

Faculté des bioingénieurs

Crop Type Mapping Using Sentinel-1 and Sentinel-2 Data in the Smallholder Cropping System of Cotton Belt in Mali

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List of Acronyms

BOA	Bottom of Atmosphere
CAP	Common Agricultural Policy
CART	Classification and Regression Trees
CNN	Convolution Neural Network
DT	Decision Tree
EABC	Experienced Artificial Bee colony
ESA	European Space Agency
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GEE	Google Earth Engine
GLCM	Gray Level Co-occurrence Matrix
GRRF	Guided Regularized Random Forest
K-NN	K-Nearest Neighbor
LISS III	Linear Imaging Self-Scanning Sensor III
LISS IV	Linear Imaging Self-Scanning Sensor IV
LUCAS	Land Use and Cover Area Frame Survey
MGRS	Military Grid Reference System
MLP	Multi-Layer Perceptron
MSI	Multispectral Imager
MSI	Multi-Spectral Instrument
MXL	Maximum Likelihood
NDMI	Normalized Difference Moisture Index
NDRE	Normalized Difference Red Edge Index

NDVI	Normalized Difference Vegetation
NN	Neural Networks
OA	Overall Accuracy (OA)
PA	Producer's Accuracy (PA)
RF	Random Forest
RNN	Recurrent Neural Network
S1	Sentinel-1
S2	Sentinel-2
SAR	Synthetic Aperture Radar
SCL	Scene Classification Layer
SMT	Spectral Matching Technique
SRTM	Shuttle Radar Topography Mission
SSA	Sub-Saharan Africa
SVM	Support Vector Machine
SWIR	Shortwave Infrared
UA	User's Accuracy (UA)

1. Introduction

Agriculture is the backbone of food industry, providing essential items indispensable for people's lives (Vyas et al., 2025). Therefore, each part of the world is required to produce intensive agricultural crops in ample quantities and on time to meet the food demand of 9.3 billion people by the year 2050 (Felegari et al., 2021; United Nations, 2011). Nevertheless, in Sub-Saharan Africa (SSA), smallholder farming systems relentlessly experience high soil fertility challenges, climate risk as well as demographic pressure. Globally, smallholder farmers contribute more than half of the world's annual cereal output. In SSA, these farming systems are particularly vital, accounting for over 80% of the cultivated land and strengthening the livelihoods of millions of rural households (Lambert et al., 2017).

Agriculture is the main driver of the Malian economy. In agricultural production, approximately 80% of the labor force is employed and contributing more than 35 % of country's GDP where cotton production alone accounts for 15% (FAO, 2017). Dioila circle is the prime cereal production area in Mali and produces 33% of the cotton in the Fana region. The major crops cultivated in Dioila are cotton, sorghum and maize and dominated by smallholder rainfed farming pattern (Baquedano et al., 2010).

In smallholder farming system, crop production significantly fluctuates in space and time resulting in prolonged food insecurity (Lambert et al., 2018). More than 50% of the rural population in developing countries is hosted by smallholder rainfed agricultural systems but still produce 90% of the food (Morton, 2007). Although there is pervading difference in smallholder farming systems between countries and agro-ecological zones, they frequently have similar features for instance lack of resource availability, insufficient labor supply, inefficient labor output, and economic decision making to manage risk (Cousins, 2010; Dixon et al., 2001). Therefore, some interventions of agricultural development, for instance livestock and fertilizer supply, market access, microcredit, diversification and so on frequently assumed that they worked in the same way to a large proportion of farmers in a certain landscape. But these general universal approaches do not meet specific needs for an area like complex smallholder farming system in semi-arid SSA. Therefore, efficient crop type classification mapping is crucial for crop health monitoring, yield estimation, acreage, agricultural productivity, food security and to reduce farmer vulnerability (Singh et al., 2019; Lambert et al., 2017).

Remote sensing has become ubiquitous as an effective method to map crop types in smallholder cropping patterns due to its spatial, spectral and temporal resolutions of satellite images (Lambert et al., 2017). To map crop types, most widely used method in remote sensing is application of optical images. Sentinel-2 has been used several research areas for product classification due to its distinct as well as sophisticated specifications (Tricht et al., 2018). Nevertheless, cloud and cloud shadows are two key obstacles of using optical sensors since sunlight rays cannot penetrate the cloud. Consequently, there remain temporal gaps in optical images and lead to significant difficulty in crop monitoring and classification as well. The method of integrating radar sensors brings complete solution to cloud and shadows. In radar satellites, sensors transmit energy and assess its reflection, allowing them to benefit from

different parts of the electromagnetic spectrum. After the inauguration of Sentinel-1 mission, SAR images became freely available. SAR images assess plant structure as well as moisture content while optical images are useful to identify vegetation biophysical processes, the integration of optical and SAR images supplies a source of complementary data (Felegari et al., 2021).

2. Literature Review

In the recent era, cultivated land use has been going through high expansion in different parts of the world (Lambin and Meyfroidt, 2011). The reason behind this is the population blast, leading to growing food demand. Hence, to meet the demand, crop classification techniques in monitoring crop health, acreage and yield estimation is one of the pressing needs (Singh et al., 2019)

Crop type and land cover mapping have been advancing tremendously due to satellite imagery and available data storage over the last few decades. Crop inventory maps have been developed in many countries based on such multispectral, free and consistent satellite data (Kpienbaareh et al., 2021).

2.1 Smallholder cropping system and remote sensing

Sub-Saharan Africa (SSA) is prevalent with smallholder farming systems which cover large part of all cultivated areas (Lambert et al., 2017). In SSA, smallholder farming systems experience high inter-annual climatic risk, variability in precipitation patterns from year to year, soil fertility challenges as well as demographic pressure (Lambert et al., 2017). Moreover, due to small parcel size, strong within-field heterogeneity, irregular field boundaries, smallholder landscapes remain challenging (Akinyemi et al., 2023; Lambert et al., 2018), leading to crop production fluctuation strongly from local to landscape scales and end up with chronic food insecurity. Fortunately, remote sensing has brought strong prowess in crop performance monitoring at levels of granularity which is highly compatible with smallholder farming. Jin et al. (2017) used the high-resolution satellite imagery to map yields of smallholder farming by using multiple regression techniques while the major obstacles for their study were cloudy satellite images. Random Forest (RF) classification algorithm was used to make crop type as well as land cover mapping in complex heterogeneous agricultural landscapes with the integration of multitemporal dual polarized Sentinel-1 Synthetic Aperture Radar (SAR) data and multispectral Sentinel-2 and PlanetScope optical data (Kpienbaareh et al., 2021). They revealed that both individual Sentinel-1 and Sentinel-2 images were unable to generate high-accuracy land cover and crop type maps. Due to data constraints, this study did not adequately detect the individual crops on such intercropped fields. Lambert et al. (2017) obtained overall accuracy of 85% for the crop type map based on Sentinel-2 satellite and RF classifier smallholder farming systems in Mali. Rao et al. (2021) examined the Sentinel-1, Sentinel-2, and Planet Scope imagery to identify four major crop types (maize, mustard, tobacco, and wheat) in eastern part of India applying SVM and found that Sentinel-1, Sentinel-2, and PlanetScope imagery can be applied to generate accurate map crop type in heterogeneous small cultivated area. The limitations of this research work were that their study area was so small, and the availability of optical data. In China, Sun et al. (2020) developed a technique combining time series Sentinel-1 and Sentinel-2 features for the typical oasis crop distribution mapping in heterogeneous areas of smallholder farming. The result of integration of Sentinel-1 and Sentinel-2 was excellent. This study was limited to a small area.

2.2 Optical crop type classification

Pre harvest crop type classification using Sentinel-2 time series and machine learning classifiers, such as Decision Tree (DT), K-Nearest Neighbor (k-NN), Support Vector SVM, RF and Maximum Likelihood (ML) was done by Maponya et al. (2020). The prime findings of this study were that the crops can be effectively classified in this study with images that are collected from the beginning of June up to September and the performance of RF and SVM was best in all experiments. The major limiting factor of this research was acquiring suitable training and test datasets. Correspondingly, with the integration of Landsat and Sentinel-2 data, most prominent crop types were discriminated by using harmonized NDVI (Normalized Difference Vegetation Index) time-series in small scale cropping systems in eastern Uganda while this research work was bounded only in small area (Liepa et al., 2024). Lambert et al. (2018) estimated specific crop production based on high-resolution Sentinel-2 time series as well as ground data in the commune of Koningue, Mali. This study confirmed that crop type can be mapped by using Sentinel-2 data with strong overall accuracy. However, clear resolution of intra-landscape variability in production levels was not precisely resolved in this research work. Crop types and cropping systems mapping with Sentinel-2 imagery was done by employing RF technique in Nigeria (Ibrahim et al., 2021). This study expanded existing crop type mapping procedures to map maize and potato, and intercropping mixtures with both crops while the accuracy validation of the delineated field boundaries using cadaster information was not performed. In India, Jayanth et al. (2022) used Experienced Artificial Bee colony (EABC) algorithm with remote sensing and GIS-Based approach for crop classification. Significant strong accuracy was in classification due to use Linear Imaging Self – Scanning Sensor III (LISS III), LISS IV (Linear Imaging Self – Scanning Sensor IV), Landsat 7 and Landsat 8 and Sentinel 2A Images in this research. Nonetheless, limited access of remote sensing data as well as temporal observation period were major obstacles for this study. By employing Sentinel-2 data and machine learning approach, Panjala et al. (2021) classified crop types in Jhansi, India. They explored that ground data plays a key role in crop type classification and the main lacking in their study was that very high cloud cover for satellite data during kharif season. Mapping agricultural land by the application of deep learning and Sentinel-2 satellite data was done by Singh et al. (2022). This work concluded that the performance of U-Net-based deep learning was better than RF based machine learning techniques for vegetation class categories. The major challenges involved in this study were the full customization lacking different technique parameters, inability to distinguish the entire input raster when minimum values of factors were identified and limitation of accuracy in object-level detection. Neetu and Ray (2019) explored machine learning classification techniques for distinguishing crop type by Sentinel-2 data while they found out that overall accuracies ranged from 73% to 93%, in which RF performed better as compared to Maximum Likelihood (MXL), SVM and Classification and Regression Trees (CART). Moreover, all the classifiers were able to discriminate different types of crops and achieved more than 68% accuracy for all crop types. This study did not consider the multiple dates of satellite data. Similarly, pilot study regarding crop type mapping using Sentinel-2 imagery in India was conducted by Duraisamy (2019). Their result showed that the crop classification accuracy varies from 57% to 86% and the overall classification accuracy was 70% with KAPPA index of 61% attained applying RF technique. The main limitation for this

study was misclassification of sugarcane due to smaller field size. Hudait and Patel (2022) performed crop type mapping as well as acreage estimation in smallholding plots based on Sentinel-2, RF and K - Nearest Neighbor (K-NN). They obtained highest accuracy for different crop land types while RF technique demonstrated best performance. This study was limited by up-to-date data availability. Crop type was identified with spatial mapping in India by using Sentinel-2 data and a Spectral Matching Technique (SMT) method. This research showed that the temporal signatures of mustard, chickpea, and wheat are easy to distinguish, achieving 84% of overall accuracy, where mustard and wheat attained 94% and 86% accuracy, respectively. The major limitation of this study was that the data availability due to persistent cloud cover during cropping season (Gumma et al., 2020). On the other hand, Koppaka and Moh (2020) used Recurrent Neural Network (RNN), Convolution Neural Network (CNN), SVM and RF , and Sentinel-2 satellite temporal remote sensing image data for crop classification while they found out that SVM has the best F1 score as well as the estimated areas of major crop have 95.9% analogous with the crop area of ground survey. Another study in India regarding crop type classification using cloud free Sentinel-2 image was done by Gupta and Verma, (2026). To classify Crop types, XGBoost classification technique integrating with NDVI time series and multispectral data was utilized when the results showed a significant improvement in accuracy. The consistent cloud cover in the study area was prime limitation of this study. In China, Feng et al. (2019) identified crop type by mapping, employing Sentinel-2 time series data with RF and SVM algorithms. Their results showed that overall accuracies of conventional classification as well as machine learning classification of 88.96% and 98%, respectively and the information of short-wave infrared demonstrated a remarkable effect on distinguishing soybean, rice and corn. European wide crop type mapping based on Sentinel-2, Land Use and Coverage Area frame Survey (LUCAS) data and machine-learning algorithms such as SVM as well as RF was conducted by Ghassemi et al. (2022). They compared the results to a similar study employing Sentinel-1 images and confirmed that slightly better accuracy will be possible with the use of Sentinel-2 data, despite the reduction of the spatial coverage of Sentinel-2 images. One major problem in this study was using LUCAS data. At a larger scale, Defourny et al. (2019) explored the feasibility of developing a technique and evolving an open-source system which able to produce cloud-free composites, crop type maps, dynamic cropland masks, and vegetation status indicators on national scale. This study proposed principles for indicating the new difficulties related to the processing of observation of agricultural vegetation. The main constraints of this research work were cloud cover during growing season and mixed cropping system. In global aspect, Tommaso et al. (2023) mapped short and tall crops at the global scale using NASA's Global Ecosystem Dynamics Investigation (GEDI) spaceborne LiDAR and Sentinel-2 data based on RF algorithm while they got at least 87% and often above 90% classification accuracy for East Asia, Europe and America although they had limited ground data.

2.3 Optical and SAR data for crop type classification

Munghemezulu et al. (2021) concluded that in smallholder farms, single-date Sentinel-1 along with Sentinel-2 data were adequate in crop mapping in maize farms while they applied model Stacking (ST), RF, SVM Machine learning methods. There were three major limitations in this study such as limited number of sample points due to the corrugated shape of the terrain, high expenses of conducting fieldwork and accessibility of data collection. Eisfelder et al. (2024) investigated cropland and crop type classification by using RF models based on Sentinel-1 and Sentinel-2 time-series data in Ethiopia. Their findings indicated that accuracy of classification was strong when Sentinel-2 spectral bands were included. However, they have not considered to experiment how RF will perform for another area or year. In Kenya, another study regarding crop type mapping by Guided Regularized Random Forest (GRRF) for variable selection and the RF for classification in an agro natural heterogeneous landscape using both Sentinel-1 and Sentinel-2 data was conducted by Aduvukha et al. (2021). The strongest overall accuracy was obtained by using the GRRF and there were limitations in terms of mixed cropping patterns classes in this study. Similarly, Forkuor et al. (2014) integrated the optical and SAR Imagery to improve crop mapping. This research showed that both optical and SAR data throughout the cropping season improved classification accuracy though continuous monitoring was limited. Likewise, Faye et al. (2020) combined optical (Sentinel-2) and radar (Sentinel-1) data to map crops in Senegal and indicated that optical satellite data provides a better result to the end of rainy season while radar data demonstrated that combined VV and VH can identify differences between crops at the beginning of season. Betbeder et al. (2014) monitored crop with the integration of multi-temporal optical and radar data fusion in an intensive agricultural area applying SVM technique and Kappa statistic in Brittany, France. In this research work, classification accuracy was significantly enhanced due to radar based temporal indicators, although the comparison between optical and radar time series parameters was not performed. To get strong classification accuracy, Sentinel-2 time series or SAR data were suggested by Xie and Niculescu (2022) for crop mapping specifically to lessen the suspicion between grasslands and winter barley or other crop types. However, the classification technique was expensive and required more complicated processing approaches. Ampofo et al. (2021) obtained higher performance for the optical time series than the use of radar time series in crop type mapping with attention based Deep Learning (DL) techniques. Vizzari et al. (2025) achieved high overall accuracy for winter crops using Sentinel-1, Sentinel-2 and European CAP data based on RF technique in Italy. The main challenge was in determining similar structural crops. Using limited number of Sentinel-2 and Sentinel-1 Images, reliable crop classification was done by Hejmanowska et al. (2021) in Poland. The highest classification accuracy was attained for the integration of Sentinel-2 images in this study. Another comprehensive investigation on classification of land cover and crop types using deep learning approach based on Landsat 8 and Sentinel - 1 images was conducted by Kussul et al. (2017) in Ukraine. They reported that Convolutional Neural Network CNNs outperformed the MLPs (Multi-Layer Perceptron's), allowing better discrepancies for certain summer crop types. Nonetheless, the final classification map of 2-D CNNs was misclassified in some cases. Earlier, Kussul et al. (2014) classified summer crops in Ukraine with satellite SAR images applying DT, Neural Networks (NN) and SVM. Their significant findings were about using SAR images

for sunflowers as well as sugar beet classes. However, this study was limited by the availability of SAR images which restricted cover across vegetation period. In Iran, Felegari et al. (2021) conducted crop mapping with the integration of Sentinel-1 and Sentinel-2 data by applying stochastic forest classification techniques. They recommended combined use of radar and optical data, since this combination accelerates the chances of experimenting with the details compared to the single-sensor classification technique and aid to achieve more trustworthy information. The key drawback of this study was distinguishing grasslands from winter crops which lead to classification errors. In Iraq, Ibrahim et al. (2021) improved classification of crop with Sentinel-1 and Sentinel-2 images using RF and CART when they reported that the effectiveness of combination of radar and optical data enhance crop classification accuracy. This work also experienced difficulties associated with data availability, perplexity of data combination, requirements of computation, and different crops and regions generalizability. In India Singh et al. (2019) assessed sentinel-1 and sentinel-2 imagery for crop type classification based on SVM. The result showed that the combined application of optical and radar imagery produces better classification accuracy than applying them separately. However, this study was limited by the availability of ground reference data. Kumari et al. (2022) experimented soyabean mapping based on object-based machine learning approach employing temporal Sentinel-1 and Sentinel-2 data and the results of this study reported that the surpassing of Extreme Gradient Boosting (OB-XGBoost) over RF and SVM. The persistent cloud cover during crop growing period, intercropping, erratic rainfall and small areas were key limitations of this research work. While Sreedhar et al. (2022) used deep learning approach to map sugarcane crops with optical and SAR sentinel images. They obtained strong accuracies in sugarcane and non-sugarcane classification using optical along with SAR time-series datasets. Like other studies, this study was also limited by cloud cover for optical images. Crop spectral profile with Sentinel-2 Multi Spectral Instrument (MSI) as well as backscatter profile employing Sentinel-1 data were applied to develop classification of crops by RF classifiers in the study of Verma et al. (2019). This study stated that the spatial spectral, high temporal agility of Sentinel satellite are immensely suitable for monitoring of kharif crop while polarimetric SAR data and phase information did not consider in this work. Nihar et al. (2022) distinguished sugarcane crop type and mapped area at field scale with Sentinel-1, Sentinel-2 images and machine learning approaches. The results of this study noted that to delineate small-sized farms and classify sugarcane crop types, Sentinel-2 images demonstrate promising capabilities and consider them as a convenient asset. Cloud cover was a major obstacle for this study. Qadir et al. (2020) improved mapping of monsoon cropland classification by radar and optical Satellite data with RF classifier. They reported that 90% overall accuracy was attained by only SAR method, while the combined approach was 93%. Geometric error was the major challenge in classification accuracy. In Canada, Robertson et al. (2019) assessed the multi-frequency SAR data for mapping and classification of crop type using an operational DT classifier technique. This study demonstrated that the overall accuracies were strong due to the combination of multi-frequency SAR with fewer typical optical as well as single frequency SAR data. However, this study was confined to homogenous agricultural areas and did not employ any advanced machine learning approach. On the other hand, in China, Chong et al. (2021) used monthly composites of Sentinel-1 and Sentinel-2 data for major crop mapping based on region with RF classification technique. The analysis revealed that when Sentinel-1 and Sentinel-2

images are both available, the overall accuracy increased more than 80%. The major challenges were the quality of the monthly composite Sentinel-2 data, cloud mask algorithm and the accuracy of reference data in this study. Song et al. (2021) evaluated crop type mapping using Landsat, Sentinel-2, Sentinel-1 and MODIS data while their key finding was that the integration of data from all sensors significantly accelerate the accuracy for both corn and soybean. Cloud and shadow lessened the number of clear-view images in this research study.

The above-mentioned literature review shows that Sentinel-based remote sensing as well as machine learning methods have proven effective for crop type classification. However, most studies were limited by small study areas, short observation periods, and insufficient data availability. Furthermore, several studies did not compare radar and optical time-series features and very few studies examined Sentinel-1 and Sentinel-2 data together. Misclassification in heterogeneous agricultural fields also remains common. It is explicitly clear that further research is essential to integrate radar and optical data, cover full cropping seasons, and validate results across larger and more complex areas. This research work investigates these limitations by using single and combined radar and optical remote sensing data with advanced machine learning technique for accurate crop type classification

3. Research Objectives

The selected study area is Mali because of its challenging smallholder heterogeneous fragmented agricultural fields and strong seasonal variability. The region is mostly driven by a monsoon growing season, during which persistent cloud cover often limits the availability of optical satellite observations. Moreover, the adequate in situ field data for major crops, including maize, millet, sorghum, peanut, cotton, and sesame, offers trustworthy training and validating crop classification models. These characteristics make Mali a suitable test case to evaluate the effectiveness of optical and radar remote sensing data for crop-type classification.

Rich spectral information for crop separation is provided by optical Sentinel-2 imagery. Nonetheless, its performance is often influenced by cloud cover during the growing season. On the other hand, with the limited spectral discrimination capabilities, SAR data can acquire observations under all weather conditions. Hence, integrating Sentinel-1 and Sentinel-2 data has the capability to enhance crop classification accuracy by utilizing the complementary strengths of both sensors.

Based on the research gaps, this study aims to assess how accurately major crop types can be distinguished in a complex and heterogeneous agricultural landscape in Dioila, Mali, West Africa, using the Random Forest algorithm and applying Sentinel-1 and Sentinel-2 imagery individually and their combined datasets throughout the main cropping season, which will progress through the following aims:

- i. How effectively do crop types of classification perform with Sentinel-1 and Sentinel-2 data separately and in combination in Mali heterogeneous agricultural field?
- ii. How does the classification accuracy vary across spatially and temporarily in Mali complex crop lands?
- iii. Which spectral, textural, or temporal features from Sentinel-1 and Sentinel-2 contribute most to distinguishing different crop types?

4. Study Area and Data

4.1 Study Area

The study area Dioila region (12.490°N 6.789°W) is situated at the southeast part of the Koulikoro Region of Southwestern Mali (Figure 1). It is an administrative subdivision of the country. This area is a key agricultural zone, falls in Malis cotton belt where most of the farmers are smallholders and cotton remain prime cash crop. According to the Köppen-Geiger climate classification, the study area is in the Sudano-Sahelian zone which is classified as Tropical Savanna Climate. The mean annual temperature in the study area varies between 27° c to 29° c and the mean annual precipitation is between 600 and 1200 mm while the most rainfall occurs between June and September (WorldClim - Fick & Hijmans, 2017). In the month from November to April experience persistent dry season. During this period, crop production entirely relies on irrigation due to the increase of temperature and saturation vapour deficit (Traore et al., 2013). Elevation ranges including whole Dioila boundary between 200 to 541 meters above sea level (USGS derived DEM). The soils are characterized by a Sudanese peneplain featuring a mix of soil types in the study area. The pedology of this area consists of clayey soil, common in depressions; lateritic soils on slopes and plateaus, often forming rocky surfaces; and alluvio-sandy soils in water bodies and low-lying areas (Food and Agriculture Organization, 2017).

The economy of the Dioila region is mainly based on agriculture, where family farms are the source of 95% of agricultural labor (ICRISAT, 2023). Major cereal crops are sorghum, maize, millet, and fonio, which ensure food security. Besides cereal crops, there are also some cash crops such as cotton, peanuts, sesame, and cowpeas. In seasonally flooded areas, rice is cultivated.

Dioila environment has diverse ecosystem, which is typical of the Sudan savanna, including grasslands along with shea and acacia trees, gallery forests and river. Various birdlife, small mammals and baobabs adapted to semi-arid conditions are supported by gallery forests (Convention on Biological Diversity, 2026). However, deforestation and soil erosion are the prevalent environmental issues driven by fuelwood collection and agricultural expansion. There has been significant pressure on natural vegetation in this area over the last two decades due to tree cover loss (Global Forest Watch, 2024; Traoré et al., 2020)

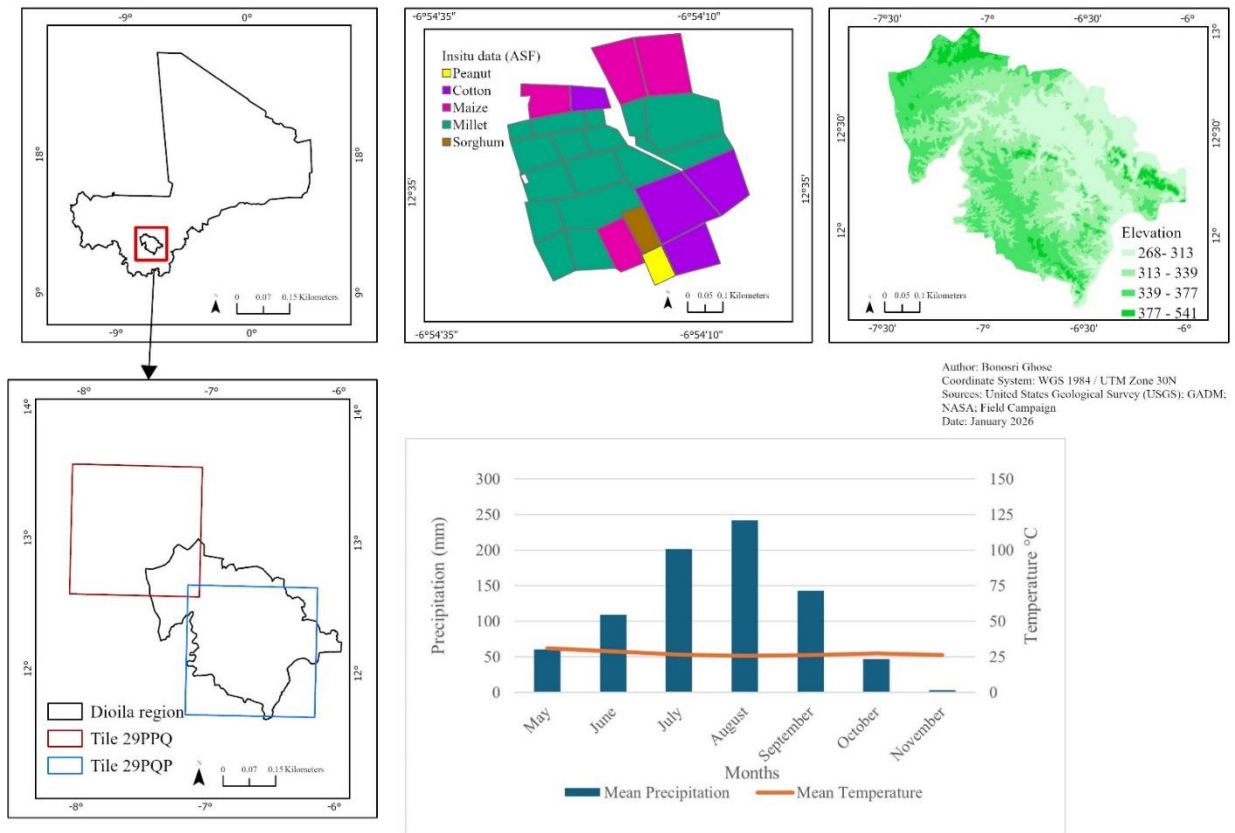


Figure 1: Location of the Dioila study area in Mali, distribution of Area Sample Frames (ASF) crop classes, elevation, Sentinel-2 tile coverage (29PPQ and 29PQP), and monthly precipitation and temperature patterns in crop growing season 2024.

The effective study area used in this study is occupied by two Sentinel-2 Military Grid Reference System (MGRS) tiles, namely 29PPQ and 29PQP (Figure 1). The entire Dioila study area is encompassed by these tiles collectively. The reason behind selecting these two tiles was ensuring complete spatial coverage throughout the cropping season.

4.1.1 Seasonal Pattern of Agricultural Activities and Crop Development

Different timing period of key agricultural activities such as field preparation, sowing, and harvesting for major crop types of Mali's cotton belt has been shown in agricultural calendar (Figure 2). To understand the phenological patterns of cultivating crops in the study area and to interpret the satellite imagery in the following chapters, this calendar is essential. The agricultural season is initiated by the major cash crop cotton in the region. Land preparation starts from early February – March and continuing into April. From late May to early June, sowing begins with significant rains and two key weeding activities with urea fertilization and ridging is usually done subsequently in June and July. Peak vegetative growth happens around September, along with systematic insecticide in the phase of flowering and boll-setting. Cotton is harvested in October and November typically.

For maize, field preparation happens later than cotton. Cleaning activities begin in March and April, followed by sowing period from late May to June. Weeding and urea fertilization is mainly in July, followed by ridging in August. Grain filling usually occurs through September whereas harvesting starts as early as the end of September and continues to end of October.

In May, sorghum and millet season begins with field cleaning. In between end of May and early August, sowing takes place. Weddings and fertilization occur from July through August. Typically harvesting occurs late October into November which is slightly later than maize and cotton.

For minor crops, which are different legumes and vegetables, sowing typically starts in July and harvesting takes place at the end of September to October. Overall, there is explicit sequence of activities in the agricultural calendar of Malis cotton belt which are strongly tied to the patterns of seasonal rainfall.

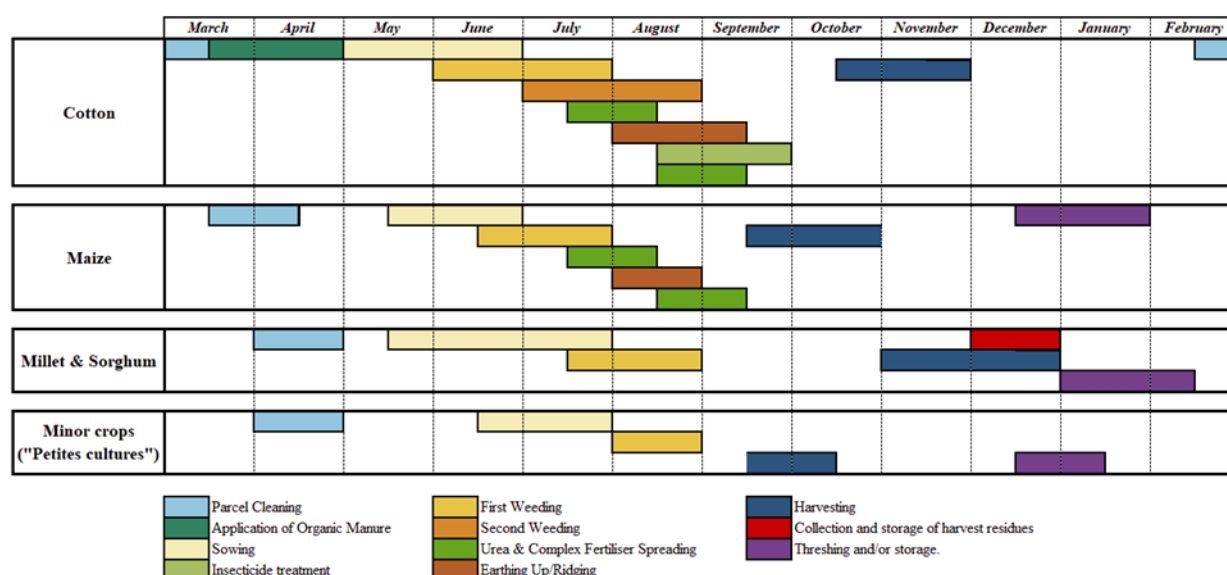


Figure 2: Agricultural calendar showing main crop cultivation periods and timing of agricultural activities in the region. Translated and adapted from Soumaré (2008)

4.2 Data

4.2.1 In-situ data

In October and November 2024, in situ data for this study was collected under the FAO-EOSTAT program during comprehensive field campaign with the primary goal of acquiring field data to generate precise cotton maps across Malis cotton belt. Around 10,000 geolocated crop points by a windshield survey and 4,332 were digitized and labelled by enumerators in Area Sample Frames (ASF) during this campaign. Each surveyed parcel included crop type, cropping system, as well as field heterogeneity. Collected crop information was for primary, secondary, and tertiary crops, while cropping systems were categorized as monocropped, intercropped, mixed, empty plots, or not available. Furthermore, heterogeneity in parcel-level was evaluated using a five-level scale ranging from very low to very high. Supplementary field observations and photographs to support data verification and interpretation were collected by enumerators. Collected data was synchronized with the help of high-resolution Pléiades satellite imagery across selected 10 km x 10 km areas to get a snapshot of the parcels that were assessed. 10 km x 10 km area contains a diverse range of crop types, heterogeneous field structures, and sufficient field observations for training and validating crop classification models. Hence, it is indicative of the smallholder farming systems that characterize the study area. The data derived from the ASF approach was used for the analysis in this study.

Parcels categorized as bare fields denote agricultural land with exposed soil and little or no vegetation cover at the time of the survey, including recently prepared fields, fallow land, or fields where sowing had not yet occurred.

4.2.1.1 Crop Type and Non-Cropland Class Distribution by Tile and AFS

Crop distribution varied significantly between tiles (Table 1 and 2). Bare Field occupied 71.18% of the total area in the independent tile 29PPQ (Table 1), although it represented 31.21% of the total count. This states that a substantial portion of the tile remained uncultivated in the observation period. Highest portion was covered by sorghum, accounting for 12.09% of the area and 29.04% of the count, followed by maize and cotton among the cultivated crops. Other crops such as bean, okra, rice, cowpea, tomato, and watermelon occupied only marginal shares, representing limited cultivation in the tile.

In contrast, Table 2 also demonstrated that independent tile 29PQP had a more heterogeneous agricultural landscape with a smaller percentage of bare field (8.71% of the total area). The dominant crop was cotton, occupying 24.86% of the area as well as 19.21% of the count, followed by sorghum and maize, which also covered substantial proportions. Rice, millet, peanut, sesame, and other culture classes covered moderate proportions, indicating notable crop diversity and high crop production activity compared to independent tile 29PPQ (Table 1). Yam, cowpea, ground pea, and okra are considered as minor crops, which had relatively small portion of the overall distribution (Table 1).

Table 1: Crop type and non-Cropland class distribution in independent tile (29PPQ)

Tile: 29PPQ				
Crops	Number of Parcel	Area (ha)	Area Proportion (%)	Parcel Proportion (%)
Bare Field	388	1267.87	71.18	31.21
Sorghum	361	214.93	12.09	29.04
Maize	108	69.91	4.02	8.69
Cotton	79	63.35	3.64	6.36
Other Culture	108	56.3	3.16	8.69
Millet	96	50.54	2.91	7.72
Sesame	46	27.99	1.57	3.70
Peanut	24	10.5	0.59	1.93
Bean	9	6.13	0.34	0.72
Okra	6	2.67	0.15	0.48
Rice	6	2.31	0.13	0.48
Cowpea	3	1.59	0.09	0.24
Tomato	3	0.78	0.04	0.24
Non crop	5	0.72	0.04	0.40
Watermelon	1	0.62	0.04	0.08

Table 2: Crop type and non-Cropland class distribution in independent tile (29PQP)

Tile: 29PQP				
Crops	Number of Parcel	Area (ha)	Area Proportion (%)	Parcel Proportion (%)
Cotton	703	922.65	24.86	19.21
Sorghum	515	664.62	17.91	14.07
Maize	514	586.05	15.79	14.05
Bare field	513	323.25	8.71	14.02
Rice	392	316.30	8.52	10.71
Millet	204	276.87	7.46	5.58
Other Culture	215	189.80	5.11	5.88
Peanut	172	182.64	4.92	4.70
Sesame	176	176.50	4.75	4.81
Sorrell	34	29.80	0.80	0.93
Non crop	195	26.36	0.71	5.33
Bean	10	9.52	0.26	0.27
Okra	8	2.90	0.08	0.22
Yam	6	2.34	0.06	0.16
Cowpea	1	1.34	0.04	0.03
Ground pea	1	0.99	0.03	0.03

4.2.1.2 Field Size Variability Across Crop Classes

Figure 3, illustrated that the parcel area distribution differed over the different crop types, reflecting field size variability among crops. The largest mean parcel area (1.26 ha) was for cotton, representing that compared to other crops, it is usually cultivated on relatively large fields. Average values ranging from 1.00 to 1.10 ha were exhibited by millet, maize, and sorghum which were comparatively high mean parcel sizes.

On the other hand, sesame and other crops were cultivated on relatively heterogeneous field pattern and in smaller fields, with mean areas of 0.92 ha and 0.76 ha respectively. With a mean area of 0.99 ha, peanuts also demonstrated moderate parcel size.

Considerable variability within most crop classes has been further explored by the violin plots distributions, as proved by the long upper tails and widespread distributions. This provides confirmation of the coexistence of both smallholders and relatively large agricultural parcels over the study area. Overall, the figure emphasizes explicit differences in field size structure among crop types, while cotton is usually linked with larger parcels and other crops associated with smaller fields.

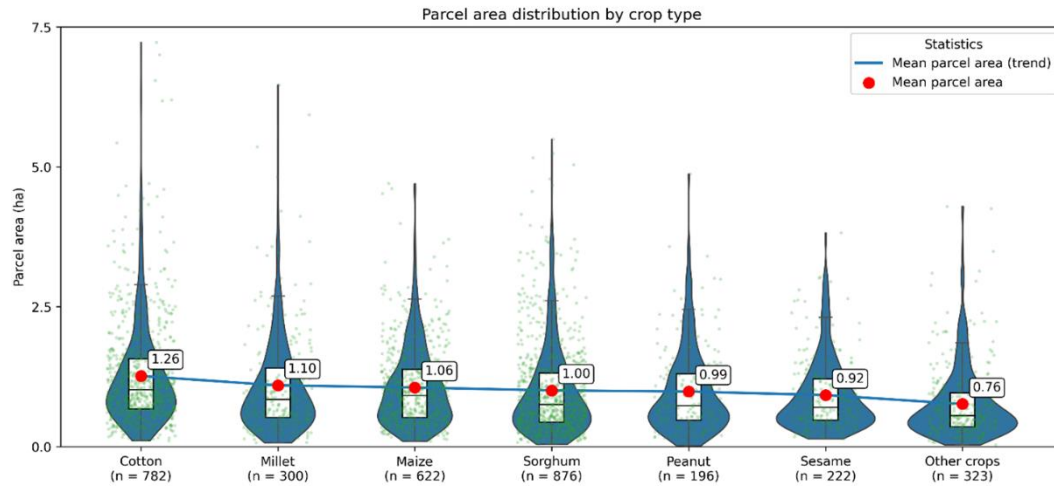


Figure 3: Violin plot of parcel area for main crop types

4.2.1.3 In-Situ Dataset Preparation

The in-situ data was merely collected from croplands. To classify the different land cover classes on the landscape, additional noncropland features are also essential. This additional data is necessary to provide thorough classification framework that can differentiate between crop land and non-crop land features. By comprehensive visual interpretation of Google satellite image in QGIS, the data was collected. It is worth noting that the landscape of the study area is strongly heterogeneous. There were mainly built-up areas, waterbody, lateritic rock, asphalt road, grassland, forest, clay soil and bare soil. To lessen the misclassification and classification confusion, lateritic rock, asphalt road, clay soil and bare soil aggregated into a single bare soil class. Through a process of single digitization, the non-crop land samples were collected. Only the six main crops maize, sorghum, millet, peanut, sesame and cotton and the low feature count crops okra, rice and tomato were selected for the classification. A 7m inward buffer for the crops parcel was used to avoid mixed edge effects and parcel boundary delineation inaccuracy. Applying a larger buffer such as 10 m would have notably reduced the number of sufficient usable pixels for training and validation. The total number of polygons for each noncropland classes used in this study was 180, 180, 159, 111, 67, 65, 60, and 55 for built up area, waterbody, grassland, forest, bare soil, clay soil, asphalt road, lateritic rock, respectively (Table 3).

Table 3: Total Non-cropland landcover samples

Non crop land Class	Number of Total Polygons	Description
Built-Up Area	180	Residential compounds, buildings, and infrastructure with concrete or metal roofing materials
Water body	180	Water bodies include rivers, ponds, and reservoirs permanent or seasonal
Grassland	159	Grass-dominated areas used for grazing or left fallow
Forest	111	Dense tree including gallery forests and woodland
Bare Soil	67	Reddish-brown in appearance
Clay Soil	65	Appearing predominantly white or light-colored
Asphalt Road	60	Roads paved with asphalt
Lateritic Rock	55	Compacted lateritic gravel and rock fragments

4.2.2 Remote sensing data

For this study, Sentinel-1 and Sentinel-2 data were selected since they offer complementary information for classifying crop types. Sentinel-1 is a C-band Synthetic Aperture Radar (SAR) mission which provides continuous observation throughout the cropping season regardless of cloudy and noncloudy weather conditions (European Space Agency, 2024). The C-band wavelength is sensitive to crop structure, canopy development, and vegetation moisture, which specifically useful for monitoring crop growth under cloudy conditions during the rainy season (Veloso et al., 2017; Khabbazan et al., 2019). Furthermore, dual-polarization VV and VH observations provide complementary information on crop characteristics, improving the differences among different crop types (Verma et al., 2019).

A high-resolution multispectral mission is Sentinel-2. It has five-day revisit period and 13 spectral bands ranging from the visible to the shortwave infrared regions of the electromagnetic spectrum (Drusch et al., 2012; European Space Agency, 2024). To map the small and fragmented agricultural fields that dominate the Dioila region, 10 m resolution is suitable which is provided by this mission. Moreover, it offers red-edge, near-infrared, and shortwave infrared bands which are effective to monitor crop phenology, vegetation vigor, as well as moisture conditions (Immitzer et al., 2016; Belgiu & Csillik, 2018). Monitoring crop development throughout the growing season is possible due to its high temporal frequency. This study utilizes the synergistic strengths of Sentinel-1 and Sentinel-2 sensors which are capable to provide reliable and accurate crop-type classification in complex agricultural landscapes like Dioila (Kussul et al., 2017; Chong et. al., 2021).

4.2.2.1 Data Acquisition and Availability

In the 2024 crop growing season, the number of cloud-free satellite imagery (Sentinel 2) was highly limited due to consistent cloud cover (Figure 4). Most acquired images were cloudy between May and September while July, August, and September had no usable cloud-free observations which was further confirmed by the NDVI temporal profiles (Figure 20). There was notable data gap during these months. The inadequate continuous NDVI observations in this period highlights the limitation of cloud-free imagery. In contrast, there was an increase in available observations from October onward, enabling clearer observation of crop growth as well as vegetation dynamics.

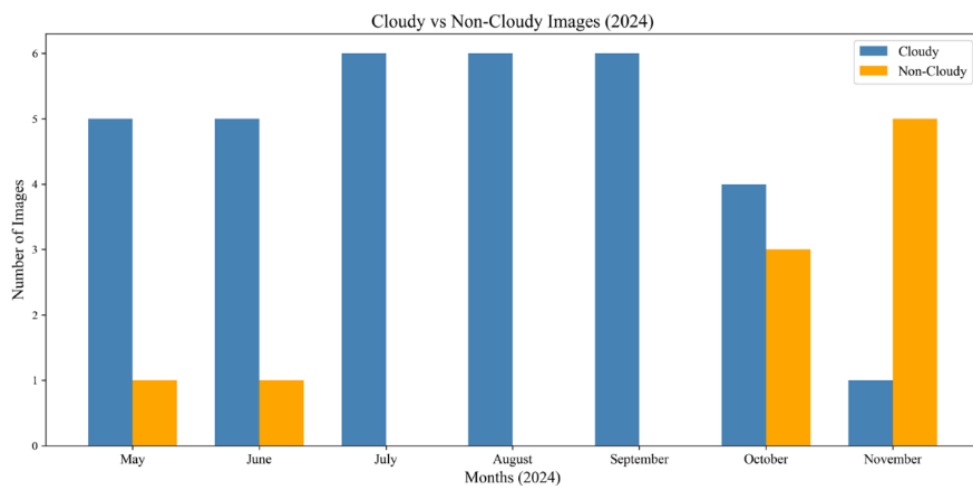


Figure 4: Monthly availability of Sentinel-2 images with less than 20% cloud cover during the 2024 crop growing season

5. Methodology

This chapter explains the machine learning framework developed for crop type classification in the Dioila region employing Sentinel-1, Sentinel-2, and fusing Sentinel-1/Sentinel-2 datasets. The procedure contains remote sensing data preprocessing, feature extraction, feature stacking and fusion, tile-based classification, model training and validation, temporal analysis, inter-phase analysis and accuracy assessment. Two spatial configurations were employed for classification: (i) independent tile based, corresponding to the two Sentinel-2 tile extents covering the study area, and (ii) a combined tile based, in which both spatial subsets were merged into a single dataset prior to the classification. Sentinel-1 and Sentinel-2 features were extracted over the same spatial extents to enable a consistent comparison among datasets. For each configuration, classifications were performed using Sentinel-1 SAR features, Sentinel-2 optical features, and their fused feature set to assess the contribution of individual and combined data sources to crop separation. A Random Forest classifier was applied using in situ data. In situ data was split for training (70%) and validation (30%). Performance of classification was evaluated using overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and F1-score metrics. After the selection of the best-performing classification framework, a temporal analysis was conducted further to evaluate the contribution of different crop growth stages and inter-phase combinations to crop type discrimination. The overall methodological workflow is given in Figure 5.

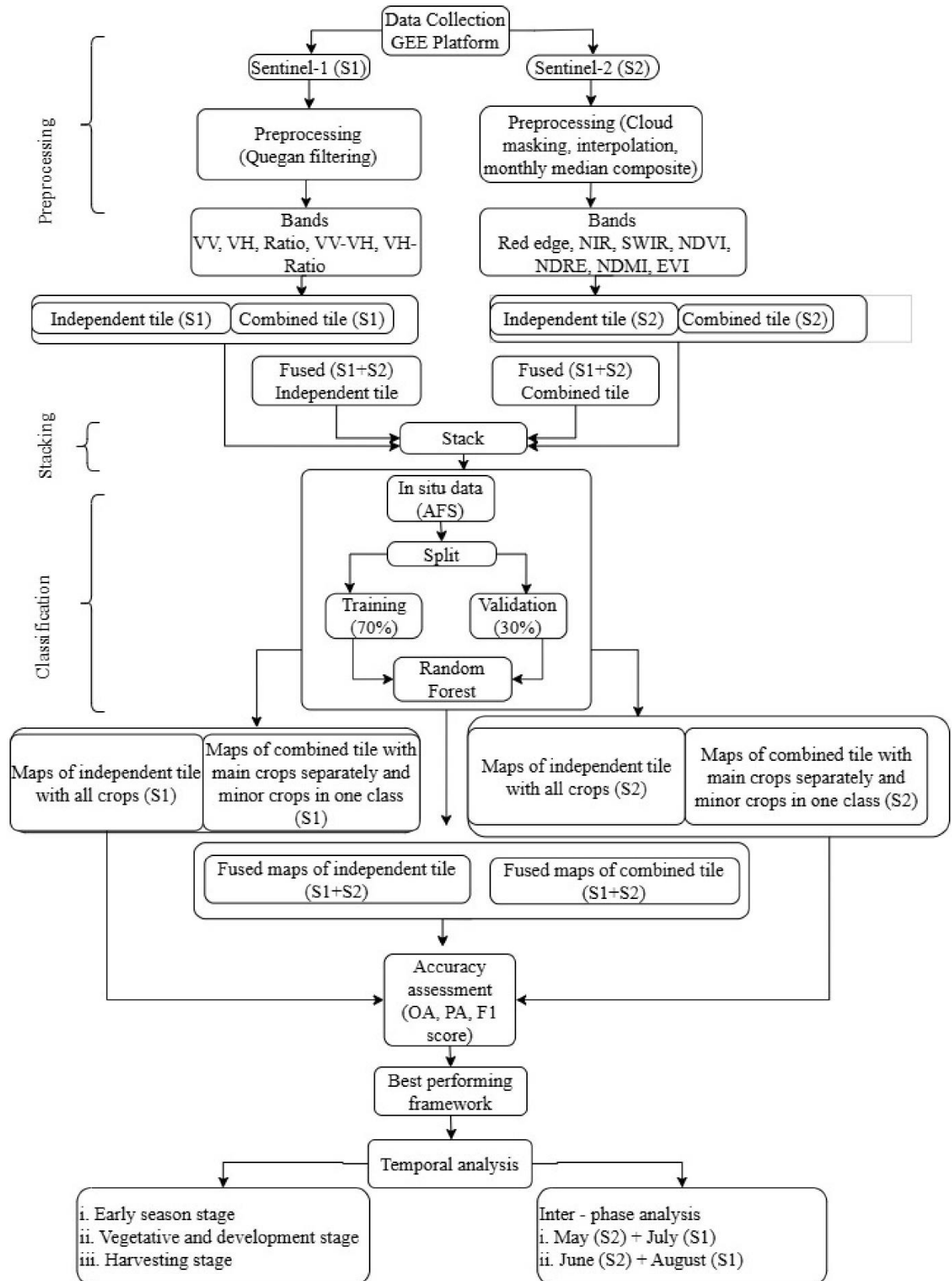


Figure 5: Flowchart of methodology

5.1 Processing of Remote sensing data

5.1.1 Preprocessing of Sentinel-1 imagery

From Google Earth Engine (GEE), Sentinel-1 Ground Range Detected (GRD) data were collected. Based on the study tile, study period, instrument mode, polarization, as well as spatial resolution, images were filtered. Only between May and November 2024 images were utilized in the analysis because this period covers entire planting, growth and harvesting stages in the study area. With dual VV and VH polarizations, the images were acquired in Interferometric Wide Swath (IW) mode and 10m spatial resolution. To adequately capture the small and fragmented agricultural fields characteristic of the Dioila region, 10m spatial resolution was retained which maintain the consistency with Sentinel-2 imagery as well.

The preprocessed Sentinel-1 GRD products are accessible on Google Earth Engine (GEE) platform. The preprocessing steps included thermal noise removal, radiometric calibration, terrain correction employing the Shuttle Radar Topography Mission (SRTM), Digital Elevation Model as well as conversion of backscatter coefficients to sigma nought (σ^0) values in decibel (dB) scale (Singha et al., 2023).

To lessen low-quality observations and border noise, an incidence angle mask was employed by keeping only pixels which are between incidence angles 31° and 45° in this study. After that, the Sentinel-1 images were segregated according to orbit direction. Ascending orbit images were utilized for further processing as the ascending-orbit acquisitions were only available.

The backscatter values of VV and VH were transformed from decibel scale to linear scale before speckle filtering. A multi-temporal Quegan filter was employed independently for the VV and VH bands to lessen speckle noise intrinsic in SAR imagery, conserving spatial as well as textural information crucial for crop classification (Lê et al., 2015). The reason behind selecting the Quegan filter was that it efficiently minimizes speckle employing temporal information from multiple SAR acquisitions without extensively smoothing field boundaries, which is distinctly crucial in smallholder agricultural systems distinguished by small and fragmented crop fields. The backscatter values were transformed back to decibel scale after filtering

For the months June, July, August, September, October and November 2024, monthly median composites were created. The median value of all obtained Sentinel-1 observations was calculated and clipped to the study area for each month. A single multi-band Sentinel-1 feature image was created from monthly features stacking. Finally, at 10 m spatial resolution, the processed Sentinel-1 dataset was exported for subsequent crop classification analysis.

5.1.2 Preprocessing of Sentinel-2 imagery

Through Google Earth Engine (GEE) platform, Sentinel-2 imagery was obtained for the 2024 growing season. According to the study tile, acquisition period, cloud percentage, and MGRS tile, imagery was filtered. Cloud coverage was less than 20% and between May and November 2024 were selected for the analysis.

By Sen2Cor processor in Google Earth Engine, the Sentinel-2 surface reflectance products are already atmospherically corrected and provided as Bottom-of-Atmosphere (BOA) surface reflectance data.

Applying the Scene Classification Layer (SCL), cloud as well as invalid pixels were removed. Pixels which have no data, saturated or defective pixels, cloud shadows, medium-probability clouds, high-probability clouds, cirrus clouds, and snow or ice were masked from the analysis. The surface reflectance values were scaled by dividing by 10,000, after masking

For May, June, October, and November 2024, monthly median composites were generated. July, August, and September were excluded from the analysis due to consistent cloud cover during the peak rainy season resulted in insufficient cloud-free observations for generating reliable monthly composites. A single multi-band feature image stack was generated subsequently from the available monthly composites.

5.2. Feature Extraction

Sentinel-2 imagery was employed to retrieve spectral features using red-edge, near-infrared, and shortwave infrared bands. The reason for selecting those bands was their sensitivity to crop structure, vegetation condition, and moisture variability (Verma et al., 2019).

From Sentinel-2 imagery, various vegetation indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE), Normalized Difference Moisture Index (NDMI), and Enhanced Vegetation Index (EVI) were calculated to detect crop growth dynamics as well as vegetation condition. Furthermore, maximum, minimum, mean, and amplitude values were obtained from the vegetation indices since temporal phenological metrics assist to identify seasonal crop variability.

To detect spatial heterogeneity, crop structure, and field pattern variability, Gray-Level Co-occurrence Matrix (GLCM) texture features such as entropy, contrast and homogeneity were extracted using 3×3 moving window from Sentinel-2 spectral bands (Verma et al., 2019). The classification dataset incorporated texture measures to enhance crop classification as well as to aid feature importance assessment. Temporal features were obtained from monthly Sentinel-1 and Sentinel-2 composites which reflect various crop development stages.

Using VV and VH polarizations from Sentinel-1 imagery, SAR backscatter features were acquired. Information on crop canopy structure, vegetation density, and moisture conditions are provided by the VV and VH backscatter coefficients. Additional SAR derived variables included the VV/VH ratio, the difference between VV and VH, and the difference between VH and the VV/VH ratio were calculated to enhance sensitivity to crop structural and biophysical characteristics. These metrics assist to differentiate crop types since different crops demonstrate

varying canopy architectures, biomass accumulation patterns, and moisture dynamics throughout the growing season. As a result, SAR backscatter features provide complementary information that develops discrimination among crop and non-crop classes (Verma et al., 2019).

The Sentinel-1 feature stack contained 30 predictor variables derived from VV, VH, VV/VH, VV–VH, and VH–VV/VH across six monthly periods. The Sentinel-2 feature set contained 52 predictor variables, including 49 stacked spectral, vegetation-index, and phenological predictors, together with three GLCM texture features such as entropy, contrast, and homogeneity. Hence, the fused Sentinel-1/Sentinel-2 dataset contained 82 predictor variables used as inputs to the Random Forest classifier

5.3 Selection of Classification Algorithm

Due to robustness, high classification performance, and capability of handle high-dimensional remote sensing datasets, the Random Forest (RF) algorithm was chosen for crop classification. RF is an ensemble classifier that builds several decision trees and assesses the final class by majority voting (Forkuor et al., 2014). The algorithm is widely used in agricultural mapping because it efficiently handles non-linear relationships, multi-source satellite data, and heterogeneous crop characteristics (Aduvukha et al., 2021). RF classification technique was employed in Google Earth Engine (GEE) using Sentinel-1, Sentinel-2, and fused Sentinel-1/Sentinel-2 datasets for this study.

5.3.1 Model Training

5.3.1.1 Training and Validation Data Preparation

The in-situ data was employed for model training and validation. For independent tiles, separate data sets were prepared to support classification, while combined dataset was produced by merging in- situ data from both tiles.

The classification was done by using the remote sensing data from June to November 2024. May was excluded from the classification process although satellite data were available from May onward. In this month crop emergence was limited, resulting in weak vegetation signals, spectral and backscatter signal among crop types were highly similar, lessening their discriminatory capability for crop classification. Hence, June to November was the most appropriate period for extracting crop development as well as phenological variability.

To classify independent tiles, only the reference polygons which were within the corresponding tile boundaries used for training and validation. On the other hand, the combined tile-based classification used merged polygons from both tiles to generate a generalized training dataset usable across the entire study area.

In combined tile analysis, minor crop classes which had limited number of samples were aggregated into a single “Other Crops” class to lessen class imbalance as well as improve classification consistency, while major crop classes were kept as separate classes.

The training and validation data sets were randomly split into 70% and 30% through a consistent polygon-based random split. Unique polygon identifiers were used in randomization ensuring that training and validation pixels were not coming from same parcel simultaneously.

The number of total polygons by tile for major and minor crop classes used in the classification is presented in Table 4 and 5. After partitioning the data, the number of polygons used for training and validation for each class was calculated individually for independent and combined tile classification frameworks. The extracted number of sampled pixels from each parcel for model training and validation is presented in Appendix (Table 17, 18, 22, 23, 27, 28, 31, 32, 35, 36, 40, 41, 44, 45, 48, 49, 52, 53, 56, 57, 59, 60).

Directly from each polygon, image pixels were sampled using a fixed number of pixels per parcel. Sampling densities were dependent on the tile characteristics as well as classification framework to maintain class balance. Regarding independent tile-based models, for independent tile (29PPQ), 50 pixels per parcel were sampled, whereas 13 pixels per parcel were sampled for another independent tile (29PQP). In the combined tile-based models, 9 pixels per parcel were sampled. The sampled pixel number per parcel varied among datasets since the availability of reference parcels differed between tiles. Fewer reference parcels remain in 29PPQ tile than tile 29PQP. Hence, a larger number of pixels (50 pixels per parcel) were sampled to obtain enough training observations. For tile 29PQP and the combined dataset, fewer pixels per parcel were required due to the larger number of available reference parcels. Before model training, null values were removed from sampled pixels. Different datasets were made for Sentinel-1, Sentinel-2, and fused Sentinel-1/Sentinel-2 classifications.

Table 4: Sample of crop types in independent tile (29PPQ)

Tile: 29PPQ	
Crop types	Number of Total Polygons
Sorghum	361
Maize	108
Millet	96
Cotton	79
Sesame	46
Peanut	24
Okra	6
Rice	6
Tomato	3
Total	729

Table 5: Sample of crop types in independent tile (29PQP)

Tile: 29PQP	
Crop types	Number of Total Polygons
Cotton	703
Sorghum	515
Maize	514
Tomato	215
Millet	204
Sesame	176
Peanut	172
Rice	10
Okra	8
Total	2517

5.3.1.2 Classification Frameworks

In this study, two classification frameworks were implemented: (i) independent tile-based classification and (ii) combined tile-based classification.

5.3.1.2.1 Independent Tile-Based Classification Using Single Sensor Data

In independent tile-based classification, separate RF models were implemented individually for two tiles using Sentinel-1 data. Only the in-situ samples located within the respective tile boundaries were used to train each model. The same approach was applied using Sentinel-2 data to assess the performance of optical imagery independently.

The RF models were trained using 250 decision trees with parameters including bag fraction (0.7), minimum leaf population (2) to optimize classification performance.

After classification, a majority filter with 3x3 neighboring pixels was applied to reduce salt-and-pepper noise in the classified maps.

The classification outputs were assessed employing independent validation samples, and confusion matrices were produced to compute overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), omission error, commission error and F1-score (Long et al., 2025).

5.3.1.2.2 Combined Tile-Based Classification Using Single Sensor Data

For the combined tile-based classification, the in-situ datasets from two tiles were merged into a unified dataset. Independent RF models were then trained using Sentinel-1 and Sentinel-2 datasets separately.

The similar polygon-based train-test split, pixel sampling approach, and post-classification filtering method applied in the independent tile-based framework were also employed in the combined analysis.

The outputs of RF classification were assessed using confusion matrices and accuracy metrics such as overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), omission error, commission and F1-score.

5.3.1.2.3 Classification Using Fused Sentinel-1 and Sentinel-2 Data

In fusion classification, June, October, and November Sentinel-2 imagery were combined with Sentinel-1 data obtained during July, August, and September. Due to the consistent cloud cover in July, August, and September, cloud-free Sentinel-2 observations were unavailable for these months. Hence, Sentinel-2 classification was conducted based on only June, October, and November imagery. In contrast, radar observations are not affected by cloud cover, they were available throughout the growing season. This fusion strategy allowed the integration of optical information from cloudless periods with radar observations from the cloudy mid-season months, leading to uninterrupted temporal representation of crop growth throughout the crop growing season.

To assess the benefits of integrating radar and optical information, Sentinel-1 and Sentinel-2 datasets were fused into a combined feature stack and used as input for RF classification. The fused datasets incorporated complementary information from radar backscatter and optical spectral-temporal characteristics to improve crop discrimination.

Independent RF models were first constructed individually for the fused Sentinel-1 and Sentinel-2 datasets. Thereafter, a combined tile-based model was trained applying the merged in-situ samples from both tiles. Like the prior combined framework, minor crop classes were aggregated into a single “Other Crops” class whereas major crop classes remained separate.

The classification outputs and performance were assessed by majority filter and standard accuracy, respectively like before. This allowed comparison between radar-only, optical-only, and fused-data classification methods.

5.3.1.2.4 Temporal Classification Based on Growing Season and Inter-Phase Analysis

The temporal and inter-phase assessment assisted comparison of classification performance across different crop growth stages as well as aid to identify the phenological periods that influence most accurately to crop type discrimination within the study area.

After the selection of best performing classification framework, an additional temporal assessment was performed to assess the importance of different crop growth phases. The goal of this temporal analysis was to identify best phenological phase to discriminate crop types.

The temporal classification was performed based on crops growing phase and interphase stage. Growing phase was divided into three major phenological stages according to crop development patterns such as, (i) Early Season, (ii) Vegetative Stage and (iii) Harvest Stage.

The observations acquired during May and June were used for early season classification, corresponding to crop establishment and early canopy development.

July to August period considered for the vegetative and development stage classification. In this period, crops reached active leaf area development. Due to the absence of cloud-free Sentinel-2 images during these months, only Sentinel-1 radar data were employed for this stage. Continuous temporal information during the peak growing period was provided by Sentinel-1 as radar signals are not influenced by cloud conditions.

The observations between September to November were used for harvest stage classification, corresponding to crop maturity, senescence, as well as harvesting activities.

Moreover, to assess whether transitional crop conditions improved classification performance, an inter-phase analysis was also conducted by combining observations from consecutive phases. Two separate inter-phase classification models were constructed. The first model integrated Sentinel-2 observations from May with Sentinel-1 observations from July, whereas the second model integrated Sentinel-2 observations from June with Sentinel-1 observations from August. These integrations were performed to combine optical information from the early growth period with radar observations from the vegetative period, specifically the periods impacted by cloud cover.

A 3×3 majority filter like the main classification framework was employed to the temporal classification outputs to reduce salt-and-pepper noise prior to accuracy assessment.

For each phase, independent RF models were constructed to assess the contribution of each season phenological characteristics to classify crops. Classification performance was evaluated by overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), omission error commission error and F1-score.

5.4 Feature Importance Analysis

To gain deeper understanding about the importance of individual variables in crop classification performance, a feature importance analysis was performed. The goal of the analysis was to identify the dominant spectral, radar, texture, and temporal variables contributing to crop discrimination across the study area for each growing phase and interphase stage.

The feature importance assessment was performed directly within the RF classification workflow implemented in Google Earth Engine (GEE). The generated values represented the relative contribution of each predictor variable to the classification process.

The feature importance was analyzed in JupyterLab using Python to detect the most important variables. Based on RF importance scores, the variables were ranked. Comparisons were conducted between temporal phases to assess the most contributing sensor variables that accurately discriminate against crops during different stages of crop development.

The values with higher importance indicated more pronounced contribution to the classification decision process. The grouped ranked variables were sensor source (Sentinel-1 or Sentinel-2) and feature category (spectral, texture, temporal feature and SAR). This process facilitated the identification of the notable influential variables for each growing season phase and inter phase stage.

6. Results

The results of crop type classification applying various classification methods based on SAR data, optical data, and fused Sentinel-1 and Sentinel-2 datasets have been presented in this chapter. The comparison of independent tile-based models and combined tile-based models to evaluate their effectiveness for crop discrimination in a heterogeneous agricultural landscape also presented. Moreover, this section investigates how sensor fusion as well as tile combination affects crop classification consistency and overall model performance over different crop classes, temporal classification according to different growth phase and interphase and feature importance.

In this chapter, Tile 1 refers to Sentinel-2 Tile 29PPQ and Tile 2 refers to Sentinel-2 Tile 29PQP. Sentinel-1 data clipped to the same spatial extents.

6.1 Independent Tile-Based Classification Using Single Sensor Data

6.1.1 Sentinel-1 Classification

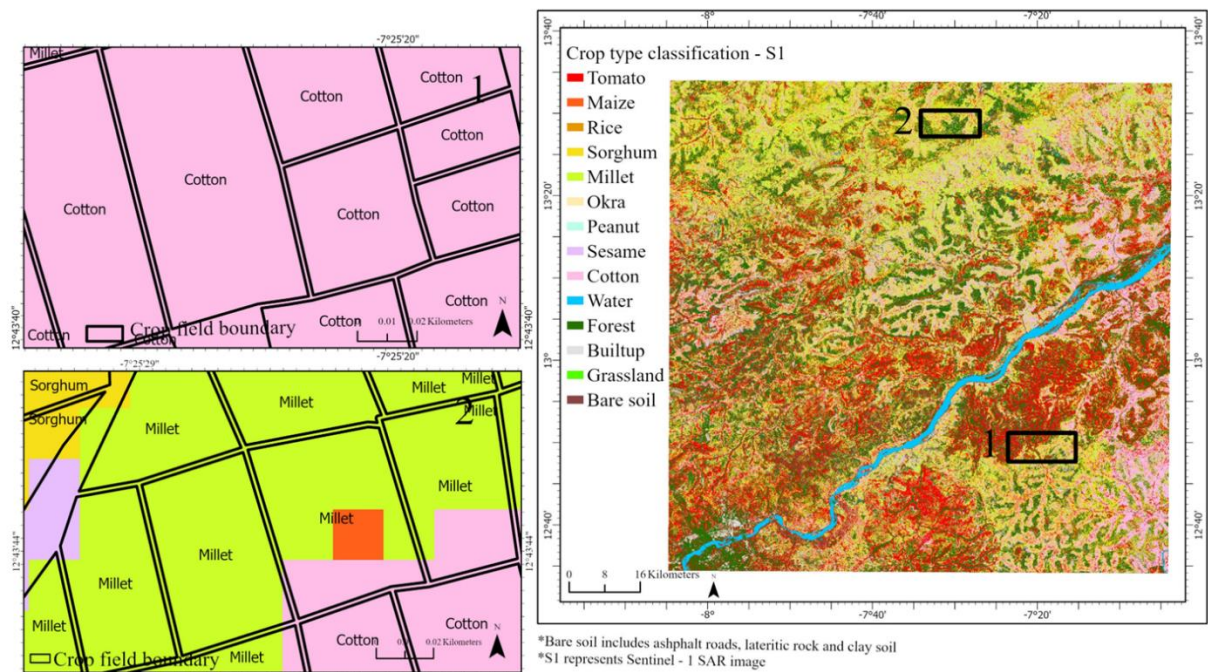
The classification of independent tiles using Sentinel-1 data generated moderate classification performance for both tiles. In Table 6, for independent (Tile 1), overall accuracy reached 0.42 and 0.38 was for another independent tile (Tile 2). Using radar information alone, comparatively lower classification performance illustrates the limited separability of some crop classes

Figure 6 showed the Sentinel-1 classification maps. Which explained capability of radar data to capture the general spatial distribution of agricultural fields over the study area. Key agricultural areas and broad land-cover patterns were reasonably identified.

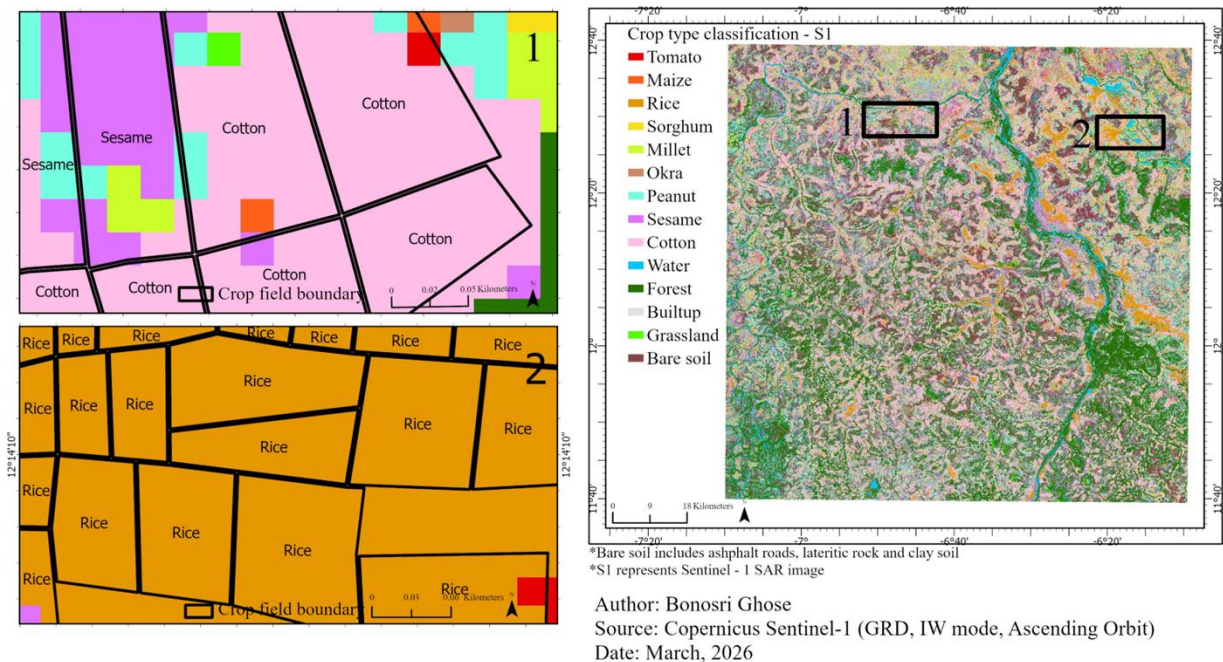
In crop classes, the best classification performance was achieved by cotton in independent tile (Tile 1) with an F1-score of 0.58, denoting relatively better separability of cotton fields employing radar backscatter information (Table 6). Rice obtained the highest crop classification performance with an F1-score of 0.62 in another independent tile (Tile 2) (Table 6). The moderate classification performance was for maize and sorghum in both tiles while peanut, sesame, tomato, and okra demonstrated lower F1-scores because of similar crop structure and radar responses (Table 6). Due to low training samples and heterogeneous field conditions, weaker performance was shown by minor crop classes.

Stronger classification performance was exhibited by the non-cropland classes than many crop classes. The highest classification accuracy in both tiles attained by water, with F1-scores of 0.94 and 0.97 for both independent tiles (Tile 1 and 2) respectively (Table 6). Due to the distinct structural characteristics in radar imagery, forest areas are also reasonably well classified. In contrast, the class of grassland and bare soil demonstrated relatively poorer accuracies because of similarities of spectral and structural with surrounding agricultural fields. Performance of confusion matrices are provided in Appendix (Table 20, 21).

Spatially, the Sentinel-1 classification maps exhibited pixel-level variability and salt-and-pepper noise despite the application of majority filtering.



Author: Bonosri Ghose
 Source: Copernicus Sentinel-1 (GRD, IW mode, Ascending Orbit)
 Date: March, 2026



Author: Bonosri Ghose
 Source: Copernicus Sentinel-1 (GRD, IW mode, Ascending Orbit)
 Date: March, 2026

Figure 6: Sentinel-1 classification map for independent tiles. The upper panel shows Tile 1 and the down panel shows Tile 2.

Table 6: Classification Report of independent tiles using Sentinel-1 image

Crop Types	Tile: 1				Tile: 2			
	Validation (%)	Recall	Precision	F1-score	Validation (%)	Recall	Precision	F1-score
Maize	15.70	0.44	0.37	0.40	11.21	0.34	0.31	0.32
Peanut	1.32	0.16	0.25	0.20	8.36	0.29	0.19	0.23
Cotton	10.33	0.76	0.48	0.58	11.21	0.55	0.33	0.41
Sorghum	19.55	0.41	0.43	0.42	11.21	0.08	0.17	0.11
Millet	12.17	0.35	0.27	0.31	9.74	0.23	0.24	0.24
Sesame	6.14	0.16	0.18	0.17	10.10	0.29	0.31	0.30
Rice	0.07	0.00	0.00	0.00	11.21	0.68	0.57	0.62
Okra	1.22	0.00	0.00	0.00	2.95	0.00	0.00	0.00
Tomato	16.62	0.19	0.28	0.22	10.18	0.19	0.27	0.22
Water	7.95	0.89	1.00	0.94	8.70	0.95	0.98	0.97
Forest	5.78	0.55	0.64	0.59	1.32	0.69	0.62	0.66
Built up	0.15	0.22	0.67	0.33	0.15	0.00	0.00	0.00
Grassland	1.68	0.00	0.00	0.00	1.84	0.13	0.29	0.18
Bare soil	1.32	0.10	0.24	0.14	1.82	0.12	0.22	0.15
Overall Accuracy		0.42				0.38		

6.1.2 Sentinel-2 Classification

Using Sentinel-2 data, the independent tile-based classification produced increased performance compared to Sentinel-1 classification. Table 7 showed the overall accuracy elevated to 0.58 for independent tile (Tile 29PPQ) and 0.54 for other one (Tile 29PQP), representing the remarkable capability of optical imagery for crop differentiation.

Figure 7 displayed the Sentinel-2 classification maps. Maps showed distinct field boundaries and more homogeneous spatial representation of crop parcels. The optical image datasets provided notable separability between crop classes compared to Sentinel - 1 due to distinctions in spectral reflectance as well as vegetation characteristics.

In Tile 29PPQ, there was relatively significant classification performance for sorghum and cotton, with F1-scores of 0.64 and 0.52, respectively. Rice achieved the strongest crop classification accuracy with an F1-score of 0.77, followed by cotton (0.65) in the tile 29PQP (Table 7). Moderate classification performance achieved by both maize and millet across both tiles. Nonetheless, peanut, sesame, tomato, and okra kept producing relatively lower F1-scores, highlighting continuous confusion among minor crop classes due to similar phenological characteristics and lack of training data. There was also observed misclassification among different crops. Confusion matrices for both independent tiles were given in Appendix (Table 25, 26).

In the Sentinel-2 framework, non-Cropland classes exhibited consistently notable classification performance. Water was the best classified class overall with F1-scores close to 1.00 in both tiles (Table 7). Forest areas also demonstrated high classification accuracy. Bare soil and grassland classes showed moderate classification performance which was better than the Sentinel-1 results.

Smoother spatial patterns and less salt-and-pepper noise were there in the Sentinel-2 classification maps. Field boundaries were closer with observed parcel geometries, especially in bigger and homogeneous cultivation areas (Figure 7).

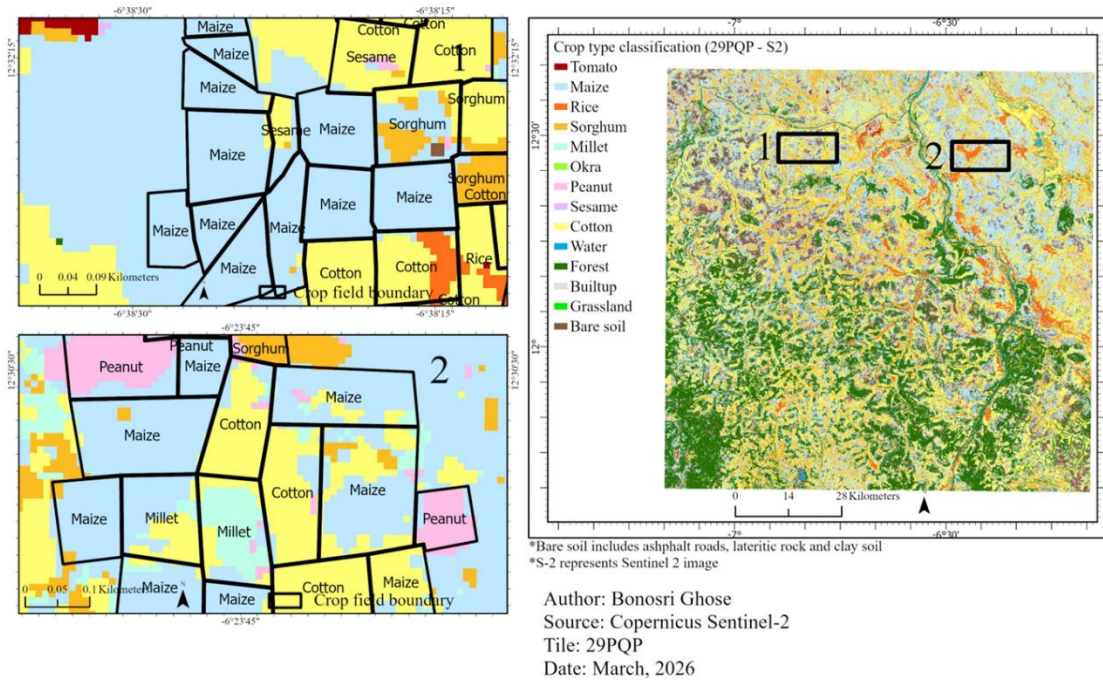
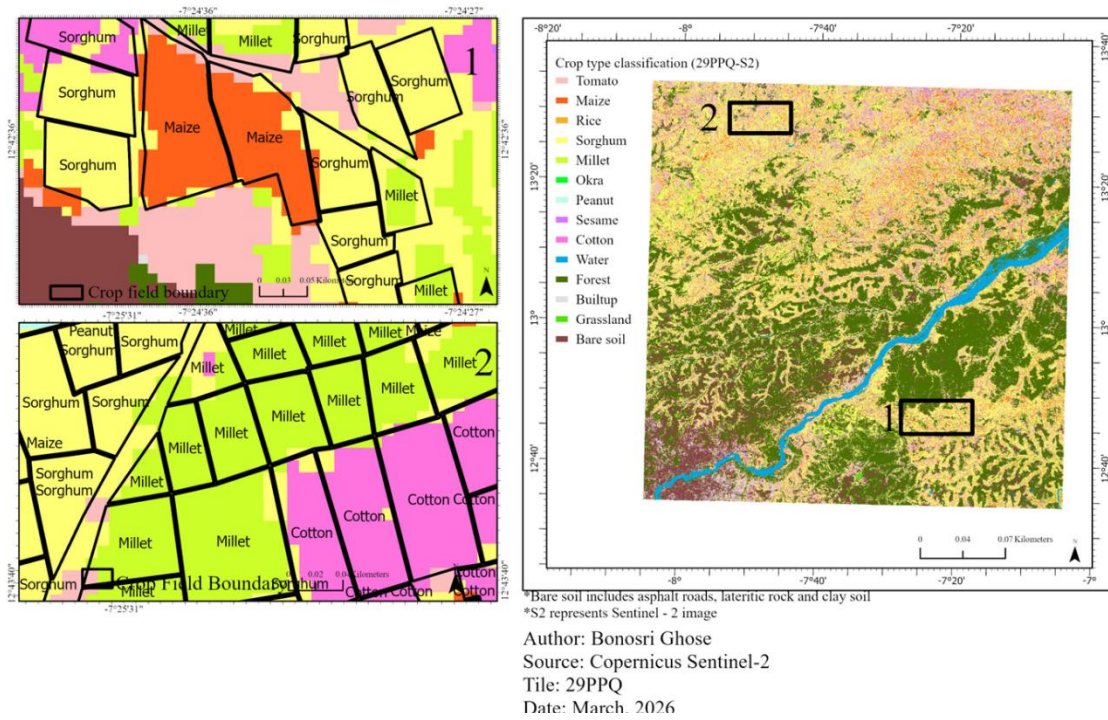


Figure 7: Sentinel-2 classification map for the independent tiles. The upper panel shows Tile 29PPQ and the down panel shows Tile 29PQP

Table 7: Classification Report of independent tile using Sentinel-2 images

Crop Types	Tile: 29PPQ				Tile: 29PQP			
	Validation (%)	Recall	Precision	F1-score	Validation (%)	Recall	Precision	F1-score
Maize	12.06	0	0.57	0.42	16.27	0.52	0.38	0.44
Peanut	1.80	0.06	0.4	0.1	5.50	0.14	0.41	0.21
Cotton	8.67	0.59	0.47	0.52	23.19	0.74	0.57	0.65
Sorghum	32.17	0.84	0.52	0.64	16.43	0.56	0.46	0.51
Millet	10.41	0.37	0.71	0.49	6.87	0.31	0.63	0.42
Sesame	4.83	0.19	0.56	0.28	5.90	0.22	0.49	0.3
Rice	0.34	0	0	0	13.24	0.73	0.82	0.77
Okra	1.05	0	0	0	1.72	0.11	0.61	0.19
Tomato	13.65	0.35	0.62	0.45	5.89	0.16	0.33	0.22
Water	11.81	0.99	1	0.99	3.32	0.99	1	0.99
Forest	1.08	0.6	0.26	0.36	0.78	0.56	0.91	0.69
Built up	0.17	0.31	0.25	0.28	0.07	0.3	1	0.46
Grassland	1.17	0	0	0	0.34	0	0	0
Bare soil	0.79	0.19	0.56	0.28	0.47	0.49	0.49	0.49
Overall Accuracy		0.58				0.54		

6.2 Combined Tile-Based Classification Using Single Sensor Data

6.2.1 Sentinel-1 Classification

An overall accuracy of 0.38 achieved by the combined tile-based classification using Sentinel-1 data (Table 8). The classification map indicates that the radar-based classification was capable to extract the general spatial distribution of agricultural areas across the merged study area (Figure 8). However, significant confusion among crop classes stayed, specifically inside scattered agricultural landscapes.

Cotton demonstrated the best classification performance with an F1-score of 0.41, followed by sesame and other crops with F1-scores of 0.36. Relatively lower classification performance was shown by maize, millet, sorghum, and peanut, representing analogous crop structure and radar backscatter traits among the crop classes (Table 8). Slightly improved classification consistency compared to the independent tile-based framework has been observed in the aggregation of minor crop classes into the “Other crops” category but still there was notable misclassification among the crops. Confusion metrics have been provided in Appendix (Table 30)

Water and forest exhibited relatively stronger classification performance because of their distinct radar features, while grassland and bare soil had relatively lower performance because of surrounding agricultural fields (Table 8).

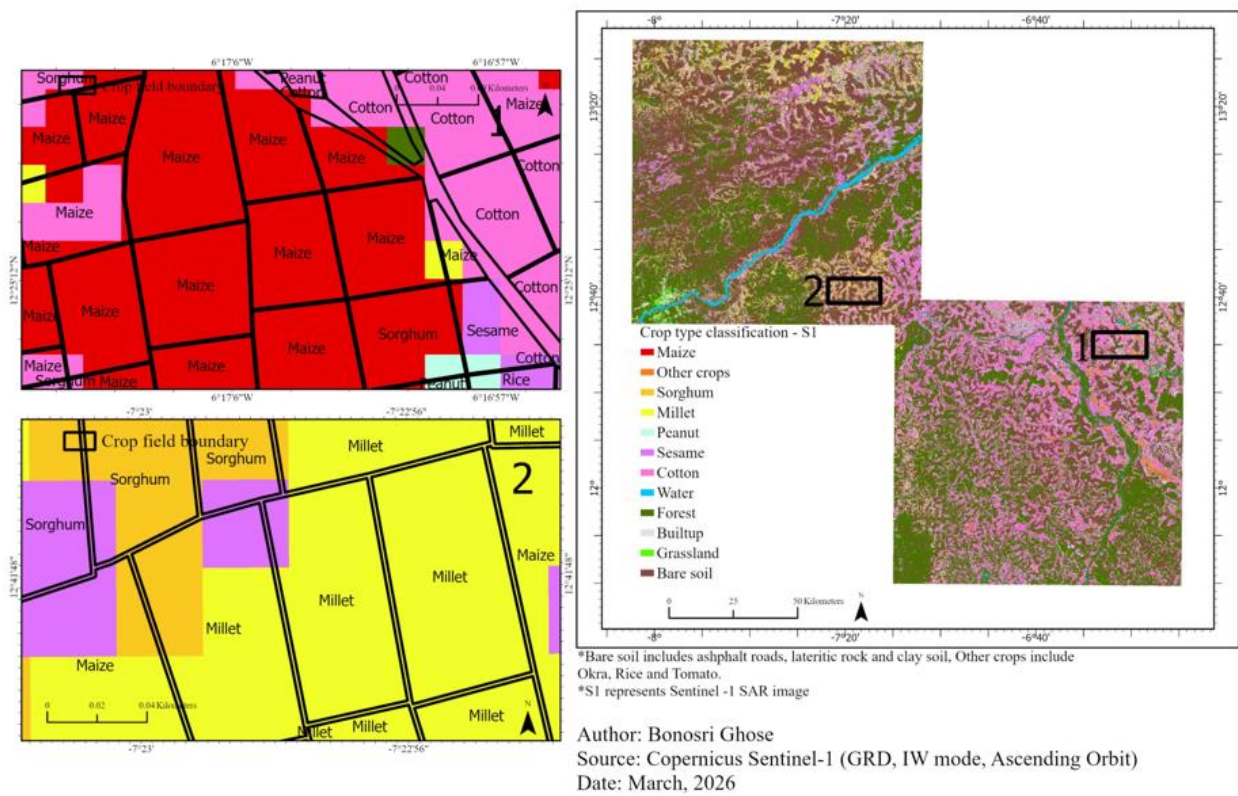


Figure 8: Classification map for the Combined tile using Sentinel-1 image

Table 8: Classification report of Combined tile using Sentinel-1 images

Crop Types	Tile: 1+2			
	Validation (%)	Recall	Precision	F1-score
Maize	11.61	0.32	0.27	0.29
Peanut	11.59	0.21	0.23	0.22
Cotton	11.61	0.5	0.35	0.41
Sorghum	11.61	0.18	0.23	0.2
Millet	11.61	0.23	0.24	0.23
Sesame	11.08	0.35	0.37	0.36
Other crops	11.61	0.33	0.39	0.36
Water	11.61	0.96	0.98	0.97
Forest	2.37	0.82	0.43	0.56
Built up	0.39	0.12	0.44	0.19
Grassland	2.57	0.14	0.27	0.18
Bare soil	2.32	0.27	0.33	0.3
Overall Accuracy	0.38			

6.2.2 Sentinel-2 Classification

Table 9 showed improved overall accuracy of 0.52 in the combined tile-based classification using Sentinel-2 data compared to the Sentinel-1 framework and Figure 9 showed the Sentinel-2 classification map.

Other crops exhibited the best classification performance with F1-score of 0.58, followed closely by cotton (0.57) and sorghum (0.54) among the crop classes. Moderate classification performance with an F1-score of 0.45 achieved by maize (Table 9). On the other hand, peanuts, millets, and sesame had lower F1-scores, which indicated continuous confusion among crop classes. The confusion metrics have been provided in Appendix (Table 34).

Generally, the non-cropland classes were better represented in the Sentinel-2 classification, which showed notable classification consistency because of their distinct spectral traits.

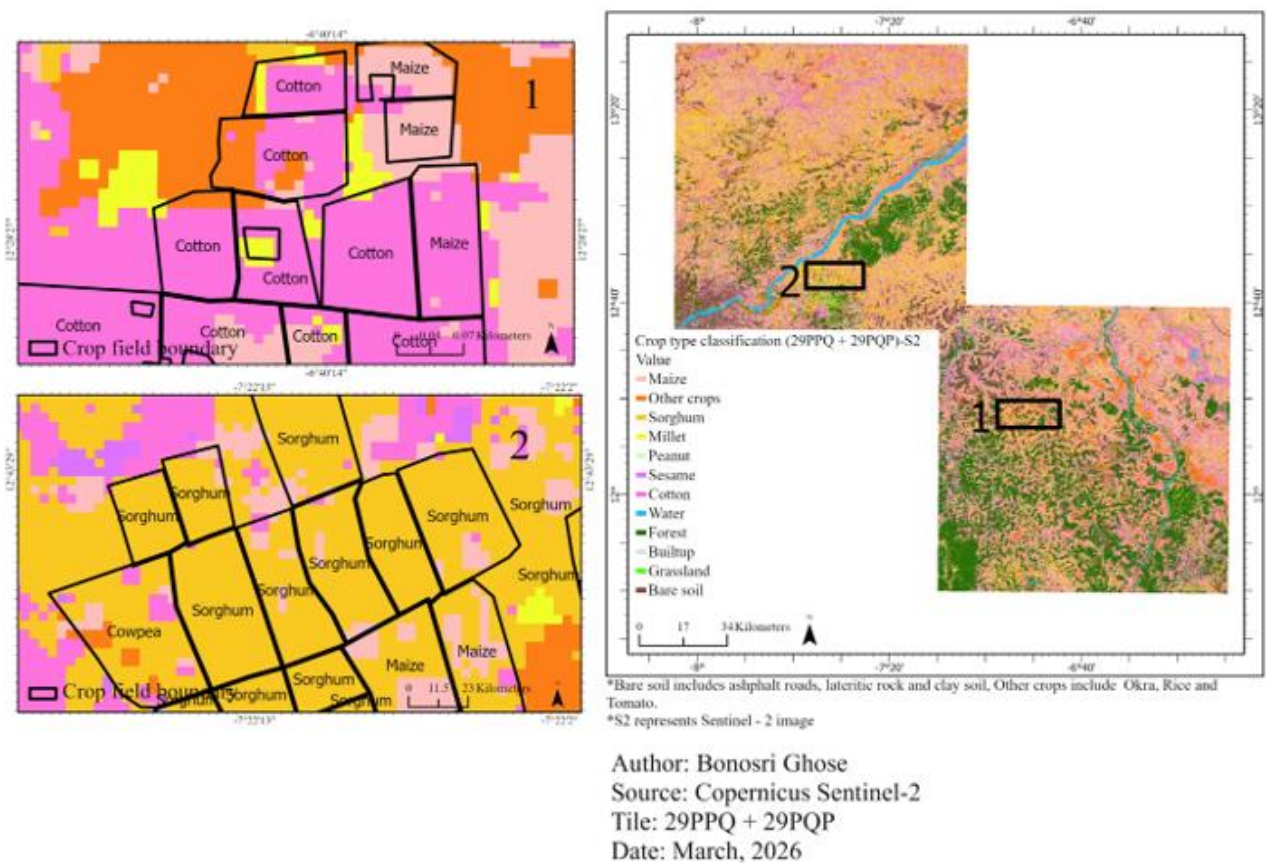


Figure 9: Classification map of combined tile using Sentinel-2 images

Table 9: Classification report of Combined tile using Sentinel-2 images

Crop Types	Tile: 29PPQ + 29PQP			
	Validation (%)	Recall	Precision	F1-score
Maize	15.17	0.52	0.39	0.45
Peanut	5.49	0.05	0.25	0.08
Cotton	18.35	0.67	0.5	0.57
Sorghum	21.09	0.59	0.51	0.54
Millet	7.70	0.24	0.4	0.3
Sesame	4.97	0.21	0.38	0.27
Other crops	19.17	0.54	0.63	0.58
Water	4.59	0.94	0.99	0.97
Forest	1.27	0.67	0.83	0.74
Built up	0.45	0.29	1	0.45
Grassland	0.73	0.05	0.6	0.09
Bare soil	1.02	0.64	0.79	0.71
Overall Accuracy	0.52			

6.3 Classification Using Fused Sentinel-1 and Sentinel-2 Data

6.3.1 Independent Tile-Based Model Using Fused Sentinel-1 and Sentinel-2 Data

Employing fused Sentinel-1 and Sentinel-2 datasets, the independent tile-based classification produced significant classification accuracy compared to the separate sensor-based approaches. The radar and optical information integration boosted crop separability by incorporating structural information from Sentinel-1 with spectral and vegetation traits from Sentinel-2 imagery.

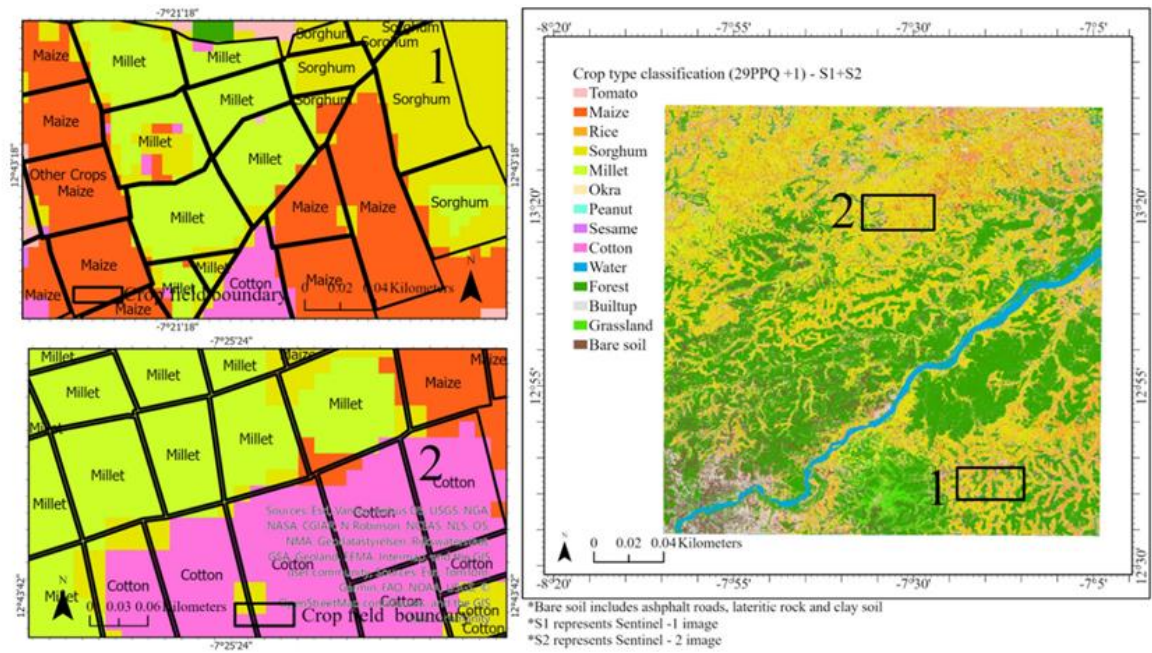
The overall accuracy of 0.64 obtained by the fused classification in independent tile (29PPQ +1) (Table 10), which was stronger than the performances of using Sentinel-1 or Sentinel-2 independently. The map Figure 10 showed better spatial consistency and field boundaries compared to the single-sensor classifications.

Among the crop classes, F1-scores of 0.67 and 0.66 were achieved by sorghum and cotton respectively in independent tile (Tile 29PPQ + 1) which was the highest classification performance Table 10). Maize exhibited moderate classification performance, whereas peanut, sesame, rice, and okra were comparatively hard to distinguish due to closely related crop characteristics and shortage of validation samples.

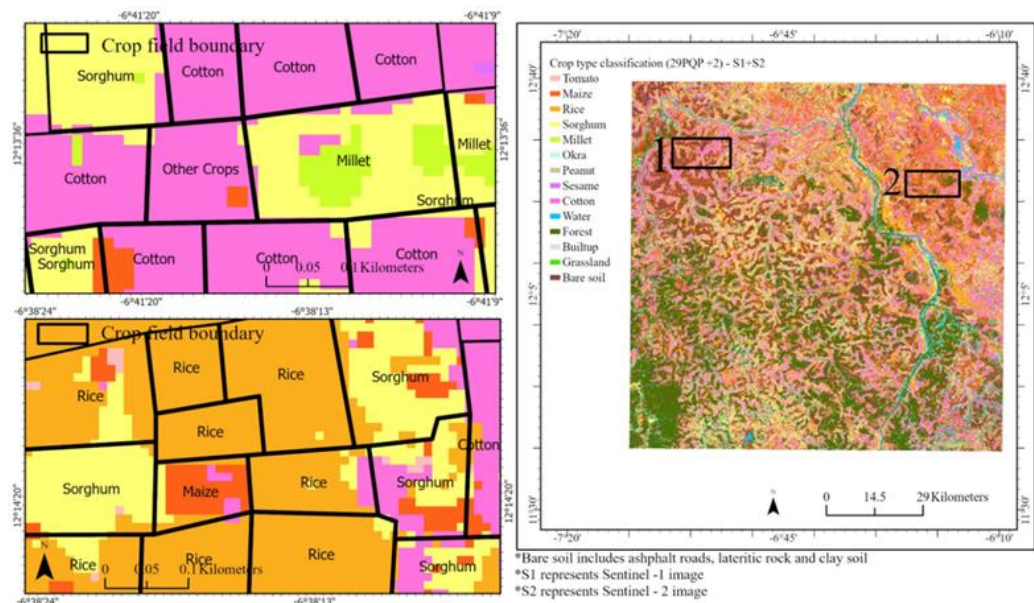
Likewise, compared to the single-sensor approaches, the fused classification for other independent tiles (Tile 29PQP + 2) also exhibited elevated classification accuracy (Table 10). Better representation of agricultural parcels and more homogeneous crop patterns across the

tile was shown in Figure 10 in which rice, cotton, sorghum, and maize were more clearly separable.

Water and Forest showed strong classification performance because of their distinct spectral and radar characteristics. Water obtained the best overall classification consistency with an F1-score of 0.98 (Table 10). The misclassification among crops and non-cropland have been provided in confusion metrics table (Table 38, 39).



Author: Bonosri Ghose
 Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit and
 Copernicus Sentinel - 2
 Date : April, 2026



Author: Bonosri Ghose
 Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit and Copernicus Sentinel - 2
 Date : April, 2026

Figure 10: Classification map of fused independent tiles. The upper panel shows Tile 29PPQ +1 and the down panel shows Tile 29PPQ+2

Table 10: Classification report of independent tiles using fused Sentinel-1 and Sentinel-2 images

Crop Types	S1+S2 Tile: 29PPQ + 1				S1+S2 Tile: 29PQP + 2			
	Validation (%)	Recall	Precision	F1-score	Validation (%)	Recall	Precision	F1-score
Maize	9.53	0.4	0.51	0.45	18.09	0.58	0.45	0.51
Peanut	2.31	0.03	0.53	0.06	5.14	0.14	0.35	0.2
Cotton	8.23	0.73	0.61	0.66	21.29	0.74	0.52	0.61
Sorghum	30.55	0.87	0.55	0.67	17.16	0.56	0.47	0.51
Millet	8.57	0.32	0.51	0.39	5.79	0.26	0.5	0.34
Sesame	4.35	0.14	0.74	0.24	5.50	0.27	0.49	0.35
Rice	0.07	0	0	0	11.82	0.7	0.78	0.74
Okra	0.55	0	0	0	1.40	0.12	0.45	0.18
Tomato	12.90	0.28	0.69	0.4	7.06	0.13	0.62	0.22
Water	18.99	0.98	0.99	0.98	4.01	0.97	0.98	0.97
Forest	2.48	0.62	0.71	0.66	1.10	0.87	0.99	0.93
Built up	0.14	0.44	0.44	0.44	0.06	0.18	1	0.31
Grassland	0.23	0	0	0	0.94	0.13	0.65	0.22
Bare soil	1.12	0.28	0.88	0.43	0.61	0.37	0.75	0.5
Overall Accuracy		0.64				0.54		

6.3.2 Combined tile-based model using fused Sentinel-1 and Sentinel-2 data

The classification of combined tile-based based on fused Sentinel-1 and Sentinel-2 datasets derived enhanced classification performance in contrast to the separate sensor-based and the independent tile-based methods. Integration of radar and optical information in a unified training dataset, the fused model improved crop separability and spatial consistency over the study area.

An overall accuracy of 0.57 (Table 11) achieved by the combined fused classification. The map (Figure 11) showed improved representation of agricultural parcels, field boundaries, and smoother spatial patterns.

With an F1-score of 0.64, cotton attained strong classification performance followed by other crops (0.60), sorghum (0.59), and maize (0.52) (Table 12). The moderate performance was shown by millet and sesame, while due to similarities with surrounding crop classes and limited sample representation, classifying peanut was relatively difficult.

The fused datasets emphasized crop discrimination by integrating radar-based structural information with optical spectral traits. Particularly, the Sentinel-1 observations assisted temporal continuity during cloudy periods, whereas Sentinel-2 imagery increased crop separability during cloud-free conditions.

Water, forest, and bare soil, also showed relatively notable classification consistency among non-crop land classes. The reason for this is distinct spectral and radar characteristics (Table 11). Confusion metrics have been given in Appendix (Table 43).

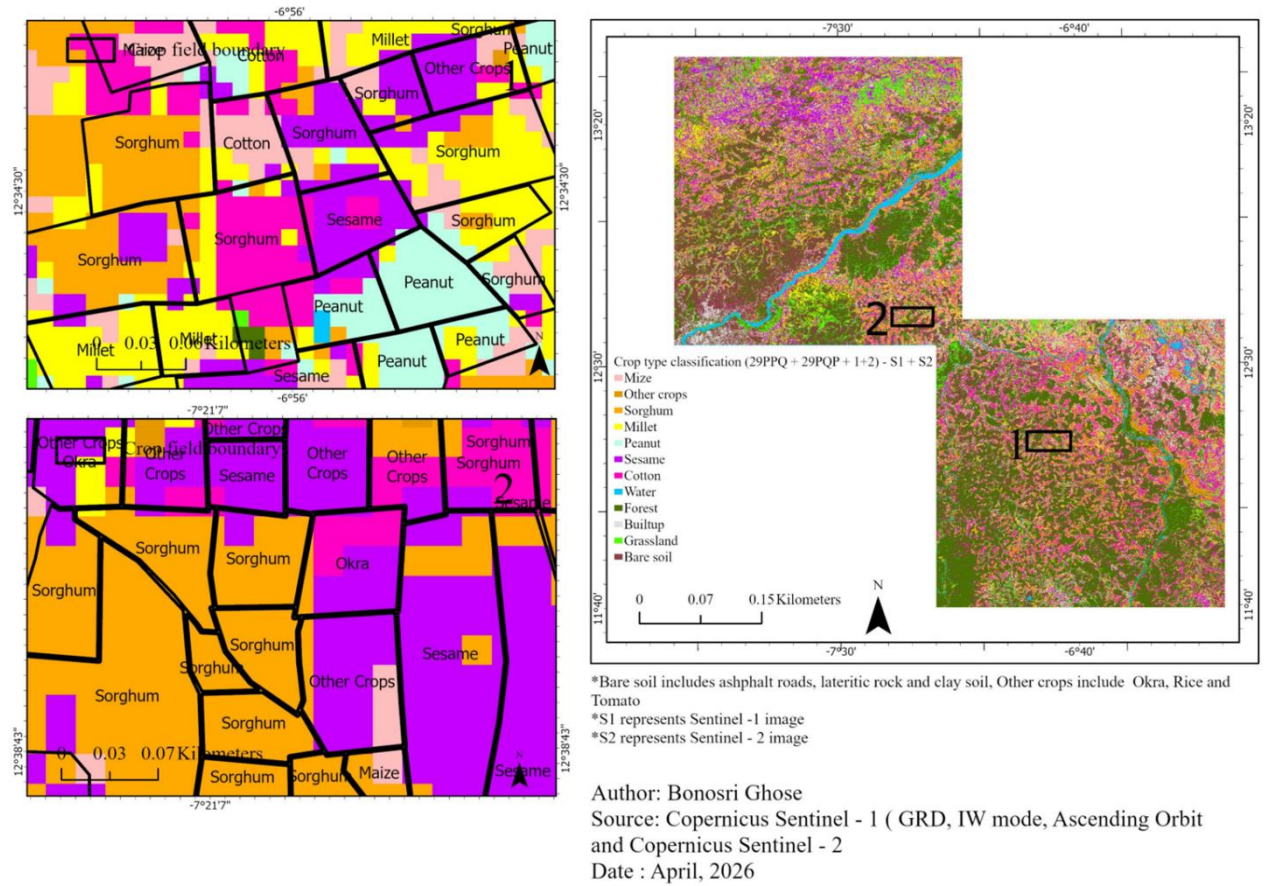


Figure 11: Classification map of fused combined tile (29PPQ+29PQP+1+2) classification

Table 11: classification report of combined tile using fused Sentinel-1 and Sentinel-2 images

Crop Types	S1+S2 Tile: 29PPQ + 29PQP+1+2			
	Validation (%)	Recall	Precision	F1-score
Maize	15.03	0.53	0.5	0.52
Peanut	4.58	0.35	0.25	0.29
Cotton	18.54	0.63	0.65	0.64
Sorghum	21.87	0.55	0.63	0.59
Millet	7.17	0.52	0.38	0.44
Sesame	5.15	0.51	0.29	0.37
Other crops	18.00	0.5	0.75	0.6
Water	6.10	0.96	0.96	0.96
Forest	1.18	0.74	0.57	0.65
Built up	0.19	0.63	0.83	0.71
Grassland	1.12	0.32	0.48	0.39
Bare soil	1.07	0.78	0.7	0.74
Overall Accuracy	0.57			

Summary of Classification Frameworks

By comparing all classification approaches, fused Sentinel-1 and Sentinel-2 datasets consistently surmounted the separate sensor-based frameworks. Sentinel-1 usually derived lower crop discrimination capability than Sentinel -2 because of stronger spectral separability of optical imagery, whereas Sentinel-1 contributed most for the cloudy periods.

The independent fused classification obtained the strongest overall accuracy (0.64) among all frameworks (Table 12). Nonetheless, the combined fused classification yielded a more balanced as well as generalized performance across crop classes by lessening class imbalance and enhancing class-wise consistency.

Overall, the framework of the combined fused Sentinel-1 and Sentinel-2 was selected as the most suitable approach for following temporal phase analysis and feature importance assessment.

Table 12: Summary of all classification framework

Classification Frameworks	Sensors Used	Mean F1-score	Overall Accuracy	Crop Classification Performance
Independent	S1	0.26	0.42	Moderate
Independent	S1	0.31	0.38	Moderate
Independent	S2	0.36	0.58	High
Independent	S2	0.46	0.54	High
Combined	S1	0.27	0.38	Moderate–Low
Combined	S2	0.44	0.52	High
Independent	S1 + S2	0.43	0.64	Best Performance
Independent	S1 + S2	0.44	0.54	High
Combined	S1 + S2	0.49	0.57	Very High

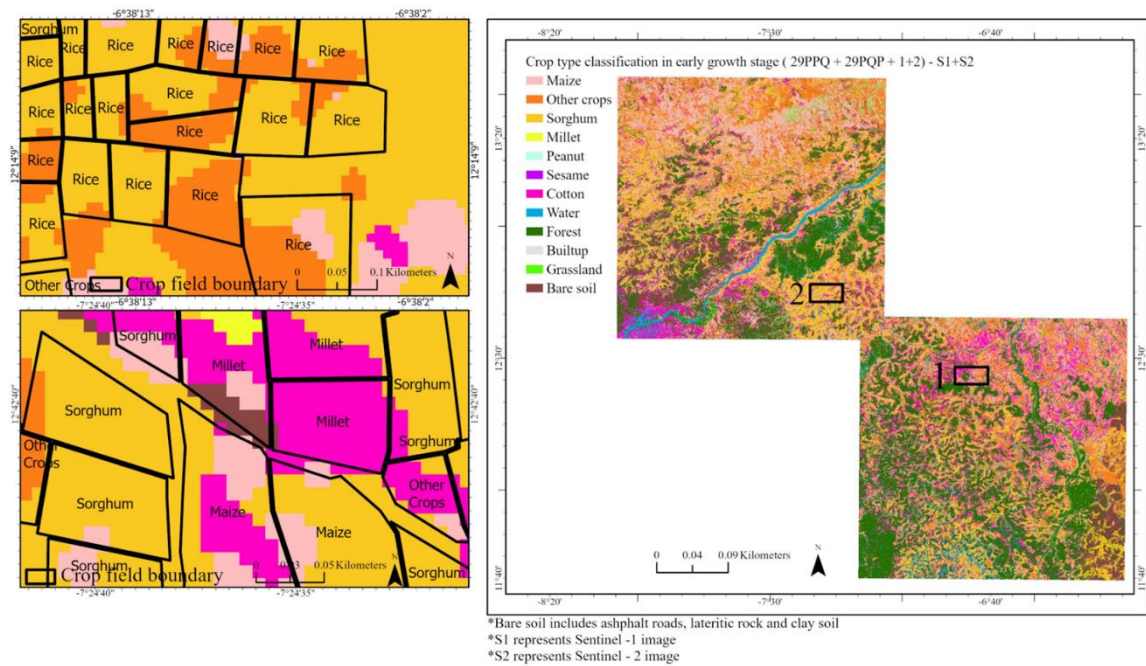
6.4 Temporal Classification Based on Growing Season and Inter-Phase Analysis

The best-performing fused Sentinel-1 and Sentinel-2 combined tile approach was further examined across different crop growth stages. The temporal classification output according to early growth, vegetative, and harvesting stages, as well as inter-phase combinations presented in this section to evaluate how crop discrimination and classification accuracy differ throughout the growing season.

6.4.1 Early Season Classification

Based on observations collected during May–June, the classification of early season performed and achieved an overall accuracy of 0.40 (Table 13). The classification map (Figure 12) highlights that crop discrimination in the early growth stage was notably restricted since most crops were still in the phase of establishment as well as demonstrated analogous spectral and structural features.

In the crop classes, other crops (0.49), sorghum (0.45) and cotton (0.39) attained comparatively better classification accuracy, while maize performed with moderate accuracy (Table 13). Conversely, peanuts, sesame, millet and sesame had low classification performance due to limited crop separability during the early phenological stage. Noticeable mixing among agricultural classes was also exhibited in the classification map for the limited vegetation development in this period. However, Misclassification among crops has been provided in Appendix (Table 47).



Author: Bonosri Ghose
 Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit and
 Copernicus Sentinel - 2
 Date : April, 2026

Figure 12: Classification map of early growth stage

Table 13: Classification report of early growth stage

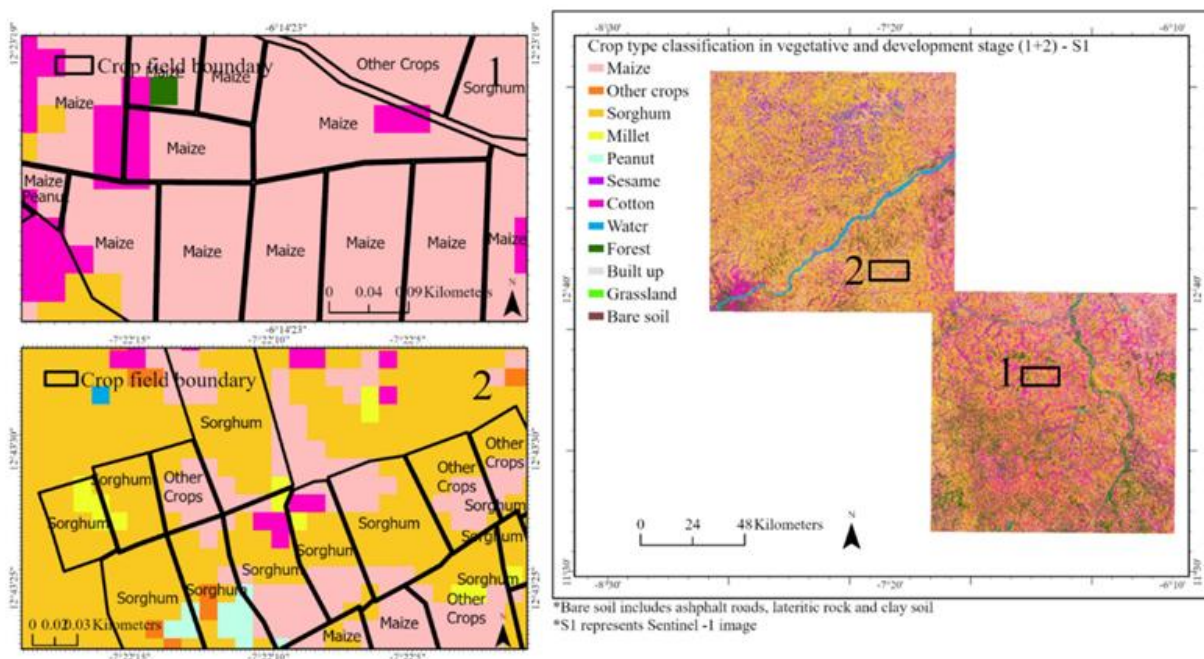
Crop Types	Validation (%)	Recall	Precision	F1-score
Maize	12.18	0.34	0.2	0.25
Peanut	5.02	0.01	0.1	0.02
Cotton	18.61	0.41	0.37	0.39
Sorghum	19.30	0.59	0.36	0.45
Millet	5.69	0.02	0.13	0.03
Sesame	5.74	0.03	0.46	0.05
Other crops	18.86	0.44	0.54	0.49
Water	5.87	0.89	0.91	0.9
Forest	1.93	0.68	0.62	0.65
Built up	0.54	0.27	1	0.43
Grassland	3.64	0.1	0.93	0.17
Bare soil	2.62	0.58	0.74	0.65
Overall Accuracy		0.40		

6.4.2 Vegetative Stage Classification

July–August observations were employed for this classification. Overall accuracy of 0.30 (Table 14) was attained for the vegetative stage. Persistent cloud cover limited the availability of cloud-free Sentinel-2 imagery during this phase. Therefore, primarily Sentinel-1 radar data were used for this classification approach.

Cotton and other crops obtained F1 - scores (0.31) which was the best classification performance, followed by maize (0.28) and sorghum (0.26). Peanut, millet, and sesame obtained weak classification accuracy (Table 14). The map of classification displayed (Figure 13) significant confusion among crop classes and limited clearly differentiated field boundaries. The misclassification among crops has been provided in Appendix (Table 51)

This stage reflects the lack of relying mainly on SAR information during the peak rainy season, when structures of crop canopies were relatively similar across different crop types.



Author: Bonosri Ghose
Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit
Date : April, 2026

Figure 13: Classification map of vegetative and development stage

Table 14: Classification report on vegetative and development stage

Crop Types	Vegetative and development stage			
	Validation (%)	Recall	Precision	F1-score
Maize	13.08	0.42	0.21	0.28
Peanut	4.56	0.09	0.09	0.09
Cotton	16.78	0.32	0.3	0.31
Sorghum	20.16	0.23	0.29	0.26
Millet	6.88	0.09	0.12	0.1
Sesame	5.29	0.07	0.09	0.08
Other crops	17.46	0.28	0.36	0.31
Water	7.86	0.84	0.9	0.87
Forest	1.94	0.42	0.3	0.35
Built up	0.53	0	0	0
Grassland	2.85	0	0	0
Bare soil	2.62	0.15	0.21	0.18
Overall Accuracy	0.30			

6.4.3 Harvest Stage Classification

The classification approach of harvest stage conducted in September–November observations and obtained the strongest classification overall accuracy (0.53) among all growing season phases (Table 15). The spectral as well as phenological differences in different crops increased for crop maturity and senescence, resulting in better crop discrimination.

The best performance of classification with an F1-score of 0.64 was obtained by cotton, followed by other crops (0.58) and sorghum (0.53) (Table 15). Maize attained improved classification accuracy compared to the earlier growth stages classification. Conversely, peanuts, millet, and sesame continued to exhibit comparatively lower performance of classification. Misclassification is also observed at this stage which has been presented in Appendix (Table 55).

The classification map showed clearer field boundaries, smoother spatial patterns, and improved representation of agricultural parcels compared to the early and vegetative stage classification maps (Figure 14).

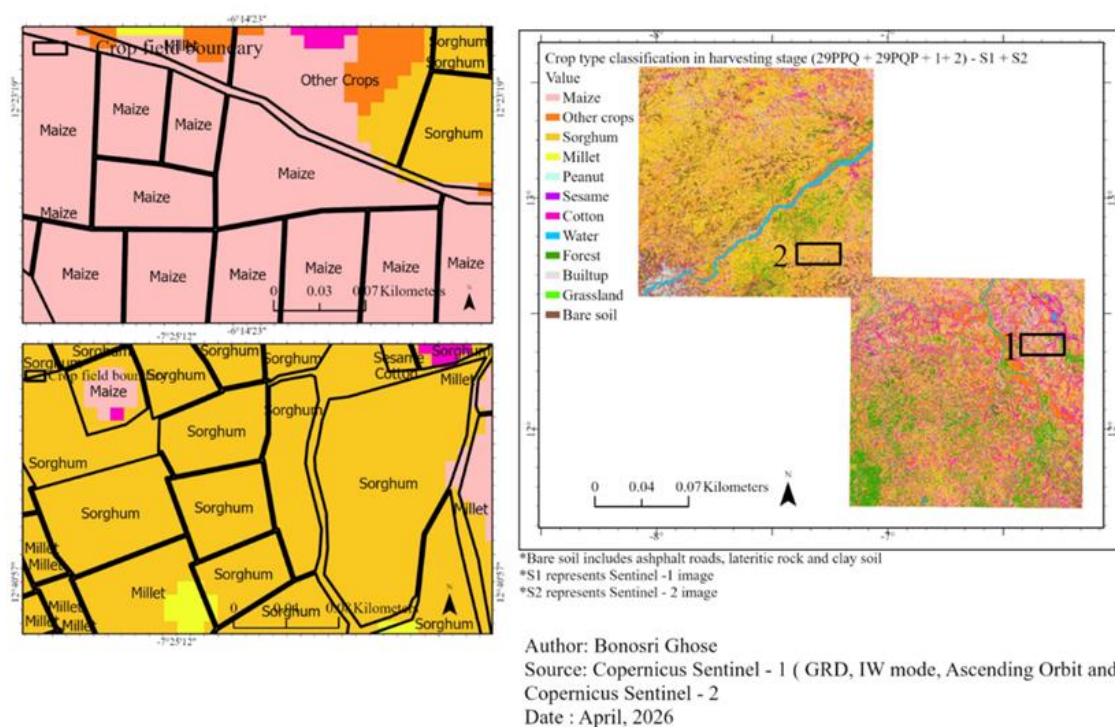


Figure 14: Classification map of harvesting stage

Table 15: Classification report on harvesting stage

Harvesting stage				
Crop Types	Validation (%)	Recall	Precision	F1- score
Maize	15.05	0.50	0.39	0.44
Peanut	4.18	0.05	0.24	0.09
Cotton	18.24	0.71	0.58	0.64
Sorghum	19.33	0.65	0.45	0.53
Millet	6.61	0.15	0.50	0.24
Sesame	4.96	0.10	0.37	0.16
Other crops	17.49	0.57	0.59	0.58
Water	6.21	0.94	0.97	0.96
Forest	1.93	0.60	0.78	0.68
Built up	0.39	0.24	0.71	0.36
Grassland	2.91	0.03	0.83	0.06
Bare soil	2.71	0.48	0.84	0.61
Overall accuracy	0.53			

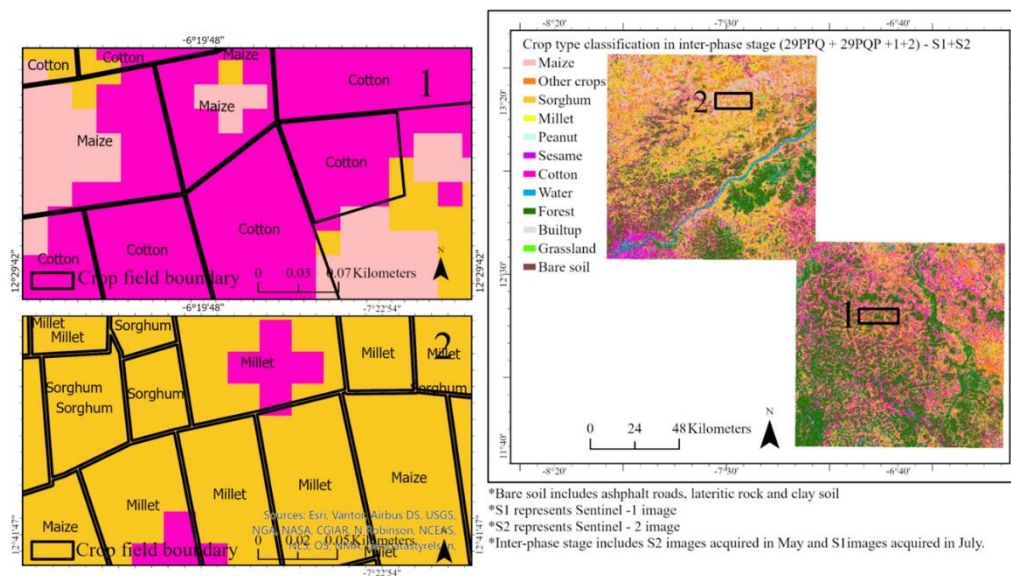
6.4.4 Inter-Phase Analysis

To assess the contribution of integrating Sentinel-2 observations from the early growing phase with Sentinel-1 radar observations collected during the cloudy vegetative stage, the inter-phase analysis was conducted. Two inter-phase combinations were evaluated: May from Sentinel-2 with July from Sentinel-1, and June from Sentinel-2 with August from Sentinel-1.

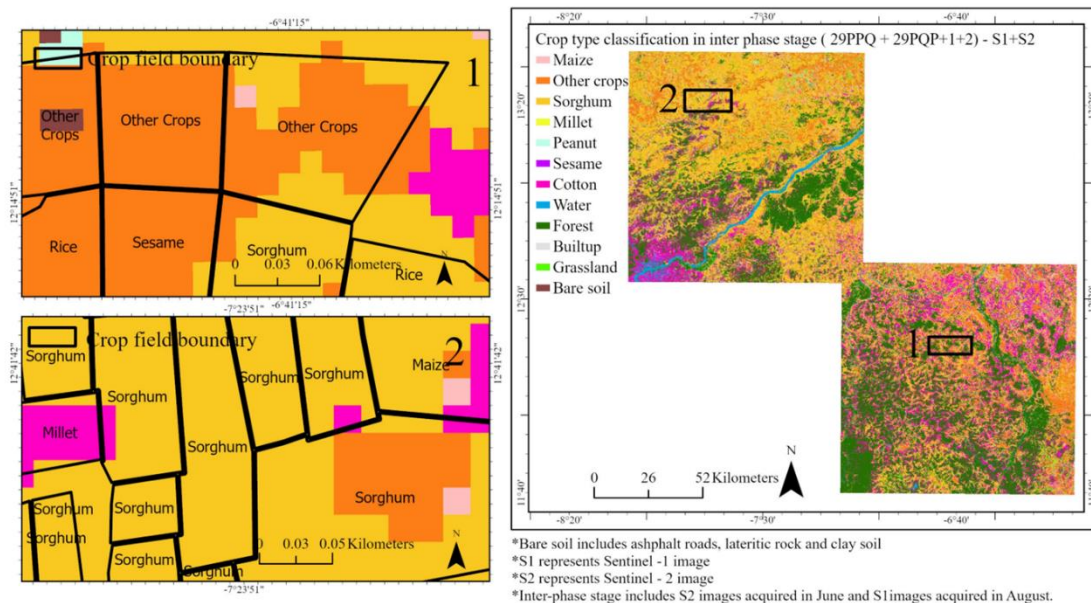
The May–July inter-phase classification achieved an overall accuracy of 0.36, while slightly higher overall accuracy (0.40) produced by the June–August inter-phase stage (Table 16). The classification maps (Figure 15) exhibited moderate crop separability capability and enhanced spatial consistency compared to the vegetative-stage classification based merely on Sentinel-1 observations.

Cotton, sorghum, and other crops exhibited relatively better classification accuracy in both inter-phase integrations. Slightly improved F1-scores obtained by the June–August combination for most major crop classes, specifically sorghum (0.42), cotton (0.41), and other crops (0.48), highlighting that the combination of later Sentinel-2 observations emphasized crop discrimination (Table 16). Conversely, peanut, millet, and sesame continued to show relatively weaker classification performance due to similarities in crop traits and weak separability in intermediate growth stages.

The findings of the inter-phase analysis are that integrations optical observations from the early season with radar observations from cloudy periods enhanced classification accuracy compared to the vegetative-stage classification alone. Nonetheless, the classification performance was lower than the harvest-stage classification performance, stating that late-season phenological characteristics supported the significant crop discrimination capability across the study area.



Author: Bonosri Ghose
 Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit and Copernicus Sentinel - 2
 Date : May, 2026



Author: Bonosri Ghose
 Source: Copernicus Sentinel - 1 (GRD, IW mode, Ascending Orbit and Copernicus Sentinel - 2
 Date : May, 2026

Figure 15: Classification maps of inter-phase stage. *The upper panel shows Inter phase stage (May S2 + July S1) and the down panel shows Inter phase stage (June S2 + August S1)*

Table 16: Classification report of interphase stage

Crop Types	Inter phase stage (May S2 + July S1)				Inter phase stage (June S2 + August S1)			
	Validation (%)	Recall	Precision	F1-score	Validation (%)	Recall	Precision	F1-score
Maize	12.19	0.35	0.2	0.26	12.18	0.36	0.21	0.27
Peanut	5.03	0.02	0.1	0.03	5.02	0	0.04	0.01
Cotton	18.63	0.41	0.3	0.35	18.61	0.45	0.37	0.41
Sorghum	19.32	0.46	0.32	0.38	19.30	0.54	0.34	0.42
Millet	5.70	0.06	0.3	0.1	5.69	0.03	0.18	0.05
Sesame	5.75	0.01	0.33	0.02	5.74	0.01	0.4	0.02
Other crops	18.88	0.36	0.5	0.42	18.86	0.42	0.55	0.48
Water	5.77	0.87	0.92	0.89	5.87	0.91	0.91	0.91
Forest	1.93	0.62	0.56	0.59	1.93	0.69	0.61	0.65
Built up	0.54	0.18	0.8	0.3	0.54	0.09	0.5	0.15
Grassland	3.64	0.08	0.92	0.15	3.64	0.06	0.56	0.11
Bare soil	2.63	0.57	0.57	0.57	2.62	0.49	0.79	0.6
Overall Accuracy		0.36				0.40		

6.5 Feature Importance Analysis

To understand the impact of different variables to crop classification performance further, feature importance analysis was performed employing the best-performing classification technique. The importance of different features was analyzed based on 2,588 agricultural field polygons, including 413 maize polygons, 141 peanut polygons, 533 cotton polygons, 601 sorghum polygons, 206 millet polygons, 154 sesame polygons, and 540 polygons representing other crop classes. This part describes the relative importance of Sentinel-1 SAR features, Sentinel-2 spectral features, temporal variables as well as textural features across different crop growth phases and inter-phase classifications. The output of this section aid to detect the most influential variables contributing to crop separation throughout the growing season.

6.5.1 Early Season

Figure 16 showed the strongest contribution was by Sentinel-2 features to the classification process, representing approximately 87% of the total feature importance, whereas Sentinel-1 SAR features contributed around 13%. The most significant variables were Sentinel-2 vegetation indices such as NDVI, NDMI, and NDRE, along with different texture features obtained from Bands 8, 11, and 12.

Furthermore, the result of feature class analysis demonstrated that textural features had the strongest contribution (40.3%), followed by spectral features (27.4%), temporal features (19.3%), and SAR features (13.0%) (Figure 17).

Overall, the early season analysis found out that Sentinel-2 optical and texture-based features played the notable role in crop type separation in the early growth stage, while complementary structural information was provided by Sentinel-1 SAR observations.

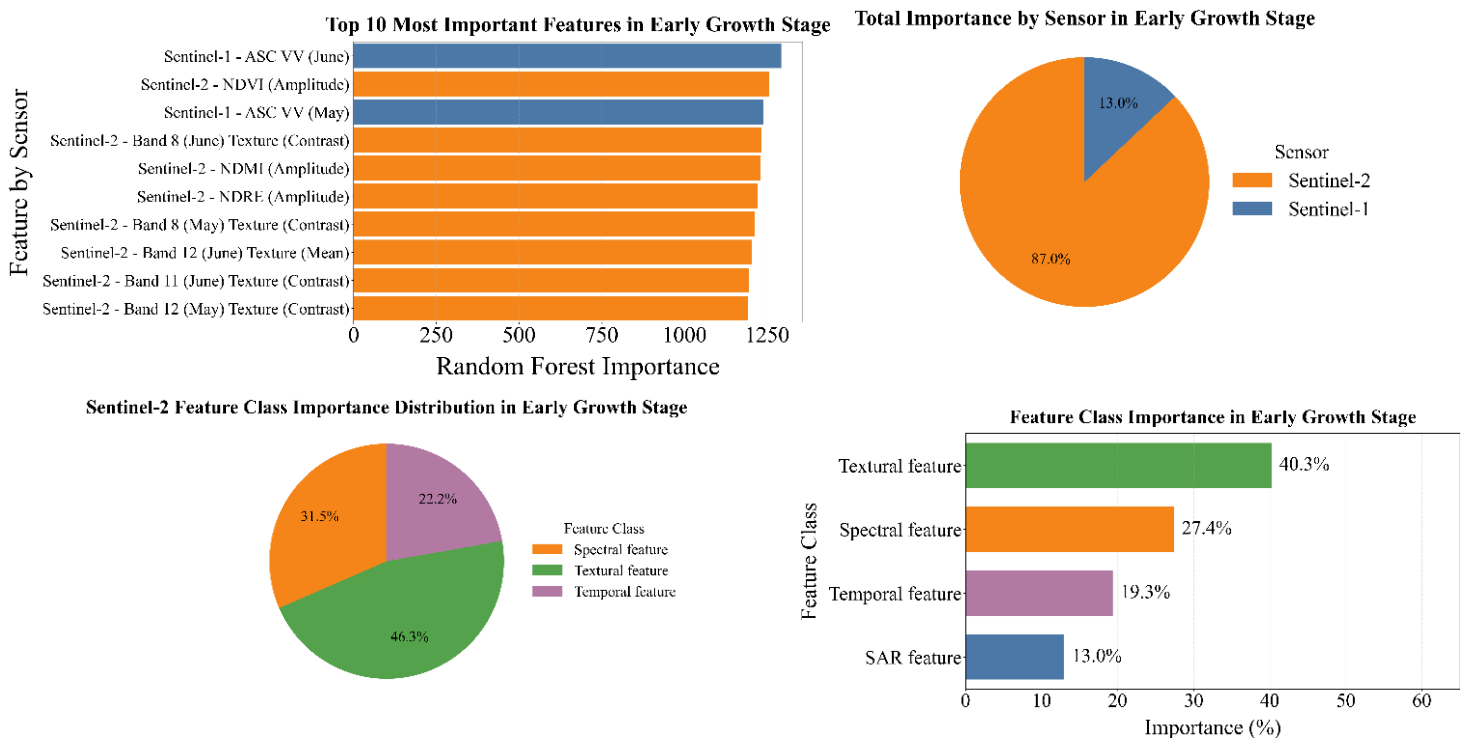


Figure 16: Bar charts and Pie charts of feature importance analysis in early growth stage

6.5.2 Vegetative stage

The analysis of feature importance for the vegetative and development stage (Figure 17) showed that due to lack of cloud-free Sentinel-2 observations during this period, Sentinel-1 radar-derived variables played a significant role in crop classification.

VV backscatter, VV/VH ratio, and VH backscatter played strong roles in the classification process among the radar variables. The most important variables during this stage were texture-based SAR features, particularly GLCM homogeneity and GLCM contrast. Local mean as well as local standard deviation features also demonstrated comparatively high contributions, while GLCM entropy showed comparatively weak importance (Figure 17).

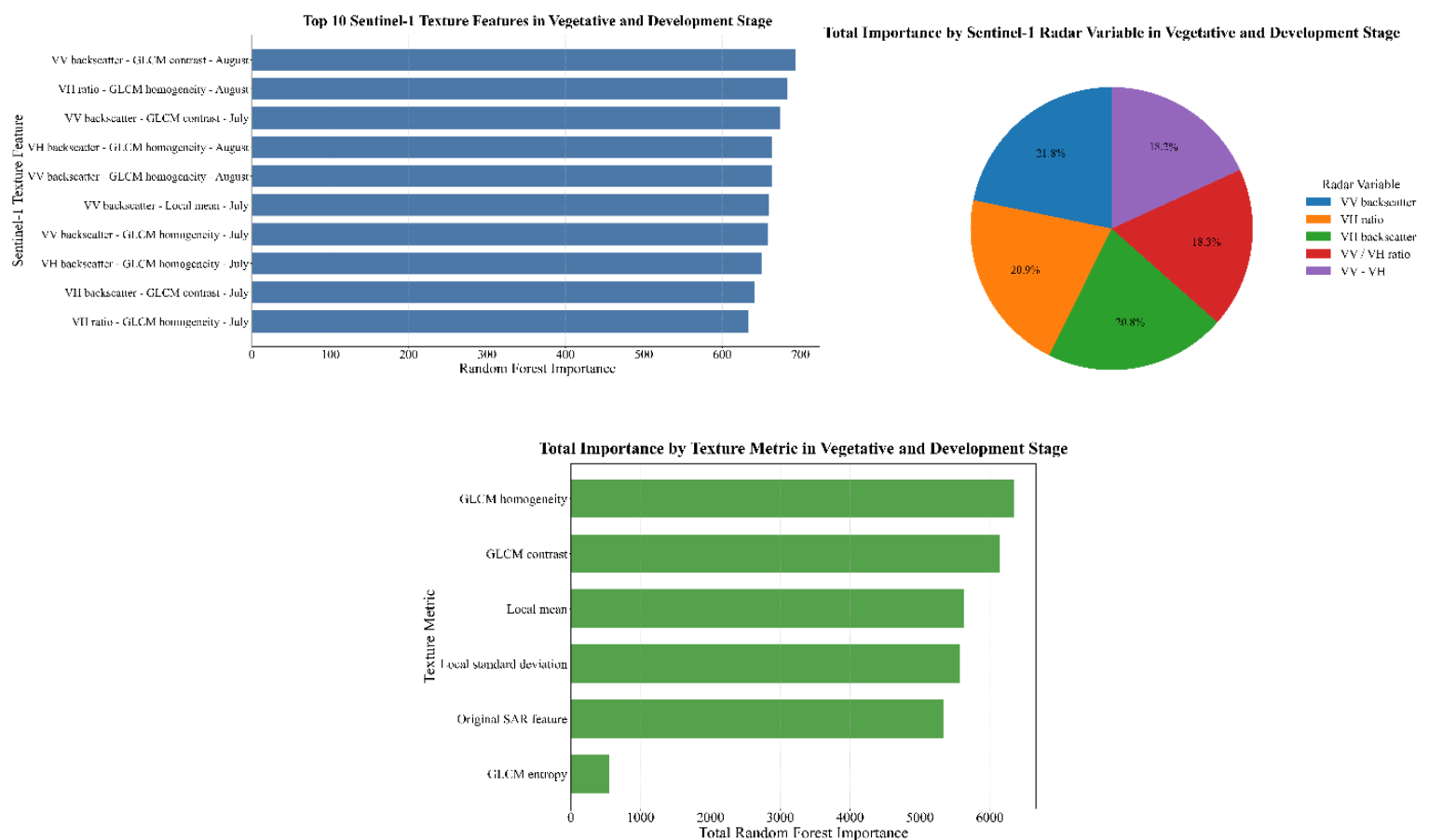


Figure 17: Bar charts and Pie charts of feature importance analysis in vegetative and development stage

6.5.3 Harvest Stage

For this stage, feature importance result showed that optical variables contributed more strongly than SAR variables. Sentinel-2 contributed approximately 81.6% of the total importance, while Sentinel-1 was about 18.4% (Figure 18).

Among the strongest important variables, Sentinel-2 texture features generated from Band 8, 11, and 12 in October and November demonstrated high importance values. Spectral indices such as NDRE also played role significantly. Sentinel-1 VV and VH backscatter features from

September and October were notable, but the contribution was lower compared to optical features.

The feature class analysis found out that textural features had the strongest overall contribution (37.3%), followed by spectral features (26.3%). SAR features as well as temporal features contributed 18.4% and 18.1%, respectively (Figure 18).

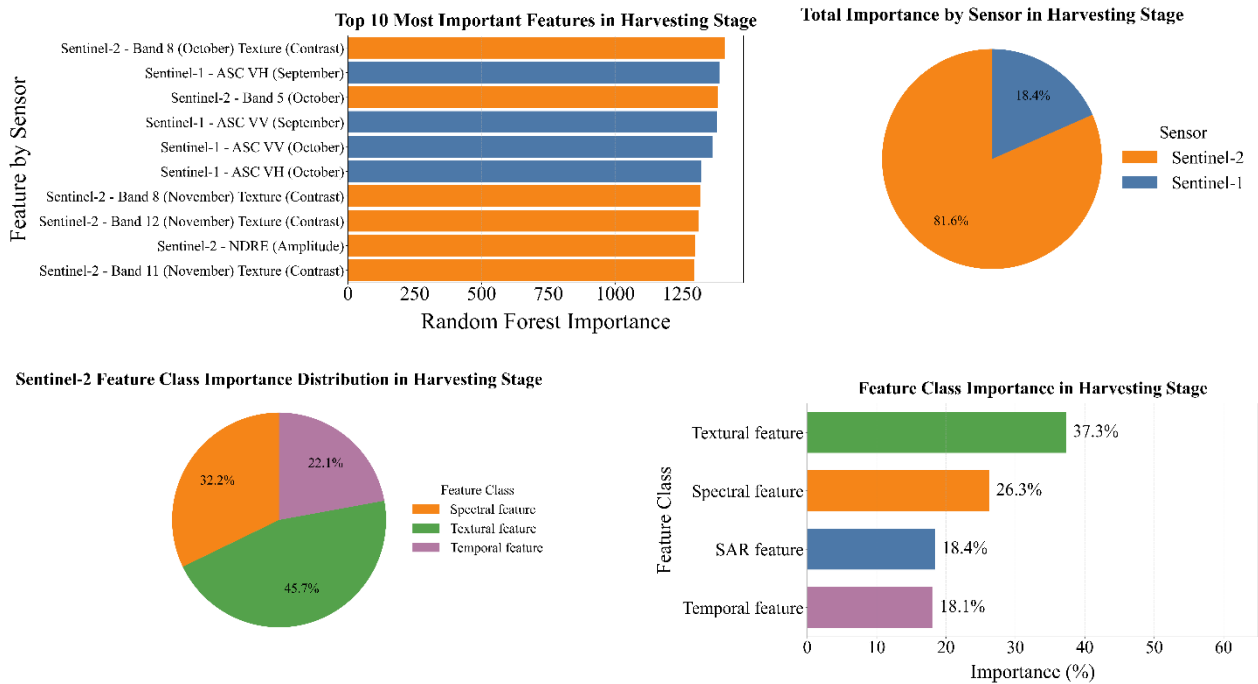


Figure 18: Bar charts and Pie charts of feature importance analysis in harvesting stage

6.5.4 Inter-Phase stage

Sentinel-2 variables contributed the strongest importance, representing approximately 82% of the total contribution, while Sentinel-1 SAR variables contributed around 18% in the feature importance analysis on interphase stage (Figure 19, 20).

Sentinel-2 NDVI, Band 12, Band 11, Band 8A, and Band 6 features from May and June were dominant among the most important features, VH, and VH ratio variables from Sentinel -1 from July and August also showed among the top-ranked features, stating that the significance of integrating optical and SAR information (Figure 19, 20).

The distribution of feature class exhibited that spectral features had the most significant contribution (about 36%), followed closely by temporal features (about 34%). Around 18% was contributed by SAR features, while textural features showed relatively lower importance, about 12%. Overall, the findings indicate that inter-phase classification notably relied on spectral and temporal differences between crop growth stages, while provided additional complementary information for crop discrimination supported by SAR variables.

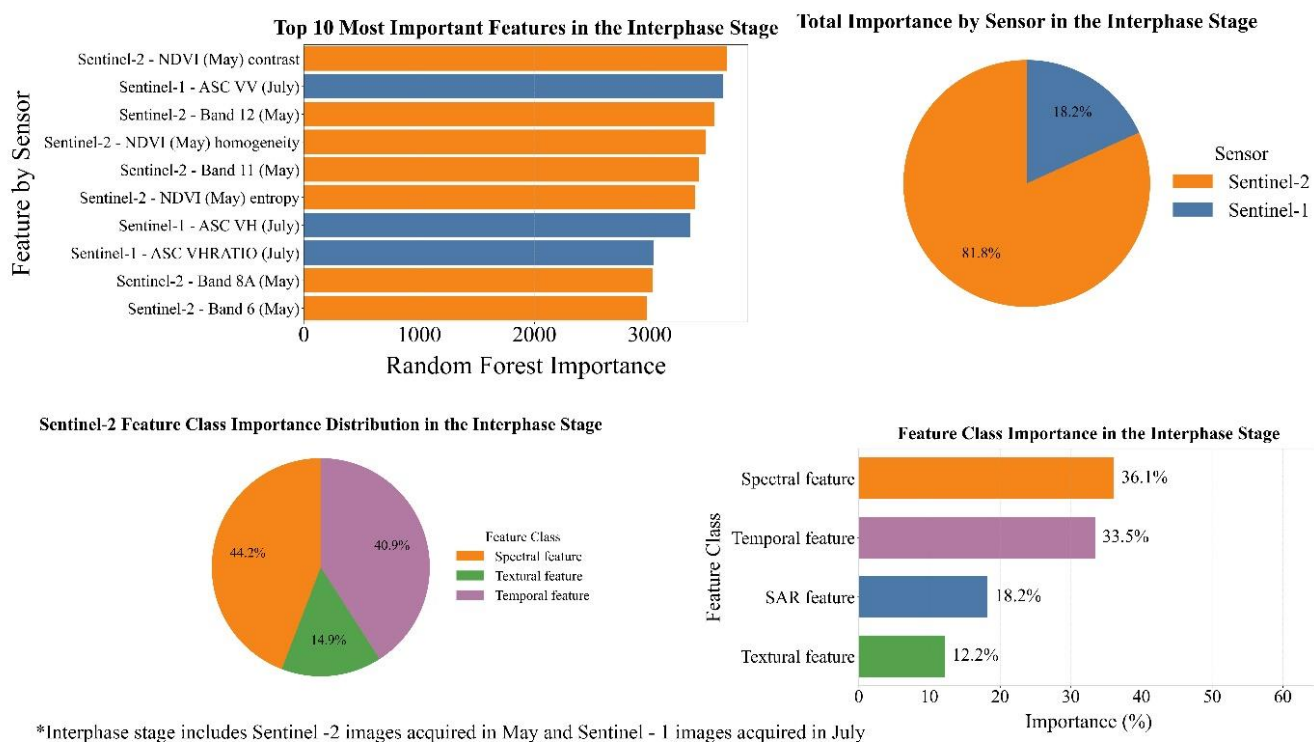


Figure 19: Bar charts and Pie charts of feature importance analysis in inter-phase stage using Sentinel-2 images from May and Sentinel-1 images from July

7. Discussion

The efficiency of Sentinel-1 SAR data, Sentinel-2 optical data, and fused Sentinel-1 and Sentinel-2 datasets for crop type classification within a diverse agricultural field were examined by this study. Various classification strategies were assessed, incorporating independent tile-based classification, combined tile-based classification, temporal growth-stage classification, inter-phase analysis, and feature importance analysis. The findings dismantled that significant disparities in classification performance rely on the sensor type, temporal phase, as well as spatial classification framework.

Sentinel-1 SAR data for the independent tile-based classifications generated comparatively poorer overall performances and crop-wise F1-scores than classifications using Sentinel-2 optical imagery. Difficulty exhibited in Sentinel-1 classifications in discriminating crop classes such as peanut, sesame, millet, and tomato. This is probably due to similar canopy structures and moisture conditions during the adopted acquisition periods, resulting overlapping SAR backscatter responses. The result of previous research work analogous with this observation . They have stated that SAR-only crop classification might be not be sufficient while crop structural traits are not adequately distinct, particularly in fragmented agricultural systems (Veloso et al., 2017; Nasrallah et al., 2018). However, radar performed relatively well for water and forest classes, achieving consistently high recall and precision values. This result indicates the SAR backscatter sensitivity to moisture conditions and surface roughness.

Better crop type classification was obtained by using Sentinel-2 than Sentinel-1 classifications. Crops such as cotton, sorghum, rice, and maize achieved relatively stronger recall, precision, and F1-scores in different tile-based frameworks. The significant performance of Sentinel-2 is probably associated with the contribution of spectral reflectance information as well as vegetation-sensitive indices, which are efficient for discriminating crop phenology and canopy conditions. Belgiu and Csillik (2018) and Van Tricht et al. (2018) have shown that optical data from Sentinel-2, especially vegetation indices and red-edge bands, are notably suitable for crop classification since they extract chlorophyll content, canopy vigor, and phenological variation.

Several crop types still demonstrated moderate or low classification performance although Sentinel-2 had improved performance. Peanut, sesame, millet, and okra steadily got lower F1-scores across various experiments. This perhaps be related with narrow agricultural field sizes, class imbalance in validation samples, mixed pixels, and spectral similarity among crop classes. Smallholder farming systems contain irregular distributed and fields that rise within-class variability and lessen discrimination between crop types. Similar challenges have been obtained in crop mapping researches which conducted in heterogeneous agricultural fields across Africa and Asia (Kussul et al., 2017; Zhong et al., 2019).

The fusion of Sentinel-1 and Sentinel-2 observation considerably elevated classification accuracy in most classification accuracy. Fused independent and combined tile-based experiments generated higher overall performances and less imbalanced crop-wise performance than single-sensor frameworks. Overall, the integrated combined tile-based classification experiment yielded the strongest and most stable performance . This result conveys the information regarding complementary relationship between optical and SAR

observations. Spectral and phenological information are provided by Sentinel-2, whereas Sentinel-1 supported structural and moisture-related insight that enhanced discrimination among spectrally similar crops. Aduvukha et al. (2021), Van Tricht et al. (2018), and Fage Ibrahim et al. (2023) got the similar findings where they have revealed that optical–SAR fusion improved crop mapping accuracy compared to individual sensors only.

However, peanut and sesame continuously yielded low recall and F1-scores even in fused experiments. This indicated that further temporal observations or higher spatial resolution data might be essential to emphasize separability for these crop classes. Nevertheless, the fused classifications achieved more balanced crop-wise outputs compared to independent tile-based models, representing stronger spatial generalization as well as robustness across heterogeneous tiles.

The analysis of temporal classification dismantled the remarkable disparities in crop discrimination in different growth stages. Relatively low overall accuracy was produced by early-season classification. Many crops are still developing initial canopy structures in this stage. As a result, similar spectral and SAR responses across crop types, leading to reduced crop separability at this stage. Relatively better performed crops were sorghum and cotton than peanut and millet during the early phase. Early-season crop classification is challenging due to immature vegetation signatures and strongly similarities among crop types found out by Zhong et al. (2019).

Moderate performance produced by the vegetative and development stage classification. Sorghum, maize, and cotton had better stable classification performance, while peanut, sesame, and millet consistently showed low F1-scores. The lower performance may also reflect differences in planting dates and crop management practices among farmers within the study area in this stage. In smallholder systems, reduced temporal consistency and increased spectral variability within crop classes are the result of asynchronous planting and heterogeneous crop development.

Harvesting stage produced the best crop classification performance among all growing stages. There was clear improvements in recall, precision, and F1-score values during harvesting for cotton, sorghum, millet, and other crops. This might be because of association with stronger phenological contrast between crops about to be matured and harvested. During this period, crops showed more distinguishable canopy structures, moisture conditions, and senescence traits, resulting improved spectral and SAR separability. This finding is in line with Pelletier et al. (2016) and Veloso et al. (2017). They have reported that late-season imagery often provides significant crop discrimination in order to enhanced phenological divergence among crop classes.

Furthermore, inter-phase analysis demonstrated the necessity of integrating imagery from different growth periods. Inter-phase experiments incorporating Sentinel-2 imagery from earlier months with Sentinel-1 imagery from later months gained increased overall performance compared to several single-stage classifications, explaining that combining temporal information across crop growth stages can emphasize crop discrimination by detecting complementary phenological conditions.

Additional insight provided by feature importance analysis into the contribution of different variables and sensors. Sentinel-2 features contributed the majority of total importance, often surpassed 80% of total feature contribution across most experiments. Especially, during the harvesting stage, consistent strong importance values demonstrated by spectral features and textural features. Sentinel-2 bands 8, 11, and 12 derived vegetation indices NDVI, NDRE, and NDMI, along with textural metrics which were among the most significant variables. Crop canopy structure, moisture status, and phenological development are likely captured by these features

Important complementary information also contributed by Sentinel-1 SAR variables, particularly by VV, VH, and VH ratio features. SAR variables were useful especially when fused with temporal and textural information. Analogous output was achieved by Felegari et al. (2021) and Nasrallah et al. (2018). Their study emphasized the value of integrating SAR backscatter and optical vegetation information for agricultural monitoring.

Particularly, textural features demonstrated significant importance during harvesting-stage classifications, indicating that crop canopy heterogeneity becomes gradually important near crop maturity. Inter-phase analyses also influenced by texture features. Indicating that crop phenology provides a critical role in enhancing crop discrimination. These findings supported by Pelletier et al. (2016). They emphasized the importance of multi-temporal and texture-based methods for agricultural classification in heterogeneous landscapes.

Overall, the fused Sentinel-1 and Sentinel-2 classifications combined with temporal analysis derived a more reliable framework for crop type mapping than single-sensor frameworks. The combined tile-based fused classification obtained the best balance between overall accuracy and class-wise consistency, indicating the most suitable approach for further agricultural monitoring and crop inventory applications within the study area. Moreover, this study also exhibits the necessity of considering temporal growth stages, feature selection, and spatial heterogeneity when improving crop classification frameworks for smallholder farming systems.

7.1 Limitations of the Study

The results of this study should be interpreted with some limitations. To begin with, crop types such as peanut, sesame, okra, and rice had relatively small number of sample size in contrast to major crops such as sorghum, cotton, and maize. This imbalance class decreased classification reliability and decreased the F1-scores for minority crop types. Secondly, Sentinel-1 and Sentinel-2 spatial resolution might not entirely detect the complexity of fragmented smallholder agricultural fields. Overlap of mixed pixels and field boundary probably contributed to confusion among spectrally similar crops. Thirdly, cloud cover as well as temporal irregularity in Sentinel-2 imagery might have affected spectral feature quality during some growth stages. Despite Sentinel-1 data lessening this limitation through all-weather capability, there was weaker crop discrimination shown by SAR-only classifications. Finally, the temporal availability of imagery was another crucial limitation of this study. The dates of image acquisition probably do not accurately represent all phenological transitions for every crop type across the study area.

7.2 Recommendations for Future Work

According to the results of this study, future research should focus on incorporating denser multi-temporal image series which will cover the entire crop calendar. The combination of higher spatial resolution datasets, for instance PlanetScope or UAV imagery, might further improve separation of small and fragmented agricultural fields. In contrast to traditional Random Forest classification, Convolutional Neural Networks (CNNs) and Tree-based techniques may also emphasize spatial and temporal feature extraction. However, field management and social context related information, such as sowing dates, irrigation systems, and crop calendars, may assist increasing classification consistency for minorities as well as spectrally similar crop classes.

Overall, future work should consider developing generalized spatial patterns, temporal modelling and classification strength for heterogeneous smallholder agricultural systems.

8. Conclusion

This research work investigated the applicability of Sentinel-1 SAR data, Sentinel-2 optical data, and fused Sentinel-1 and Sentinel-2 datasets for crop type classification in a spatially diverse agricultural landscape. Various classification frameworks were examined, for instance independent tile-based classification, combined tile-based classification, fused sensor classification, temporal growth-stage classification, and inter-phase analysis.

The results explored that usually Sentinel-2 optical data generated better crop discrimination than Sentinel-1 SAR data for the significant influence of spectral and vegetation-related information. However, structural and moisture-related information supported by Sentinel-1 improved classification performance when fused with Sentinel-2.

Among all examined methods, the fused Sentinel-1 and Sentinel-2 classifications steadily yielded stronger accuracies and more stable class-wise performance in contrast to single-sensor classifications. Specifically, the approach of combined tile-based fused classification attained the best balance between overall accuracy (0.57) and crop-wise consistency (0.49), highlighting its effectiveness for crop mapping in spatially dispersed agricultural systems.

Further, temporal analysis exhibited that crop classification accuracy differed significantly across crop growth stages. Lower accuracies produced by early-season and vegetative-stage classifications because of crop spectral and structural characteristics were still alike during these stages. On the other hand, the best results produced in harvesting-stage classification (0.53) while cotton achieved highest F1-score 0.64 since crop maturity as well as harvesting traits elevated phenological discrimination among crop types.

Combining information from different growth periods enhanced classification consistency compared to single-stage methods was revealed by inter-phase analysis. The feature importance investigation also stated that textural (37.3% - 40.3%) and spectral variables (26.3% - 27.4%) influenced most notably to classification performance, whereas SAR variables supported pivotal complementary information. During the harvesting stage, textural features (37.3%) remained specifically important.

Despite several crop types such as peanut, sesame, and millet becoming challenging to separate due to spectral similarity and limited number of validations, the overall results ensure the significance of integrating multi-source and multi-temporal remote sensing data for crop type mapping.

Overall, fused Sentinel-1 and Sentinel-2 datasets, combined with temporal analysis and tile-based classification approaches, can remarkably enhance crop classification performance in heterogeneous smallholder agricultural systems. The improved framework supports effective groundwork for crop distribution mapping, future agricultural monitoring, and food security applications in similar environments.

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Appendix

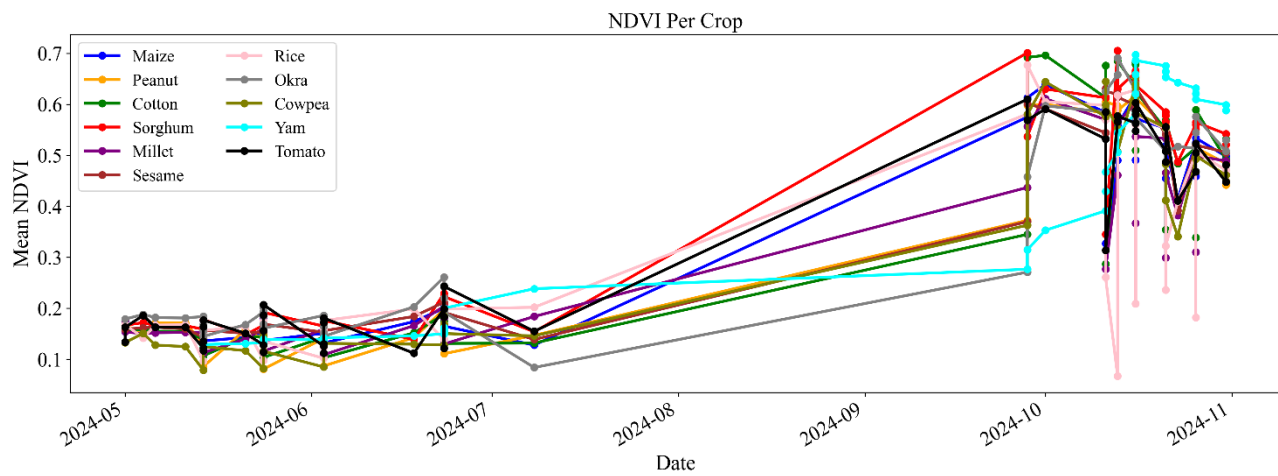


Figure 20: Mean NDVI temporal profiles averaged across AFS polygons for each crop type

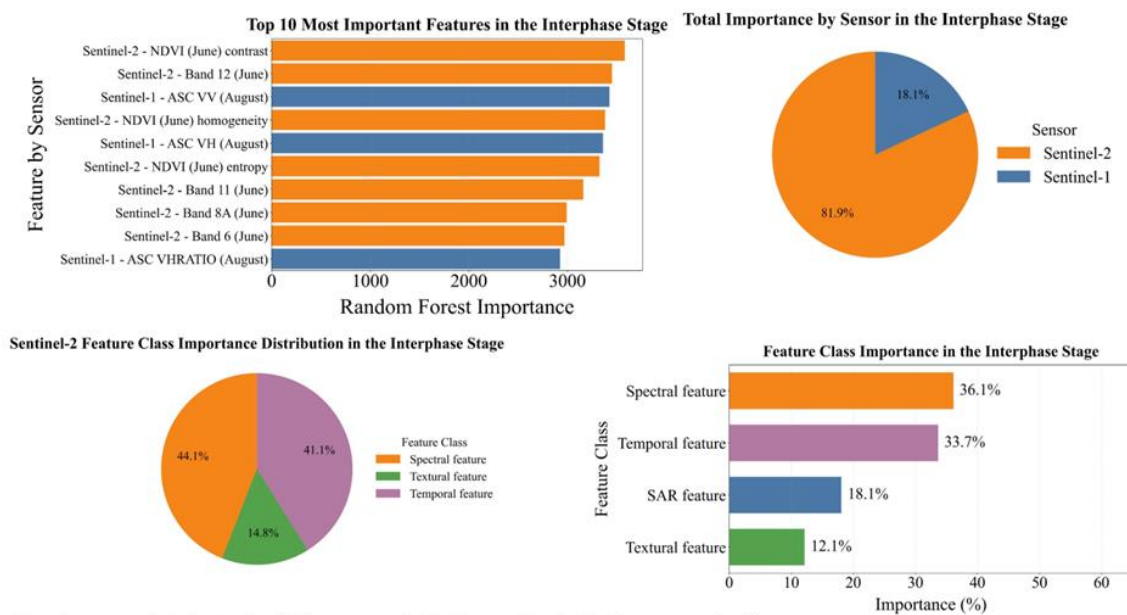


Figure 21: Bar charts and Pie charts of feature importance analysis in inter-phase stage using Sentinel -2 images from June and Sentinel-1 images from August

Table 17: Total samples for classification for independent tiles using Sentinel-1 images

S1			
Dataset	Tile: 1		Tile: 2
	Number of Samples		Number of Samples
Training	14,320		20,813
Validation	6,138		8,920
Total	20,458		29,733

Table 18: Total samples per crop for independent tiles using Sentinel-1 images

S1						
Crop Types	Tile: 1 - Samples			Tile: 2-Samples		
	Training	Validation	Total	Training	Validation	Total
Maize	2249	964	3213	2333	1000	3333
Peanut	189	81	270	1741	746	2487
Cotton	1479	634	2113	2333	1000	3333
Sorghum	2800	1200	4000	2333	1000	3333
Millet	1743	747	2490	2028	869	2897
Sesame	879	377	1256	2102	901	3003
Rice	9	4	13	2333	1000	3333
Okra	175	75	250	614	263	877
Tomato	2380	1020	3400	2119	908	3027
Water	1139	488	1627	1811	776	2587
Forest	828	355	1183	275	118	393
Built up	21	9	30	30	13	43
Grassland	240	103	343	383	164	547
Bare soil	189	81	270	378	162	540

Table 19: Error metrics for independent tiles using Sentinel-1 images

S1				
Crop Types	Tile:1		Tile: 2	
	Omission Error	Commission Error	Omission Error	Commission Error
Maize	0.56	0.63	0.66	0.69
Peanut	0.84	0.75	0.71	0.81
Cotton	0.24	0.52	0.45	0.67
Sorghum	0.59	0.57	0.92	0.83
Millet	0.65	0.73	0.77	0.76
Sesame	0.84	0.82	0.71	0.69
Rice	1.00	1.00	0.32	0.43
Okra	1.00	1.00	1.00	1.00
Tomato	0.81	0.72	0.81	0.73
Water	0.11	0.00	0.05	0.02
Forest	0.45	0.36	0.31	0.38
Built up	0.78	0.33	1.00	1.00
Grassland	1.00	1.00	0.87	0.71
Bare soil	0.90	0.76	0.88	0.78

Table 20: Confusion metrics for independent tile (Tile 1) using sentinel-1 images

Tile:1 - S1															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	427	1	144	110	179	14	0	0	89	0	0	0	0	0	964
Peanut	28	13	18	2	7	4	0	0	9	0	0	0	0	0	81
Cotton	86	0	479	39	2	21	0	0	6	0	1	0	0	0	634
Sorghum	200	28	138	495	161	61	0	0	113	0	4	0	0	0	1200
Millet	198	0	96	114	264	29	0	0	43	0	2	1	0	0	747
Sesame	16	3	30	118	109	62	0	0	39	0	0	0	0	0	377
Rice	0	2	0	0	0	2	0	0	0	0	0	0	0	0	4
Okra	11	0	8	9	32	6	0	0	9	0	0	0	0	0	75
Tomato	178	2	87	226	212	124	0	0	191	0	0	0	0	0	1020
Water	0	0	0	0	0	2	0	0	6	432	48	0	0	0	488
Forest	1	0	0	17	5	9	0	0	104	0	196	0	0	23	355
Built up	1	0	0	4	0	1	0	0	1	0	0	2	0	0	9
Grassland	4	3	8	12	2	6	0	0	50	0	15	0	0	3	103
Bare soil	0	0	0	7	4	2	0	0	19	0	41	0	0	8	81
Total	1150	52	1008	1153	977	343	0	0	679	432	307	3	0	34	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S1* represents Sentinel - 1

Table 21: Confusion metrics for independent tile (Tile 2) using sentinel-1 images

Tile: 2 – S1															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	336	94	281	57	108	28	42	3	31	0	6	0	12	2	1000
Peanut	123	215	116	44	74	61	33	0	64	0	2	0	6	8	746
Cotton	132	94	547	58	81	23	23	1	32	0	2	0	6	1	1000
Sorghum	141	155	212	77	117	128	88	6	62	6	1	0	4	3	1000
Millet	153	127	115	99	201	70	31	0	55	0	8	0	4	6	869
Sesame	76	124	90	42	81	257	103	1	113	0	0	0	13	1	901
Rice	35	53	68	25	48	50	682	0	31	1	2	0	0	5	1000
Okra	13	76	36	22	22	29	31	0	31	2	0	0	1	0	263
Tomato	70	107	156	20	90	131	122	2	173	1	7	0	5	24	908
Water	6	3	12	0	0	0	0	0	0	740	9	0	0	6	776
Forest	0	6	12	1	1	5	1	0	0	0	82	0	0	10	118
Built up	0	4	2	0	1	3	1	0	0	0	1	0	0	1	13
Grassland	10	16	32	4	5	28	23	0	14	0	10	0	22	0	164
Bare soil	3	41	1	15	7	10	17	0	41	3	2	0	3	19	162
Total	1098	1115	1680	464	836	823	1197	13	647	753	132	0	76	86	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S1* represents Sentinel - 1

Table 22: Total samples for classification for independent tiles using Sentinel-2 images

S2		
Dataset	Tile: 29PPQ Number of Samples	Tile: 29PQP Number of Samples
Training	21718	34,011
Validation	9308	14,718
Total	31026	48,729

Table 23: Total samples per crop for classification for independent tiles using Sentinel-1 images

S2						
Crop Types	Tile 29PPQ - Samples			Tile 29PQP-Samples		
	Training	Validation	Total	Training	Validation	Total
Maize	2646	1134	3780	5208	2232	7440
Peanut	394	169	563	1762	755	2517
Cotton	1902	815	2717	7420	3180	10600
Sorghum	7058	3025	10083	5260	2254	7514
Millet	2284	979	3263	2198	942	3140
Sesame	1059	454	1513	1888	809	2697
Rice	75	32	107	4240	1817	6057
Okra	231	99	330	551	236	787
Tomato	2996	1284	4280	1885	808	2693
Water	2592	1111	3703	1064	456	1520
Forest	238	102	340	250	107	357
Built up	37	16	53	23	10	33
Grassland	33	14	47	110	47	157
Bare soil	173	74	247	152	65	217

Table 24: Error metrics for independent tiles using Sentinel-2 images

S2				
Crop Types	Tile: 29PPQ		Tile: 29PQP	
	Omission Error	Commission Error	Omission Error	Commission Error
Maize	0.66	0.43	0.48	0.62
Peanut	0.94	0.6	0.86	0.59
Cotton	0.41	0.53	0.26	0.43
Sorghum	0.16	0.48	0.44	0.54
Millet	0.63	0.29	0.69	0.37
Sesame	0.81	0.44	0.78	0.51
Rice	1	1	0.27	0.18
Okra	1	1	0.89	0.39
Tomato	0.65	0.38	0.84	0.67
Water	0.01	0	0.01	0
Forest	0.4	0.74	0.44	0.09
Built up	0.69	0.75	0.7	0
Grassland	1	1	1	1
Bare soil	0.81	0.44	0.51	0.51

Table 25: Confusion metrics for independent tiles (Tile 29PPQ) using sentinel-2 images

Tiles:29PPQ - S2															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	381	1	58	617	14	1	13	0	46	0	2	0	0	1	1134
Peanut	3	10	64	80	0	0	0	0	12	0	0	0	0	0	169
Cotton	30	0	482	260	3	18	0	0	19	0	3	0	0	0	815
Sorghum	107	4	246	2554	48	25	0	0	41	0	0	0	0	0	3025
Millet	46	0	22	513	361	11	0	0	26	0	0	0	0	0	979
Sesame	19	0	75	249	8	85	0	0	18	0	0	0	0	0	454
Rice	0	2	0	21	0	0	0	0	9	0	0	0	0	0	32
Okra	0	0	0	53	5	0	0	0	41	0	0	0	0	0	99
Tomato	73	8	75	528	63	9	0	2	451	0	56	13	0	6	1284
Water	0	0	1	6	1	0	0	0	1	1095	7	0	0	0	1111
Forest	2	0	9	0	0	0	0	0	29	0	61	0	0	1	102
Built up	2	0	0	1	2	0	0	0	3	0	0	5	0	3	16
Grassland	0	0	0	9	4	4	0	0	30	0	63	0	0	0	110
Bare soil	0	0	1	12	0	0	0	0	4	0	41	2	0	14	74
Total	663	25	1033	4903	509	153	13	2	730	1095	233	20	0	25	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel - 2

Table 26: Confusion metrics for independent tiles (Tile 29PQP) using sentinel-2 images

Tiles:29PQP - S2															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	1158	33	577	351	25	4	70	0	14	0	0	0	0	0	2232
Peanut	202	106	176	109	31	70	10	13	38	0	0	0	0	0	755
Cotton	410	19	2367	230	59	33	33	2	26	1	0	0	0	0	3180
Sorghum	463	4	318	1271	41	25	69	0	63	0	0	0	0	0	2254
Millet	146	14	110	328	295	10	18	0	21	0	0	0	0	0	942
Sesame	165	15	233	134	9	177	23	2	51	0	0	0	0	0	809
Rice	179	12	79	146	1	17	1335	0	48	0	0	0	0	0	1817
Okra	68	24	52	51	1	2	2	27	9	0	0	0	0	0	236
Tomato	191	28	210	151	9	22	66	0	131	0	0	0	0	0	808
Water	0	0	3	0	0	0	3	0	0	450	0	0	0	0	456
Forest	15	0	0	0	0	0	0	0	0	0	60	0	0	32	107
Built up	5	0	1	0	0	0	0	0	0	0	0	3	0	1	10
Grassland	18	0	25	4	0	0	0	0	0	0	0	0	0	0	47
Bare soil	16	2	6	0	0	0	3	0	0	0	6	0	0	32	65
Total	3036	257	4157	2775	471	360	1632	44	401	451	66	3	0	65	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel - 2

Table 27: Total samples for classification for combined tiles (Tile 1+2) using Sentinel-1 images

S1	
Dataset	Tile: 1 +2
Number of Samples	
Training	20,061
Validation	8,611
Total	28672

Table 28: Total samples per crop for classification for combined tiles (Tile 1+2) using Sentinel-1 images

S1			
Crop Types	Tile: 1+2 – Number of Samples		
	Training	Validation	Total
Maize	2333	1000	3333
Peanut	2329	998	3327
Cotton	2333	1000	3333
Sorghum	2333	1000	3333
Millet	2333	1000	3333
Sesame	2226	954	3180
Other crops	2333	1000	3333
Water	2333	1000	3333
Forest	476	204	680
Built up	79	34	113
Grassland	516	221	737
Bare soil	467	200	667

Table 29: Error metrics for combined tile (Tile 1+2) using Sentinel-1 images

S1		
Crop Types	Tile 1+2	
	Omission Error	Commission Error
Maize	0.68	0.73
Peanut	0.79	0.77
Cotton	0.5	0.65
Sorghum	0.83	0.77
Millet	0.78	0.76
Sesame	0.65	0.63
Other crops	0.67	0.61
Water	0.04	0.02
Forest	0.18	0.57
Built up	0.88	0.56
Grassland	0.86	0.73
Bare soil	0.73	0.67

Table 30: Confusion metrics for combined tiles (Tile 1+2) using sentinel-1 images

Tile:1+2 - S1													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	320	96	235	72	155	49	40	0	18	0	11	4	1000
Peanut	193	209	151	93	109	112	81	0	22	0	16	12	998
Cotton	128	106	503	68	77	54	42	0	9	0	10	3	1000
Sorghum	134	99	178	175	158	115	101	0	17	0	10	13	1000
Millet	215	94	147	131	225	71	80	0	19	0	9	9	1000
Sesame	55	130	98	91	88	338	106	0	22	0	9	17	954
Other crops	86	135	94	83	83	130	327	2	22	1	12	25	1000
Water	3	1	4	2	1	1	5	960	10	0	1	12	1000
Forest	2	0	2	2	3	3	3	0	168	4	5	12	204
Built up	0	2	1	1	1	4	7	0	12	4	0	2	34
Grassland	34	8	11	22	34	37	28	3	10	0	31	3	221
Bare soil	4	16	3	12	11	5	17	11	65	0	2	54	200
Total	1174	896	1427	752	945	919	837	976	394	9	116	166	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S1* represents Sentinel – 1, *Other crops include Okra, Rice and Tomato.

Table 31: Total samples for classification for combined tile (Tile 29PPQ+29PQP) using Sentinel-2 images

S2	
Dataset	Tile: 29PPQ +29PQP
	Number of Samples
Training	20061
Validation	8611
Total	28672

Table 32: Total samples per crop for classification for combined tile (Tile 29PPQ+29PQP) using Sentinel-2 images

S2			
Crop Types	Tile: 29PPQ+29PQP –		
	Number of Samples		
	Training	Validation	Total
Maize	2977	1276	4253
Peanut	1078	462	1540
Cotton	3600	1543	5143
Sorghum	4139	1774	5913
Millet	1512	648	2160
Sesame	975	418	1393
Other crops	3761	1612	5373
Water	901	386	1287
Forest	250	107	357
Built up	89	38	127
Grassland	142	61	203
Bare soil	201	86	287

Table 33: Error metrics for combined tile (Tile 29PPQ+29PQP) using Sentinel-2 images

S2			
Crop Types	Tile 29PPQ+29PQP		
	Omission Error	Commission Error	
Maize	0.48	0.61	
Peanut	0.95	0.75	
Cotton	0.33	0.5	
Sorghum	0.41	0.49	
Millet	0.76	0.6	
Sesame	0.79	0.62	
Other crops	0.46	0.37	
Water	0.06	0.01	
Forest	0.33	0.17	
Built up	0.71	0	
Grassland	0.95	0.4	
Bare soil	0.36	0.21	

Table 34: Confusion metrics for combined tiles (Tile 29PPQ+29PQP) using sentinel-2 images

Tile: 29PPQ + 29PQP – S2													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	663	10	230	211	31	13	115	0	1	0	0	2	1276
Peanut	144	22	130	87	19	23	36	0	1	0	0	0	462
Cotton	219	8	1031	150	43	15	77	0	0	0	0	0	1543
Sorghum	242	6	248	1039	93	24	118	0	3	0	0	1	1774
Millet	128	10	100	208	154	16	32	0	0	0	0	0	648
Sesame	42	7	97	88	7	89	88	0	0	0	0	0	418
Other crops	218	23	181	230	30	51	871	2	6	0	0	0	1612
Water	4	0	9	7	1	0	0	364	1	0	0	0	386
Forest	2	0	1	2	2	0	24	0	72	0	2	2	107
Built up	8	1	2	4	0	1	1	0	0	11	0	10	38
Grassland	11	0	21	15	0	0	9	0	2	0	3	0	61
Bare soil	8	1	3	3	2	0	13	0	1	0	0	55	86
Total	1689	88	2053	2044	382	232	1384	366	87	11	5	70	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel – 2, *Other crops include Okra, Rice and Tomato.

Table 35: Total samples for classification for independent tiles using fused sentinel-1 and Sentinel-2 images

Dataset	S1+S2	
	Tile: 29PPQ +1	Tile: 29PQP+2
	Number of Samples	
Training	26,522	43,736
Validation	11,366	18,886
Total	37,888	62,622

Table 36: Total samples per crop for classification for independent tiles using fused sentinel-1 and Sentinel-2 images

Crop Types	S1+S2					
	Tile: 29PPQ+1			Tile: 29PQP+2		
	Number of Samples					
	Training	Validation	Total	Training	Validation	Total
Maize	2527	1083	3610	7551	3236	10787
Peanut	614	263	877	2147	920	3067
Cotton	2182	935	3117	8888	3809	12697
Sorghum	8101	3472	11573	7163	3070	10233
Millet	2273	974	3247	2415	1035	3450
Sesame	1153	494	1647	2296	984	3280
Rice	19	8	27	4933	2114	7047
Okra	145	62	207	586	251	837
Tomato	3421	1466	4887	2947	1263	4210
Water	5035	2158	7193	1675	718	2393
Forest	658	282	940	460	197	657
Built up	37	16	53	26	11	37
Grassland	61	26	87	392	168	560
Bare soil	296	127	423	257	110	367

Table 37: Error metrics for independent tiles using fused sentinel-1 and Sentinel-2 images

S1 +S2				
Crop Types	Tile: 29PPQ + 1		Tile: 29PQP + 2	
	Omission Error	Commission Error	Omission Error	Commission Error
Maize	0.6	0.49	0.42	0.55
Peanut	0.97	0.47	0.86	0.65
Cotton	0.27	0.39	0.26	0.48
Sorghum	0.13	0.45	0.44	0.53
Millet	0.68	0.49	0.74	0.5
Sesame	0.86	0.26	0.73	0.51
Rice	1	1	0.3	0.22
Okra	1	1	0.88	0.55
Tomato	0.72	0.31	0.87	0.38
Water	0.02	0.01	0.03	0.02
Forest	0.38	0.29	0.13	0.01
Built up	0.56	0.56	0.82	0
Grassland	1	1	0.87	0.35
Bare soil	0.72	0.12	0.63	0.25

Table 38: Confusion metrics for independent tiles using fused Sentinel-1 and sentinel-2 images

Tiles: 29PPQ + 1 - S1+S2															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	434	0	39	556	12	3	0	0	37	0	1	0	0	1	1083
Peanut	17	9	47	142	0	3	0	0	45	0	0	0	0	0	263
Cotton	29	0	684	211	4	4	0	0	3	0	0	0	0	0	935
Sorghum	89	5	165	3032	116	5	0	0	51	0	9	0	0	0	3472
Millet	121	0	19	526	307	0	0	0	1	0	0	0	0	0	974
Sesame	17	0	39	365	3	70	0	0	0	0	0	0	0	0	494
Rice	0	0	0	8	0	0	0	0	0	0	0	0	0	0	8
Okra	11	0	4	32	9	0	0	0	6	0	0	0	0	0	62
Tomato	130	3	115	587	137	10	0	39	415	1	16	9	0	4	1466
Water	8	0	10	15	1	0	0	0	7	2111	6	0	0	0	2158
Forest	0	0	0	30	2	0	0	0	2	0	175	0	73	0	282
Built up	1	0	0	4	0	0	0	0	4	0	0	7	0	0	16
Grassland	0	0	0	2	0	0	0	1	5	0	18	0	0	0	26
Bare soil	0	0	1	15	6	0	0	0	25	24	20	0	0	36	127
Total	857	17	1123	5525	597	95	0	40	601	2136	245	16	73	41	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel - 2, S1 represents Sentinel - 2

Table 39: Confusion metrics for independent tiles using fused Sentinel-1 and sentinel-2 images

Tiles: 29PPQ + 2 - S1+S2															
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Rice	Okra	Tomato	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	1893	34	762	425	37	11	57	0	17	0	0	0	0	0	3236
Peanut	257	127	251	174	38	37	25	0	11	0	0	0	0	0	920
Cotton	571	20	2821	308	28	18	23	15	5	0	0	0	0	0	3809
Sorghum	527	56	519	1729	109	62	36	11	15	6	0	0	0	0	3070
Millet	206	24	152	357	264	8	20	0	3	0	0	0	0	1	1035
Sesame	109	25	306	190	27	266	35	0	26	0	0	0	0	0	984
Rice	235	1	167	175	3	46	1471	0	9	7	0	0	0	0	2114
Okra	43	19	46	70	0	24	16	29	4	0	0	0	0	0	251
Tomato	283	50	278	202	15	69	185	10	170	0	0	0	0	1	1263
Water	5	0	8	10	0	0	0	0	0	695	0	0	0	0	718
Forest	0	1	0	2	0	0	0	0	0	3	171	0	12	8	197
Built up	0	0	5	0	1	0	0	0	0	0	0	2	0	3	11
Grassland	44	2	48	26	0	4	15	0	6	0	0	0	22	1	168
Bare soil	8	2	27	19	3	1	0	0	8	0	1	0	0	41	110
Total	4181	361	5390	3687	525	546	1883	65	274	711	172	2	34	55	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel – 2, S1 represents Sentinel - 2

Table 40: Total samples for classification for combined tile using fused sentinel-1 and Sentinel-2 images

S1+S2	
Dataset	Tile 29PPQ +29PPQ +1+2
Number of Samples	
Training	19,358
Validation	8,296
Total	27,654

Table 41: Total samples per crop for classification for combined tile using fused sentinel-1 and Sentinel-2 images

S1+ S2			
Crop Types	Tile: 29PPQ+29PPQ 1+2		
	Number of Samples		
	Training	Validation	Total
Maize	2909	1247	4156
Peanut	887	380	1267
Cotton	3589	1538	5127
Sorghum	4233	1814	6047
Millet	1388	595	1983
Sesame	996	427	1423
Other crops	3484	1493	4977
Water	1181	506	1687
Forest	229	98	327
Built up	37	16	53
Grassland	217	93	310
Bare soil	208	89	297

Table 42: Error metrics for combined tile using fused sentinel-1 and Sentinel-2 images

Crop Types	S1+S2	
	Tile: 29PPQ+29PQP+1+2	
	Omission Error	Commission Error
Maize	0.47	0.5
Peanut	0.65	0.75
Cotton	0.37	0.35
Sorghum	0.45	0.37
Millet	0.48	0.62
Sesame	0.49	0.71
Other crops	0.5	0.25
Water	0.04	0.04
Forest	0.26	0.43
Built up	0.38	0.17
Grassland	0.68	0.52
Bare soil	0.22	0.3

Table 43: Confusion metrics for combined tile using fused Sentinel-1 and sentinel-2 images

Tile: (29PPQ + 29PQP – S2) + (1+2 - S1)													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	660	95	129	159	102	37	48	1	5	0	8	3	1247
Peanut	46	134	57	38	38	35	17	0	3	0	0	12	380
Cotton	195	65	975	65	79	86	55	0	10	0	5	3	1538
Sorghum	184	107	145	992	198	115	57	10	1	0	4	1	1814
Millet	68	24	20	115	311	37	18	0	0	0	0	2	595
Sesame	26	33	45	38	24	217	41	1	0	0	0	2	427
Other crops	113	86	106	145	65	215	741	9	1	2	8	2	1493
Water	0	0	0	0	0	0	2	486	18	0	0	0	506
Forest	1	0	3	4	0	2	4	0	73	0	7	4	98
Built up	4	0	0	0	1	1	0	0	0	10	0	0	16
Grassland	9	2	15	5	5	4	9	0	14	0	30	0	93
Bare soil	1	0	4	6	0	7	0	0	2	0	0	69	89
Total	1307	546	1499	1567	823	756	992	507	127	12	62	98	

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato, S1* represents Sentinel – 1, S2* represents Sentinel - 2

Table 44: Total samples for classification for early growth stage

Early Growth Stage	
Dataset	Number of Samples
Training	9,429
Validation	4,041
Total	13,470

Table 45: Total samples per crop for classification in early growth stage

Early Growth Stage			
Crop Types	Number of Samples		
	Training	Validation	Total Samples
Maize	1148	492	1640
Peanut	474	203	677
Cotton	1755	752	2507
Sorghum	1820	780	2600
Millet	537	230	767
Sesame	541	232	773
Other crops	1778	762	2540
Water	553	237	790
Forest	182	78	260
Built up	51	22	73
Grassland	343	147	490
Bare soil	247	106	353

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 46: Error metrics for early growth stage

Early growth stage			
Crop Types	Omission error	Commission error	
Maize	0.66		0.80
Peanut	0.99		0.90
Cotton	0.59		0.63
Sorghum	0.41		0.64
Millet	0.98		0.87
Sesame	0.97		0.54
Other crops	0.56		0.46
Water	0.11		0.09
Forest	0.32		0.38
Built up	0.73		0.00
Grassland	0.90		0.07
Bare soil	0.42		0.26

* Bare soil includes asphalt road, lateritic rock, and clay soil, S1* represents Sentinel – 1, *S2 represents Sentinel – 2, *Other crops include Okra, Rice and Tomato.

Table 47: Confusion metrics for early growth stage

Early growth stage													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	166	1	138	144	6	1	32	0	2	0	1	1	492
Peanut	59	2	40	78	2	0	20	0	0	0	0	2	203
Cotton	175	5	311	188	5	1	60	0	0	0	0	7	752
Sorghum	141	4	116	460	6	1	49	1	0	0	0	2	780
Millet	38	2	66	114	4	2	4	0	0	0	0	0	230
Sesame	46	4	34	87	2	6	52	1	0	0	0	0	232
Other crops	135	2	111	163	3	1	335	9	3	0	0	0	762
Water	6	1	3	8	0	0	2	212	4	0	0	1	237
Forest	4	0	0	7	0	0	8	2	53	0	0	4	78
Built up	5	0	6	1	0	0	0	0	0	6	0	4	22
Grassland	35	0	12	19	0	1	54	2	9	0	14	1	147
Bare soil	8	0	6	4	2	0	3	6	15	0	0	62	106
Total	818	21	843	1273	30	13	619	233	86	6	15	84	

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 48: Total samples for classification for vegetative and development stage

Vegetative and development Stage	
Dataset	Number of Samples
Training	9,262
Validation	3,969
Total	13,231

Table 49: Total samples per crop for classification for vegetative and development stage

Vegetative and development Stage			
Crop Types	Number of Samples		
	Training	Validation	Total Samples
Maize	1211	519	1730
Peanut	422	181	603
Cotton	1554	666	2220
Sorghum	1867	800	2667
Millet	637	273	910
Sesame	490	210	700
Other crops	1617	693	2310
Water	728	312	1040
Forest	180	77	257
Built up	49	21	70
Grassland	264	113	377
Bare soil	243	104	347

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 50: Error metrics for vegetative and development stage

Vegetative and development stage			
Crop Types	Omission error	Commission error	
Maize	0.58	0.79	
Peanut	0.91	0.91	
Cotton	0.68	0.70	
Sorghum	0.77	0.71	
Millet	0.91	0.88	
Sesame	0.93	0.91	
Other crops	0.72	0.64	
Water	0.16	0.10	
Forest	77	1.94%	
Built up	21	0.53%	
Grassland	113	2.85%	
Bare soil	104	2.62%	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S1* represents Sentinel – 1, *Other crops include Okra, Rice and Tomato.

Table 51: Confusion metrics for vegetative and development stage

Vegetative and development stage													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	218	30	116	61	39	9	31	0	14	0	0	1	519
Peanut	56	17	22	29	16	10	28	0	1	0	1	1	181
Cotton	228	20	216	83	27	14	54	0	18	0	2	4	666
Sorghum	221	43	123	185	50	37	111	2	12	0	3	13	800
Millet	94	13	51	50	25	5	24	3	2	0	1	5	273
Sesame	48	11	27	45	14	15	33	6	5	0	1	5	210
Other crops	121	40	114	124	24	40	191	8	6	0	6	19	693
Water	5	1	3	12	2	4	12	262	4	0	0	7	312
Forest	4	2	9	11	2	4	7	4	32	0	0	2	77
Built up	4	1	4	2	0	3	6	0	0	0	0	1	21
Grassland	31	7	17	17	4	9	8	5	12	0	0	3	113
Bare soil	11	6	8	24	2	11	22	2	1	0	1	16	104
Total	1041	191	710	643	205	161	527	292	107	0	15	77	

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 52: Total samples for classification in harvesting stage

Harvesting Stage	
Dataset	Number of Samples
Training	12,666
Validation	5,428
Total	18,094

Table 53: Total samples per crop for classification in harvesting stage

Crop Types	Harvesting Stage		
	Number of Samples		
	Training	Validation	Total Samples
Maize	1906	817	2723
Peanut	530	227	757
Cotton	2310	990	3300
Sorghum	2448	1049	3497
Millet	838	359	1197
Sesame	628	269	897
Other crops	2214	949	3163
Water	786	337	1123
Forest	245	105	350
Built up	49	21	70
Grassland	369	158	527
Bare soil	343	147	490

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 54: Error metrics for harvesting stage

Crop Types	Omission error	Commission error
Maize	0.50	0.61
Peanut	0.95	0.76
Cotton	0.29	0.42
Sorghum	0.35	0.55
Millet	0.85	0.50
Sesame	0.90	0.63
Other crops	0.43	0.41
Water	0.06	0.03
Forest	0.40	0.22
Built up	0.76	0.29
Grassland	0.97	0.17
Bare soil	0.52	0.16

Table 55: Confusion metrics for harvesting stage

Harvesting Stage													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	407	8	140	194	5	5	58	0	0	0	0	0	817
Peanut	64	12	43	59	3	2	44	0	0	0	0	0	227
Cotton	112	3	707	100	8	2	54	1	2	0	1	0	990
Sorghum	123	7	96	687	12	18	105	1	0	0	0	0	1049
Millet	94	0	31	167	55	1	11	0	0	0	0	0	359
Sesame	43	7	55	68	4	28	64	0	0	0	0	0	269
Other crops	124	10	102	143	7	16	542	2	3	0	0	0	949
Water	7	0	0	8	1	0	2	318	0	0	0	1	337
Forest	7	0	4	18	2	0	5	2	63	0	0	4	105
Built up	3	0	3	5	0	1	1	0	0	5	0	3	21
Grassland	36	2	31	45	3	1	21	3	6	0	5	5	158
Bare soil	12	0	5	27	9	1	14	0	7	2	0	70	147
Total	1032	49	1217	1521	109	75	921	327	81	7	6	83	

* Bare soil includes asphalt road, lateritic rock, and clay soil, *Other crops include Okra, Rice and Tomato

Table 56: Total samples for classification in interphase stage

Inter phase stage (May S2 + July S1)	
Dataset	Number of Samples
Training	2, 824
Validation	1,213
Total	4,037

Table 57: Total samples per crop for classification in interphase stage

Inter phase stage (May S2 + July S1)			
Number of Samples			
Crop Types	Training	Validation	Total Samples
Maize	344	148	492
Peanut	142	61	203
Cotton	526	226	752
Sorghum	546	234	780
Millet	161	69	230
Sesame	162	70	232
Other crops	533	229	762
Water	163	70	233
Forest	55	23	78
Built up	15	7	22
Grassland	103	44	147
Bare soil	74	32	106

Table 58: Error metrics for interphase stage

Inter phase stage (May S2 + July S1)			
Crop Types	Omission error	Commission error	
Maize	0.65	0.65	0.80
Peanut	0.98	0.98	0.90
Cotton	0.59	0.59	0.70
Sorghum	0.54	0.54	0.68
Millet	0.94	0.94	0.70
Sesame	0.99	0.99	0.67
Other crops	0.64	0.64	0.50
Water	0.13	0.13	0.08
Forest	0.38	0.38	0.44
Built up	0.82	0.82	0.20
Grassland	0.92	0.92	0.08
Bare soil	0.43	0.43	0.43

Table 59: Confusion metrics for interphase stage

Inter phase stage (May S2 + July S1)													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	170	1	133	132	3	1	41	2	3	0	0	6	492
Peanut	65	4	55	61	0	0	15	0	0	0	0	3	203
Cotton	148	9	312	203	4	1	63	0	1	0	0	11	752
Sorghum	161	7	177	361	15	1	51	0	1	0	0	6	780
Millet	37	1	87	86	13	0	4	0	0	0	0	2	230
Sesame	57	6	52	67	5	2	43	0	0	0	0	0	232
Other crops	131	8	166	165	3	0	271	5	8	0	0	5	762
Water	4	0	9	9	0	0	2	203	5	0	0	1	233
Forest	10	1	3	3	0	0	2	4	48	0	1	6	78
Built up	3	0	8	1	0	1	1	0	0	4	0	4	22
Grassland	46	0	18	27	0	0	35	2	6	0	12	1	147
Bare soil	8	2	5	1	0	0	10	5	14	1	0	60	106
Total	840	39	1025	1116	43	6	538	221	86	5	13	105	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel – 2, S1 represents Sentinel - 2

Table 60: Total samples for classification in interphase stage

Inter phase stage (June S2 + AugustS1)	
Dataset	Number of Samples
Training	2,829
Validation	1,212
Total	4,041

Table 61: Total samples per crop for classification in interphase stage

Inter phase stage (June S2 + AugustS1)			
Crop Types	Number of Samples		
	Training	Validation	Total Samples
Maize	344	148	492
Peanut	142	61	203
Cotton	526	226	752
Sorghum	546	234	780
Millet	161	69	230
Sesame	162	70	232
Other crops	533	229	762
Water	166	71	237
Forest	55	23	78
Built up	15	7	22
Grassland	103	44	147
Bare soil	74	32	106

Table 62: Error metrics for interphase stage

Inter phase stage (June S2 + AugustS1)			
Crop Types	Omission error	Commission error	
Maize	0.21	0.64	
Peanut	0.04	1.00	
Cotton	0.37	0.55	
Sorghum	0.34	0.46	
Millet	0.18	0.97	
Sesame	0.40	0.99	
Other crops	0.55	0.58	
Water	0.91	0.09	
Forest	0.61	0.31	
Built up	0.50	0.91	
Grassland	0.56	0.94	
Bare soil	0.79	0.51	

Table 63: Confusion metrics for interphase stage

Inter phase stage (June S2 + AugustS1)													
Crop Types	Maize	Peanut	Cotton	Sorghum	Millet	Sesame	Other crops	Water	Forest	Built up	Grassland	Bare soil	Total
Maize	178	2	162	112	4	0	29	0	0	0	2	3	492
Peanut	57	1	42	71	3	0	27	0	1	1	0	0	203
Cotton	197	3	342	158	4	1	43	0	2	0	0	2	752
Sorghum	154	5	143	419	8	0	50	0	0	0	0	1	780
Millet	51	2	64	91	6	0	15	0	0	0	0	1	230
Sesame	33	5	34	105	6	2	44	1	0	0	0	2	232
Other crops	116	3	93	207	2	1	321	10	4	1	1	3	762
Water	2	0	0	14	0	1	0	216	3	0	0	1	237
Forest	0	0	1	8	0	0	8	3	54	0	4	0	78
Built up	4	2	5	7	0	0	0	1	0	2	0	1	22
Grassland	34	1	29	24	0	0	41	0	9	0	9	0	147
Bare soil	3	2	11	7	1	0	8	7	15	0	0	52	106
Total	829	26	926	1223	34	5	586	238	88	4	16	66	

* Bare soil includes asphalt road, lateritic rock, and clay soil, S2* represents Sentinel – 2, S1 represents Sentinel - 2

Crop Type Mapping Using Sentinel-1 And Sentinel-2 Data in the Smallholder Cropping System of Cotton Belt in Mali

Bonosri Ghose

Abstract

Effective crop type mapping is crucial for farmland monitoring, assessment of food security, and sustainable land management, particularly in heterogeneous smallholder farming systems. This study investigated the prospect of Sentinel-1 SAR data, Sentinel-2 optical imagery, and fused Sentinel-1 and Sentinel-2 datasets for crop discrimination applying tile-based and temporal classification methods. Preprocessing of Sentinel datasets and Random Forest classification were employed using field survey data for training and validation on Google Earth Engine platform.

Independent tile-based classification, combined tile-based classification, fused sensor classification, and temporal growth-stage analysis were compared in this study. Findings showed that Sentinel-2 optical data generally provided better performance than Sentinel-1 SAR data for the stronger spectral and vegetation-related information. However, the fusion of Sentinel-1 and Sentinel-2 increased classification steadily and crop separability by integrating spectral, structural, and moisture-related characteristics. The fused combined tile-based classification produced the most balanced overall performance (0.57) among all approaches.

Temporal analysis exhibited that classification performance differed across crop growth stages. Lower crop separability showed in early growth and vegetative stages, while harvesting-stage classification derived the best performance (0.53) due to stronger phenological differences among crops. Furthermore, feature importance analysis stated that textural variables (37.3% - 40.3%) and spectral (26.3% - 27.4%) contributed most significantly to classification accuracy, whereas SAR variables supported by providing complementary information. Overall, the study reveals that multi-source as well as multi-temporal data integration can remarkably improve crop type mapping in complex agricultural landscapes.