deficit in terms of protein in developing economies, chickpea is highly advised as a component of a balanced diet (Maurya et. al. 2018).

Temporal satellite data are used to analyze information on land cover dynamics. High-resolution data can be used to extract this data at a separate class level. In addition to spectral data with other classes, temporal data is useful to identify the seasonal trend in a given plant class(Zhang et. al. 2017). However, several previously published algorithms, including Support Vector Machine (SVM) (Zheng et. al. 2015), Random Forest (RF), and Maximum Likelihood Classifier (MLC) (Murthy et. al. 2003), have been employed for temporal analysis. These techniques are unable to extract extremely detailed information about a class.

Information about crop growth can be obtained through specific crop mapping using temporal remote sensing data (Jose et. al. 2022; Musande et. al. 2013). Our planet's ecosystem depends heavily on vegetation, which determines the dynamics and productivity of the land cover (Ferchichi et. al. 2022). Time-series vegetation indices make it possible to determine the target plant's cropping patterns, typical vegetable types, and phenology (Tingting et. al. 2010). In classifying crops, remote sensing information is crucial.

Digital image classification is fundamental in extracting information about the Earth's surface from satellite data. According to traditional approaches, each pixel is often assigned to a single, discrete land cover class called hard classification, known as a pure pixel. Contrarily, there isn't a single pixel on the earth's surface that belongs to a single land-use class in the real world. In reality, satellite images do not fall into a single category; instead, they are composed of various pixel types, making it challenging to classify them and yield accurate findings (Dutta et. al. 2010). Mixed pixels are exceptional regarding the satellite image's spatial resolution, which is notably coarse compared to class size (Jensen 1983). For the mixed pixel, fuzzy-based classifications were suggested. When there are mixed pixels present, the fuzzy logic approach yields a superior result since it assigns a membership value to each pixel that belongs to the relevant class. The most often employed, simplest fuzzy algorithms in soft classification are FCM (Fuzzy *c*-Means)(Bezdek et. al. 1984), PCM (Possibilistics *c*- Means) (Krishnapuram et. al. 1993), and

NC (Noise Clustering)(Dave et. al. 1997). Once the sample is given, a membership degree in two or more clusters using the FCM clustering technique can be calculated. PCM uses "degree of belongings" instead of "degree of sharing" to reduce and eliminate noise brought on by outliers. To minimize the impact of outliers, the noise clustering technique introduced a distinct class that incorporates all the noisy points. Homogeneity within samples cannot be maintained during sample collection. As a result, when employing traditional statistics, categorized outputs reflect heterogeneity. One fuzzy-based classification strategy that uses heterogeneity within the class to increase classification accuracy is "Individual sample as mean" (Suman et al. 2021).

In this study, the NC and PCM classifiers used two distinct techniques to select training samples to map and classify the chickpea crop. Training samples applied as "mean" and "individual training sample as mean" are two different methods of choosing training samples. Individual training sample as mean is a novel methodology, whereas training sample applied as "mean" is a conventional technique. Here, in this research work it has been tried to evaluate both ("mean" and "individual sample as mean") training sample techniques applied in NC and PCM classifiers on two temporal indices databases to discover which is most effective. The Class-Based Sensor Independent-Modified Soil Adjusted Vegetation Index 2 (CBSI-MSAVI2) (Sivaraj et al. 2022) and Modified Soil Adjusted Vegetation Index 2 (MSAVI2) (Narayanan et. al. 2013) temporal database indices were used to minimize the spectral dimensionality of temporal images. The various stages of the plant's crop cycle were taken into consideration using the temporal vegetation indices. These indices improve biophysical quality and provide the target crop a distinctive signature by providing information on temporal stage variations from other crops. The albedo/shadow effect in photographs was likewise eliminated by the indices. The overall objective was to study the 'individual sample as mean' training parameter technique in PCM and NC classifier to handle heterogeneity, compare it with the 'mean' approach and map the chickpea crop.

2.1. Material and Methods

Root Mean Square Error (RMSE), Mean Membership Difference (MMD), Variance, and (Sum of Square Error) SSE were computed to compare the results. Here, MMD computes in two different methods. The first method uses the same training and testing sample of chickpeas to produce the proximity result. In contrast, the second method uses different training and testing samples of chickpeas and other crops (cumin and fennel) to produce the departure result.

2.1.1. Explanations of fuzzy classifier mathematical models

The mathematical explanations of the fuzzy machine learning models employed in this study are discussed in this section. This study applied the fuzzy machine learning models PCM and NC. Fuzzy classifiers PCM and NC were chosen since they could map just one class of interest.

2.1.2. Possibilistic c- Means (PCM)

The constraint of the FCM clustering technique is minimized by the PCM algorithm. The FCM algorithm's hyper-line constraint is made easier by this PCM algorithm. High membership values are assigned by the PCM algorithm to representative factor points, whereas low membership values are unrepresentative. The PCM classifier's objective function is described in equation (1).

$$J_m = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ji}^m \left\|x_j - c_i\right\|^2 + \sum_{i=1}^{C} \eta_i \sum_{j=1}^{N}\left(1 - u_{ji}\right)^m \quad (1)$$

$$\eta_i = \frac{\sum_{j=1}^{N} u_{ji}^m \left\|x_j - c_i\right\|^2}{\sum_{i=1}^{N} u_{ij}^m} \quad (2)$$

$$u_{ji} = \left[\sum_{i=1}^{c}\left\{\frac{\left\|x_j - c_i\right\|}{\eta_i}\right\}^{\frac{2}{m-1}}\right]^{-1} \quad (3)$$

Here, η_i =parameter that depends on the distribution of pixels in the cluster in equation (2), m = Fuzziness factor (it contains any real value greater than 1), u_{ji}= Degree of membership represents of i[th] pixel for cluster j, x_j= j[th] d-dimensional measured data, c_i = mean value (cluster center) of the i[th] class, c_i = mean value (cluster center) of the i[th] class, N = total no of a pixel in the image, c =Number of classes, and $\left\|x_j - c_i\right\|$= distance between x_j and c_i.

2.1.3. Noise Clustering (NC)

(Dave et al. 1997) suggested a noise clustering classifier to deal with the noise. The NC method proposes an additional, distinct class that includes all the noise and outliers. The equation (4) for the objective function of the NC algorithm

$$J_m = \sum_{j=1}^{N}\sum_{i=1}^{C} u_{ji}^m \left\|x_j - c_i\right\|^2 + \sum_{j=1}^{N} \delta^2 \left(1 - \sum_{i=1}^{C} u_{ji}\right)^m \quad (4)$$

The membership value equation (5) and fuzzy mean equation (6) can be derived from the equation. (4):

$$u_{ji} = \frac{1}{\sum_{k=1}^{c}\left[\frac{\left\|x_j - c_i\right\|^2}{\left\|x_j - c_k\right\|^2}\right]^{\frac{1}{m-1}} + \left[\frac{\left\|x_j - c_i\right\|^2}{\delta^2}\right]^{\frac{1}{m-1}}} \quad (5)$$

$$v_j = \frac{\sum_{j=1}^{N}\left(u_{ji}\right)^m x_i}{\sum_{j=1}^{N}\left(u_{ji}\right)^m} \quad (6)$$

$$\delta^2 = \lambda\left[\frac{\sum_{i=1}^{C-1}\sum_{j=1}^{N}\left\|x_j - c_i\right\|^2}{n(c-1)}\right] \quad (7)$$

$\left\|x_j - c_k\right\|$= distance between x_j and c_k and δ= Noise Distance

2.1.4. 'Individual sample as mean' training approach

The following steps were used to develop sample parameters for "individual sample as mean" approaches in PCM and NC classifiers.

Step 1: For both algorithms, n training samples were chosen for each class.

Step 2: For the PCM and NC classifier algorithms, the values of the chosen training samples were used to modify the mean values (c_i) in the computation of the membership value. (For PCM and NC, equations (1) and (4) respectively substitute n for each training sample.)

Step 3: Determined each pixel's membership value for each training sample for a particular class.

Step 4: The most extreme membership value is assigned to each pixel for each sample within that class.

2.1.5. Modified Soil Adjusted Vegetation Index 2 (MSAVI-2)

In sites having exposed soil surfaces, the MSAVI-2 is a modified soil-adjusted vegetation index that provides advantages over the NDVI. The L soil brightness compensation factor, which runs from 0-1, very high vegetation to very low vegetation, is the drawback of the SAVI Soil Adjusted Vegetation Index. 0.5 is used for vegetation cover that is in the middle. L = 0 expresses the NDVI equivalents of SAVI (Huete 1988). MSAVI was changed to MSAVI-2 to make calculations less difficult. Equation 8, mentions the formula used to calculate CBSI-MSAVI2.

$$\text{MSAVI2} = \frac{2(NIR)+1-\sqrt{(2(NIR)+1)^2-8(NIR-RED)^2}}{2} \qquad (8)$$

Where, NIR- Reflectance in the near IR band & RED – Reflectance in the RED band

2.1.6. Class-Based Sensor Independent Modified Soil Adjusted Vegetation Index 2 (CBSI-MSAVI-2)

To minimize dimensionality, CBSI-MSAVI2 Indices are used. To determine the required crop's maximum enhancement, this index does not require knowledge of sensor properties. Additionally, this maintains the preservation of temporal dimensionality while reducing spectral dimensionality. Equation (9) mentions the formula used to calculate CBSI-MSAVI2.

$$\text{CBSI-MSAVI2} = \frac{2(\rho_{max})+1-\sqrt{(2(\rho_{max})+1)^2-8(\rho_{max}-\rho_{min})^2}}{2} \qquad (9)$$

Here, ρ_{max} = maximum reflectance value &ρ_{min}=minimum reflectance value

2.2. Study Area and Dataset

The study region taken into consideration for this paper is situated in the Nagaur district of India's state of Rajasthan. The study area's boundary is located at latitudes 26.63 degrees and 73.94 degrees and longitude 26.5 degrees and 74.09 degrees, respectively. Chickpeas are sown between October and November as a Rabi crop. Specifications for the sensors on the PlanetScope and Sentinel-2 satellite are shown in Table 1.

Table 1. Specification of Sentinel-2 and PlanetScope satellite image

Specification	Sentinel 2	PlanetScope
Spatial Resolution(m)	10 m	3 m
Spectral Resolution	13 bands	4 bands
Revisit Period	10 days	1 day
Image acquired on	3rd Nov 2021, 23thNov 2021, 28th Nov 2021, 8th Dec 2021, 18th Dec 2021, 12th Jan 2022, 27th Jan 2022, 1st Feb 2022, 06th Feb 2022, 8th Feb 2022, 16th Feb 2022, and 21st Feb, 26thFeb 2022, 13th Mar 2022, 18thMar 2022 and 23th Mar 2022	

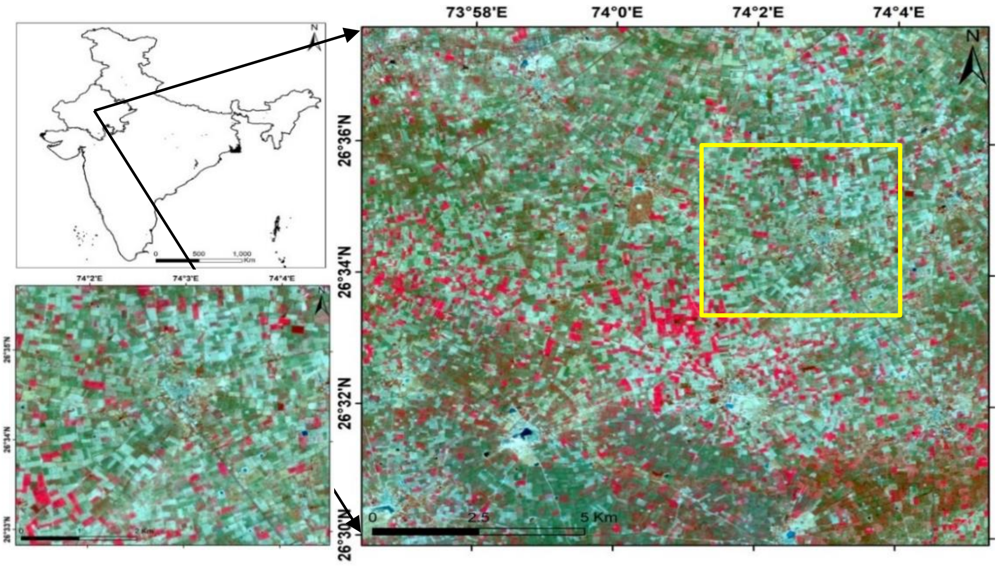


Figure 1. Study area (which contains chickpea crops) has been shown with a bounding box on the image

In this study area, Sentinel 2 and PlanetScope satellites data were employed. Sentinel-2 satellite data was classified, while PlanetScope satellite data was used as a reference dataset. The research area is shown in figure 1, with the actual study area denoted by the image's border. On January 11, 2022, fieldwork was carried out to gather geo-tagged samples for training and testing samples.

2.3. Adopted Methodology

Initially, Sentinel-2 satellite images were employed to pre-process temporal multispectral images in order to create the temporal indices database. The CBSI-MSAVI-2 and MSAVI-2 indices techniques have created a temporal indices database. The primary objective of the temporal indices database was to implement the phonological character of the chickpea plant and reduce the spectral dimension by preserving the temporal dimension and encoding items as vectors to be applied in NC and PCM classifiers.

The supervised NC and PCM algorithms were employed in this study, with the training sample acting as the "mean" and the "individual sample as the mean". The methodology is shown in figure 2.

The following procedures were used using the temporal dataset to map chickpea crop fields.

- Temporal images were utilized to calculate the CBSI-MSAVI-2 and MSAVI-2 indices for the chickpea crop using the MSAVI-2 and CBSI-MSAVI-2 formulae described in Equations 8 and 9, respectively.
- Calculate the CBSI-MSAVI2 value to identify optimized temporal images representing specific unique stages of the chickpea crop.
- The CBSI-MSAVI2 and MSAVI-2 values computed in step (2) revealed that the dates of 13th, 18th, and 23rd Mar 2022 are not suitable to consider for obtaining an optimized temporal indices database (Table 2), whereas the remaining temporal images are employed to do so.
- Training samples (45 samples) were taken from the CBSI-MSAVI-2 and MSAVI-2 databases after taking into account the ground truth data collected from sample locations around the study region.
- CBSI-MSAVI-2 and MSAVI-2 temporal databases were classified by NC and PCM classifier using training sample as ‘mean’ and ‘individual sample as mean.’
- Finally, Compute the Accuracy Assessment (RMSE) between Sentinel 2 and Planet Scope temporal images after that, compare all results to find the best one.
- The MSAVI-2 and CBSI-MSAVI-2 values for the chickpea class from the temporal images for various dates are displayed in Table 2.

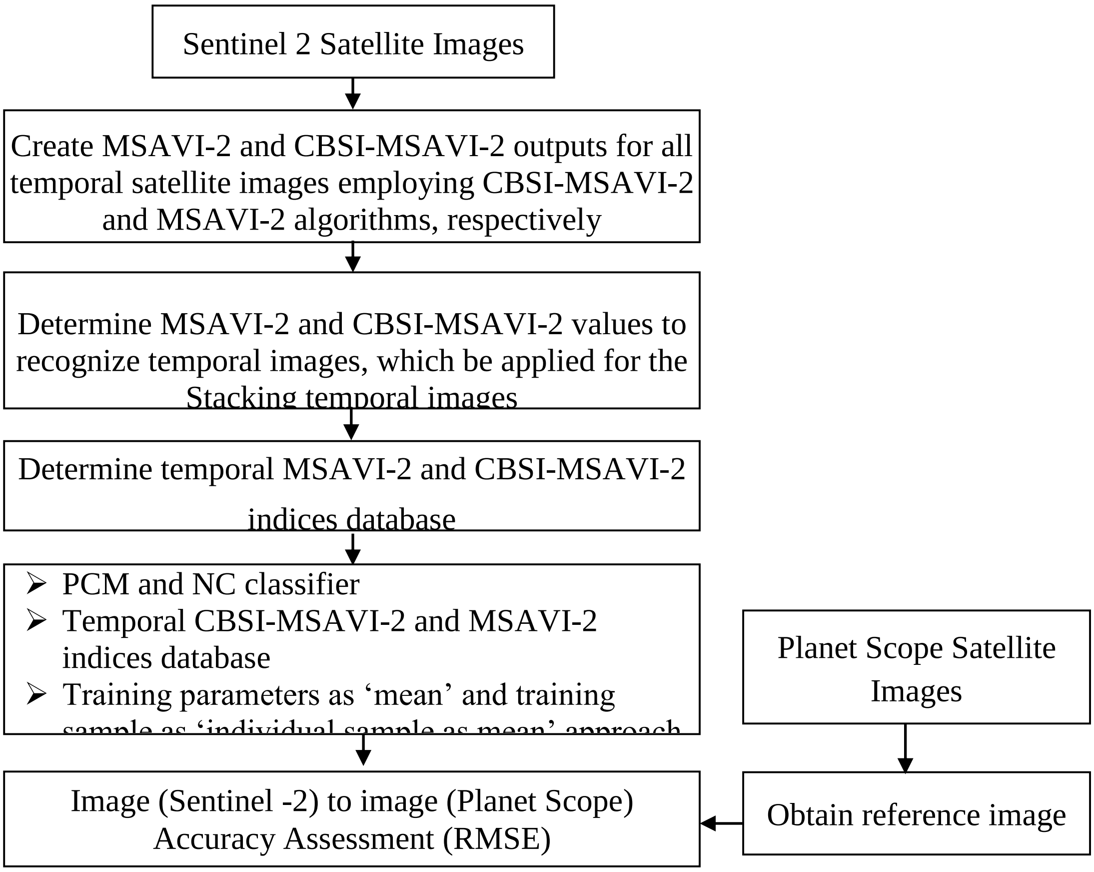


Figure 2. Methodology Adopted

3. Result and Discussion

3.1. Optimizing MSAVI2, CBSI-MSAVI2 and NDVI value

The MSAVI-2, CBSI-MSAVI-2 and NDVI values for the chickpea class from the temporal images for various dates are displayed in Table 2.

Table 2. CBSI-MSAVI-2 and MSAVI-2 value for chickpea for sentinel 2 Images

Dates	Chickpea crop		
	CBSI-MSAVI-2 value	MSAVI-2 value	NDVI
03-Nov-21	0.78	0.72	0.63
23-Nov-21	0.86	0.81	0.72
28-Nov-21	0.82	0.78	0.69
08-Dec-21	0.82	0.77	0.67
18-Dec-21	0.89	0.86	0.73
12-Jan-22	0.83	0.81	0.71
27-Jan-22	0.82	0.77	0.67
01-Feb-21	0.82	0.79	0.68
06-Feb-22	0.80	0.76	0.63
08-Feb-22	0.80	0.77	0.66
16-Feb-22	0.81	0.75	0.65
21-Feb-22	0.83	0.73	0.62
26-Feb-22	0.77	0.72	0.59
13-Mar-22	0.65	0.62	0.57
18-Mar-22	0.68	0.60	0.53
23-Mar-22	0.66	0.63	0.52

3.2. Optimizing Fuzziness factor (m)

This section illustrates how the fuzziness factor (m) affects the CBSI-MSAVI2 and MSAVI2 temporal indices databases that were classified with PCM and NC classifiers using training samples as "mean" and "individual samples as mean." the value of m ranges from 1.1 to 3 with an interval of 0.2. The optimal value of m was determined using Mean Membership Difference (MMD) analysis for each value of m. By comparing the membership value of the chickpea training fields to the chickpea test fields, the MMD showed proximity results, while comparing the membership value of the chickpea training fields to the cumin and fennel, respectively, the MMD showed the Departure result.

The MMD proximity result for the different values of m is shown in Table 3 for the NC and PCM classifier using the training sample as "mean" and "individual sample as mean" on the CBSI-MSAVI2 and MSAVI2 temporal indices database (1.1-3). The MMD exhibiting departure of the NC and PCM classifier applying the training sample as “mean” and “individual sample as mean” on the CBSI-MSAVI2 and MSAVI2 temporal indices database for the various value of m (1.1-3) shown in Table 4 and 5 respectively.

Table 3. Analysis of MMD Outputs Illustrating the exhibiting Proximity Between Chickpea Training and Testing Fields Using PCM and NC Classifiers with Different Training Approaches and Varied m Values (1.1-3) on the MSAVI2 and CBSI-MSAVI2 Temporal Indices Database.

	PCM				**NC**			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
m=1.1	0.08088	0.03845	0.05294	0.01961	0.00520	0.00980	0.00049	0.00046
m=1.3	0.13922	0.02206	0.05588	0.04559	0.03971	0.01137	0.01225	0.01127
m=1.5	0.13039	0.03529	0.05784	0.05294	0.04265	0.025	0.02647	0.025
m=1.7	0.11569	0.04363	0.06078	0.05686	0.04608	0.03431	0.0348	0.03382
m=1.9	0.10147	0.04951	0.06422	0.06225	0.04804	0.04020	0.04118	0.03627
m=2.1	0.08971	0.05147	0.06765	0.06716	0.04951	0.04510	0.04461	0.0402
m=2.3	0.06863	0.05539	0.06961	0.06912	0.04951	0.04804	0.04608	0.0402
m=2.5	0.06373	0.05882	0.07108	0.06912	0.05	0.05197	0.04608	0.04069
m=2.7	0.07353	0.05931	0.07304	0.07108	0.05098	0.05343	0.04608	0.04412
m=2.9	0.13333	0.06029	0.0799	0.07696	0.05882	0.05441	0.04755	0.04461
m=3.0	0.125	0.05784	0.10686	0.10392	0.124	0.50980	0.04755	0.04559

Table 4. Analysis of MMD Outputs Illustrating the exhibiting Departure Between Chickpea Training and Cumin Testing Fields Using PCM and NC Classifiers with Different Training Approaches and Varied m Values (1.1-3) on the MSAVI2 and CBSI-MSAVI2 Temporal Indices Database.

	PCM				**NC**			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
m=1.1	0.82804	0.83137	0.77922	0.84118	0.85804	0.86422	0.86784	0.87353
m=1.3	0.72431	0.70088	0.67804	0.73971	0.75294	0.76373	0.76667	0.77059
m=1.5	0.32235	0.27598	0.27412	0.33627	0.34333	0.36373	0.36157	0.36912
m=1.7	0.32039	0.26813	0.26235	0.32745	0.33216	0.3598	0.36157	0.36667
m=1.9	0.31961	0.25196	0.24628	0.31471	0.27569	0.35196	0.35529	0.35539
m=2.1	0.31530	0.22745	0.22157	0.29559	0.23255	0.33578	0.34863	0.35490
m=2.3	0.27804	0.19363	0.18510	0.26422	0.15177	0.31372	0.34510	0.32745
m=2.5	0.27216	0.14755	0.13647	0.22402	0.09490	0.27647	0.31530	0.29020
m=2.7	0.25608	0.29559	0.08471	0.16863	0.04118	0.22402	0.26980	0.27686
m=2.9	0.24980	0.42160	0.03490	0.12206	0.00914	0.16225	0.21765	0.25049
m=3.0	0.21882	0.00588	0.00549	0.11765	0.00568	0.12941	0.21098	0.25049

Table 5. Analysis of MMD Outputs Illustrating the exhibiting Departure Between Chickpea Training and Fennel Testing Fields Using PCM and NC Classifiers with Different Training Approaches and Varied m Values (1.1-3) on the MSAVI2 and CBSI-MSAVI2 Temporal Indices Database

	PCM				**NC**			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
m=1.1	0.76177	0.78950	0.77402	0.84163	0.79755	0.82397	0.81373	0.86562

m=1.3	0.75784	0.78601	0.76667	0.77015	0.79167	0.82375	0.81226	0.85320
m=1.5	0.44559	0.47577	0.45196	0.46644	0.47745	0.51917	0.5	0.53599
m=1.7	0.43284	0.45813	0.43137	0.45860	0.45980	0.51046	0.48627	0.50092
m=1.9	0.41177	0.43787	0.40980	0.44488	0.43677	0.49455	0.46324	0.45015
m=2.1	0.38530	0.41259	0.38235	0.42375	0.40637	0.47102	0.42795	0.39351
m=2.3	0.35490	0.38013	0.35294	0.4	0.375	0.43704	0.38284	0.33817
m=2.5	0.32549	0.34832	0.325	0.36972	0.34069	0.39020	0.33529	0.31477
m=2.7	0.30539	0.32697	0.30637	0.33965	0.31226	0.34009	0.30441	0.32314
m=2.9	0.30392	0.32392	0.30392	0.31394	0.30392	0.30523	0.30392	0.36867
m=3.0	0.30392	0.32	0.30196	0.30218	0.30196	0.30392	0.30194	0.38937

For PCM and NC classifiers for both the CBSI-MSAVI2 and MSAVI2 temporal databases, Table 3 demonstrates that m=1.1 offers the smallest MMD, while Tables 4 and 5 provide the highest MMD. Therefore, m=1.1 is the ideal value, which was then applied to the classification.

3.3. Accuracy Assessment Using RMSE

This section calculates the RMSE result to test the accuracy of PCM and NC classifiers applying training samples as “mean” and “individual sample as mean”. RMSE method has been used to do a quantitative analysis of the outcome. The RMSE is the sum of the squared differences in the membership values of the reference and classified data sets (Dehghan et al. 2006). In this paper, the Sentinel-2 image was used for classification, whereas the PlanetScope classified image was used as reference data. A smaller RMSE value shows a good classified result (Bostanci et al. 2013). The results of the PCM and NC classifiers using the training sample as the "mean" and the "individual sample as the mean" as well as different m (1.1-3) on the MSAVI2 and CBSI-MSAVI2 temporal indices are shown in Table 6.

3.4. Cluster Validity and Variance

The cluster validity and variance within the chickpea crop field are presented in this section. To determine which clustering technique and temporal indices database produce the best results, the sum of square errors (SSE) was used in this research work to measure cluster validity. Additionally, variance suggests which strategy effectively handled the heterogeneity within the fields. The optimum outcome is achieved with minimal SSE and variance values.

The variance within the chickpea class for PCM and NC classifiers using training sample as "mean" and "individual sample as mean" on CBSI-MSAVI2 and MSAVI-2 temporal indices database is displayed in Table 7.

The SSE within the chickpea class for PCM and NC classifiers applying training sample as “mean” and “individual sample as mean” on CBSI-MSAVI2 and MSAVI-2 temporal indices database is displayed in Table 8.

3.5. Classified Outputs

This section shows the specific chickpea crop mapping classification outputs. These classified outputs used CBSI-MSAVI2 and MSAVI2 temporal indices database while applying NC and PCM classifiers with training sample concept as “mean” and “individual sample as mean”.

The results of applying the training sample as "mean" and "individual sample as mean" to the CBSI-MSAVI2 and MSAVI2 temporal indices databases using NC and PCM classifiers are shown in figures 3 and 4 respectively. As can be observed from the outputs in figures 3 and 4, the CBSI-MSAVI2 temporal indices database with the training sample set as "individual sample as mean" produced better-classified fields in the red circle compared to other output results.

Table 6. Evaluation of RMSE Outputs for Chickpea Classification Using PCM and NC Classifiers with Training Samples as 'Mean' and 'Individual Sample as Mean' Across Different m Values (1.1-3) on MSAVI2 and CBSI-MSAVI2 Temporal Indices Database. Sentinel Images Applied as Classified, with PlanetScope Serving as the Reference Image.

	PCM				**NC**			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
m=1.1	0.29866	0.03750	0.02786	0.02745	0.38504	0.03570	0.01804	0.01802
m=1.3	0.24583	0.77104	0.21242	0.21090	0.31365	0.03804	0.03426	0.03570
m=1.5	0.20115	0.18039	0.30933	0.30853	0.32979	0.12200	0.07990	0.07990
m=1.7	0.24220	0.24990	0.35751	0.35706	0.33712	0.19505	0.14750	0.14656

m=1.9	0.28095	0.29866	0.38696	0.38640	0.35334	0.24850	0.20205	0.20170
m=2.1	0.31112	0.32979	0.40578	0.40567	0.36774	0.28611	0.24436	0.24436
m=2.3	0.33671	0.35334	0.41901	0.41890	0.37458	0.31365	0.27712	0.27668
m=2.5	0.355120	0.37135	0.42942	0.42897	0.38863	0.33712	0.30346	0.30325
m=2.7	0.36868	0.38629	0.43574	0.43551	0.40163	0.35538	0.32323	0.32301
m=2.9	0.38230	0.39776	0.44267	0.44174	0.41901	0.36774	0.34047	0.33989
m=3.0	0.38694	0.40163	0.44480	0.44597	0.43574	0.37458	0.34762	0.34762

Table 7. Variance within the class for PCM and NC classifiers applying training sample as "mean" and "individual sample as mean" on CBSI-MSAVI2 and MSAVI-2 temporal indices database

Variance within the class	PCM				NC			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
	0.34	0.20	0.18	0.18	0.27	0.19	0.15	0.13

Table 8. SSE (Cluster Analysis) for PCM and NC classifiers applying training sample as "mean" and "individual sample as mean" on CBSI-MSAVI2 and MSAVI-2 temporal indices database

SSE	PCM				NC			
	MSAVI-2		**CBSI-MSAVI-2**		**MSAVI-2**		**CBSI-MSAVI-2**	
	mean	ISM	mean	ISM	mean	ISM	mean	ISM
	13.38	7.98	7.10	6.98	10.40	7.50	5.78	5.10

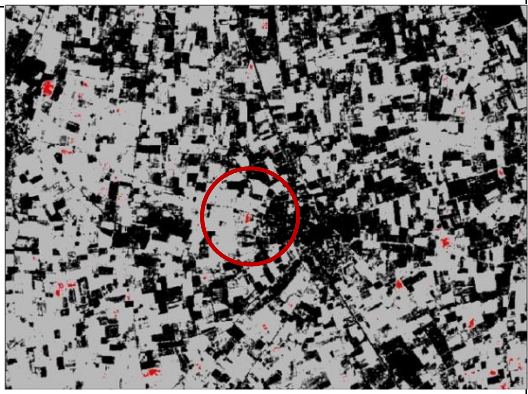
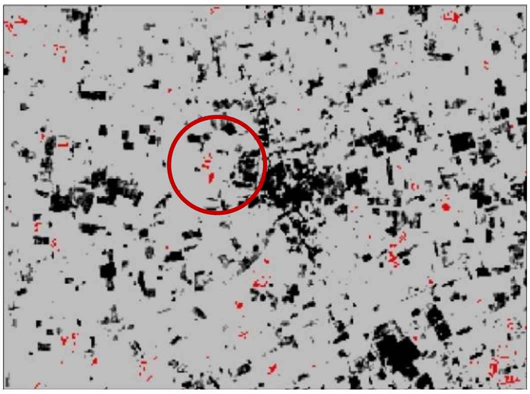
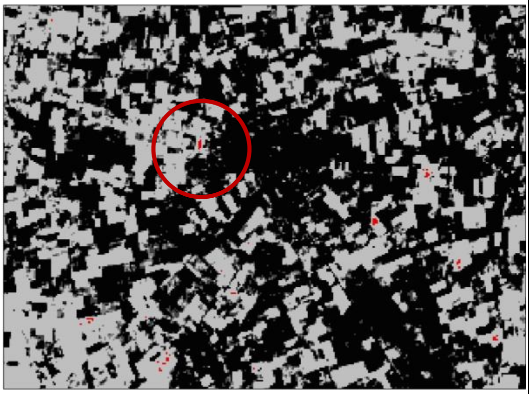
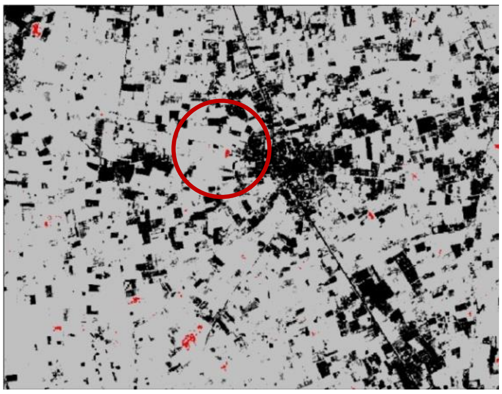
	Training sample as 'mean'	Training sample as 'individual sample as mean'
CBSI-MSAVI2 temporal indices database classified with NC classifier using training sample as 'mean' and 'individual sample as mean', respectively Chickpea		
MSAVI2 temporal indices database classified with NC classifier using training sample as 'mean' and 'individual sample as mean', respectively		

Figure 3. Comparison of Training sample approach as 'mean 'and 'individual sample as mean' outputs for NC classifiers. The red circle represents that Chickpea fields have been correctly classified, which were identified during ground truth work.

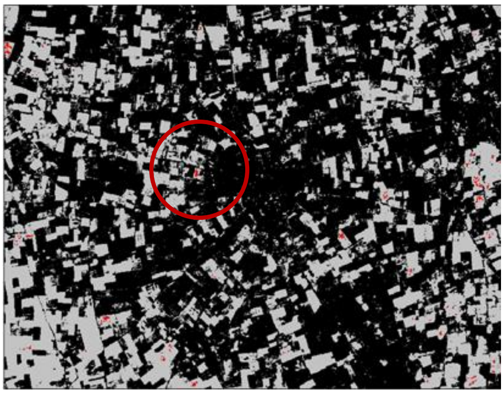
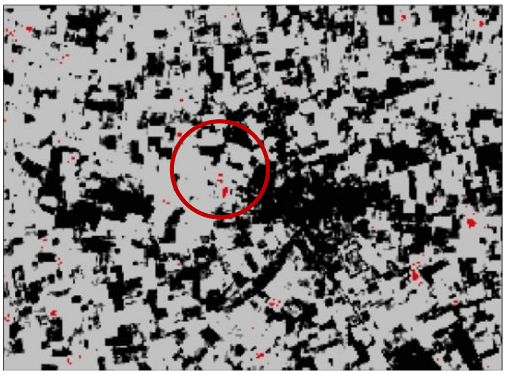
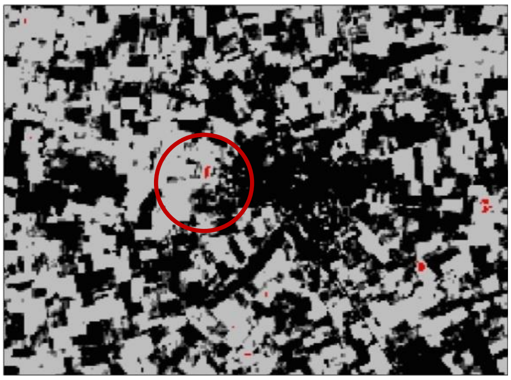
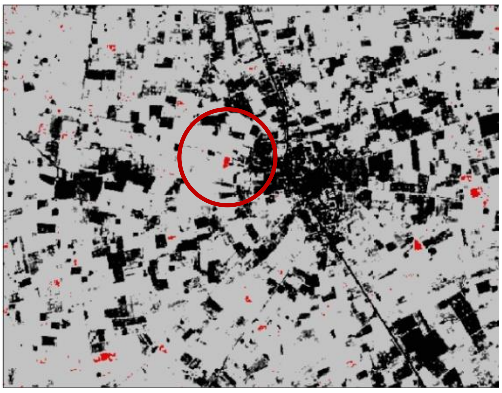
	Training sample as ‘mean’	Training sample as ‘individual sample as mean’
CBSI-MSAVI2 temporal indices database classified with PCM classifier using training sample as ‘mean’ and ‘individual sample as mean’, respectively Chickpea		
MSAVI2 temporal indices database classified with PCM classifier using training sample as ‘mean’ and ‘individual sample as mean’, respectively		

Figure 4. Comparison of Training sample approach as ‘mean ‘and ‘individual sample as mean’ outputs for PCM classifiers. The red circle represents that chickpea crop fields have been correctly classified, which were identified during ground truth work

Conclusion

In this work, using PCM and NC classifiers chickpea fields have been mapped using the training samples as “mean" and "individual training sample as mean" techniques to see which fuzzy-based algorithm performs better. When using the CBSI-MSAVI2 and MSAVI2 temporal indices database, these results were taken into account. The temporal indices database was built using Sentinel-2 satellite images collected between November 3, 2021, and March 23, 2022. RMSE, MMD, Variance, and SSE (cluster analysis) were calculated to indicate which algorithms perform better. NC classifier applying ‘individual sample as mean’ on CBSI-MSAVI2 temporal indices gives the best result. RMSE, MMD, Variance, and SSE values for NC classifier using “individual sample as mean” on CBSI-MSAVI-2 temporal indices 0.01802, 0.00046, 0.13077, and 5.10003 respectively for the m=1.1. Using the CBSI-MSAVI2 temporal indices database, the PCM classifier also offers a good result for "individual sample as mean" compared to the "mean" training sample. The RMSE, MMD, Variance, and SSE values for the PCM classifier using “individual sample as mean” on CBSI-MSAVI-2 temporal indices are 0.02745, 0.01961, 0.17885, and 6.97515, respectively, for the m=1.1. The result concluded that the NC classifier applying ‘individual sample as mean’ on CBSI-MSAVI2 temporal indices gives the best-classified result, mapped adequately, and handles the Heterogeneity within the class.

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