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Comparative Assessment of Object-Based and Pixel-Based Approaches for Crop Cover Classification

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Introduction/Importance of Study: Accurate crop identification and classification is significant for productive agro-based planning and food availability.

Novelty Statement: This study compares pixel and object-based approaches for machine learning oriented classification methods to develop crop-type maps in Rahim Yar Khan, Pakistan.

Material and Method: Using the Google Earth Engine (GEE) cloud computing platform, pre-processing steps were applied to synthetic aperture radar Sentinel-1 and Sentinel-2 data. By integrating Sentinel-1 (VV, VH), Sentinel-2 satellite bands and different indices were computed from Sentinel-2 imagery, composite images were also produced for subsequent assessment. The main objective was to assess the effectiveness of the approached to classify the major cotton, rice and sugarcane. Time specific images were also use to exploit to seasonality of the crops, for example, composite image of August was prioritized to distinguish cotton, while September composite image was used for rice and sugarcane classification. The study employs two approaches for object-based segmentation: the Simple Non-Iterative Clustering (SNIC) in GEE platform and Object based Image Analysis (OBIA) using Multi-resolution segmentation in E-Cognition software. Random Forest (RF) machine learning algorithm was used over the composite image for both pixel and object based approaches. The study utilized field sample data collected for classification, validation, and accuracy assessment. The ground survey data includes cotton, rice, sugarcane, orchard, and other crops. Comparative analysis was carried out to assess the performance of pixel-based and object-based approaches.

Result and Discussion: RF on pixel-based approach of Sentinel-1 and Sentinel-2 imagery bands with indices composite showed superior results. RF on pixel based approached classification achieved 98% accuracy and kappa 92%, while RF on SNIC in GEE achieved 96% accuracy and kappa 95%, and OBIA in E-Cognition achieved accuracy of 89%.

Concluding Remarks: We also conclude that the tuning of segmentation in both E-Cognition and SNIC algorithm can improve the accuracy of object-based classification.

Keywords: Sentinel-1, Sentinel-2, Google Earth Engine (GEE), Random Forest (RF), Simple Non-Iterative Clustering (SNIC), Vegetation Indices, Crop classification, Object Based Image Analysis (OBIA)

Introduction:

Agriculture is widely accepted as the essential foundation of human existence, possessing significant influence over economy [1]. Monitoring agricultural areas is essential to reduce global issues including rising food demand due to population growth, and climate change [2].Crop classification plays a vital role in estimating crop production, the accurate and timely information on crop types is in high demand [3][4]. To address these challenges, both spatial and temporal data on crop distribution is required. Remote sensing is commonly used to quickly and effectively map crop distribution globally[5]. To create crop maps, multi-spectral and multi-temporal remote sensing data has been in use, demonstrating their capacity to evaluate vegetation status across time[6]. Crop-type classification depend heavily on single-source optical satellite data for many years. The potential of using multi-source satellite imagery has become more widely accepted as sensor technology and processing power increase. In the context of crop type classification, the combination of optical and radar data is especially attractive since it enables the explanation of the advantages of both sensor types[7]. Sentinel-2 data offered a unique combination of high spectral and spatial resolution with a short revisit duration (5 days). Sentinel-1 (SAR) data provides the ability to fulfill the strict data requirements required for effective crop monitoring. SAR data frequency and polarization offer a better representation of condition of topography, soil moisture, roughness, and canopy structure even when there is a cloud cover [8]. However, optical data makes use of electromagnetic radiation in the visible, near-infrared, and shortwave infrared range. This allows scientists to obtain crucial data regarding the moisture content, leaf colors, and general health of the vegetation [9]. To improve data availability and accuracy, multiple sensors with various spatial and temporal resolutions can be combined [10]. A range of spectral bands from multi-spectral time-series data can be used for the classification. Vegetation indices such as NDVI,NDWI,NDMI,BSI generated from multi-spectral images have also been used along with time-series data to enhance the information and improve the accuracy of crop types [11].

Applying a pixel-based approach to integrated Sentinel-1 and Sentinel-2 data suffers from the salt-and-pepper phenomenon of the classification results, which reduces the integrity of the crop field [12][13]. The technology of image segmentation partitions an image into numerous segments. Many studies indicate that image segmentation methods like Simple Non-Iterative Clustering (SNIC) offers a promising approach for analyzing high-resolution remote sensing images outperforming traditional pixel-based classification techniques. SNIC is the most advanced super pixel segmentation algorithm. It provides the benefits of faster speed and less consumption of memory. It has plenty of potential for crop mapping[14][15].Machine learning approach, Random Forest (RF), can be employed for better identification of different types of crop [16]. RF is one of the mostly used classifiers for classification, because of its great accuracy and efficiency[17] since it typically outperforms other classifiers[18]. Although SVM is a good classifier, it looks a little more complicated because it needs different input parameters and kernels to be chosen and adjusted[19]. The majority of these classification techniques depend on good training data and appropriate feature combinations, having an immediate impact on the uniformity of the classification outcomes [20].

Comparative analyses have been conducted in recent studies to evaluate Pixel-Based and Object-Based Algorithms, utilizing integrated Sentinel-1, Sentinel-2, and NDVI Data on Google Earth Engine for crop identification. GEE serves as a cloud computing platform, facilitating the automation of crop classification techniques. The objective of this study is to conduct a comparative analysis between pixel-based and object-based approaches, leveraging machine learning algorithms such as Random Forest (RF) on the integration of time series data from Sentinel-1, Sentinel-2, and NDVI. The main objective was to evaluate the efficiency of the object-based segmentation approach (in GEE and E-Cognition) and Pixel-based approach to see which method is best for classifying cotton, rice and sugarcane.

Objectives:

Specifically, the study seeks to achieve three main objectives;

- To demonstrate how integrating Sentinel-1 and Sentinel-2 data can enhance classification accuracy.
- To evaluate the accuracy of crop types by using machine learning algorithm such as RF.
- To compare the accuracy of crops using pixel-based and object-based with the application of the Simple Non-Iterative Clustering (SNIC) algorithm approaches using Google Earth Engine (GEE).

Material and Methods:

Study Area:

Rahim Yar Khan is a famous city in the south of Punjab (Pakistan), covers an area of 11,880 Square Kilometers and makes 5.79% area of Punjab and 1.4% area of Pakistan. It is situated on the bank of River Indus, divided into four Tehsils, lies between 27° 56/ to 28° 52/ N latitudes and 70° 00/ to 70° 32. The area's climate is categorized as arid subtropical continental, characterized by a mean annual rainfall of 97.2 mm, predominantly occurring during the late summer monsoon season. Summer temperatures average 33.6°C with a daily maximum of 40.3°C, while winter temperatures average 14.5°C with a daily minimum of 5.7°C. Map of the study area and its location in Punjab, Pakistan is shown in Figure 1.

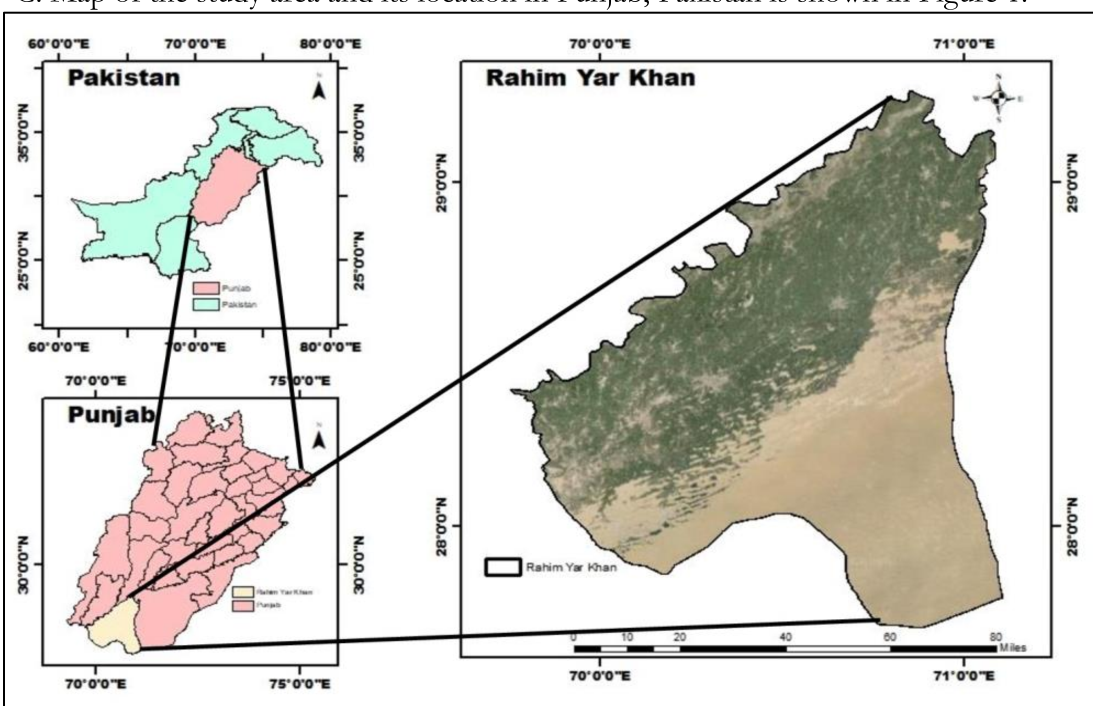

Figure 1: Study Area Map of Rahim Yar Khan in Punjab, Pakistan.

Analysis Framework:

Overall methodology adopted in this study is shown in Figure 2.

Field Survey Data:

Field information or Ground Truth Data were collected using GPS and visual observation. The ground truth was collected during the month of August and September in 2019 in Rahim Yar Khan. Major crops were found as Sugarcane, Rice & Cotton, and other land-use classes were Orchard, Built-up, Barren-Land, Water-bodies and Other-crops. Field sample points were collected in Rahim Yar Khan with the help of GPS and pictures in Kharif season in the months of August and September and 70 percent of the points were used for the purpose of classification and 30 sample points were used for validation purposes. Latitude longitude of each sample was also recorded. Distribution of all the field sample points is shown in Figure 3.

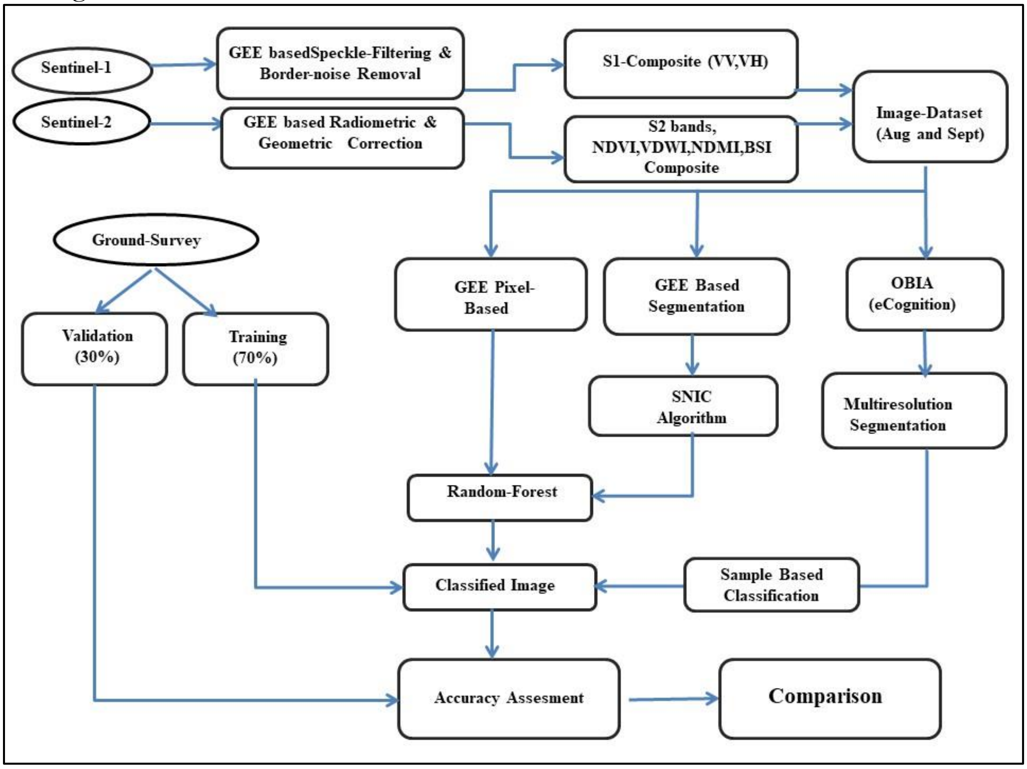

Figure 2: Methodological Flow Chart of the Study

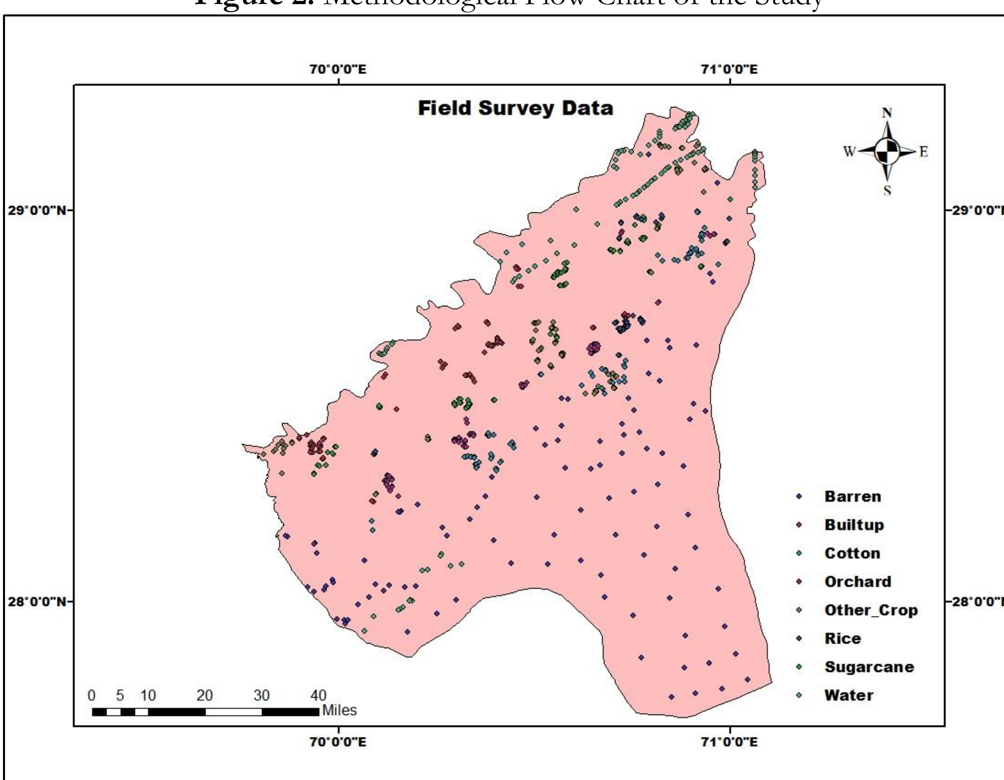

Figure 3: Field Sample Points of Cotton, Rice and Sugar Cane taken from all over the Study Area

Image Datasets and Pre-Processing:

Sentinel-1 and Sentinel-2 satellite data emphasize the importance of crop classification, especially in areas having rapid changes [21]. In this study, SAR images and optical images from the Sentinel-1 and Sentinel-2 sensors were used respectively. These two sensors were chosen mainly because they were readily available and free of cost. Temporal, spectral, and spatial resolutions. Sentinel-1 and Sentinel-2 data were both acquired using the Google Earth Engine (GEE) platform. Sentinel-1, operating in C-band SAR, offers multiple imaging modes with resolutions from 10 to 60 meters. In google earth engine S1_GRD dataset of Sentinel 1 was used. It emits microwave signals to capture reflected energy, generating SAR images based on signal delays. These images provide valuable data on Earth's surface changes, usable in all weather conditions. Overall, Sentinel-1 SAR is crucial for monitoring Earth's dynamics in environmental, disaster, and scientific applications [22].

Sentinel-2 is the second datasets that was used in this study. Sentinel-2A has 13 bands with a wavelength range of 443 to 2190 nm and high-resolution optical equipment with spatial resolutions of 10 m, 20 m, and 60 m as shown in table 1 and sentinel-2 bands used in this study are shown in table 2. Furthermore, Sentinel-2's bands B08 and B04 were used to create the normalized difference vegetation index (NDVI) as shown in eq1, bands 8A and B11 were used to create normalized difference water index NDWI as shown in eq 2, bands B08 and B11 were used to create normalized difference moisture index NDMI as shown in eq 3, bands B11 and B04 were used to create bare soil index (BSI) as shown in eq 4, which was then coupled with Sentinel-2 bands to enhance the classification method[11].

Table 1: General Specification of Sentinel-1 and Sentinel-2.

Description	Sentinel-1 (SAR)	Sentinel-2
Resolution	10 m	10,20 ,60m
Band Type	C-Band	Coastal Aerosol, Blue, Green, Red, NIR and SWIR
Revisit Time	6 days	5 Days
Orbit Height	693km	786km
Orbit Inclination	98.18^0	98.63^0
Spectral Range	3.75-7.5cm	0.44-2.19µm

Table 2: Sentinel-2 bands utilized in this study.

Band Number	Sentinel-2 Bands	Central Wavelength(nm)	Spatial Resolution(m)
Band 2	Blue	490	10
Band 3	Green	560	10
Band 4	Red	665	10
Band 5	Red Edge	705	20
Band 6	Red Edge	740	20
Band 7	Red Edge	783	20
Band 8	NIR	842	10
Band 8A	Red Edge	865	20
Band 11	SWIR	1610	20
Band 12	SWIR	2190	20

$$\mathrm{NDVI} = \frac{\mathrm{B08-B04}}{\mathrm{B08+B04}} \text{ --------------------- } (1)$$

$$\mathrm{NDWI} = \frac{\mathrm{B8A-B11}}{\mathrm{B8A+B11}} \text{ ----------------- } (2)$$

$$\mathrm{NDMI} = \frac{\mathrm{B08-B11}}{\mathrm{B08+B11}} \text{ ------------------ } (3)$$

$$\mathrm{BSI} = \frac{\mathrm{B11-B04}}{\mathrm{B11+B04}} \text{ ------------------------ } (4)$$

The initial step involves acquiring and pre-processing satellite imagery datasets from Sentinel-1 and Sentinel-2 platforms in Google Earth Engine (GEE). The filtering criteria for Sentinel-1 data involved selecting images based on crop growth periods (e.g., August 2019 for cotton, September 2019 for rice and sugarcane), using VV and VH polarizations, Interferometric Wide (IW) mode, and both ascending and descending orbits to ensure consistent imaging. Following retrieval, each Sentinel-1 image undergoes pre-processing to enhance data quality, including border noise removal to improving data quality by masking areas with inaccurate or missing data, and speckle filtering using a focal median filter to mitigate noise effects and reduce speckle, which improves image quality.

Following the processing of Sentinel-1 data, Sentinel-2 data was filtered based on crop phenology periods and selecting images with less than 20% cloud cover. Pre-processing involved cloud masking using the Quality Assessment (QA) band, geometric and radiometric correction. Radiometric correction adjusts satellite imagery to accurately represent surface reflectance, correcting for sensor and atmospheric influences. Geometric correction aligns images to remove spatial distortions caused by Earth's curvature and sensor orientation, ensuring precise spatial analysis and map overlay capabilities. Pre-processing also involves computation of indices such as NDVI, NDWI, NDMI, and BSI, clipping images to the study area, and averaging band values over the date range to enhance data consistency.

After pre-processing both datasets, the reduced mean images were stacked to create a composite image, integrating data from Sentinel-1 (VV and VH bands), Sentinel-2 (selected spectral bands), and indices. This process was applied to the month of August 2019 for cotton and September 2019 for rice and sugarcane as shown in Table 3.

Table 3: Composite Image Dates for Classification of Crop-Type.

Crop-Type	Start-Date	End-Date
Cotton	01-08-2019	30-08-2019
Rice & Sugarcane	01-09-2019	30-09-2019

This unified representation enhances the accuracy of crop classification analyses. Finally, the resulting stacked image is visually depicted on a map for ease of interpretation and analysis.

Google Earth Engine Based Classification:

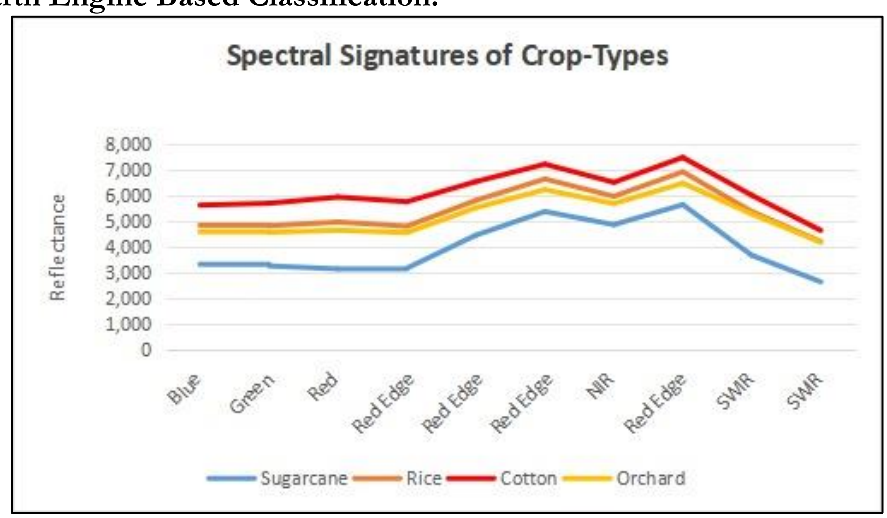

Figure 4: Spectral-Signatures of Different Crop Classes

Sentinel-1 SAR and Sentinel-2 image data were acquired using Google-Earth-Engine and then performed per-processing steps on both sentinel-1 and sentinel-2 data. Speckle-filtering and border-noise removal were applied to sentinel-1 data. Radiometric and geometric corrections were applied to sentinel-2 data. NDVI indices were derived from sentinel-2 data. After per-processing steps, reducers were applied to sentinel-1, sentinel-2 and indices. After that composite images were created using sentinel-1, sentinel-2 and NDVI data and clipped the study-area. Then pixel-based and object-based classification were performed using Random Forest algorithm to the integrated data. Simple non-iterative algorithm was used for object-based classification in GEE. E-Cognition was used for multi-resolution segmentation and OBIA. Accuracy assessment of all three methods was performed using confusion matrix and calculate overall accuracy, producer accuracy and Kappa. Classification was performed after thoroughly assessing the spectral classes of different crop types using sentinel different bands. Sentinel-2 Red edge band specially helps in identifying different crop types. The spectral signature for all the crop fields in sentinel-2 imagery are shown in Figure 4.

SNIC Image Segmentation:

The traditional pixel-based classification technique could result in "salt and pepper" noise. By using a pixel's neighboring information to segment the image into distinct regions or objects based on specific parameters, the object-based approach reduces this issue. The SNIC image segmentation technique in GEE was utilized in this study to segment images. [23]. First, initialization is done for the centroid pixels on the image's regular grid. Next, the dependence of each pixel with respect to the centroid is determined by measuring the distance between pixels in the five-dimensional space of color and spatial coordinates. Ultimately, the distance creates efficient, compact, and almost uniform polygons by integrating the normalized spatial and color distances[24].The SNIC algorithm's primary parameters are "image," "size," "compactness," "connectivity," "neighborhood size," and "seeds."

The "size" parameter determines the spatial extent of super-pixels or segments within the image. Larger sizes result in fewer but larger segments, while smaller sizes yield more but smaller segments. The "compactness" regulates the shape of the segments, influencing how closely they adhere to a regular shape such as a square. A higher compactness value leads to more regular, compact segments, while lower values allow for more irregular shapes. The "connectivity" parameter defines how neighboring pixels influence each other during segmentation. A value of 4 implies 4-connectivity, where pixels are connected horizontally and vertically, while 8-connectivity considers diagonal connections as well. The choice between 4 and 8 connectivity depends on the spatial arrangement of features in the imagery. The "seeds" parameter specifies the initial seed points from which the segmentation process begins. It is particularly relevant when the shape of objects varies significantly within the image.

The image that takes part in segmentation is referred to as a "image" among them. In this study, integrated Sentinel-1, Sentinel-2 and NDVI time series images with different time intervals composites from 01-08-2019 to 30-08-2019 for cotton and 01-09-2019 to 30-09-2019 for rice and sugarcane were segmented. According to the requirements of the study area, segmentation sizes of 5, 10, 15, and 20 were examined, with size 15 producing the best classification accuracy. The ideal neighborhood size was also determined to be 128. The majority of the parcels in the research region are rectangular in shape, the "compactness" requirement was set to 0, and "connectivity" was assessed at both 4 and 8. Since the research area portions were essentially rectangles, no particular "seeds" were established.

Random Forest:

A powerful non-parametric machine learning classifier, the Random Forest (RF) algorithm was created by Breiman (2002) and is widely used in crop classification RF leverages bootstrap aggregation (bagging) to create numerous decision trees, which are then combined by a majority voting technique to yield more accurate predictions. Its non-parametric characteristics, minimal generalization mistakes, and noise robustness validate its applicability to crop classification problems. Furthermore, RF's popularity is largely due to its capacity to handle high-dimensional remote sensing data and identify important variables[25].

The GEE platform has the RF classification algorithm installed. The RF classifier was trained using the training data, and the classification error was assessed using the verification data. Two parameters need to be set when employing the RF models in GEE, the minimum size of a terminal (min leaf), and the number of decision trees to generate per class. The crop classification was performed with various settings for min leaf and number of trees. The overall classification accuracy served as the basis for selecting the ideal parameters[26]. The number of features was set to the square root of the entire number of features in this paper, and the number of trees was set to 100.

OBIA Multi-Resolution Segmentation:

OBIA technology divides a huge image into smaller image objects with similar properties through a segmentation process. Consequently, compared to pixel-based techniques, it can employ more properties like spectral, shape, and texture. Object-oriented image processing requires image segmentation as a crucial step, and the accuracy of object-oriented algorithms' extraction is greatly impacted by the segmentation work[27].In this study, we applied multi-resolution segmentation in E-Cognition using various scales (30, 70, 90, 120) and different levels of compactness (0.5) and shape (0.3, 0.5, 0.8). This advanced segmentation technique was used to improve the accuracy of object-based crop classification. By experimenting with these parameters, we were able to refine the segmentation process, which led to more precise delineation of crop fields. This method significantly enhanced the accuracy of object-based classification, highlighting the benefits of using sophisticated segmentation tools in combination with Random Forest for optimal crop mapping outcomes.

Confusion Matrix and Accuracy Assessment:

In this study, cross-validation was used to evaluate the model's performance. This involved dividing the datasets into training and validation sets, with a portion of the training data reserved for testing the model's parameters. The model's performance was then evaluated on validation data set to determine how well it generalized. Specifically, the datasets were split into a 70% training set and a 30% validation set. Following classification, the accuracy of the model was analyzed using a confusion matrix and assessed using the kappa coefficient for consistency. The confusion matrix is an organized list of reference and map data calculated for the purpose of computation. By image comparison, we can qualitatively evaluate the classification results, while quantitative evaluation can be achieved with statistical techniques like the Kappa index and confusion matrix [22]. Overall accuracy (OA) is the proportion of correctly classified sampled pixels, whereas the Kappa coefficient measures the accuracy of classification by accounting for the chance agreement between the prediction and reference data. PA represents the proportion of a given reference class that is correctly classified, whereas UA represents the possibility of correctly classifying a specific labeled sample. Producer accuracy, user accuracy, and overall accuracy were subsequently calculated to provide further insights into the model's performance.

Table 4: Accuracy Assessment of Land-Cover Classes by using field data validation points.

Land-Cover	OA	PA	UA	Kappa	F-Score
PB-Cotton	0.9809	0.6187	0.6113	0.9207	0.6150
OB-Cotton	0.9667	0.9671	0.9684	0.9587	0.9677
OBIA-Cotton	0.8508	0.8245	0.8254	0.8023	0.8167
PB-R&S	0.9696	0.7493	0.7590	0.9083	0.7541
OB-R&S	0.9411	0.9291	0.9531	0.9241	0.9409
OBIA-R&S	0.8911	0.8543	0.8623	0.8743	0.8832

Result and Discussion:

The classification accuracy by integrating sentine-1, sentinel-2 and NDVI data by using Random Forest was evaluated for both pixels based and object-based approaches shows in the Table 4. Pixel based approach for cotton and rice achieved overall accuracy and kappa of 0.9809, 0.9696 and 0.9207, 0.9083. Object based approach for cotton and rice achieved overall accuracy and kappa of 0.9667, 0.9411 and 0.9587, 0.9241. OBIA approach for cotton and rice achieved overall accuracy and kappa of 0.0.8508, 0.8543 and 0.802, 0.8743. The object-based classification through SNIC approach produce better results as compared to pixel-based classification in Google earth engine and OBIA in E-Cognition developer. Although all the approaches produce best results because of integration of SAR and optical data. Final output maps for all three approaches are shown in Figure 5 and Figure 6.

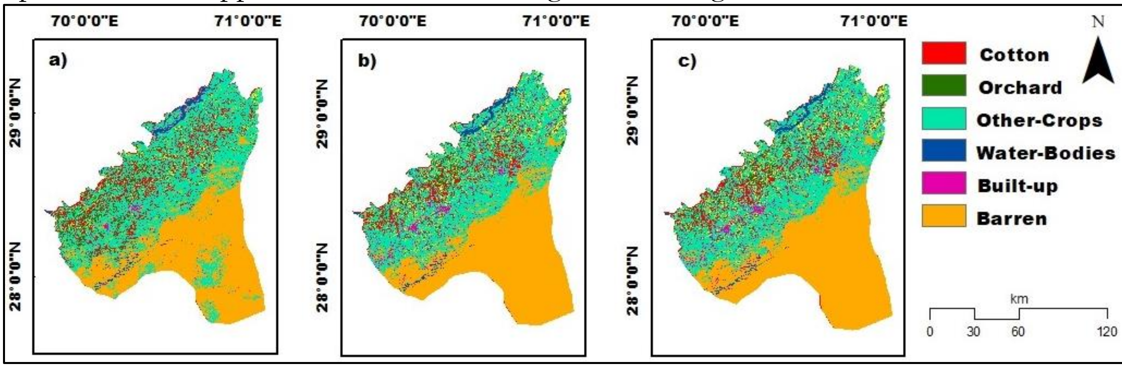

Figure 5: Classification maps for the image acquired in August (kharif crops focusing on Cotton) using the three different approaches; a) pixel-based using Random Forest classifier Google Earth Engine, b) object-based using Simple non iterative clustering SNIC and Random Forest classifier in Google Earth Engine, c) object-based using Multi-resolution segmentation and Nearest Neighbor classifier in e-Cognition

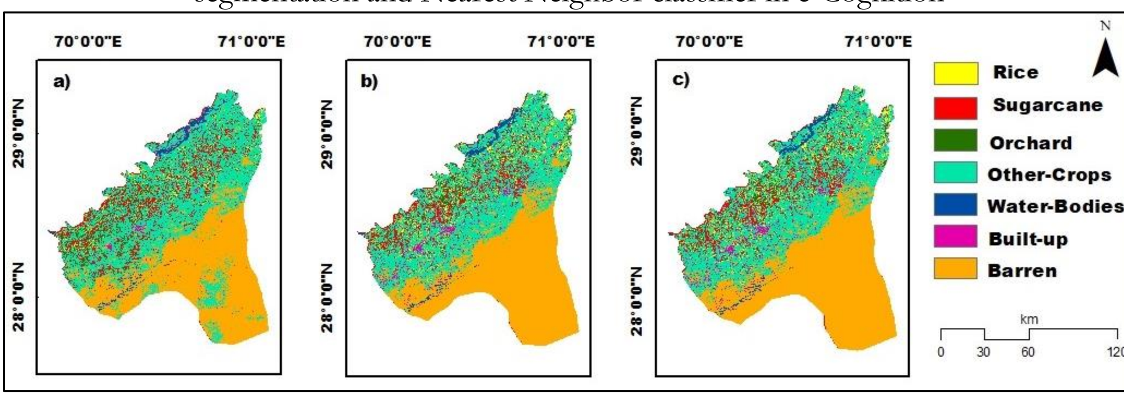

Figure 6: Classification maps for the image acquired in September (kharif crops focusing on Rice and Sugarcane) using the three different approaches; a) pixel-based using Random Forest classifier Google Earth Engine, b) object-based using Simple Non-Iterative Clustering SNIC and Random Forest classifier in Google Earth Engine, c) object-based using Multi-resolution segmentation and Nearest Neighbor classifier in e-Cognition

This study delved into the comparative efficiency of pixel-based and object-based approaches in crop classification of cotton and rice, leveraging machine learning algorithms like Random Forest (RF) on integrated Sentinel-1, Sentinel-2, and indices such as NDVI, NDWI, NDMI and BSI data within Google Earth Engine (GEE). The results show significant variation in performance across the pixel and object-based approaches, focus on the strengths and limitations of each approach. The pixel-based approach attained high overall accuracy for both cotton (0.9809) and rice (0.9696). Although, the producer's and user's accuracy (PA, UA) were remarkably lower for cotton (0.6187 and 0.6113) respectively, propose that while the pixel-based method was effective in general classification, it struggled with accurately identifying cotton pixels. This variation points to possible issues with mis-classification and the challenges of employing a pixel-based method to capture the variability of agricultural landscapes.

The object-based approach provides high accuracies, mainly for cotton, with an OA of 0.9667 and Kappa of 0.9587. Both PA and UA were around 0.97, showing a robust classification performance. For rice, the object-based approach also performed well, with an OA of 0.9411 and a Kappa of 0.9241, along with high PA and UA values (0.9291 and 0,9531) respectively. These results show the efficiency of object-based approach in capturing the spatial characteristics of the landscape, providing more accurate classification by considering groups of pixels (objects) rather than individual pixels. The segmentation process probably helped in reducing noise and improving the defining of crop boundaries, which is important in heterogeneous agricultural areas.

The object-based approach in GEE, while producing good results, did not match the performance of the OBIA. For cotton, SNIC attained an OA of 0.9667 and a Kappa of 0.9587, with PA and UA around 0.9671 and 0.9684. For rice, the SNIC results were lower as compared to cotton with an OA of 0.9411 and a Kappa of 0.9241, and PA and UA values of 0.9291 and 0.9531, respectively. Although OBIA is effective, its relatively lower performance compared to the object-based approach suggests that while segmentation improves classification, the specific methodology and tools used can significantly impact results. Object-based approach achieved high overall accuracy and kappa 0.9677 and 0.9589 as compared to OBIA overall accuracy and kappa 0.8911 and 0.8743, accurately classifying cotton and rice by leveraging spatial characteristics. Our results also indicate that pixel-based approach with different bands and indices produce better results than segmentation but it is also suggested to fine-tune the data. We recommend using hit and trial method while selecting the segment size and its compactness it significantly alters the results. While overall control in pixel base approach is better but segmentation results mainly depend on the output of segments created and then the accuracy of the samples on which classification is based.

Discussion:

The outcome of this research aligns with recent research studies that emphasize the benefits of combining advanced classification methods with multi-source satellite data for enhanced agricultural monitoring. Compared to pixel-based techniques, the object-based approach performed better, especially when utilizing Google Earth Engine's (GEE) SNIC algorithm. This finding aligns with recent research, including those conducted by [28][29], who discovered that by taking groups of pixels (objects) into consideration rather than individual pixels, object-based image analysis (OBIA) significantly reduces noise and improves classification accuracy.

The object-based technique for rice and cotton yielded high kappa values and overall accuracy, indicating its robustness in capturing the spatial properties of crops. This is consistent with the results of[30], They found that in diverse agricultural environments, object-based approaches greatly enhance the identification of crop boundaries. The pure object-based strategy used in GEE outperformed the OBIA approach, even though it was still effective. The difference demonstrates how the processing platform and segmentation method affect categorization results. Recent research by [31] highlights the significance of choosing the appropriate platform and segmentation parameters to get the best results. They showed that although OBIA has advantages, the accuracy with which segments are created and the quality of the training samples are critical factors in its effectiveness.

The study also found a number of limitations, including problems with classification errors and poor data quality, which are frequent problems in remote sensing applications. Misclassification was probably caused by the presence of mixed pixels and the heterogeneity in crop growth phases. This result is consistent with the findings of [26], who observed similar challenges in classifying agricultural landscapes. Moreover, the combination of optical data (Sentinel-2) and SAR (Sentinel-1) proved helpful, as evidenced by the recent study of [29]. They discovered that because SAR and optical data are complementary, combining them improves the robustness and accuracy of land cover classification. In order to further enhance classification accuracy, future study could overcome these limits by investigating advanced machine learning methods and combining new data sources, such as hyperspectral photography or drone-based observations. Utilizing deep learning methods as recommended by current research [32] may also provide significant improvements in managing complex agricultural landscapes. Overall, this study demonstrates how to improve crop classification accuracy by using advanced classification algorithms and multi-source satellite data, offering valuable insights for agricultural management and policy-making.

Conclusion:

Overall, integrating sentinel-1, sentinel-2 and composite images based on indices NDVI, NDWI, NDMI, and BSI proved beneficial across both approaches. The object-based approach in GEE, utilizing the SNIC algorithm, outperformed both the pixel-based and OBIA approach utilizing the multi-resolution segmentation in e-Cognition Developer. This dominance is likely due to the better handling of spatial information and the reduction of classification noise. While the pixel-based approach provided high overall accuracy, its lower PA and UA values emphasize its limitations in heterogeneous landscapes. The OBIA method, although useful, did not achieve the same level of accuracy as the object-based method in GEE, highlighting the importance of advanced segmentation techniques for improving classification accuracy.

These findings emphasize the need for careful selection of classification methods based on the specific requirements and characteristics of the study area. Future research should continue to explore and refine object-based methods, particularly in the context of integrating multi-source remote sensing data, to further enhance classification accuracy and reliability in complex agricultural landscapes.

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Author's Contribution:

All the authors had different contributions to this research work and are mentioned here accordingly. Conceptualization (A.S, S.M.I, M.U), formal analysis (A.S., S.M.I, S.A), methodology (S.M.I, A.S, S.A), writing—original draft preparation (S.M.I, A.S, S.A), writing—review and editing (S.M.I, A.S, S.A,S.U.K,M.U), visualization (S.M.I, A.S, S.A,S.U.K,M.U) All authors have read and agreed to the published version of the manuscript.

Conflict of Interest: The authors declare that there is no conflict of interest regarding the publication of this manuscript in IJIST.

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