International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Evaluating NDVI, GNDVI, EVI, and SAVI for Accurate Crop Classification: A Case Study in Mahalaxmi Kheda Village

Shivani S. Bhosle[1], Dr. Prapti D. Deshmukh[2]

[1]Research Fellow, Department of Computer Science and IT,
[2]Pricipal, Department of Computer Science and IT,
[1,2]Dr.G.Y.Pathrikar College of Computer Science and Information Technology MGM University, Chhatrapti Sambajinagar, Maharashtra, India
Shivanibhosle21@gmail.com[1], prapti.research@gmail.com[2]

ABSTRACT

Accurate crop identification is crucial for effective agricultural monitoring, resource planning, and sustainable farming. This study evaluates the performance of four vegetation indices—Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI)—derived from Harmonized Landsat and Sentinel-2 (HLS) imagery for crop classification in Mahalaxmikheda village, Gangapur Tehsil, Chh. Sambhajinagar District, India. The indices were calculated for three different dates during the crop-growing season and combined into a multitemporal dataset. The random Forest (RF) algorithm was employed for supervised classification, and the results were validated against ground truth data collected through field visits. The accuracy assessment revealed that EVI achieved the highest overall accuracy (97.97%) and kappa coefficient (0.97), followed by SAVI (97.35% and 0.96), GNDVI (94.84% and 0.92), and NDVI (90.90% and 0.87), respectively. The superior performance of EVI and SAVI can be attributed to their ability to minimize soil background effects and atmospheric influences, thereby capturing crop-specific variations more effectively. The integration of the ground truth data further strengthened the classification results by reducing errors and improving the reliability of the RF model. These findings suggest that EVI and SAVI are more robust indices for crop identification in heterogeneous agricultural landscapes than NDVI and GNDVI are. This study highlights the potential of these indices to enhance precision agriculture applications, such as crop monitoring, management, and yield estimation, contributing to more sustainable agricultural practices.

Keywords: Crop identification, Vegetation indices, NDVI, GNDVI, EVI, SAVI, Random Forest

1. Introduction

Agriculture serves as the foundation for food security and rural livelihood in numerous regions globally. Precise crop identification is essential for agricultural monitoring because it enables policymakers, researchers, and farmers to understand cropping patterns, forecast yields, and efficiently plan resource allocation[1].Access to timely information regarding crop types and distribution aids in the scheduling of irrigation, fertilizer application, and pest management, thereby enhancing productivity and fostering sustainable agricultural practices. Traditional approaches to crop identification primarily utilize ground-based surveys. Although these methods are accurate, they are labor-intensive, time-consuming, and

challenging to implement over large areas[2]. Recent advancements in satellite remote sensing have facilitated the efficient and frequent monitoring of agricultural regions on both regional and global scales. Remote sensing offers valuable spectral and temporal data, enabling the differentiation of crop types based on their distinct growth characteristics and phenological stages[3].
Vegetation indices are extensively utilized in crop identification studies because they enhance vegetation signals by minimizing the background noise from atmospheric and soil conditions. Among these, the Normalized Difference Vegetation Index (NDVI) is the most commonly employed, offering insights into plant vigor and biomass. However, NDVI is limited in areas with dense canopy cover and soil background effects[4]. To address these issues, other indices have been developed, such as the Green Normalized Difference Vegetation Index (GNDVI), which highlights chlorophyll content; the Enhanced Vegetation Index (EVI), which increases sensitivity in regions with high biomass; and the Soil-Adjusted Vegetation Index (SAVI), which adjusts for ground brightness effects in sparse vegetation conditions. Although these indices are extensively utilized for agricultural monitoring, their effectiveness in crop identification differs depending on the region and the cropping system. Consequently, a systematic evaluation of NDVI, GNDVI, EVI, and SAVI is necessary to identify the most suitable indices for a specific study area[5].
This study aims to evaluate and compare the performance of NDVI, GNDVI, EVI, and SAVI for crop identification in Mahalaxmikheda Village. These indices were derived from satellite images, and their classification accuracy was assessed using the overall accuracy and kappa statistics. These findings offer insights into the effectiveness of various vegetation indices and identify the most reliable method for crop identification in heterogeneous agricultural landscapes.

2. Literature Review

Remote sensing has become an essential tool for monitoring agriculture, particularly for crop identification and yield evaluation. Vegetation indices (VIs) derived from multispectral satellite imagery are widely used to evaluate crop health, canopy density, and growth stages. Among these, the Normalized Difference Vegetation Index (NDVI) is the most established and commonly used. It effectively distinguishes vegetation from bare soil and other land features because of the significant contrast between the red and near-infrared reflectance. However, NDVI is prone to interference from soil background and canopy saturation in densely vegetated areas, which limits its accuracy in diverse agricultural landscapes[6]
Multispectral data-derived vegetation indices have been extensively utilized for the monitoring and classification of crops. Among these, the Normalized Difference Vegetation Index (NDVI) is the most commonly used because of its effectiveness in distinguishing vegetation from bare soil[7]. Nevertheless, NDVI's sensitivity of the NDVI to soil reflectance and canopy saturation can compromise its precision in areas with dense vegetation. To overcome these limitations, the Soil-Adjusted Vegetation Index (SAVI) was created to reduce the influence of the soil background[8], while the Enhanced Vegetation Index (EVI) enhances sensitivity in regions with high biomass by incorporating adjustments for atmospheric and soil conditions[9]. Similarly, Green NDVI (GNDVI) increases sensitivity to chlorophyll by replacing the red band with a green band[10]. These indices collectively enhance vegetation monitoring, particularly in heterogeneous agricultural settings. In addition to spectral indices, classification algorithms are vital for crop identification. Random Forest (RF) has become one of the most effective classifiers because of its robustness, non-parametric design, and capability to manage multidimensional datasets[11]. RF constructs multiple decision trees and employs majority voting to improve the classification accuracy[12]. Research utilizing Sentinel-2 data has demonstrated that integrating vegetation indices with RF achieves accuracies exceeding 90% for crop mapping[13]. Moreover, multitemporal approaches, which incorporate indices from various growth stages, enhance the ability to distinguish between crop types[14]. Overall, the

literature suggests that indices such as EVI and SAVI, when combined with RF and multidate imagery, deliver reliable and accurate crop classification results in diverse agricultural landscapes.

3. Methodology

The methodology employed in this study is defined in Fig. X. The process was initiated with the acquisition of Harmonized Landsat and Sentinel-2 (HLS) imagery, followed by pre-processing procedures such as layer stacking and clipping to the Area of Interest (AOI). Vegetation indices, including NDVI, GNDVI, EVI, and SAVI, were derived for three distinct dates using the Sentinel-2 spectral bands. These index layers were subsequently integrated to form a multitemporal dataset. These layers were used as input features for crop classification via the Random Forest (RF) algorithm, which constructs an ensemble of decision trees to enhance the classification accuracy. The final phase involved an accuracy assessment using ground-truth data, wherein the overall accuracy and kappa coefficients were computed to evaluate the performance of each index.

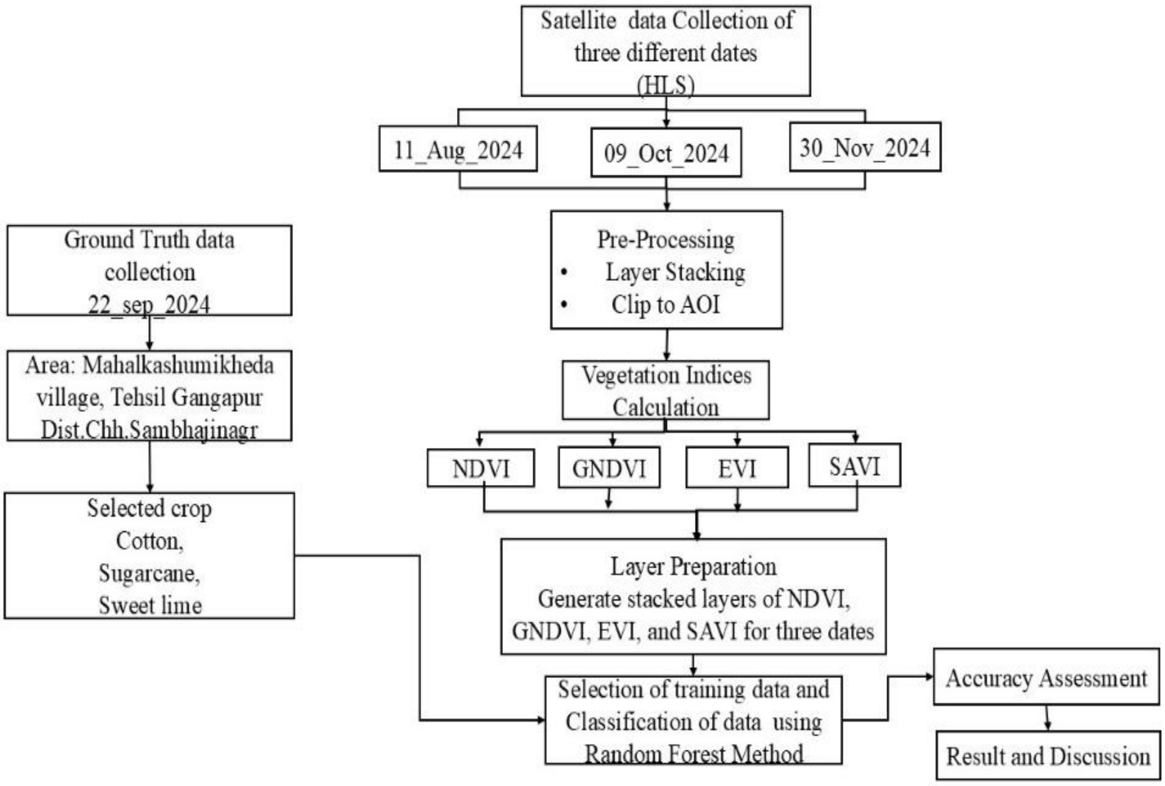

Fig.1. Methodological workflow of the study.

3.1 Study Area

This study was conducted in Mahalaxmikheda village(19.82°N, 75.03°E), Gangapur Tehsil,Chh. Sambhajinagar district, Maharashtra. The region lies in a subtropical climate zone with hot summers, a distinct monsoon season from June to September, and mild winters. Rainfall primarily depends on the southwest monsoon, which plays an important role in crop growth and productivity. The region is primarily agricultural, with fertile lands that support the cultivation of key crops, such as cotton, sweet lime, corn, wheat, and sugarcane. Both dryland and irrigated farming techniques are employed, creating a diverse landscape that is well suited for remote sensing-based agricultural studies. Geographically, the study site is situated within the jurisdiction of the Upper Jayakwadi Dam, which supplies irrigation to the adjacent agricultural lands. These lands comprise small-to medium-sized plots, which are characteristic of the region's typical farming practices. The variety of crops, soils, and cultivation methods make Mahalaxmikheda an ideal location for evaluating plant indices for crop identification.

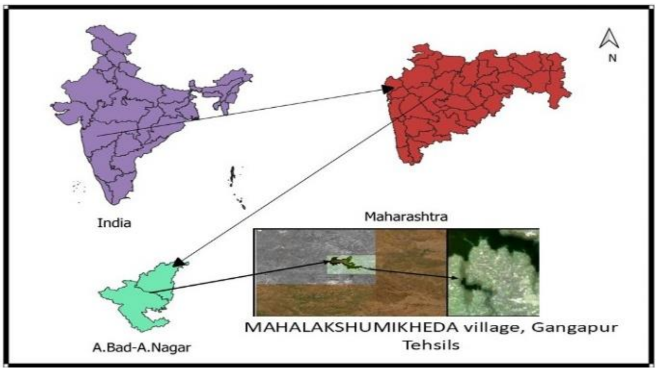

Fig.2 Study Area

3.2.1Data Collection and Band Selection

In this study, satellite imagery was sourced from the Harmonized Landsat and Sentinel-2 (HLS) dataset developed by NASA to deliver consistent, high-resolution, and frequent observations for land surface monitoring. The HLS product integrates Landsat-8 Operational Land Imager (OLI) data with Sentinel-2 Multispectral Instrument (MSI) data, ensuring compatibility in radiometry and geometry[15]. This integration facilitates the creation of a dense time series with a spatial resolution of 30 m and a revisit frequency of 2–3 d, making it highly suitable for agricultural monitoring. Cloud-free images corresponding to the crop growth stages were selected for August, October, and November 2024. These images were acquired in the surface reflectance format, which incorporates atmospheric corrections to ensure accurate spectral values for vegetation analysis, covering the visible to shortwave infrared (SWIR) range. Six bands were selected, namely B2, B3, B4, B8A, B11, and B12. These bands are important for farming. They help study plants, identify crops, and find water and soil problems.[16]. The pertinent spectral bands, blue, green, red, and near-infrared (NIR), were extracted and subsequently processed in QGIS for the computation of vegetation indices[17].

Table.1.Information of bands

Band	**Sensor**	**Wavelength Range (nm)**	**Application in This Study**
Blue	B2 (Sentinel-2) / B2 (Landsat-8)	450 – 515	Used in EVI to correct atmospheric influences
Green	B3 (Sentinel-2) / B3 (Landsat-8)	525 – 600	Used in GNDVI to estimate chlorophyll content
Red	B4 (Sentinel-2) / B4 (Landsat-8)	630 – 680	Used in NDVI, EVI, and SAVI to assess vegetation vigor
NIR (Near Infrared)	B8 (Sentinel-2) / B5 (Landsat-8)	845 – 885	Used in all indices (NDVI, GNDVI,

	EVI, SAVI) for vegetation monitoring

3.2.2Ground Truth Data

Ground truth data were gathered to aid the training and validation of the classification results. Field visits were conducted during the crop-growing season to document information on crop type, growth stage, and field boundaries in selected agricultural plots within Mahalakshumikheda, Gangapur Tehsil, Chh. Sambhajinagar District, Maharashtra State, India. In Fig.2, the locations of the sample fields are recorded using a handheld GPS device, and a GPS-enabled camera is used to capture the geo-tagged photographs. A total of 150 samples were collected across five major classes: Cotton, Sugarcane, Sweet lime, Water, and Other land uses, which were subsequently used for both the training and validation of the classification process.

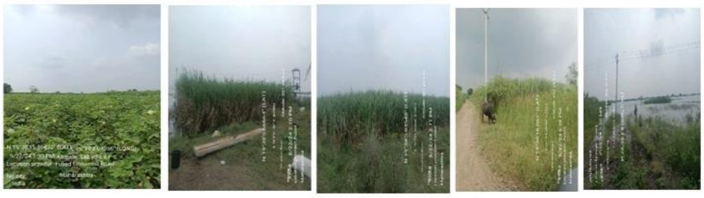

Fig.3 Ground Truth Data

4. Experimental Approach

This study followed a systematic experimental workflow for crop identification and classification using multidate HLS satellite data. The workflow included data pre-processing, preparation of vegetation index layers, classification, and accuracy assessment.

4.1 Pre-Processing

The satellite images utilized in this study have already undergone atmospheric and radiometric corrections, effectively reducing the impact of atmospheric scattering and sensor-related distortions[18]. To prepare the data for further analysis, a layer stacking technique was employed to merge the necessary spectral bands into a single composite image.The following fig shows the layer stack image of three different dates.These bands were merge into single multi-band raster contating 18 layers. Subsequently, the dataset was clipped to the Area of Interest (AOI) encompassing Mahalakshumikheda, Gangapur Taluka, and Sambhajinagar districts, as shown in Fig.2. These pre-processing steps ensured spatial consistency and provided a dependable dataset for calculating and classifying vegetation indices.

$$\mathrm{Composit_{Image}} = \mathrm{Stack}\left(B_1^{t1}, B_2^{t1}, \ldots.B_1^{t2}, B_2^{t2}{}_2, \ldots., B_n^{t2}, B_1^{t3}, B_2^{t3}, \ldots, B_n^{t3}\right) \ldots\ldots (1)$$

Where $B_1^{t1}, B_2^{t1}, \ldots.B_1^{t2}, B_2^{t2}{}_2, \ldots., B_n^{t2}, B_1^{t3}, B_2^{t3}, \ldots, B_n^{t3}$ represent the selected bands of (Red,Green,Blue,NIR and SWIR) from three different dates (early, mid, and late season observations), and Stack () is a band-compositing function that merges multiple spectral bands into a single multi-band raster dataset.

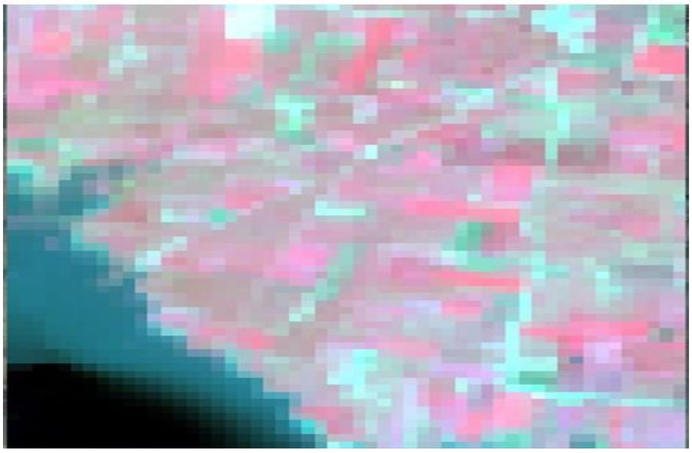

Fig.4 Layer stack Image of AOI

4.2 Vegetation Indices Calculation

To discriminate different crop types in the study area, four widely used vegetation indices were derived from the Harmonized Landsat and Sentinel-2 (HLS) dataset. The required spectral bands included Blue (B2, 490 nm), Green (B3, 560 nm), Red (B4, 665 nm), Near Infrared – NIR (B8A, 865 nm), Shortwave Infrared 1 – SWIR1 (B11, 1610 nm), and SWIR2 (B12, 2190 nm). Since the imagery was already atmospherically and radiometrically corrected, band reflectance values were directly used for index calculation[19]The following indices were computed for three different dates by applying the corresponding formulas in the QGIS Raster Calculator:

4.2.1.Normalized Difference Vegetation Index (NDVI):

The Normalized Difference Vegetation Index (NDVI) uses the contrast between near-infrared (B8A) and red (B4) reflectance to measure vegetation vigor. Healthy plants reflect more NIR and absorb red light, making NDVI effective for detecting vegetation presence, though it tends to saturate in dense canopies and is sensitive to soil background[20]

$$\mathrm{NDVI} = \frac{\mathrm{B8A} - \mathrm{B4}}{\mathrm{B8A} + \mathrm{B4}}$$

Where, B8A represent Narrow NIR and B4 represent Red
The NDVI is a robust indicator of vegetation vigor and biomass, with higher values representing dense and healthy vegetation[21].

4.2.2.Green Normalized Difference Vegetation Index (GNDVI):

The Green Normalized Difference Vegetation Index (GNDVI) modifies NDVI by replacing the red band with the Green band (B3). This makes it more sensitive to chlorophyll concentration and plant stress, offering better detection in early growth stages, but it is still influenced by soil effects[22].

$$\mathrm{GNDVI} = \frac{\mathrm{B8A} - \mathrm{B3}}{\mathrm{B8A} + \mathrm{B4}}$$

Where , B8A represent Narrow NIR and B3 represent Green

GNDVI is more sensitive to chlorophyll concentration and is useful for detecting crop stress at early stages[21, 22].

4.2.3.Enhanced Vegetation Index (EVI):

The Enhanced Vegetation Index (EVI) reduces atmospheric and soil background noise by including the blue band (B2) along with the correction factors. The gain factor (2.5), red correction (6×B4), blue correction (–7.5×B2), and canopy adjustment constant (1) make EVI more effective in high biomass regions where NDVI saturates.

$$\mathrm{EVI} = 2.5 \times \frac{(\mathrm{B8A} - \mathrm{B4})}{(\mathrm{B8A} + 6 \times \mathrm{B4} - 7.5 \times \mathrm{B2} + 1)}$$

Where, B8A represent Narrow NIR ,B4 represent Red and B2 represent Blue
EVI improves sensitivity in high-biomass regions and reduces the influence of soil and atmospheric effects[20–22].

4.2.4.Soil-adjusted vegetation index (SAVI)

The soil-adjusted vegetation index (SAVI) introduces a soil adjustment constant (L = 0.5) into the NDVI formula. This correction minimizes the influence of soil brightness, making SAVI more reliable in areas with sparse vegetation and mixed crop-soil conditions.

$$\mathrm{SAVI} = \frac{(\mathrm{B8A} - \mathrm{B4})}{(\mathrm{B8A} + \mathrm{B4} + 0.5)} \times 1.5$$

Where, B8A represent Narrow NIR and B4 represent Red
SAVI minimizes soil background noise, making it suitable for areas where vegetation is sparse or fields are exposed to soil[23]. These vegetation indices were calculated separately for each date, generating 12 index layers (NDVI, GNDVI, EVI, and SAVI for the three dates).

4.3 Preparation of Multitemporal Index Layers

Vegetation indices were calculated using data from Harmonized Landsat and Sentinel-2 (HLS) for three different dates during the crop-growing season. The indices used were the NDVI, GNDVI, EVI, and SAVI. These were derived from the HLS spectral bands: blue (B2), green (B3), red (B4), and Narrow Near-Infrared (B8A). Each index was created separately for all three dates to observe the changes in crop growth. The resulting data were combined using the Layer Stack tool in QGIS to form a single dataset with multiple bands for each date. These combined layers maintain both spectral and time-related details, providing a complete dataset for further classification and accuracy checks.

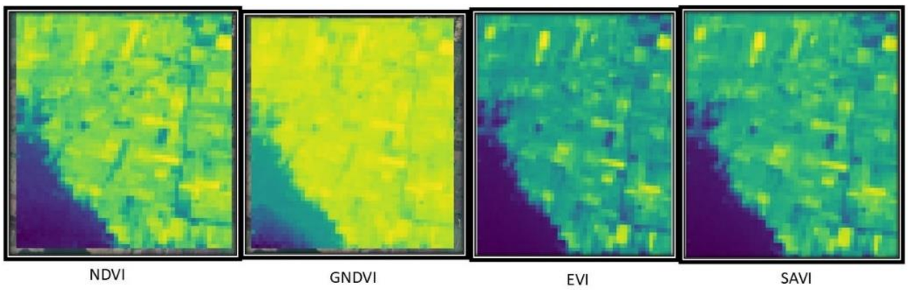

Fig. 5. Multitemporal vegetation index layer stack generated using QGIS.

The figure.4. shows the stacked layers of the NDVI, GNDVI, EVI, and SAVI. These layers were created from Harmonized Landsat and Sentinel-2 (HLS) data for three different dates. The stack combines spectral and temporal information, providing a complete dataset for studying and classifying crops.

4.4 Classification

In remote sensing, classification involves assigning each pixel in an image to a specific land cover or crop category based on its spectral and temporal characteristics. This process can be broadly categorized into unsupervised and supervised approaches[24]. Unsupervised classification groups pixels into clusters based on spectral similarity without prior knowledge of land-cover types.

By contrast, supervised classification utilizes reference data to guide the algorithm in identifying known classes. Supervised classification is generally favored in agricultural studies because it enables the precise mapping of specific crops by incorporating field knowledge and ancillary data[25].

In this study, the Random Forest (RF) algorithm was utilized for supervised classification. RF is a machine learning method based on ensembles that creates several decision trees from random subsets of data and combines their results to improve the classification precision. Each tree votes for a class, and the class with the most votes is chosen as the final result[26].

The mathematical representation of the Random Forest prediction is given as:

$$\hat{y} = \text{mode}\ \{h_1(x), h_2(x), h_3(x) \ldots\ldots, h_n(x)\}$$

Where,
$\hat{y}$ =final predicted class,
$h_i(x)$ =prediction of the i^{th} decision tree,
n=total number of decision trees in the forest.

This method is particularly effective for remote sensing, as it adeptly handles high-dimensional datasets, mitigates overfitting, and captures intricate relationships among vegetation indices[27]. By applying RF to the multitemporal vegetation index stack (NDVI, GNDVI, EVI, and SAVI), crop classification maps were produced to illustrate the distribution of cotton, sugarcane, sweet lime, water, and other land-cover classes within the study area.

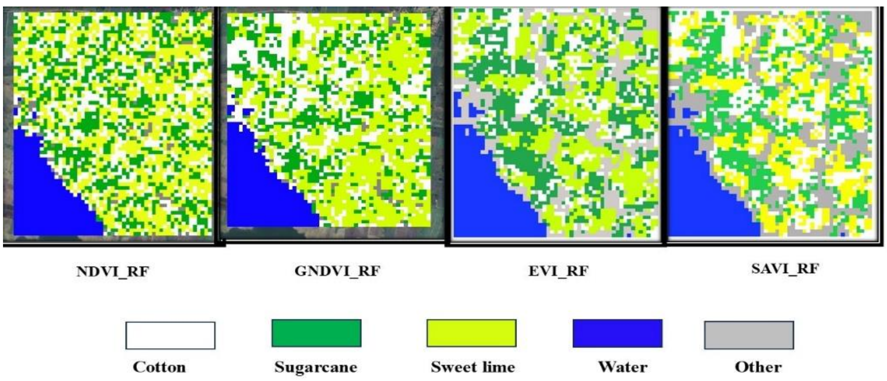

Fig. 6. Classified crop map generated using Random Forest algorithm.

Fig. 5 illustrates the spatial distribution of the predominant crop types and other land-cover categories within the Mahalakshumikheda study area, as identified through multitemporal vegetation indices.

5.Result

This section presents the results from classifying HLS-derived vegetation indices, including NDVI, GNDVI, EVI, and SAVI. Each index was assessed for its effectiveness in distinguishing major crop classes—cotton, sugarcane, and sweet lime—as well as water and other land-use categories.

5.1Accuracy Assessment

The accuracy of the classification results was assessed using a confusion matrix that was used to determine the overall accuracy (OA) and kappa coefficient (κ). These metrics provide information on the percentage of correctly classified pixels and the degree of agreement between the classified data and reference data, beyond chance. The results highlighted variations in performance among the vegetation indices. The Enhanced Vegetation Index (EVI) achieved the highest accuracy, with an overall accuracy of 97.97% and a kapp value of 0.97, indicating excellent classification reliability. The Soil Adjusted Vegetation Index (SAVI) also performed admirably, with an overall accuracy of 97.35% and a kappa value of 0.96. The Green Normalized Difference Vegetation Index (GNDVI) recorded an overall accuracy of 94.84% and kappa of 0.92, whereas the Normalized Difference Vegetation Index (NDVI) demonstrated comparatively lower accuracy, with an overall accuracy of 90.90% and kappa of 0.87.The following table shows a comparison of the vegetation indices for crop classification.

Table 1. Accuracy assessment of crop classification using NDVI, GNDVI, EVI, and SAVI.

Vegetation Index	Overall Accuracy (OA, %)	Kappa Coefficient (κ)
NDVI	90.90	0.87
GNDVI	94.84	0.92
EVI	97.97	0.97
SAVI	97.35	0.96

5.2Results and Discussion

The analysis of vegetation indices derived from HLS imagery revealed noticeable differences in the classification performance of crop identification in the study area. NDVI and GNDVI were effective in detecting vegetation presence but showed moderate accuracy owing to their sensitivity to soil background, atmospheric effects, and canopy saturation, especially in areas of dense vegetation. In contrast, EVI and SAVI achieved significantly higher accuracies. The stronger performance of these indices can be attributed to their ability to minimize external influences, which reduces soil background effects by incorporating a soil adjustment factor, making them particularly useful in fields with partial or sparse vegetation, while EVI applies correction coefficients that counteract atmospheric scattering and reduce saturation problems in high biomass regions. These characteristics enable EVI and SAVI to capture crop-specific variations more effectively, particularly for cotton, sugarcane, and sweet lime.

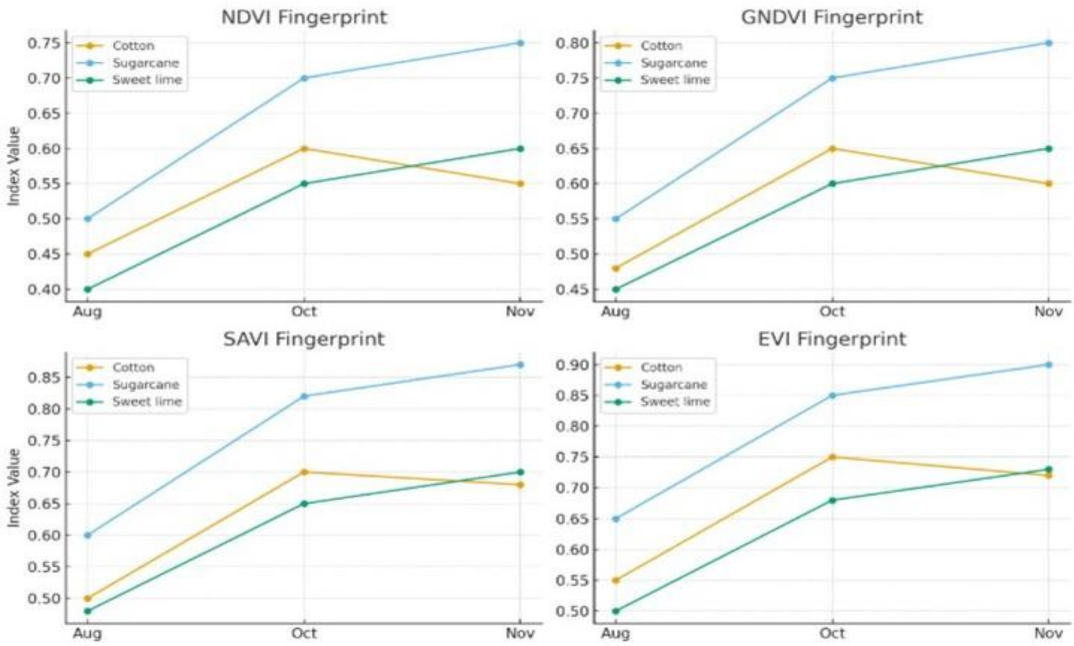

Fig. 7: Temporal fingerprints of different vegetation indices (NDVI, GNDVI, EVI, SAVI) for major crops in the study area across three time periods (August, October, and November). The Y-axis represents the vegetation index values (–1 to +1), while the X-axis shows the observation dates.

Fig. 7 illustrates the fingerprint line graphs of NDVI, GNDVI, SAVI, and EVI for cotton, sugarcane, and sweet lime. The temporal patterns reveal that while NDVI and GNDVI capture overall vegetation dynamics, they exhibit overlapping trends among crop types, which diminishes their separability. Conversely, SAVI and EVI offer clearer distinctions, especially during peak growth stages, due to their ability to minimize soil background effects and saturation issues. Notably, EVI demonstrates the strongest separability between crops, corresponding with its higher classification accuracy (97.97%, Kappa 0.97). This indicates that EVI effectively enhances crop-specific spectral responses by correcting for canopy density and atmospheric effects, whereas SAVI improves performance in heterogeneous fields by accounting for soil reflectance. These findings confirm that indices incorporating correction factors, such as EVI and SAVI, provide more reliable crop discrimination than NDVI and GNDVI.

The integration of the ground truth data further strengthened the classification results. Field observations collected using a GPS camera ensured that crop types were correctly represented in the training and validation processes. By providing accurate reference points, the ground truth data reduced the classification errors, improved the reliability of the Random Forest model, and validated the superior performance of EVI and SAVI over NDVI and GNDVI. This demonstrates that the combination of remote sensing indices and field-based observations can provide robust and realistic outcomes for agricultural crop mapping in heterogeneous landscapes.

6.Conclusion

This study explored the efficacy of vegetation indices derived from Harmonized Landsat and Sentinel-2 (HLS) data for accurate crop identification in Mahalakshumikheda, Gangapur Tehsil, Chh. Sambhajinagar District, India. This study evaluated four vegetation indices, NDVI, GNDVI, EVI, and SAVI, through supervised classification, with validation against ground truth data obtained from field visits. The analysis demonstrated that NDVI (Overall Accuracy: 90.90%, kappa: 0.87) and GNDVI (Overall Accuracy:

94.84%, kappa: 0.92) were proficient in capturing broad vegetation patterns, but were hindered by issues related to soil reflectance sensitivity and canopy saturation. In contrast, the EVI (Overall Accuracy: 97.97%, kappa: 0.97) and SAVI (Overall Accuracy: 97.35%, kappa: 0.96) exhibited superior classification accuracy. The inclusion of a soil adjustment factor in SAVI and atmospheric correction in EVI significantly improved their ability to reduce background noise and saturation effects, yielding results that were more consistent with the field-verified ground truth data. These findings suggest that EVI and SAVI are more robust and dependable indices for crop identification in diverse agricultural landscapes than NDVI and GNDVI. These indices have the potential to enhance precision agriculture applications by improving crop monitoring, management, and yield estimation, thereby contributing to more sustainable agricultural practices.

Acknowledgements
The Authors would like to acknowledge the SARTHI Fellowship; CSMNRF 2022/2022-23/2341 for financial assistance and Dr. G. Y.Pathrikar college of Computer Science and Information Technology, MGM University, Chhatrapati Sambhajinagar for providing resources for the study

References

1. K, R., V, B.: Optimizing Crop Yield Prediction through Multiple Models: An Ensemble Stacking Approach. Int. J. Data Informatics Intell. Comput. 3, 52–58 (2024).
2. Maimaitijiang, M., Daloye, A.M., Erkbol, H., Sidike, P., Fritschi, F.B., Sagan, V.: Crop Monitoring Using Satellite/UAV Data Fusion and Machine Learning. Remote Sens. 12, 1357 (2020).
3. Gerardo, R., De Lima, I.P.: Applying RGB-Based Vegetation Indices Obtained from the UAS Imagery for Monitoring the Rice Crop at the Field Scale: A Case Study in Portugal. Agriculture. 13, 1916 (2023). .
4. Mutanga, O., Skidmore, A. K.: Narrow band vegetation indices overcome the saturation problem in biomass estimation. Int. J. Remote Sens. 25, 3999–4014 (2004).
5. Da Silva, V.S., Salami, G., Da Silva, M.I.O., Silva, E.A., Monteiro Junior, J.J., Alba, E.: Methodological evaluation of vegetation indexes in land use and land cover (LULC) classification. Geol. Ecol. Landscapes. 4, 159–169 (2019).
6. Ali, A., Barbanti, L., Martelli, R., Lupia, F.: Assessing Multiple Years' Spatial Variability of Crop Yields Using Satellite Vegetation Indices. Remote Sens. 11, 2384 (2019).
7. Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W.: Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Prog. Rep. RSC 1978-1. (1973).
8. Huete, A.R.: A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25, 295–309 (1988).
9. Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G.: Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83, 195–213 (2002).
10. Gitelson, A.A., Kaufman, Y.J., Merzlyak, M.N.: Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sens. Environ. 58, 289–298 (1996).
11. Thanh Noi, P., Kappas, M.: Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery. Sensors. 18, 18 (2017).
12. Pal M. Random forest classifier for remote sensing classification. Int. J. Remote Sens. 26, 217–222 (2005).

13. Chen, Y., Li, X., Huang, C., Hou, J., Zhang, Y.: Mapping Maize Area in Heterogeneous Agricultural Landscape with Multitemporal Sentinel-1 and Sentinel-2 Images Based on Random Forest. Remote Sens. 13, 2988 (2021).
14. Ade, C., Hestir, E.L., Khanna, S., Lay, M., Ustin, S.L.: Genus-Level Mapping of Invasive Floating Aquatic Vegetation Using Sentinel-2 Satellite Remote Sensing. Remote Sens. 14, 3013 (2022).
15. Berra, E.F., Breunig, F.M., Fontana, D.C., Yin, F.: Harmonized {Landsat} and {Sentinel}-2 {Data} with {Google} {Earth} {Engine}. Remote Sens. 16, 2695 (2024).
16. Kobayashi, N., Tani, H., Wang, X., Sonobe, R.: Crop classification using spectral indices derived from Sentinel-2A imagery. J. Inf. Telecommun. 4, 67–90 (2019).
17. Jiménez-Jiménez, S.I., Sánchez-Cohen, I., Sifuentes-Ibarra, E., Marcial-Pablo, M.D.J., Ojeda-Bustamante, W., Inzunza-Ibarra, M.A.: VICAL: Global Calculator to Estimate Vegetation Indices for Agricultural Areas with Landsat and Sentinel-2 Data. Agronomy. 12, 1518 (2022).
18. Rumora, L., Miler, M., Medak, D.: Impact of Various Atmospheric Corrections on Sentinel-2 Land Cover Classification Accuracy Using Machine Learning Classifiers. ISPRS Int. J. Geo-Information. 9, 277 (2020).
19. Sabie, R., Fernald, A., Buenemann, M., Steele, C., Bawazir, A.S.: Calculating Vegetation Index-Based Crop Coefficients for Alfalfa in the Mesilla Valley, New Mexico Using Harmonized Landsat Sentinel-2 (HLS) Data and Eddy Covariance Flux Tower Data. Remote Sens. 16, 2876 (2024).
20. Matsushita, B., Chen, J., Onda, Y., Qiu, G., Yang, W.: Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to Topographic Effects: A Case Study in High-Density Cypress Forest. Sensors (Basel). 7, 2636–2651 (2007).
21. Glenn, D.M., Tabb, A.: Evaluation of Five Methods to Measure Normalized Difference Vegetation Index (NDVI) in Apple and Citrus. Int. J. Fruit Sci. 19, 191–210 (2018).
22. Stanton, C., Brewer, M., Elliott, N., Chu, T., Maeda, M.M., Starek, M.J.: Unmanned aircraft system-derived crop height and normalized difference vegetation index metrics for sorghum yield and aphid stress assessment. J. Appl. Remote Sens. 11, 26035 (2017).
23. Msadek, J., Chouikhi, F., Tarhouni, M., Tlili, A., Ragkos, A.: Assessing the Impacts of Climate Change Scenarios on Soil-Adjusted Vegetation Index in North African Arid Montane Rangeland: Case of Toujane Region. Climate. 13, 59 (2025).
24. Bhosle, S.S., Nagne, A.D.: Remote Sensing Identification and Analysis of Various Crop Management Systems. Ind. Eng. Journa. Vol.XVI &, 24–41 (2023).
25. Shivani S. Bhosle and Shriram P. Kathar, A.D.N.: COMPARING MAXIMUM LIKELIHOOD AND MINIMUM DISTANCE CLASSIFIERS FOR LAND COVER MAPPING USING LISS-III IMAGERY. Int. J. Adv. Soft Comput. Intell. Syst. 4, 1–13 (2025).
26. Mohapatra, N., Shreya, K., Chinmay, A.: Optimization of the {Random} {Forest} {Algorithm}. Presented at the January (2020).
27. Sun, R., Su, H., Mi, C., Jin, N., Chen, S.: The Effect of NDVI Time Series Density Derived from Spatiotemporal Fusion of Multisource Remote Sensing Data on Crop Classification Accuracy. ISPRS Int. J. Geo-Information. 8, 502 (2019).