INTERNATIONAL JOURNAL OF DIGITAL EARTH
2024, VOL. 17, NO. 1, 2378815
https://doi.org/10.1080/17538947.2024.2378815

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Dryland cropping in different Land uses of Senegal using Sentinel-2 and hybrid ML method

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ABSTRACT

In rainfed and dryland agricultural areas with smallholder farms (less than 2 ha), crop diversity is high due to farmers' decisions and local climatic conditions, leading to a complex spatial–temporal distribution of crops. Monitoring and mapping crops is crucial for food security and implementing agricultural support programs. This study aims to map crop types across Senegal using Sentinel-2 satellite imagery and the limited ground reference data available, which has been increasing recently. The study compares conventional supervised classification algorithms to unsupervised classification algorithms using high-resolution satellite imagery. Crop type classification for 2020 in Senegal employed supervised machine learning algorithms, including Classification and Regression Trees (CART), Random Forest (RF), and Support Vector Machine (SVM) on the Google Earth Engine (GEE) cloud platform, and the unsupervised Iso-clustering classification algorithm with Spectral Matching Techniques (SMTs). Due to limited ground data, supervised classifiers achieved 45-55% accuracy, whereas the unsupervised semi-automatic approach achieved over 75% accuracy. The study indicates that supervised classifiers' performance depends on ground data quantity, while SMT shows good performance even with limited ground data. This SMT approach is valuable for classifying crop types in dryland areas with smallholder farms and diverse cropping patterns.

ARTICLE HISTORY
Received 17 January 2024
Accepted 7 July 2024

KEYWORDS
Cropping pattern; sentinel-2; machine learning algorithms; spectral matching techniques; semi-arid; Crop type mapping

Highlights

- Applied different Machine learning (ML) algorithms on heterogeneous crop ecosystems.
- Cropping type mapping was done using limited ground data and ML Techniques
- ML algorithms on cloud computing platforms and SMTs aided in identifying fragmented crop.

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This article was originally published with errors, which have now been corrected in the online version. Please see Correction (http://dx.doi.org/10.1080/17538947.2024.2390726)

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1. Introduction

Earth observation and geospatial sciences have great potential to enable environmental monitoring and sustainable agricultural development (Im 2020). When an agricultural area needs to be assessed at the state or national level, satellite images offer a reliable option (Lobell et al. 2003; Thenkabail et al. 2010; Thiruvengadachari and Sakthivadivel 1997). Notably, cropland maps, can be used along with weather/climate and socioeconomic data to pinpoint regions where productivity is impacted (Diancoumba et al. 2023; Jha et al. 2023). Additionally, spatial maps can be a significant input parameter for calculating agricultural yield (Akinseye et al. 2023; Sarr and Sultan 2023). Satellite based spatial–temporal imagery is used to monitor crop fields quickly, extensively, economically, and continuously (Anderson et al. 2012; Brown et al. 2007; McCarthy et al. 2018; Qiu et al. 2017; Thenkabail et al. 2012). There have been numerous studies on Land Use and Land Cover (LULC) monitoring utilizing different resolutions of satellite imagery and different techniques from local to global scales. The most effective method for tracking the spatial distribution of agricultural croplands and LULC classes is through remote sensing (Pittman et al. 2010). Numerous global land cover products are available at low, moderate, and high resolution, such as Global Land Cover 2000 (Tateishi et al. 2014), Globe Cover (Bicheron et al. 2008), Global Irrigated Areas (GIAM) (Thenkabail et al. 2009), and Landsat-derived Global Cropland Extent Product (GCEP30) (Thenkabail et al. 2021) but not crop type. Numerous approaches and methods have been used for crop classification, including using time-based vegetation-based algorithms (Dong et al. 2015; Jeganathan, Dash, and Atkinson 2014; Pan et al. 2015; Qiu et al. 2022; Xiong et al. 2017a), classification decision tree (DT) and regression algorithms (Deng and Wu 2013; Egorov et al. 2015; Friedl and Brodley 1997; Ozdogan and Gutman 2008), Spectral Matching Techniques (SMT) (Gumma et al. 2018; Thenkabail et al. 2007b), SpectralGPT (Hong et al. 2024), and RF algorithms (Millard and Richardson 2015; Oliphant et al. 2019; Phalke et al. 2020; Teluguntla et al. 2018; Xie et al. 2019). These studies were carried out at a regional to a global scale, which often lack the accuracy and specificity needed for management at the field scale. Consequently, high-resolution farmland monitoring is crucial for decision-making and enhancing agricultural output. The sen2agri (Sentinel-2 for agriculture) project of the European Space Agency creates a crop-type map with 4–5 primary crops of the region at a spatial resolution of 10 m (Inglada et al. 2015).

Researchers have employed machine learning algorithms to categorize satellite data and its derivatives into different crop types. These techniques include Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and many more (Salcedo-Sanz et al. 2020). Using RF and SVM algorithms, Saini R et al. achieved crop classification on a single-date Sentinel-2 image (Panjala, Gumma, and Teluguntla 2022; Saini and Ghosh 2018). Crop classification utilizing machine-learning techniques SVM, ANN, and RF employing a mix of spectral bands, derived textural measures, and vegetation indices from Sentinel-1 SAR, Sentinel-2, and Landsat-8 optical datasets has been performed by Sun et al. 2019, but not at a country extent (Sun et al. 2019). They successfully employed Sentinel-2 time-series data as inputs to RF and SVM classification algorithms to extract spectral bands, textural characteristics, vegetation indices, and phenological parameters. They investigated how to distinguish between crops using Sentinel-2 data's short-wave infrared (SWIR) and water vapor bands.

Although machine learning methods are observed to be useful to classify croplands, they require large amounts (thousands) of quality training data (Phalke and Özdoğan 2018). Unsupervised methods like SMT can reduce the requirement of ground data. SMTs have been used in numerous studies to analyze optical data for various LULCs studies (Gumma et al. 2016; Thenkabail et al. 2007a). MODIS Normalized Difference Vegetation Index (NDVI) data has used SMTs to: map rice ecosystems in South Asia for 2000–2001 (Gumma, Thenkabail, and Nelson 2011); track the spatial spread of chickpea (Gumma et al. 2016); separate between canal and groundwater irrigation areas (Gumma, Thenkabail, and Nelson 2011); map of rice-fallows for agricultural intensification of short-duration legumes (Gray et al. 2014; Gumma et al. 2018); and map stress prone areas across India (Gumma, Nelson, and Yamano 2019). Machine learning algorithms have been successfully applied to map cropland in Africa (Lee et al. 2022; Samasse et al. 2020). Many studies have

shown the value of the cloud based image analysis platform Google Earth Engine (GEE) to monitor land use/land cover and crop monitoring at various scales (Hussain et al. 2022; Johnson and Mueller 2021; Li and Xu 2020; Qichi et al. 2023; Shelestov et al. 2017)

Accurate and timely monitoring of agricultural area in Senegal is critical, as the agriculture sector accounted for 16.1% of GDP in 2017, up from 7.2% in 2012 (Rigaud et al. 2021). Senegal has a great agricultural tradition that employs almost half of the working population. Senegal is situated in a region where extreme climatic events are common and these conditions have a large impact on agricultural production (Nguru and Mwongera 2022). There are limited studies using remote sensing data to monitor LULC and crop types across the entire nation of Senegal, but research has targeted smaller areas of economic interest such as the Senegal River valley (Busetto, Zwart, and Boschetti 2019), the Delta region (MMbengue et al. 2022), and the groundnut basin (Gayane et al. 2020), in an attempt to monitor farmland and crop types.

In the present study, high-resolution (10 m) satellite data was used to map LULC and crop types across Senegal with limited ground data using SMT's and also supervised machine learning algorithms. The results obtained from all methods were compared to identify the method that produced the highest accuracy crop type maps with limited ground data available.

2. Study area and data

2.1. Study area

Senegal is geographically situated between latitudes 12.308° N and 16.691° N and longitudes 11.355° W and 17.687° W in the far western region of the African continent (see Figure 1) and experiences a climate with distinct dry and wet seasons. The dry season spans from November to April, while the wet season extends from May to October, driven by the movement of the Inter Tropical Convergence Zone (ITCZ). Throughout the wet season, the ITCZ blankets the study area, shifting

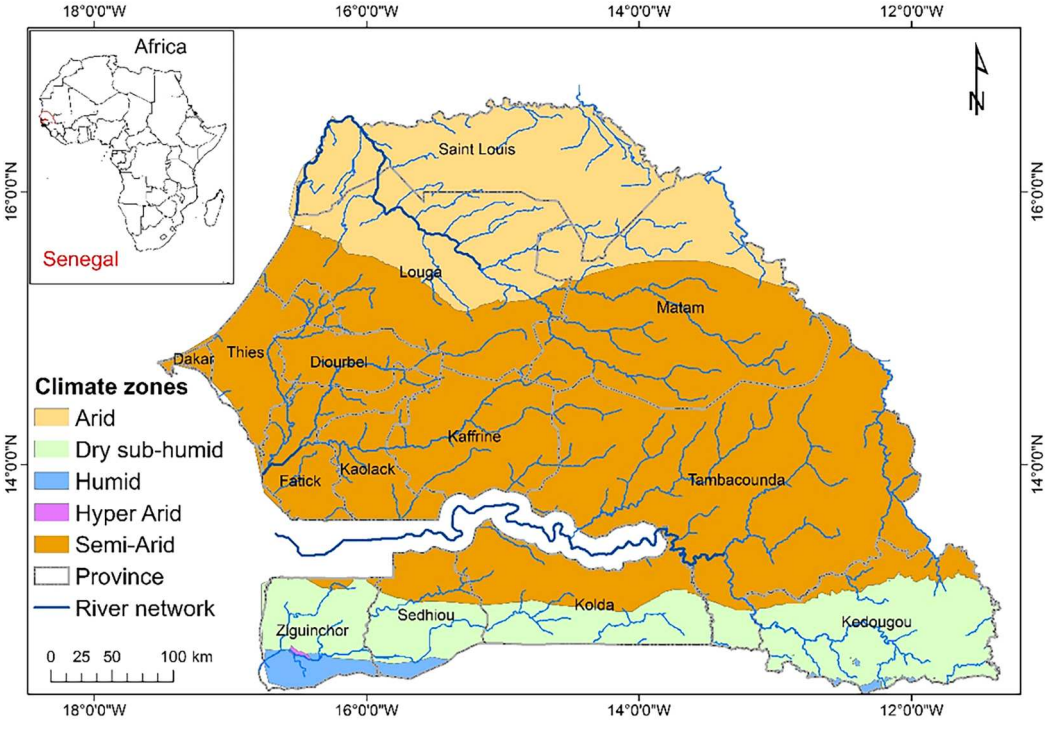

Figure 1. Study area covering Senegal and its climatic zones situated in Africa.

northward towards the Sahara's edge until August and September. Notably, the majority of rainfall occurs in August, with July and September also receiving significant precipitation (Sarr et al. 2013). The annual cumulative rainfall varies from north to south (200–400 mm/year in the north and 800–1200 mm/year in the south).

The crop growing regions are mostly located in the Southwest and the Northern regions of Senegal. Over 95% of agriculture is rainfed and the agriculture economy of the country is characterized by the dominance of smallholder farmers. Originally a food-producing, family-based agricultural system, it has since been heavily focused on cash crops (groundnuts and cotton).

While the groundnut sector, traditionally the backbone of Senegal's economy, is currently grappling with a significant crisis, there is a contrasting upward trend in the production of cereals (such as cowpeas, millet, rice, and maize), fruits, vegetables, and cassava, driven by the rising local demand. The introduction of irrigation, particularly in the Senegal River valley, has led to improvements in the rice sector's performance. Additionally, the production of millet, a rainfed crop with historical significance, has been on the rise. Many farmers are diversifying their crops, cultivating cash crops like groundnuts and cotton alongside subsistence food crops like millet, sorghum, and maize (Faye et al. 2021). Horticulture is flourishing in the Niayes area along the coast and in irrigated lands along the Senegal River, where rice cultivation has also seen significant development.

2.2. Sentinel-2 data

Sentinel-2 surface reflectance data from the EU Copernicus Program is well-suited for monitoring vegetation at a fine scale (Xiong et al. 2017b). In this research, the study utilized the Sentinel-2 products repository available on Google Earth Engine (GEE), offering 6-day images with a spatial resolution of 10 meters. The cloud is removed with 'Cloud pixel percentage' in GEE and further with the monthly maximum NDVI, which removes the noise pixels. NDVI images were derived using normalised difference of Red and NIR bands and maximum value composite (MVC) of each month i.e. maximum NDVI of all images in a month, was created for every month in the year, which forms 12 images. The images obtained above were stacked from January to December 2020 forming a data cube. This data cube was used for the crop type classification.

2.3. Ground survey data

In 2020, a ground survey conducted by experienced agricultural remote sensing researchers collected 270 sample points, encompassing the primary crop types (as shown in Table 1 & Figure 2). This data comprised two separate sets: one for training and another for validation purposes. The accuracy of the ground data was confirmed by cross-referencing it with imagery from Google Earth to ensure GPS locations collected in the field matched satellite imagery. Additionally, detailed information was gathered at specific locations, including class identification and labeling.

The collected location-specific information also encompassed cropping patterns during various seasons, which were gathered through interviews with farmers and locals. The minimum

Table 1. Crop wise number of samples collected across the study area.

S.No	Crop	Number of samples
1	Groundnut	47
2	Millet	46
3	Rice	45
4	Sugarcane	44
5	Beans	45
6	Maize	44
7	Groundnut	48
8	Millet	45
9	Vegetables	40

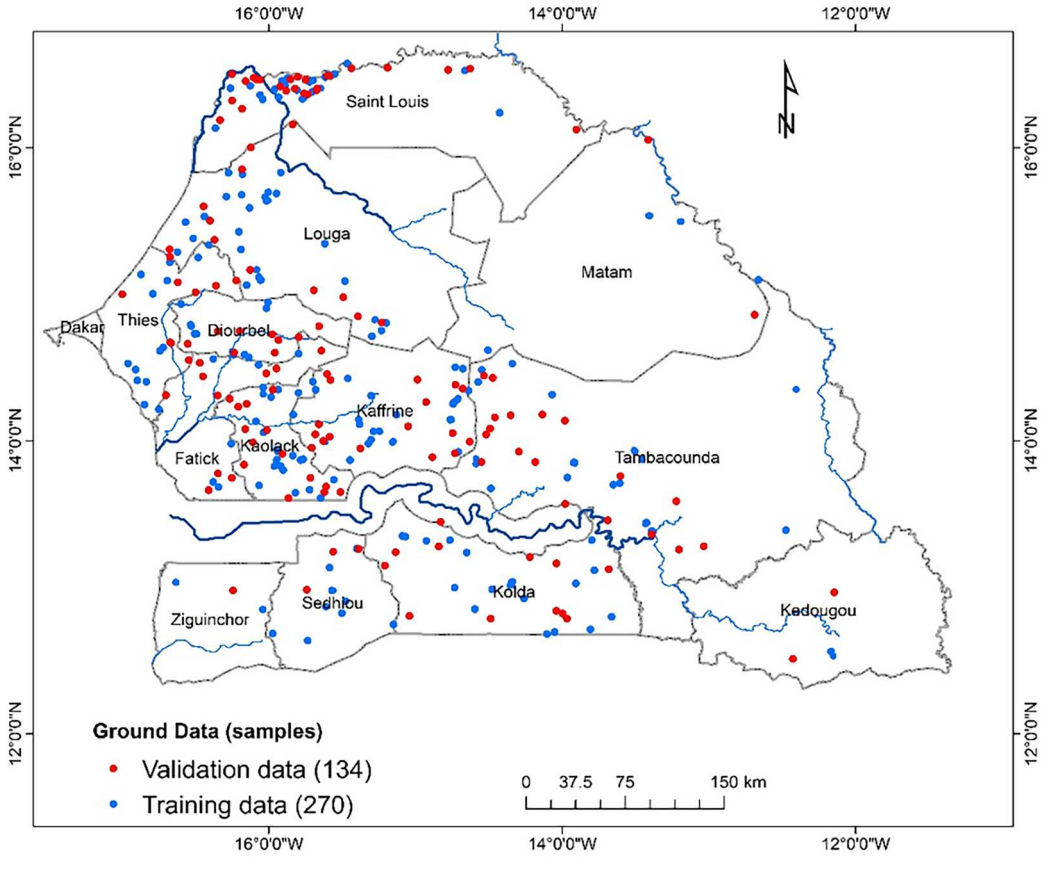

Figure 2. Ground data sample distribution for crop type mapping and accuracy assessment.

mapping unit taken into account for sampling was a 30 m by 30 m (900 m^2) area to ensure each field was larger than a 10 m by 10 m (100 m^2) Sentinel-2 pixel. The sampling strategy employed was simple random sampling, ensuring coverage of a substantial portion of the cultivated areas in Senegal.

3. Methods and approaches

The methodology is adopted to classify and map Land Use Land Cover (LULC) and crop type across Senegal consists of three main parts: 1. Acquisition and processing satellite data and extraction of satellite pixel values for the ground training samples; 2. Supervised classification framework; 3. Unsupervised classification framework (Figure 3). A LULC map was produced with the help of unsupervised K-means classifier and spectral matching techniques (Section 3.3). This LULC map provides the crop mask as a base layer for mapping crop types using supervised machine learning algorithms (step 2) and SMT (step 3).

3.1. Machine learning algorithms and spectral matching techniques

3.1.1. Classification and regression tree (CART)

CART is a decision tree (DT) supervised classifier that uses the notion of information entropy to take training data as inputs. The training data attributes (band pixel values here) are separated

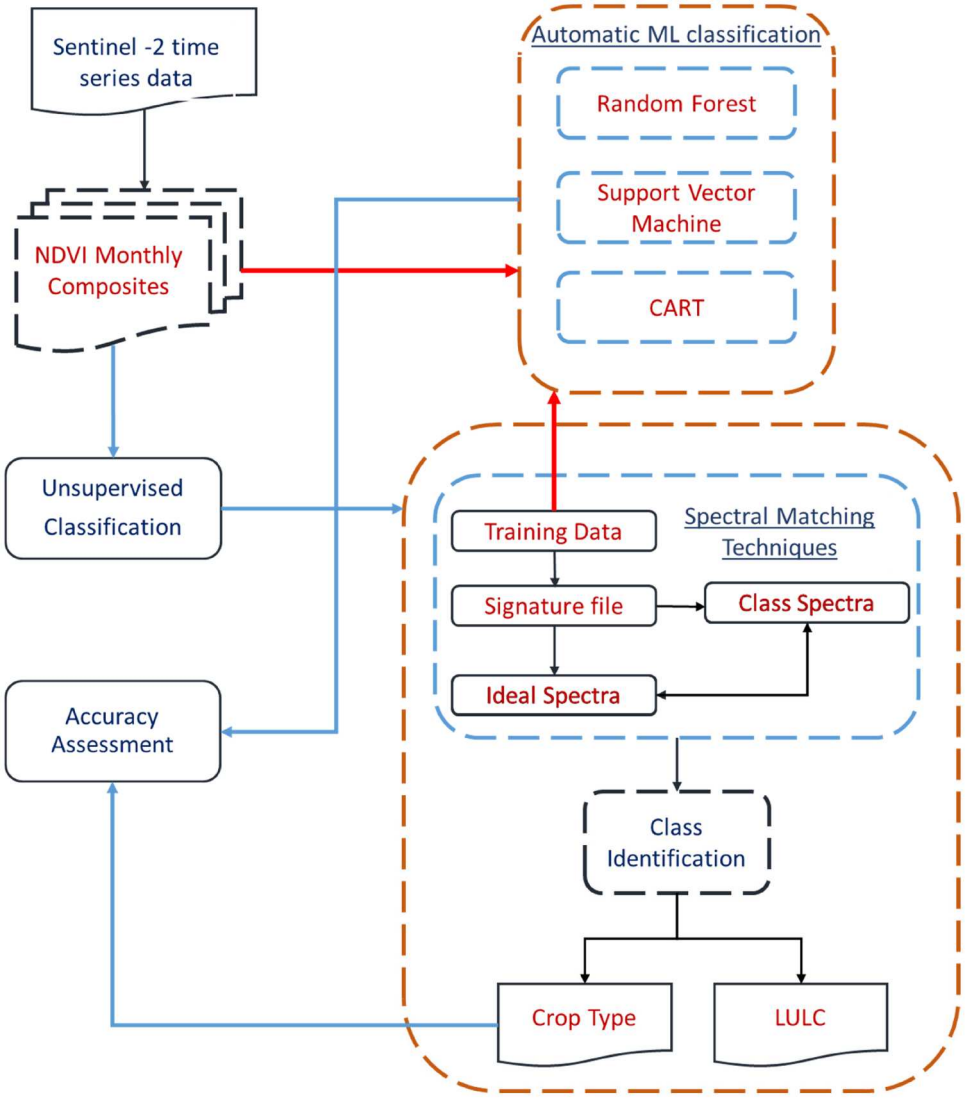

Figure 3. Workflow for mapping of LULC and crop types in the Senegal.

into subsets at each node of the tree and are then filtered into the appropriate class. The main advantages of tree models are their ability to capture the dataset's non-linearity and data standardization is not required because they do not compute distances between the data. The fundamental drawback of CART is that it relies heavily on training data; slight errors in the training data can result in a large change in classification, which is known as high sensitivity.

"Sample code:
//CART Algorithm
// Train a CART classifier with parameters.
//smileCart is the function used to run CART classifier involving bands and training
var trained_cart = ee.Classifier.smileCart().train(trainingSampled, 'Map', bands);
// Classify the image with the same bands used for training.
var classified_cart = dataset.classify(trained_cart);"

3.1.2. Random forests (RF)

The RF classifier addresses the sensitivity issue of the CART classifier by building a collection of DT. The overfitting of training data is corrected by RF by using a different random subset of training data to create each tree and the final classification is the result of the majority votes from all trees (Breiman 2001).

"Sample code:
// Random Forest algorithm
// smileRandomForest is the function used to run RF classifier involving bands and //training data and number of trees as 250
var classifier_rf =ee.Classifier.smileRandomForest(250).train(trainingSampled,"Map");
// apply classifier on composite to create a classification map
var classified_rf = dataset.classify(classifier_rf);"

3.1.3. Support vector machines (SVM)

SVM utilizes optimization techniques for data analysis in classification and regression tasks (Cortes and Vapnik 1995). This establishes a margin, which represents the perpendicular distance between the decision boundary and the nearest data points. This margin provides SVM with the flexibility to classify data in both linear and non-linear manners. In linear classification, data points are separated by a straight line in space, while in non-linear classification, inputs are mapped into high-dimensional feature spaces using kernel methods to enable more complex, non-linear separation of data.

Sample code:
//SVM Algorithm
// libsvm is the function used to run SVM classifier involving bands with kernel type // poly, degree as 2, gamma as 0.5 and cost as 10
//the values can be changed based on the requirements
var classifier_svm = ee.Classifier.libsvm({
kernelType: 'POLY',
degree: 2,
gamma: 0.5,
cost: 10
});
// Train the classifier.
var trained = classifier_svm.train(trainingSampled, 'Map', bands);
var classified_svm = dataset.classify(trained);

3.1.4. Spectral matching techniques (SMT)

SMT is a widely recognized technique for crop classification using NDVI time series data. Its primary function is to create ideal spectral signatures based on ground data and then compare and correlate them with class spectral signatures in order to assign labels to the classes, making it a valuable tool in crop classification.

3.2. Crop type classification using automatic supervised ML algorithms

The data cube created in the GEE platform undergoes a classification process using training data. The crop mask derived from the LULC layer is applied to extract data specific to croplands from the data cube. Subsequently, the refined data cube is prepared for crop type classification using supervised machine learning algorithms such as RF, SVM, and CART. The default parameters were used for CART, and the default parameters with 250 trees were used for RF. The parameters for SVM were kernel type = poly, degree = 2, gamma = 0.5, and cost = 10.

3.3. Spectral matching techniques (SMTs)

The procedure of SMTs includes three major steps, 1. generation of class spectra 2. generation of ideal spectra 3. matching class spectra with ideal spectra.

3.3.1. Generation of class spectra signatures

The data cube prepared in GEE platform were set to unsupervised classification i.e. K-Means classifier with 60 classes. The respective class spectra were generated for each class obtained from unsupervised classification. Each class spectra shows the NDVI behavior throughout the crop year.

3.3.2. Generation of ideal spectra

The ideal spectral signatures were generated using a data cube with precise information about croplands, relying on distinct reference samples acquired from ground data. These reference samples were categorized according to their specific classes and then grouped into homogeneous classes, taking into account LULC categories and different crop types for a more accurate representation.

3.3.3. Matching class spectra with ideal spectra: grouping similar class spectra and matching with ideal spectra

The initial 60 classes derived from unsupervised classification, referred to as class spectra, were systematically organized based on their spectral similarities. This involved comparing the class spectra with ideal spectra, considering spectral correlation similarity (SCS) with R-square values exceeding 0.80. When highly significant correlations were established between a group of class spectra and ideal spectra, an initial class name was assigned, typically adopting the name of the ideal spectra.

To further validate this preliminary labeling, ground data for each class, very high-resolution imagery, and data from auxiliary sources such as existing maps were employed. This comprehensive process was applied to identify and label all 60 classes, leading to the establishment of the final class designations. In cases where spectral signatures did not align with all classes, the outlined protocols were employed to mask and reclassify them accordingly (Gumma et al. 2014).

4. Results

4.1. Spatial distribution of land use and land cover

The spatial distribution of LULC was mapped using satellite imagery, ground data, and SMT. The classification encompasses diverse classes including Tree cover, Shrubland, Grasslands, Cropland, Built-up areas, Barren lands, Rangelands, Waterbodies, Seasonal water/flood, and Wetlands, as depicted in Figure 4.

As shown in Table 2, nearly 41 percent of total land cover of Senegal contains Tree cover and Grasslands whereas nearly 16 percent of total land use is under cultivation of crops i.e. 3.2 million hectares.

There is a high scope of intensification of croplands and also conversion of other LULC to croplands. It is also observed that significant area of waterbodies, seasonal water and wetlands occupies nearly 3 percent of total LULC map covering the nation of Senegal.

4.2. Spatial distribution of cropland extent in Senegal

The spatial distribution of cropland extent was mapped using methodology as shown in Figure 3. With the help of crop mask from ESA LULC (Zanaga et al. 2022) and Figure 4, the cropland was classified using RF, CART, and SVM in GEE platform whereas SMT was carried out using a semi-automatic approach in which much of the process was carried out in the GEE platform. Class identification and labeling was done manually (Figure 5). The related GEE code can be found in this link. https://code.earthengine.google.com/1fc067b457ffee563e60b028d80a64ba?noload=1.

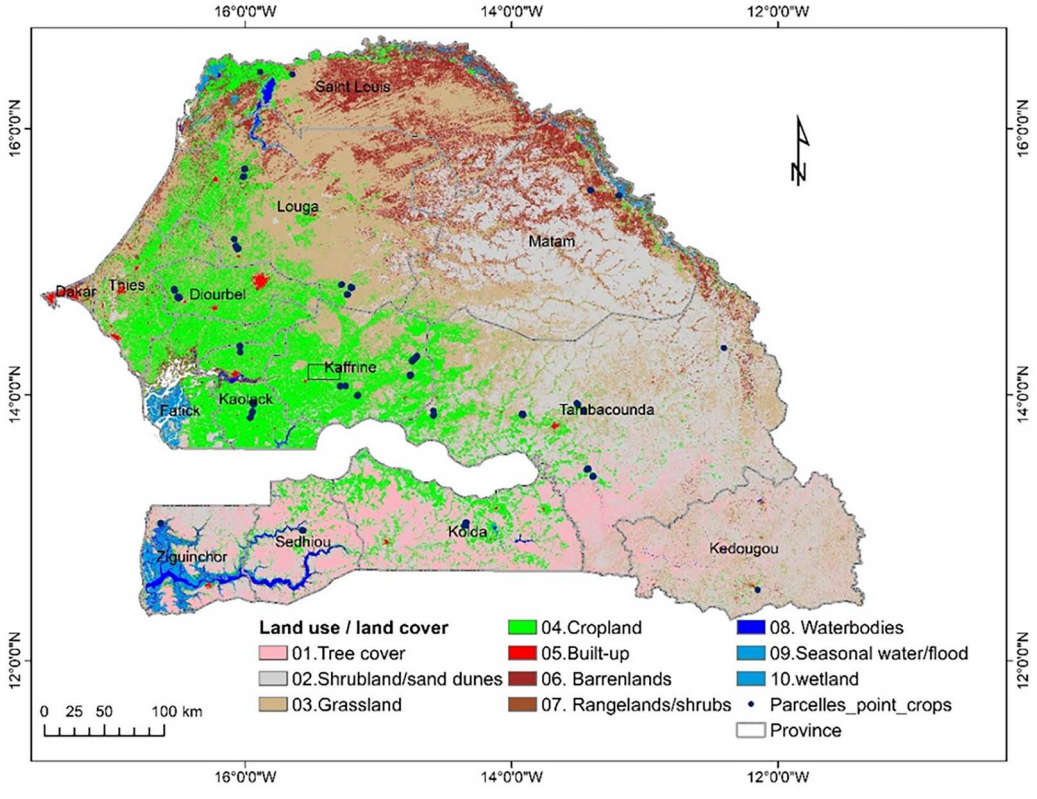

Figure 4. Spatial distribution of LULC areas derived from the Sentinel-2 for the year 2020 in Senegal.

Table 2. Area statistics of LULC of Senegal.

LULC#	Area (000′ ha)	% of total area
01.Tree cover	1937	10%
02.Shrubland/sand dunes	6018	31%
03.Grassland	6116	31%
04.Cropland	3234	16%
05.Built-up	112	1%
06. Barren lands	1373	7%
07. Rangelands/shrubs	251	1%
08. Waterbodies	186	1%
09.Seasonal water/flood	244	1%
10.wetland	150	1%
Total Area	19,623	100%

The analysis shows that the majority of croplands are concentrated in the Southwest and Northern regions of Senegal, exhibiting diverse range of cropping patterns (Figure 6). Groundnut and millet are the predominant crops cultivated, with notable areas with rice, maize, and sugarcane production in Senegal.

It is noted that area statistics obtained through multiple approaches show variations across the different approaches as shown in Table 3. For instance, the area under groundnut cultivation ranges from 410 to 420 thousand hectares when using SVM, RF and SMT while CART estimates it at 370 thousand hectares. Similarly, millet area spans over 600 thousand hectares with RF and SMT, whereas CART and SVM indicate an area of 490–520 thousand hectares. Variations in areas are also observed for rice, sugarcane, and maize. This can be attributed to differences in classifiers

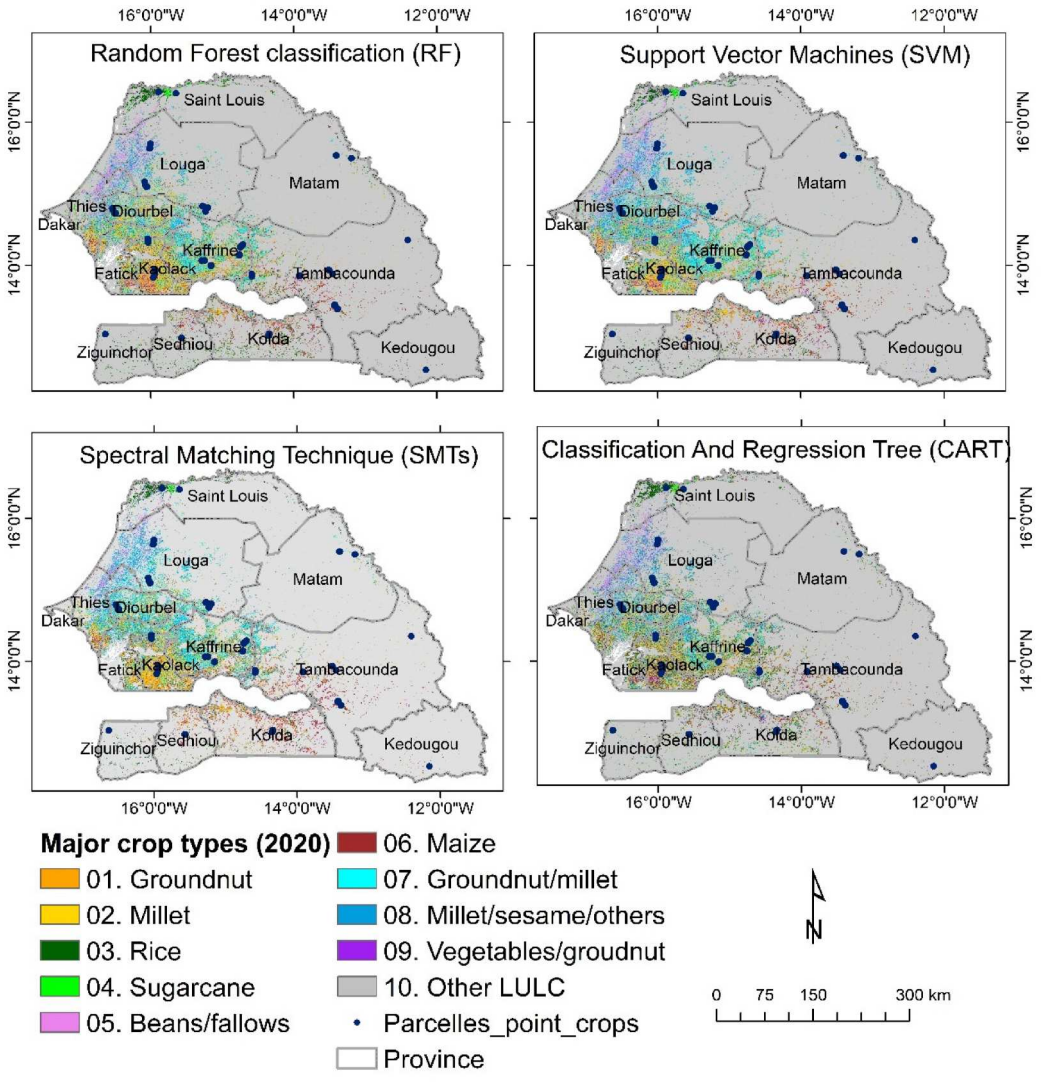

Figure 5. Spectral patterns of various crops in the study area. Imagery is derived from monthly Normalized Difference Vegetation Index (NDVI) maximum value composites created from Sentinel-2 imagery from 2020.

and the presence of smallholding farms and mixed cropping patterns, such as groundnut/millet and millet/sesame which are difficult to separate using satellite remote sensing.

4.3. Accuracy assessment

The accuracy assessment involved the utilization of independent ground data points for validation purposes. A total of 124 samples were used, and accuracy assessment was performed using the standard error matrix method. The individual error matrix table for each classification type can be found in the appendix for reference.

Among the four different approaches (Table 4), SMT demonstrated the highest accuracy, reaching nearly 76 percent. On the other hand, CART, RF, and SVM achieved accuracies ranging from 40 to 55 percent. It is worth noting that SMT exhibited good user and producer accuracy across all classes, while RF, SVM, and CART showed good user and producer accuracy in only a few classes.

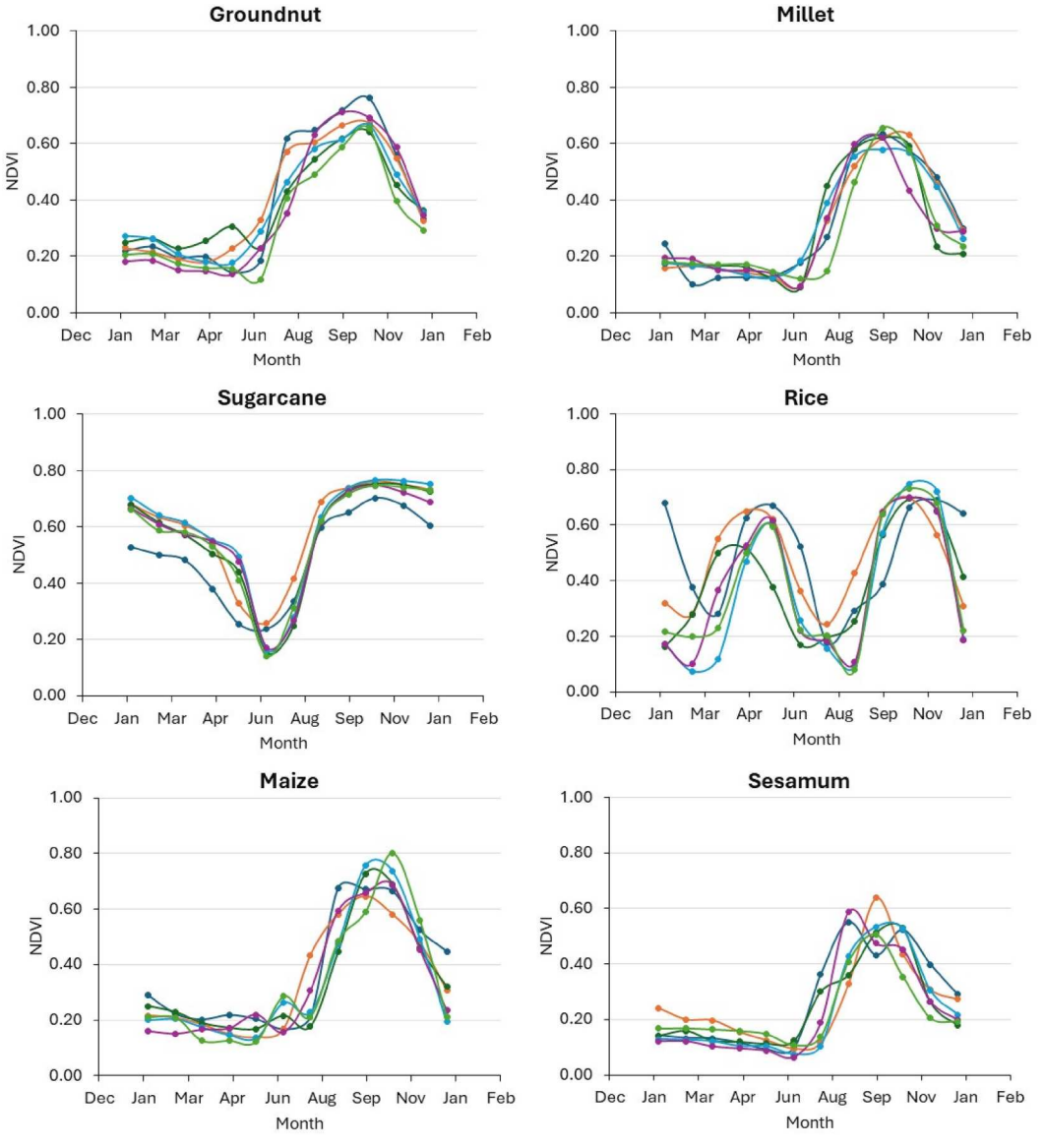

Figure 6. Spatial distribution of various crop types across Senegal using different supervised machine learning algorithms and SMT.

Table 3. The area statistics of each LULC and crop types from different classification approaches in Senegal for the year 2020.

	Area ('000 ha)			
Major crop type	CART	RF	SVM	SMT
01. Groundnut	409(2.1%)	371(1.9%)	409(2.1%)	419(2.1%)
02. Millet	495(2.5%)	696(3.5%)	523(2.7%)	621(3.2%)
03. Rice	344(1.8%)	219(1.1%)	143(0.7%)	116(0.6%)
04. Sugarcane	130(0.7%)	89(0.5%)	62(0.3%)	24(0.1%)
05. Beans/fallows	259(1.3%)	278(1.4%)	287(1.5%)	174(0.9%)
06. Maize	346(1.8%)	357(1.8%)	291(1.5%)	347(1.8%)
07. Groundnut/millet	474(2.4%)	581(3%)	677(3.5%)	742(3.8%)
08. Millet/sesame/others	466(2.4%)	436(2.2%)	631(3.2%)	533(2.7%)
09. Vegetables/groundnut	320(1.6%)	217(1.1%)	220(1.1%)	268(1.4%)
10. Other LULC	16,380(83.5%)	16,380(83.5%)	16,380(83.5%)	16,379(83.5%)
Total Area	19,623(100%)	19,623(100%)	19,623(100%)	19,623(100%)

This suggests that the supervised machine learning algorithms performed well when the ground data points were well-distributed and extensive.

4.4. Significance of SMT in crop type mapping

Crop type classification based on Sentinel-2 NDVI monthly time-series using SMT was successful in distinguishing cropping patterns in groundnut, millet, rice, and sugarcane compared to classification performance in supervised methods. SMT has accurately classified crops in dryland areas, where a strong difference between temporal signatures of different crops was identified. However, in some areas it was not possible to fully separate crops (classes 05, 07, 08, and 09) due to intercropping/mixed planting (Table 4). In addition to higher accuracies, the crop-type map generated by SMT generated a map with more defined field boundaries. As shown in Figure 7, the millet fields are identified correctly in SMT and their classified boundaries match the field boundaries created by hand digitizing very high-resolution imagery in Google Earth whereas there are mixed classes like vegetable/groundnut and other in other ML algorithms with very nosily field boundaries.

Table 4. Accuracy assessment of multiuple machine learning algorithms and SMT.

	CART		RF		SVM		SMT	
Major crop types	Users	Producers	Users	Producers	Users	Producers	Users	Producers
01. Groundnut	38%	43%	50%	36%	57%	29%	83%	71%
02. Millet	14%	20%	40%	27%	47%	47%	63%	80%
03. Rice	46%	40%	73%	53%	62%	53%	77%	67%
04. Sugarcane	60%	64%	61%	79%	91%	71%	91%	71%
05. Beans/fallows	75%	55%	80%	73%	77%	91%	90%	82%
06. Maize	23%	21%	40%	43%	45%	36%	86%	86%
07. Groundnut/millet	50%	29%	41%	41%	58%	41%	72%	76%
08. Millet/sesame /others	45%	33%	50%	47%	45%	60%	69%	73%
09. Vegetables/groundnut	35%	67%	37%	78%	32%	78%	64%	78%
Overall	**40%**		**51%**		**54%**		**76%**	

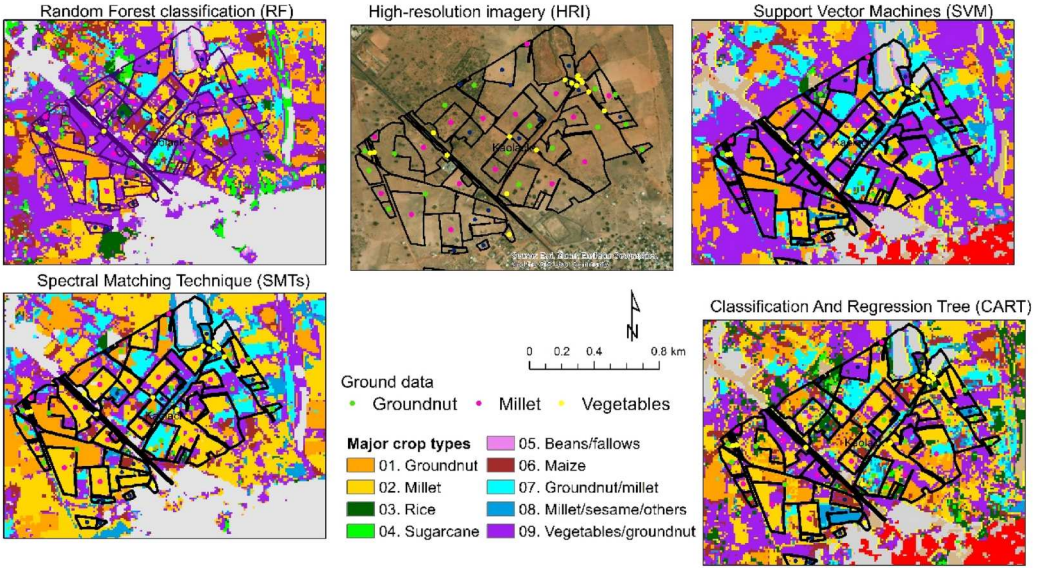

Figure 7. Field level comparison of crop type classification with SMT and other ML algorithms.

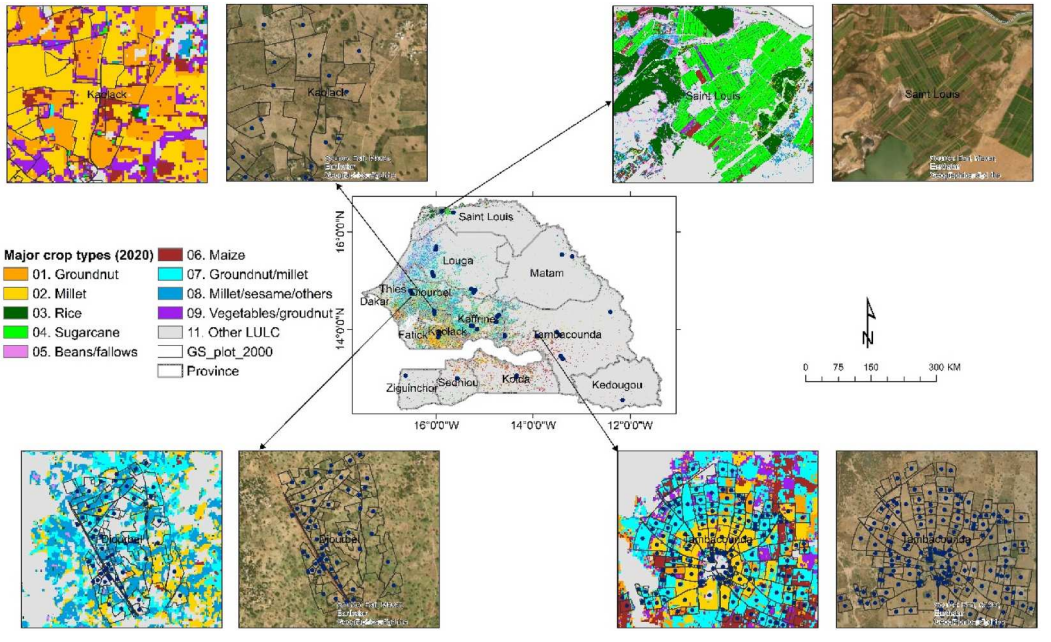

Figure 8. Plot level spatial distribution of crop types in Senegal during cropping season of 2020. Crop type maps derived by Spectral Matching Techniques (SMT) on GEE platform.

Sentinel-2 data is sufficient for crop-type mapping provided regular temporal availability exists from sufficient cloud-free images during the crop season. This study shows that machine-learning techniques like RF, SVM, and CART are highly efficient in crop-type classification when extensive and quality ground data is available. Nonetheless, traditional methods have proven ineffective when it comes to mapping crop types in small, irregularly shaped fields and regions with inter-cropping practices. This paper applied a SMT classification methodology specifically designed for efficient crop type mapping in areas characterized by small, fragmented, and multiple crop types (Figure 8). This approach is particularly well-suited for dryland regions in Africa, where ground data is severely limited, making it a valuable tool for enhancing agricultural mapping in such challenging environments.

High spatio-temporal imagery (Sentinel-2) and semi-automated algorithms like SMT are ideal to generate precise crop-type maps. Precise crop-type maps are required to generate detailed and accurate crop acreage estimates. Crop acreage estimation at village or sub-district level can help decision makers take quick interventions on particular crop.

Satellite-derived crop area statistics offer valuable tools for evaluating national agricultural data, enhancing decision-making, and facilitating planning, especially in areas that are otherwise difficult to access. Beyond national-level assessments, these crop area and extent maps, generated through this classification technique, can be harnessed for estimating crop yields at the village level, enabling micro-level crop management and tailored advisory services. Furthermore, this study demonstrates the versatility of the SMT approach, showing its applicability to high-resolution satellite data, even for studying within-field crop variability, which is particularly pronounced in the arid regions of Africa.

5. Discussion

This study demonstrated different supervised and unsupervised classification approaches for crop type mapping in Senegal for the year 2020. The crop types were mapped within a cropland mask

which was a class from a land use land cover (LULC) map of Senegal. The LULC map of Senegal was derived using Sentinel-2 imagery-based indices and spectral matching techniques (SMTs). Using SMTs to classify crop type in Senegal had some challenges including availability of satellite data and relevant phenological or spectral signatures that are required to separate different LULC types. Despite relying on limited ground collected crop type samples, the current methods used for analyzing signatures have yielded promising outcomes with reliable accuracy for classifying different land cover types. Approximately 62 percent of Senegal's landscape is covered with shrublands, sand dunes, and grasslands. Croplands cover 16 percent of the landscape in Senegal. Senegal has tremendous diversity of crop types with different growing seasons. Senegal is also a major food producer in West Africa and has high impact on the food security of the region.

This study mapped the dominant crop types in Senegal (rice, millet, and groundnuts) and minor crops (sugarcane, beans, maize, and mixed cropping fields) using supervised and supervised algorithms. The machine learning based supervised algorithms (RF, SVM, and CART) had ~25% lower overall accuracy compared to the unsupervised algorithm (SMTs). We observed that, with given data limitation, the unsupervised classifier produced a higher accuracy crop type map and was less reference data dependent than the supervised classifiers tested. We also observed that mixed cropping systems dominate the agricultural landscape of Senegal. SMTs were able to capture mixed cropping systems better than other algorithms implemented in this study. Overall, this study showed that SMTs produced a significantly more accurate crop-type map in comparison to the RF, SVM, and CART machine learning models. The results of this study can be applied to other counties in West Africa which have similar agriculture practices and have limited ground crop type data. Increasing the population of reference data to further enhance the accuracy of the generated maps is an important recommendation. However, it is important to note that this study primarily focused on evaluating the performance of classifiers under conditions of limited data availability.

6. Conclusions

This study has paved the way for exploring a suitable method to map croplands and crop types in the diverse landscape of Senegal using Sentinel-2 NDVI time-series data and the Spectral Matching Techniques (SMTs) approach, all while relying on limited ground data. With the available training data, the cropland extent of the majority of crop types in Senegal was accurately mapped. The research showcased the potential of high-resolution temporal images (Sentinel-2), even with limited ground data, to map crop types in Senegal. This was achieved by comparing various machine learning supervised algorithms like Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART), as well as an unsupervised algorithm like SMT. Mapping crop types represents a critical step in characterizing crop-growing environments, ultimately contributing to macro-level planning and the sustainable utilization of resources in dryland regions, fostering development.

Acknowledgements

This research was supported by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). We are very thankful to Mr Adam Oliphant, USGS for English editing and valuable suggestions. We would like to express our sincere gratitude to Dr Adama Sarr, CSE, Dr Mansour, AGRHYMET and Dr Aparna Phalke, NASA for their valuable initial review of the manuscript. We are grateful to Dr. Ramadjita Tabo, Dr Jat ML, Mr. Paul Bartel, from ICRISAT, Dr Bako Mamane, AGRHYMET and Mr Sibiry Traore, ICRISAT for their support and encouragement.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Data availability statement

Data used and generated in this publication is available from the ICRISAT RS/GIS portal.

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