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Sowing Information Extraction for Groundnut Crop with Temporal optical data using Fuzzy Machine Learning Model

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ABSTRACT

This interdisciplinary research integrates advanced technology, remote sensing, and AI to enhance precision farming in the Dungargarh Tehsil of Bikaner District, Rajasthan, India. The study focuses on two main objectives: groundnut crop classification (mapping) and the extraction of sowing information. Utilizing temporal optical data preprocessing, optimized temporal indices, and a contextual fuzzy model, the Modified Possibilistic c-Means (MPCM) algorithm with both conventional mean and Individual Sample as Mean (ISM) training approaches were employed. Quantitative results demonstrate that CBSI MSAVI2 achieves a significantly lower mean membership difference (MMD) of 0.00196 and a variance of 0.5 compared to conventional MSAVI2. Further experimentation identifies ADMPLICM with a 3x3 window size and the ISM training approach as the optimal algorithm based on MMD and Variance values. By integrating vegetation indices, training approaches, and fuzzy-based algorithms, this study offers a novel approach for extracting groundnut sowing information. The results provide valuable insights into the temporal dynamics of groundnut sowing, offering reliable tools for farmers, agencies, and researchers, ultimately contributing to sustainable agricultural practices.

Keywords: Groundnut crop, Modified possibilistic c-means (MPCM), Individual samples as mean (ISM), Class based sensor independent (CBSI), Modified soil adjusted vegetation index (MSAVI)

1. INTRODUCTION

In various disciplines, including earth resource applications, remote sensing has become an essential tool for research and analysis. This covers a wide range of fields, including but not limited to atmospheric modelling, forestry, agriculture, and urban studies (Jensen and Clarke 2000). The possibility of bridging gaps between datasets has been made much more feasible by the wide range of sensors on board satellites, many of which operate at different wavelengths and spatial resolutions. This feature allows for indepth investigations across multiple areas. The monitoring of agricultural growth and development has benefited greatly from recent advances in remote sensing technology, specifically in regard to various indices and temporal data obtained from satellite imaging (Dadhwal et al. 2002; Rouse et al. 1973).

Arachis hypogaea, commonly referred to as groundnut or peanut, is an essential food and cash crop that is important to world agriculture. Monitoring and understanding the temporal dynamics of groundnut sowing dates are essential for optimizing agricultural practices, resource allocation, and yield prediction (Misra et al. 2012). Traditional methods of gathering such information often involve manual surveys, which can be time-consuming and may lack spatial coverage (Hamadani H.and Rashid 2021). This research aims to implement various contextual fuzzy machine learning model for the extraction of groundnut sowing information from temporal optical data. This interdisciplinary approach bridges the gap between agriculture, remote sensing, and artificial intelligence, contributing to the advancement of precision farming practices.

The methodology encompasses preprocessing temporal optical data, extracting information from indices for groundnut sowing, and optimizing a contextual fuzzy model. This involves classifying the inherent uncertainties in the agricultural area studying two training approaches. The research has been driven by the need to provide farmers, agricultural agencies, and researchers with a reliable tool for mapping sown groundnut fields, ultimately aiding in informed decision-making and sustainable agricultural management.

2. LITERATURE REVIEW

In India, crop cultivation practices deviate from monoculture, leading to the growth of various crop varieties in close proximity. Spectral responses of different crops may overlap due to factors like planting dates and cultural practices, posing challenges in classification (Masialeti, Egbert, and Wardlow 2010). To address this issue, temporal data analysis becomes crucial for understanding crop phenology and distinguishing between different crop and vegetation classes. Several studies have utilized time series data for crop and vegetation analysis. Doraiswamy, Akhmedov, and Stern (2006) employed an 8-date composite over a 3-year time series, successfully extracting soybean using distinctive NDVI. Foerster et al. (2012) conducted spectral-temporal crop-type mapping using Landsat TM/ETM images, highlighting the importance of timing and number of image acquisitions for distinguishing crop types.

Conventional classification techniques assign individual pixels to a single class, known as hard classification. However, applying hard classification is impractical for real-world scenarios. This limitation arises from the inherent nature of satellite imagery, where each pixel may not exclusively belong to a single class, indicating mixed characteristics. Consequently, the space covered by each pixel may encompass multiple classes, necessitating diverse handling strategies (Dadhwal et al. 2002).

To extract such information, employing fuzzy logic-based or deep learning-based classifiers with a soft computing approach is recommended (Misra et al. 2012). Fuzzy classifiers are favored for crop mapping due to their ability to handle mixed pixels (Tran, Julian, and De Beurs 2014). Initially proposed by Goguen (1973), fuzzy sets inspired the development of Fuzzy c-Means (FCM) by Bezdek, Ehrlich, and Full (1984). However, FCM lacks efficient explanation of data belonging degrees (Tran et al. 2014), leading to the introduction of the Possibilistic c-Means (PCM) approach to overcome this limitation (Krishnapuram and Keller 1993). PCM's coinciding clusters drawback in single-class classification prompted the introduction of the Modified Possibilistic c-Means approach.

To address non-linearity between classes, kernel functions, common in machine learning algorithms like support vector machines (SVM), have been introduced. Kernel-based k-mean clustering and Fuzzy Kernel c-Mean clustering (FKCM) improved upon FCM, but FKCM remains sensitive to noise. To refine FKCM's drawbacks, the Kernel Possibilistic c-Mean (KPCM) algorithm, implementing the kernel approach to PCM, was introduced by Rhee, Choi, and Choi (2009). Extending the kernel function to MPCM, the Kernel-based Modified Possibilistic c-Mean (KMPCM) algorithm efficiently handles non-linearity, noise, and outliers compared to PCM and FCM (Wu and Zhou 2008). KMPCM also exhibits a faster response in terms of time elapsed and the number of iterations and clusters (Ganesan and Rajini 2010). Combining spatial and spectral information using composite kernels can enhance classification accuracy (Verrelst et al. 2016).

In small holder agricultural systems in northern Malawi, accurate prediction of groundnut yield is crucial for food security. Kpienbaareh et al. (2022) using multitemporal PlanetScope satellite data, the study employs a random forest model with five key variables to predict groundnut yield during the R5/beginning seed stage. Results indicate the model's high accuracy, with a coefficient of determination (R2) of 0.96 and a root mean square error (RMSE) of 0.29 kg/ha, showcasing its potential for effective farming and food security planning (Gbodjo, Ienco, and Leroux 2021). In Sub-Saharan Africa, where small holder farms dominate agriculture, this study leverages Sentinel satellite data and machine learning models to estimate millet yields in central Senegal. The Random Forest model explained 50% of millet yield variability, outperforming deep learning models like Convolutional Neural Network, and demonstrated stable and satisfactory accuracy in forecasting yields two weeks before harvest. Sannidi et al. (2023) in the rabi season of 2019-20 in Telangana's Mahabubnagar district, groundnut crop acreage and yield were estimated using Landsat-8-OLI satellite images and regression equations. The estimated crop area was 57,865 ha with a producer's accuracy of 100%, user's accuracy of 90%, and a relative deviation of 28.6% compared to the department of agriculture's ground estimates, while crop yields were estimated with an R2 value of 0.71 and a correlation coefficient of 0.87.

Image classification methods can be broadly divided into two categories: supervised classification and unsupervised classification. Supervised classification is preferred when training data samples are available, while unsupervised classification is employed when training data is not present. Pixel-based training typically relies on the mean or variance-covariance computed from training samples, which may not capture the full variability within a class. To overcome this limitation and address heterogeneity within a single class, individual samples are taken into consideration instead of relying solely on mean or variance-covariance. In addressing the challenge of heterogeneity within a single class, Singhal et. al., (2021) departed from relying on statistical parameters and instead considered the role of each training sample. They applied a Modified Possibilistic c-means fuzzy algorithm to accurately map individual classes such as mustard, wheat, and grass (Singhal et. al., 2021). Similarly, Jose and Kumar (2022) employed the individual sample as mean approach using the MPCM algorithm to map Psyllium Husk crops, enhancing classification accuracy by reducing heterogeneity within classes.

This study seeks to contribute to the broader field of precision agriculture and remote sensing applications by integrating cutting-edge technology and novel modelling methodologies, enabling a more data-driven and efficient agricultural environment. This research aims to develop a methodology for extracting groundnut crop sowing information using temporal optical data and a Fuzzy Machine Learning Model with two training approaches. Also, the individual sample as mean along with contextual information will be a novel approach in this study and the outcomes of this research have the potential to impact not only groundnut cultivation practices but also serve as a blueprint for similar studies focused on other crops and agricultural regions globally.

3. MATHEMATICAL CONCEPTS

3.1 Vegetation Indices

Vegetation indices are critical for optimizing crop management operations in the context of precision agriculture

(Jackson and Huete 1991). They make it possible to monitor a number of agricultural field parameters, such as crop growth cycles, yield predictions, and the evaluation of water stress. Unlike NDVI and NDRE, MSAVI2 is specifically tailored to situations with low vegetation or plants lacking chlorophyll, which can result in inaccuracies in data analysis. This is particularly noticeable during stages like germination and leaf development, where bare soil between seedlings is prevalent. In temporal studies such as vegetation mapping and change detection, it is imperative to minimize the impact of atmospheric and acquisition-related effects. One effective way to address this problem is to combine data from several spectral bands. This method helps to reduce problems caused by spectral overlap and enhances reliable and accurate when doing tasks like mapping crops and other vegetation-related evaluations. During the course of the study, two indices were tested: the CBSI-MSAVI2 and the traditional MSAVI2.

3.1.1 Conventional MSAVI2

The MSAVI2 (Modified Soil-Adjusted Vegetation Index 2) is a specialized vegetation index that effectively accounts for soil interference as shown in Eq (1). MSAVI2 helped to compensate with the effect of soil brightness on the pixel value (hence calculated index value) since its coverage is not continuous in the field, which leads to more soil exposure (Sabir and Kumar 2022b). The selection of the index in this study was influenced by the specific crop of interest, which is groundnut. During the early stages of germination and leaf development, the presence of substantial soil coverage in the field significantly amplifies the soil's influence on the overall spectral response. As a result, MSAVI2 was chosen and applied to effectively mitigate the soil's impact on the data and ensure more accurate analysis, given its ability to address this soil interference.

$$\mathrm{MSAVI} = \frac{(2\times\mathrm{NIR}+1-\sqrt{2\times(\mathrm{NIR}+1)^2-8\times(\mathrm{NIR}-\mathrm{R})}}{2} \quad (1)$$

3.1.2 CBSI-MSAVI2

The bands with the maximum and minimum values for the target class were initially selected using the class-based sensor independent (CBSI) MSAVI2 approach, and the value of the vegetation index was then calculated using these bands as mentioned in the Eq (2) (Sabir and Kumar 2000). This customization maximizes the index values for the target feature, enhancing its ability to distinguish the target feature from the background or other similar features more effectively.

$$\mathrm{CBSI-MSAVI2} = \frac{2\times\mathrm{Max}+1-\sqrt{2\times(\mathrm{Max}+1)^2-8\times(\mathrm{Max}-\mathrm{Min})}}{2} \quad \ldots (2)$$

Where Max and Min are the maximum and minimum reflectance bands for a given set of bands respectively.

3.2 Modified Possibilistic c-means (MPCM)

Fuzzy-based algorithms, such as the MPCM (Modified Possibilistic c-Means) algorithm, offer an effective approach for soft classification of images, making them well-suited for real-world applications (Suman, Kumar, and Kumar 2019). What distinguishes the MPCM algorithm is its remarkable independence from parameter initialization or optimization. Unlike many other algorithms, MPCM does not necessitate fine-tuning of parameters, streamlining the implementation process significantly (Sabir and Kumar 2022a). This algorithm's unique feature of not requiring meticulous parameter adjustments simplifies its deployment, making it more user-friendly and adaptable across diverse datasets. This advantage is particularly crucial in scenarios where data characteristics may vary, and the algorithm needs to perform reliably without intricate parameter tuning.

Furthermore, the MPCM algorithm excels in its ability to efficiently handle and classify coincident clusters. In situations where distinct groups in the data may overlap or exhibit similar characteristics, MPCM demonstrates robustness, contributing to accurate and meaningful soft classification results. This characteristic enhances the algorithm's applicability in scenarios where conventional algorithms might struggle to delineate boundaries between different classes. The objective function as mentioned in the Eq (3) that was applied to determine each pixel's membership value in the input image is

$$J_{MPCM}(\mathrm{U},\mathrm{V}) = \sum_{i=1}^{N}\sum_{j=1}^{c}(u_{ji})^{m}||\, x_i - v_j||^2 + \sum_{i=1}^{N}\eta_i\sum_{j=1}^{c}(\lambda_i - u_{ji})^{m} \quad (3)$$

where $\lambda_i > 0$.

U is the matrix containing membership values for each pixel corresponding to each class, whereas V is the matrix containing class centers. i denotes the pixels, which range from 0 to m, and j indicates the classes, which range from 0 to N, where N is the total number of classes. u_{ij} is the typicality value of pixel x_i in class j. The square of the distance between the measured value of a pixel and the cluster center is d_{ij}^2, as shown in the Eq (4) which is calculated as;

$$d_{ij}^2 = \|\, x_i - v_j \,\|^{T} A^{-1}(x_i - v_j). \quad (4)$$

The fuzzy cluster center v_j as shown in Eq (5) is calculated using equation (5):

$$v_j = \frac{\sum_{i=1}^{N} u_{ij} x_i}{\sum_{i=1}^{N} u_{ij}} \quad (5)$$

where v_j is the cluster center.

4. STUDY AREA & DATASETS USED

The research has been being carried out in the Dungargarh Tehsil of the Bikaner District in Rajasthan, India. This location was selected due to its rich abundance of agricultural fields, posing a challenge in distinguishing between fields that share similar characteristics. Rajasthan experiences comparatively low rainfall, and groundnut, a resilient and drought-tolerant crop, is commonly cultivated in this region. The selection of this study area offers the advantage of minimal haze and cloud cover in the available data, enhancing image contrast. The study area, illustrated in Fig. 1, showcases numerous agricultural fields and the field work was conducted on 27th August of 2023 geo-tagged points collected from the ground serve as training and testing data for the groundnut crop, as well as other non-target crops like Bajra, Gawar, Cotton, Moat dal, Moong, and Til within the study as shown in the Figure 2. The following Google Earth image i.e., Fig 3 shows the different geo-tagged fields. The temporal datasets utilized in this study were derived from PlanetScope, which is distinguished by a spectral resolution comprising 8 bands of wavelengths as shown in the Table 1.

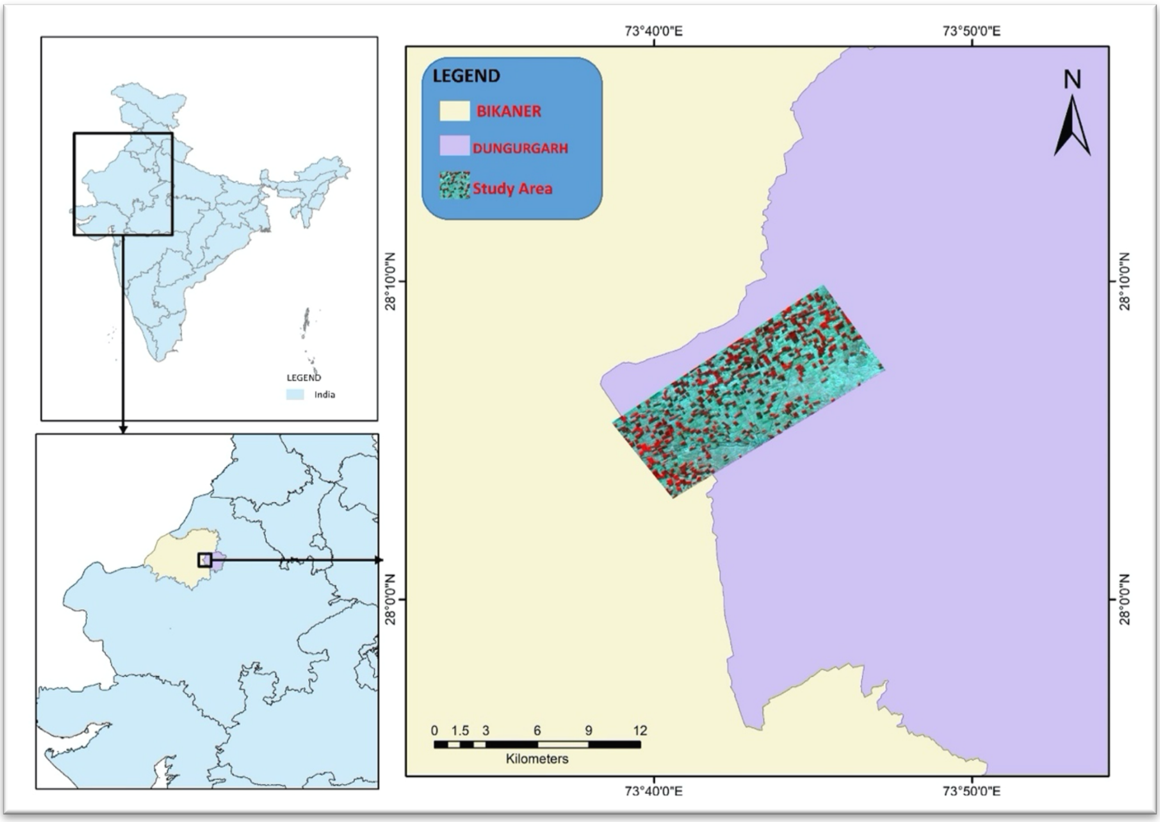

Figure 1: Map depicting study area of this research work.

Figure 2: Field work for collecting samples.

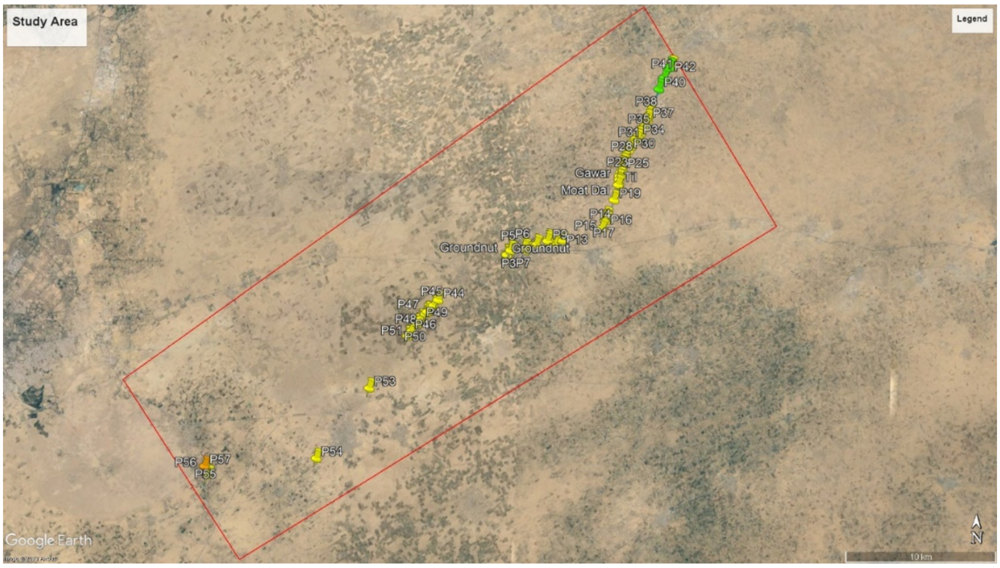

Figure 3: Google earth image showing all field sample.

Table 1: PlanetScope specifications.

Spectral Resolution	8 bands
Spatial resolution	3m
Coverage	340M km^2/day
Revisit time	Daily
Spectral Bands	Coastal Blue: 431 - 452 nm Blue: 465 - 515 nm Green 1: 513 - 549 nm Green: 547 - 583 nm Yellow: 600-620 nm Red: 650 - 680 nm Red Edge: 697-713 nm NIR: 780 - 860 nm
Dynamic Range of Camera	12 bit
Product Used	Surface Reflectance

Table 2: Temporal Dates used for generating database

TEMPORAL DATES			
05/06/2023	**01/07/2023**	**06/08/2023**	**04/09/2023**
09/06/2023	**05/07/2023**	**18/08/2023**	**07/09/2023**
13/06/2023	**12/07/2023**	**22/08/2023**	**16/09/2023**
20/06/2023		**29/08/2023**	**19/09/2023**
24/06/2023		**31/08/2023**	**23/09/2023**
28/06/2023			

4.1 Temporal Data

The choice of optical data dates in this study was crucial, significantly impacting the processing and outcomes. In particular, with regard to the various phenological stages of the groundnut crop, this reliance on temporal data was important for mapping. The selected dates ensure alignment with key moments in the crop's growth cycle, contributing to accurate identification and monitoring. In essence, the temporal dimension is critical in capturing the spectral variations related with groundnut crop development, which improves the precision of the study's conclusions. The temporal scope of the data for this project spans from June 5th to September 28th 2023, to include initial sowing to full growth stages of crop as indicated in the accompanying Table 2.

5. METHODOLOGY

Figure 4 depicts the flowchart methodology adopted. The temporal indices database, along with ground reference data, was utilized to extract samples for each target class. A separability analysis was conducted to determine the optimal number of dates for the study. This analysis aimed to maximize the separation among target classes, assessed using the Euclidean distance. In the temporal indices database, each layer or band represented specific dates corresponding to distinct crop stages in the target crop's phenology. These temporal layers played a crucial role in accurately mapping the crop throughout its phenological cycle, facilitating effective differentiation from other crops or vegetation types (Table 4 shows the phenology of groundnut in the chosen study area).

The Fuzzy-based Modified Possibilistic c-Means (MPCM) was employed to address non-linear separations among spectrally similar classes. The conventional mean training approach encountered challenges in handling heterogeneity effectively, leading to the adoption of the Individual Sample as Mean (ISM) training approach. A comparative analysis was conducted between these two training approaches, considering their use in conjunction with convolution windows.

Traditional classifiers often use statistical measures to represent a cluster or class, but in situations with high heterogeneity in training data, this may lead to inaccurate class representation. To overcome this limitation, a method using individual samples as means was developed. Incorporating this approach resulted in reduced misclassification rates and a more accurate representation of the class. This approach proves especially beneficial in scenarios where traditional classifiers struggle to accurately characterize classes with diverse and heterogeneous data.

In the context of the MPCM classifier, adjustments were made to the objective function when integrating it with the MPCM. This modification was crucial to incorporate the individual effect of each pixel, enhancing the classifier's ability to accurately represent the intricacies of the data.

After identifying sowing dates in the fields through spectral graphs aligned with ground truth data, five optimized temporal databases were considered (as mentioned in Table 3). Each of these databases was generated using relevant indices and subsequently utilized for the classification process. This approach involved leveraging the temporal evolution captured by the indices to enhance the accuracy and precision of the classification results. Figure 5 and Figure 6 shows the curves for CBSI-MSAVI2, MSAVI2 values for different sowing dates and followed by CBSI-MSAVI2 values during different phenological stages from sowing to harvesting respectively.

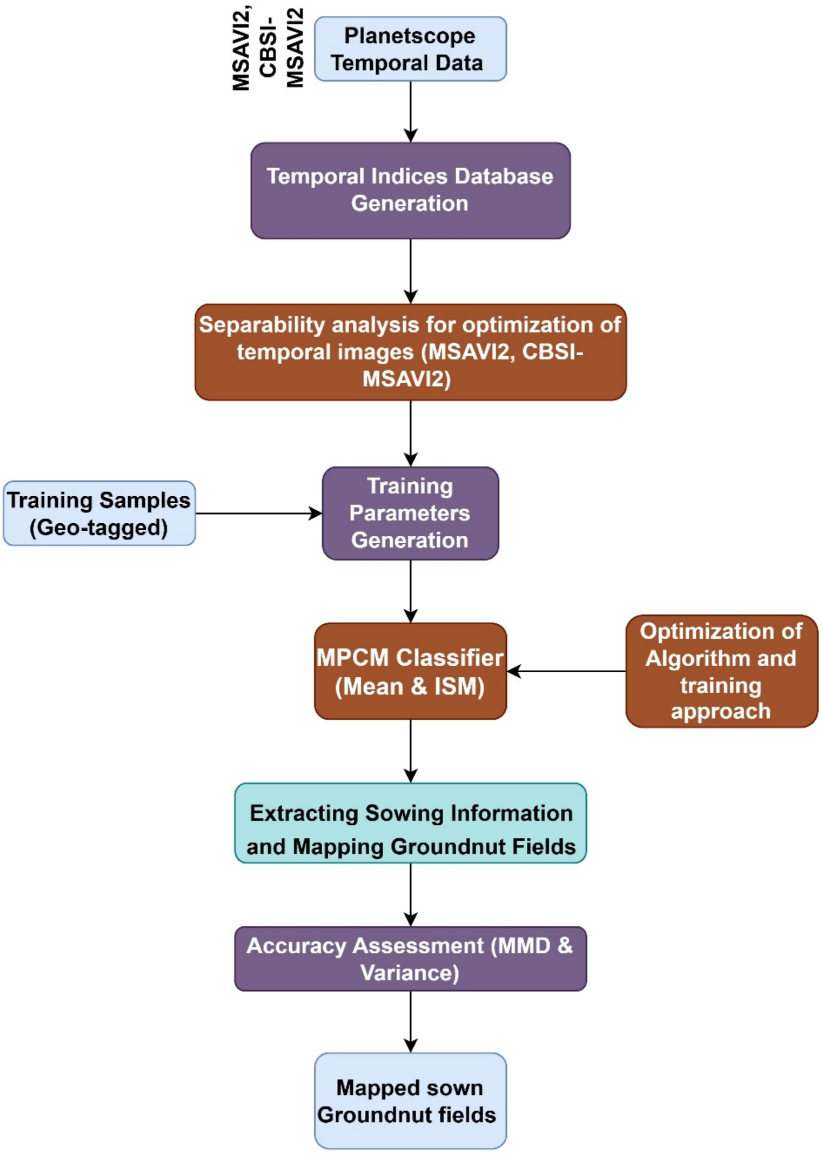

Figure 4: Methodology Flowchart.

Table 3: Bands selected for CBSI-MSAVI2 & Sowing Dates.

Date	Maximum valued Band	Minimum Valued Band	CBSI-MSAVI2 Value	MSAVI2 Value
13th June	NIR (842 nm)	Blue (490 nm)	0.6296	0.447059
20th June	NIR (842 nm)	Blue (490 nm)	0.6255	0.568627
28th June	NIR (842 nm)	Blue (490 nm)	0.7396	0.615686
01st July	NIR (842 nm)	Blue (490 nm)	0.6672	0.65098

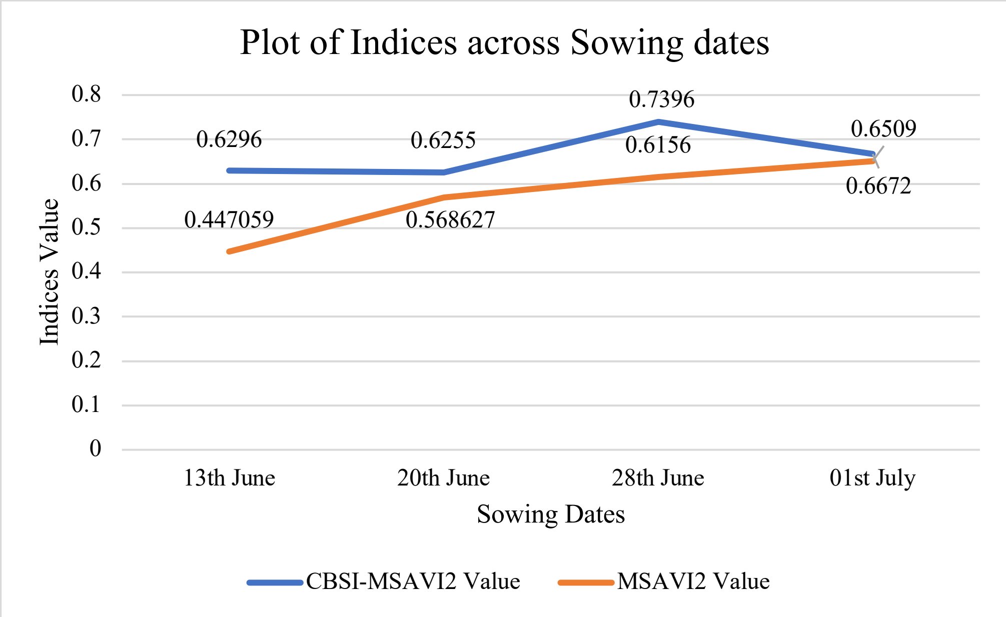

Figure 5: Plot depicting CBSI-MSAVI2 & MSAVI2 values for different sowing dates.

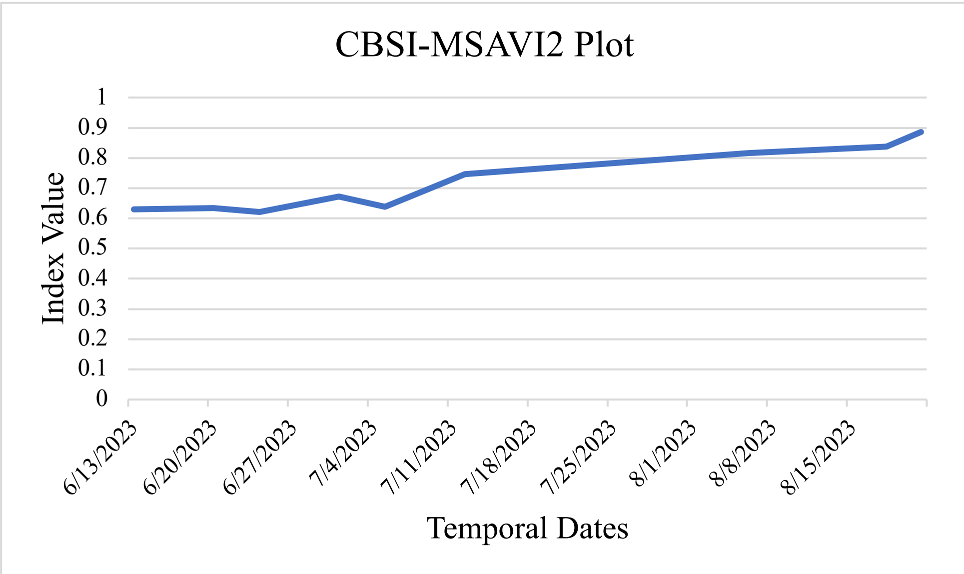

Figure 6: CBSI-MSAVI2 trends for the sowing of groundnut crops on June 13, 2023, across the temporal domain.

Table 4: Groundnut Crop Phenology Stages in the Chosen Study Area

Phenological Stage	**No. of days from sowing**	**Sample Date if sown on July 1st**
Seedling	10-15	June 8th – July 1st
Flowering	60	Sept 15th
Pod formation	120	Oct 30th
Maturity	140	Nov 20th
Harvesting	160	Dec 5th

6. RESULTS & DISCUSSIONS

Separability analysis was conducted utilizing the euclidean distance metric, comparing the groundnut crop with other sampled crops. The minimum separability values were maximized for various date combinations involving CBSI-MSAVI2 and MSAVI2. The selection of 8 temporal dates for the separability analysis in distinguishing groundnut crops from other crops was based on a balance of maximizing discrimination capability and practical considerations. The primary objective was to maximize the minimum separability value using the Euclidean distance metric, and utilizing 8 dates resulted in a high minimum separability value of 42. This indicates a substantial ability to differentiate groundnut crops with other crops. While adding more dates, such as 9, 10, or even up to 12, did slightly increase the separability values, the improvements were marginal, showing diminishing returns beyond 8 dates. Hence, this date combination was chosen as the optimal balance between achieving high separability and managing data complexity. This number of dates ensures that critical phenological stages of the groundnut crop were adequately captured, offering robust and consistent temporal coverage. Additionally, using identified combination of dates avoids overwhelming computational resources, making data processing more efficient while maintaining high classification accuracy. Therefore, the selection of this combination of temporal dates provides a comprehensive and efficient dataset for accurately distinguishing groundnut crops, facilitating better crop monitoring and management. Likewise, optimized temporal date combinations were determined for all identified sowing dates, as detailed in the Table 5, for June 13th 2023 of ground nut sowing.

Following the optimization of temporal dates, a comprehensive analysis of spectral indices was conducted to evaluate the classification performance. Two distinct indices were considered for experimentation: conventional MSAVI-2 and CBSI MSAVI-2. The primary focus was on assessing how well each index handles heterogeneity and accurately classifies groundnut fields. We have used five training samples and three testing samples for each identified sowing date.

The evaluation metrics employed for this analysis were the mean membership difference (MMD) and variance. The results revealed significant distinctions between the two indices. CBSI MSAVI2 demonstrated a significantly lower MMD value of 0.00196 and a variance of 0.5. In contrast, the conventional MSAVI2 exhibited higher values, with an MMD of 0.105 and a variance of 1. These outcomes suggest that CBSI MSAVI2 outperformed conventional MSAVI2 in handling heterogeneity within the groundnut fields, leading to a more precise and accurate classification. The minimized MMD and variance values indicate enhanced separability and better discrimination between groundnut crop and other non-target crops. This highlights the efficiency of CBSI MSAVI2 in collecting spectral variations and highlights its potential to improve groundnut crop mapping precision in the chosen study area. Consequently, CBSI-MSAVI2 was selected as the optimal index for this study.

Table 5: June 13th 2023 of ground nut sowing with CBSI-MSAVI2 Indices

Number of Images	Corresponding Dates	Minimum Separability value
1	5	4
2	5 12	29
3	5 9 12	31
4	5 9 11 12	35
5	5 8 9 11 12	35
6	2 5 8 9 11 12	36
7	2 5 8 9 10 11 12	41
8	**1 2 5 8 9 10 11 12**	42
9	1 2 4 5 8 9 10 11 12	42
10	1 2 3 4 5 8 9 10 11 12	44
11	1 2 3 4 5 6 8 9 10 11 12	44
12	1 2 3 4 5 6 7 8 9 10 11 12	45

Note: The red-highlighted numbers indicate the selected optimized temporal data.

We extended our experimentation using MPCM algorithms with exploring three types of contextual objective function to study contextual effect, including MPCM, MPCM-s, MPLICM, and ADMPLICM, employing two different window sizes: 3x3 and 5x5. Classification was performed using these algorithms, and the assessment was based on MMD and variance. Figures 7 and 8 shows the Mean Membership Difference (MMD) and Variance values for different algorithms tested with varying window sizes (3x3 and 5x5) and training approaches (Mean and ISM). For the mean training approach, the MPCM algorithm demonstrated a MMD of 0.00196 and a Variance of 0.00003, indicating its effectiveness. Similarly, the ADMPLICM algorithm with the ISM training approach showed superior performance with a MMD of 0.00196 and a Variance of 0.000003. This analysis identifies ADMPLICM 3x3 with the ISM training approach as the optimal algorithm, emphasizing its efficiency in handling heterogeneity within groundnut fields for precise and accurate classification.

The data was classified using the optimal algorithm ie ADMPLICM 3x3 with ISM training approach for various sowing dates identified and the outputs of these were shown in figures from 9 to 12.

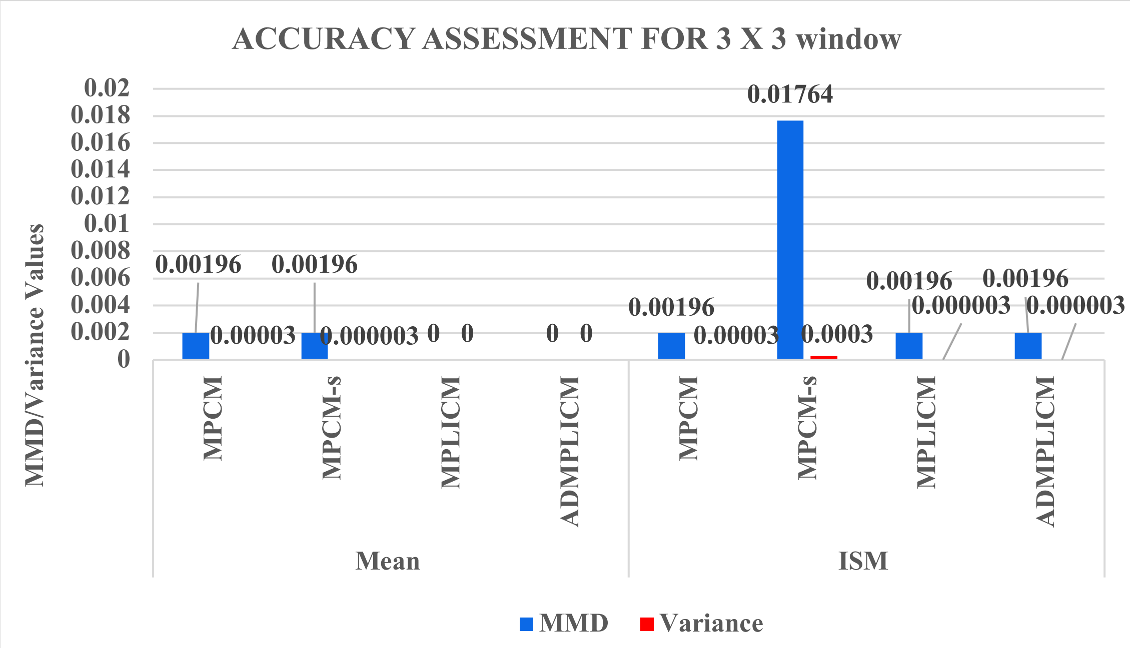

Figure 7: Plot showing accuracy assessment for various MPCM for 3x3 window.

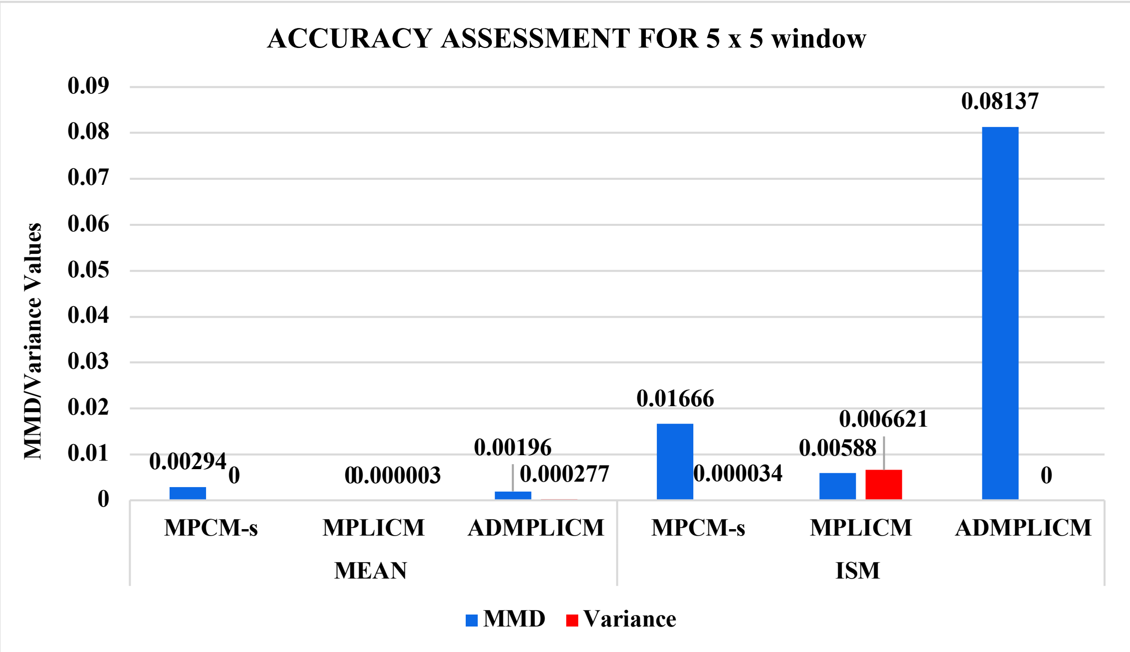

Figure 8: Plot showing accuracy assessment for various MPCM for 5x5 window.

We extended our experimentation using MPCM algorithms with exploring three types of contextual objective function to study contextual effect, including MPCM, MPCM-s, MPLICM, and ADMPLICM, employing two different window sizes: 3x3 and 5x5. Classification was performed using these algorithms, and the assessment was based on MMD and variance. Figures 7 and 8 shows the Mean Membership Difference (MMD) and Variance values for different algorithms tested with varying window sizes (3x3 and 5x5) and training approaches (Mean and ISM). For the mean training approach, the MPCM algorithm demonstrated a MMD of 0.00196 and a Variance of 0.00003, indicating its effectiveness. Similarly, the ADMPLICM algorithm with the ISM training approach showed superior performance with a MMD of 0.00196 and a Variance of 0.000003. This analysis identifies ADMPLICM 3x3 with the ISM training approach as the optimal algorithm, emphasizing its efficiency in handling heterogeneity within groundnut fields for precise and accurate classification.

The data was classified using the optimal algorithm ie ADMPLICM 3x3 with ISM training approach for various sowing dates identified and the outputs of these were shown in figures from 9 to 12.

The total accumulated date wise sowing area of groundnut was estimated to be 28 square kilometers. The trends in sowing for the study area were depicted in figure 13. The sowing trend exhibits a gradual increase starting in June, reaching its peak towards the end of June, 2023, and subsequently declining during mid-July. These trends provide valuable insights into the temporal dynamics of groundnut cultivation in the study area.

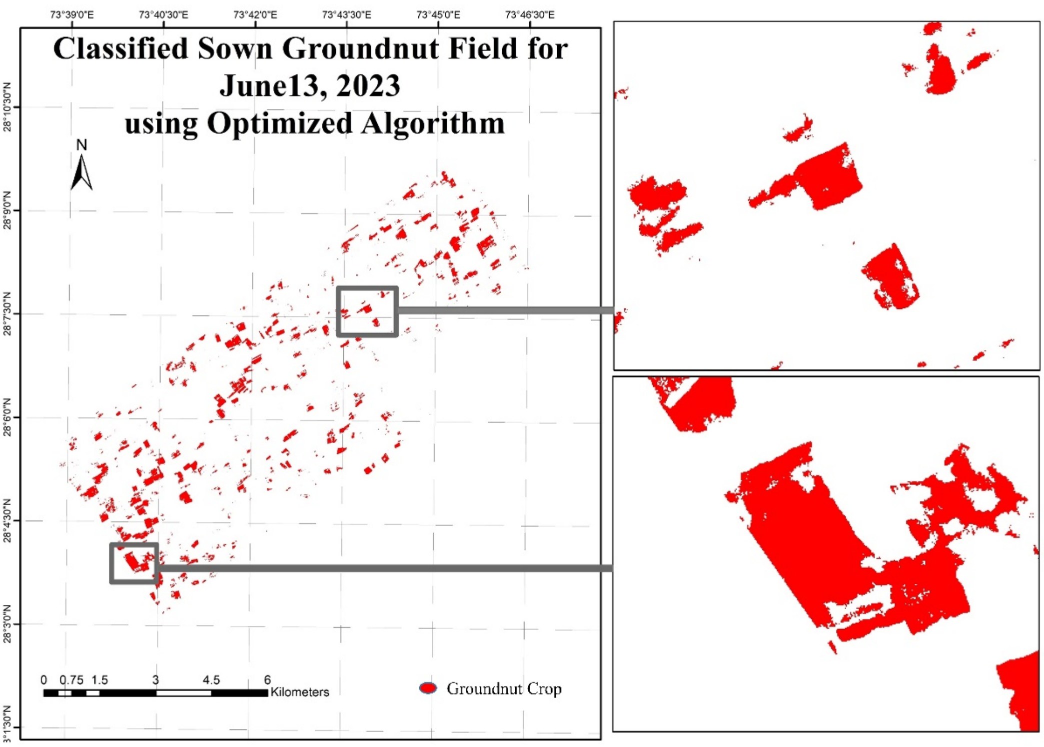

Figure 9: Classified map output for 13th of June, 2023 using ADMPLICM algorithm.

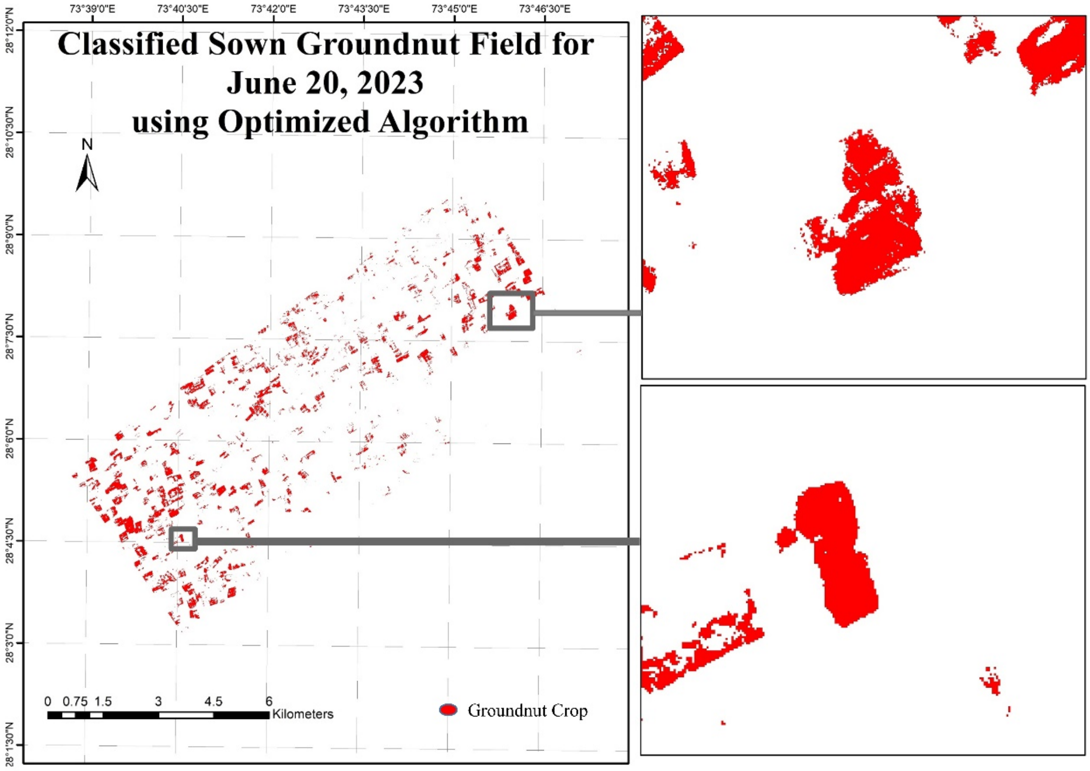

Figure 10: Classified map output for 20th of June, 2023 using ADMPLICM algorithm.

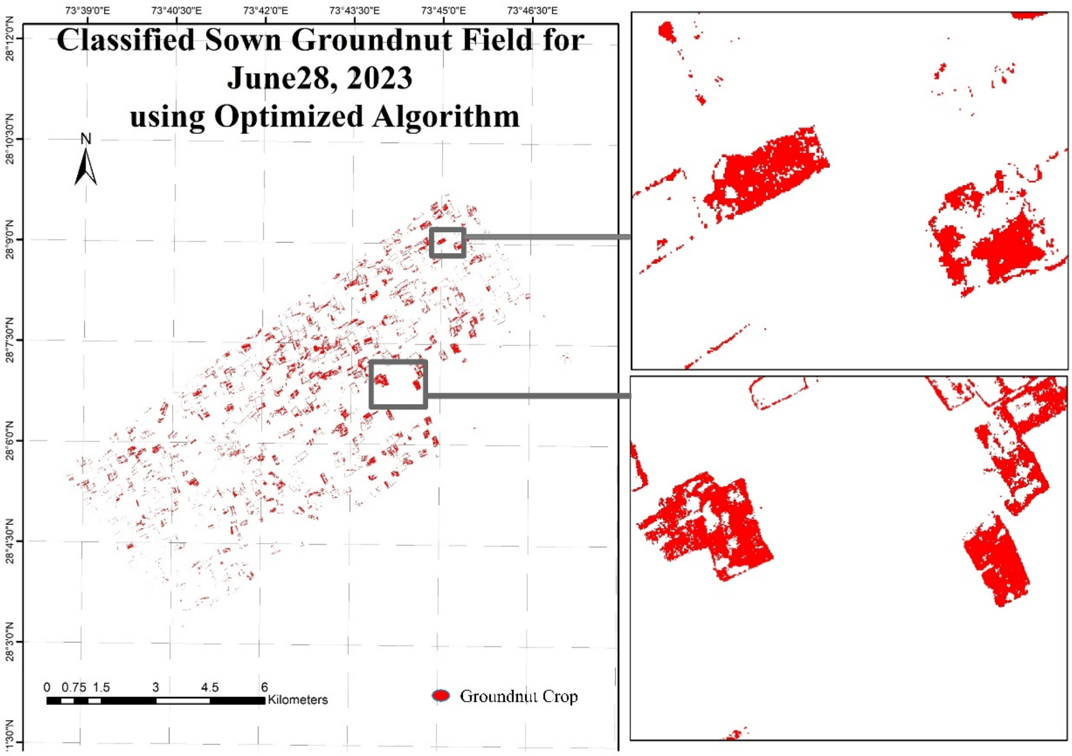

Figure 11: Classified map output for 28th of June, 2023 using ADMPLICM algorithm.

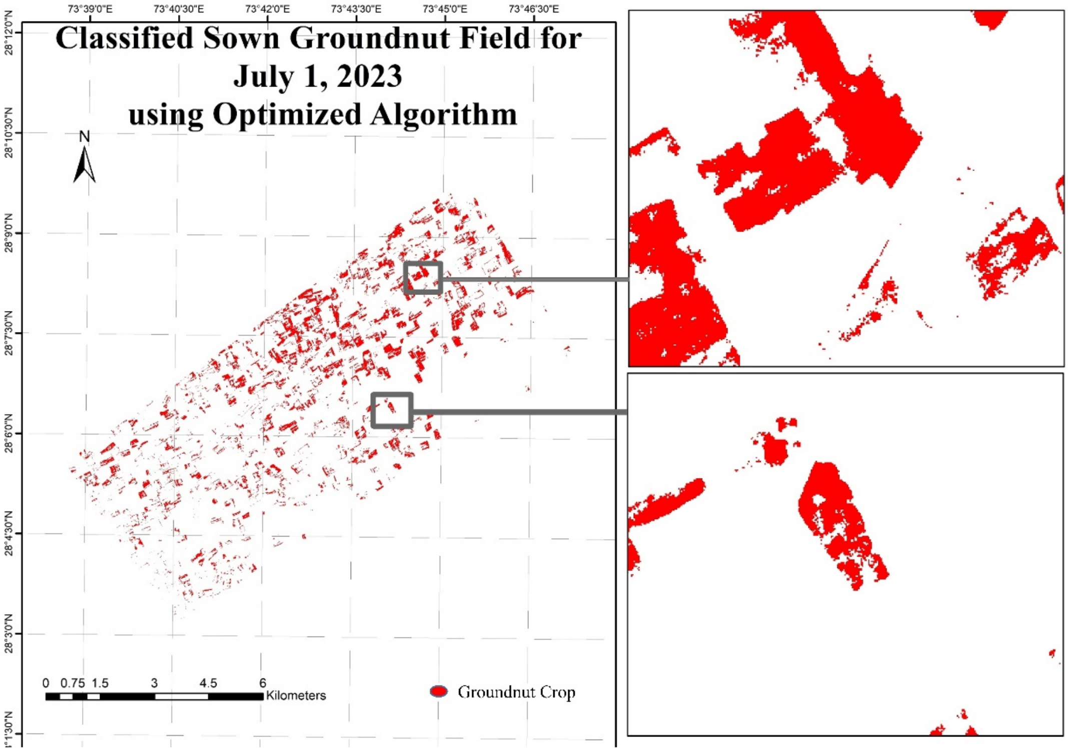

Figure 12: Classified map output for 1st of July, 2023 using ADMPLICM algorithm.

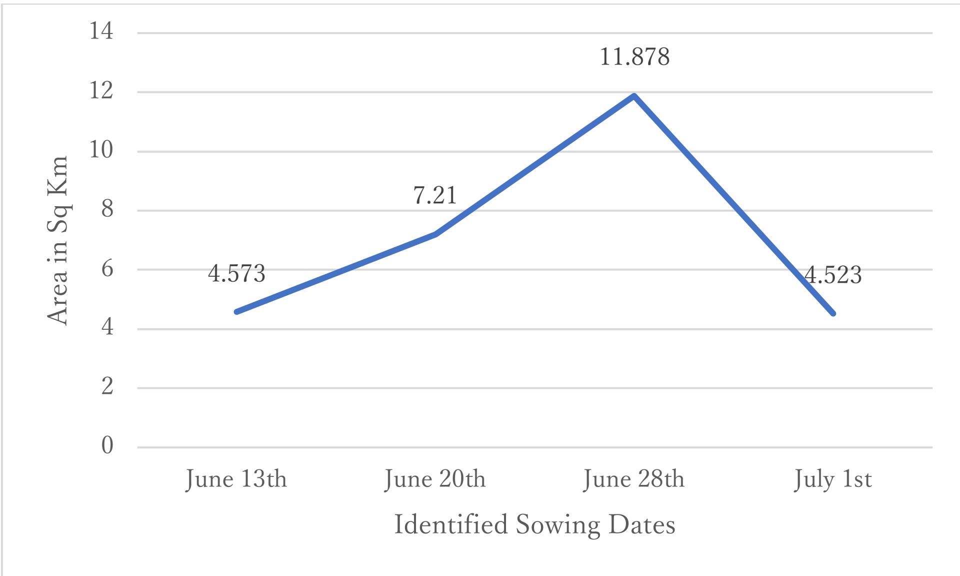

Figure 13: Trend in sowing of groundnut crop in the study area.

7. CONCLUSIONS

In conclusion, this research represents a significant contribution to the fields of precision agriculture, remote sensing, and artificial intelligence by addressing the complex task of groundnut sowing information extraction. The study, conducted employed a comprehensive methodology combining temporal optical data preprocessing, optimized temporal indices, and a contextual fuzzy model. The utilization of the Modified Possibilistic c-Means (MPCM) algorithm, particularly enhanced by the Individual Sample as Mean (ISM) training approach, proved major advantage in soft classification. The use of the ISM approach effectively handled heterogeneity, accounting for scenarios where entire groundnut fields are not sown in a single day, and variations in fertilizer application and non-uniformities in water systems, such as sprinklers, exist. Expanding the scope to MPCM algorithm variations, the research identified ADMPLICM 3x3 with the ISM approach as the optimal algorithm for this study, showcasing its effectiveness in handling complex agricultural landscapes. The integration of mathematical concepts, including vegetation indices, and the application of fuzzy-based algorithms showcased the power of these advanced technologies in extracting groundnut sowing information. The study not only contributes valuable insights into groundnut crop dynamics but also offers a reliable tool for farmers, agencies, and researchers, aiding in informed decision-making and sustainable agricultural practices. The interdisciplinary approach undertaken in this research, bridging agriculture, remote sensing, and artificial intelligence, provides a blueprint for similar studies on diverse crops and agricultural regions globally. The outcomes of this research contribute to advancing precision farming practices, emphasizing the importance of utilizing state-of-the-art technologies for efficient and data-driven agricultural management.

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