Parcel Level Crop Mapping using Temporal Satellite Data and Machine Learning Techniques

Gali Brahmavar[1]*, Nagashree M. K[2], Rama Subramoniam S[2], Muskan Sindagi[1], Ganiger R[1] & Hebbar R[2]

[1]Karnataka State Rural Development and Panchayat Raj University Gadag, Karnataka; [2] Regional Remote Sensing Center-South, NRSC, ISRO, Bengaluru, Karnataka.
*Corresponding Author's email: galibrahma29@gmail.com

Abstract

Accurate near real-time crop information at parcel level in the fragmented and multiple cropping scenarios is an important input for monitoring, preparing contingency plans and insurance claims. Advances in remote sensing, data analytics, and computational infrastructure provides an opportunity to classify and generate map crop types at parcel level. The present study was undertaken to explore the use of temporal satellite data and machine learning techniques for crop type classification during rabi season in two selected villages viz., Balabatte and Kalagi of Vijayapura district. The major rabi crops of the study areas were groundnut, wheat, sorghum besides long duration sugarcane crop. Time series Sentinel optical data was used for crop type classification. Performance of three classification algorithms namely Maximum likelihood (MXL), Support Vector Machine (SVM), and Random Forest (RF) were evaluated for classification of major crops. The spatial extent of the different crops was compared with crop survey data obtained from Department of Agriculture, Government of Karnataka. Among the three classifiers, RF performed very well compared to other two classifiers. The results revealed that Sugarcane crop showed highest User accuracy of 92%, followed by Groundnut 80%, sorghum 79 % and wheat 50%. The Kappa coefficient of Random Forest is 77%. The RS based crop map has been compared with two village crop survey data showed close matching to the extent of about 71.12%. Further, likely harvesting period of sugarcane crop was estimated using crop phenology and NDVI. The present study demonstrated the potential use of temporal satellite data for mapping and monitoring of rabi season crops at village level and further work is planned to utilize a combination of optical and SAR data for improved crop mapping during kharif and rabi season.

Keywords Parcel, crops, Remote Sensing, Optical, Machine Learning

Introduction

Agriculture holds paramount importance in India, contributing significantly to the economy, food security, rural development, and cultural heritage. However, the sector grapples with pressing challenges like the need for modernization, sustainability, and adapting to climate change. This demands consistent attention and substantial investments (FAO 2021). With a diverse and sizable population, India heavily relies on agriculture to meet its food requirements. Staple crops such as rice, wheat, pulses, and vegetables are indispensable for daily sustenance. Consequently, ensuring food security stands as a top priority for the Indian government, with agriculture playing a central role in achieving this goal (FAO 2021). Primarily a rural pursuit, agriculture acts as a cornerstone for rural communities, providing employment and income opportunities. Moreover, investments in agriculture can spur rural development, alleviating poverty and elevating living standards in these areas (WorldBank.org).

Culturally ingrained, agriculture forms an integral part of India's heritage. Beyond national borders, India is a significant player in global agricultural markets. The export of various agricultural products, including rice, spices, and cotton, not only augments the country's foreign exchange earnings but also fortifies its international trade position (IBEF, 2021-22). Furthermore, agriculture serves as the foundation for various industries, providing raw materials like cotton, jute, sugarcane, and oilseeds for textiles, sugar, and edible oil production. These industries, in turn, foster job creation and contribute to economic growth (P. Maheshwari et.al., 1959). Recognizing the environmental imperative, sustainable agricultural practices are indispensable. Soil degradation, water scarcity, and the spectre of climate change underscore the need for adopting sustainable farming methods to mitigate environmental risks (Belén Cárceles Rodríguez et. al., 2022).

Thus, the use of new dimensions (like precision agriculture, modified seeds), and advance technologies (like Internet of Things, Machine Learning, Geospatial technology), are suggested for the value additions in agriculture sector since last 20 years which increases the agriculture value up to 73% since till 2019 (FAO 2021, Zheng, et.al.,2015). This leads to an intense farming over the state with varying crops in Rabi, Kharif season. Up to-date information regarding the crop type, acreage, and yield is required by the government for the proper management and planning of crop produces (Hooda, R. S et.al., 2006, Singh, D et.al., 2021). The use of traditional ground survey methods is used in several parts of the world to estimate crops and their acreage. Thus, mapping of crops is essential. The main reason for decrease in agricultural production includes many factors like climate change, the degradation of the land, low soil fertility, land ownership, illiteracy, lack of good quality of seeds and fertilizers, traditional farming methods, technological factor.

Remote sensing (RS) and Geographic Information System (GIS) technologies have emerged to address agricultural challenges. GIS methods enhance yields, reduce costs, and predict outcomes. They also analyse farm conditions, estimate crop yields, and manage resources. RS data offers early warnings for crop conditions, improving information accuracy. This advanced technology efficiently manages databases and digital maps, aiding in agricultural decision-making (Ofori-Ampofo et.al., 2021).

Machine learning is a subset of AI that enables machines to learn without explicit programming. It involves feeding data to the machine, which then identifies patterns to make predictions or decisions. In remote sensing, machine learning automates tasks, enhancing accuracy and insights. It's applied in image classification, assigning labels to pixels for land cover identification (forests, fields, urban areas). Machine learning, combined with satellite data, aids agricultural researchers in making informed decisions, boosting crop yields, reducing resource wastage, and fostering sustainable farming. This technology contributes to enhancing food security and promoting efficient land use in agriculture.

Objectives of the study:

- Analysis of crop survey data and its spectral characteristics.
- To identify harvesting period of sugarcane and associated major crops using crop phenology (NDVI).

- Classification of major crops (Sugarcane, Groundnut, Wheat, Sorghum) using ML Techniques.
- Area estimation and accuracy assessment.

Materials and Methods

Study Area:

*T*he study area of two adjacent villages Kalagi and Balabatti are situated in the Vijayapura district, Karnataka, India. It is bounded within 16.38909||N to 16.38911||N latitude and 75.96194||E to 75.96196||E longitude. Total geographical study area of Kalagi village is 1028.9 hectares and Balabatti Village is 791.42 hectares. The average annual rainfall is 718 mm. Mean maximum temperatures in the district during summer is around 38.54^0 C, while minimum mean temperature is 23.54^0 C. Major proportion of the study area is covered by deep black soil. Crops during Kharif season are Sugarcane, Pigeon pea, Pearl millet, Maize, Sunflower. Crops during Rabi season are Sugarcane, Groundnut, Sorghum, Wheat, Marigold.

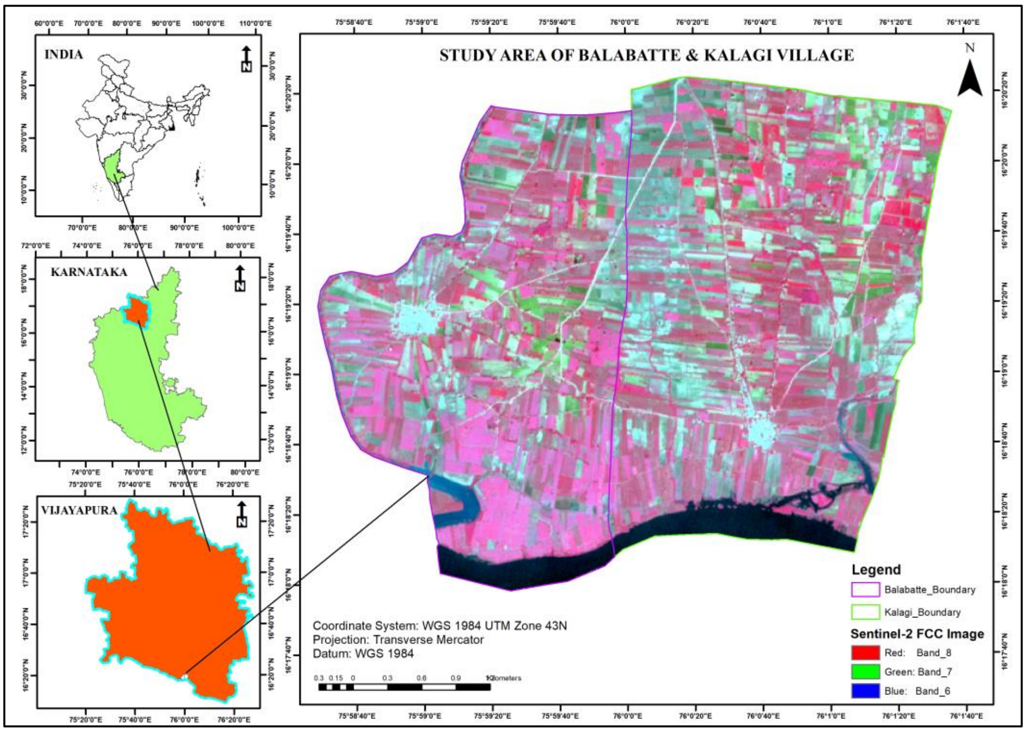

Fig. 1 Study Area Map.

Ground Truth (Crop Survey) Data:

The Crop Survey Scheme is a project of the Department of Agriculture, Government of Karnataka. It is a farmer-centric survey that aims to collect data on the crops grown, the area under cultivation, and the type of irrigation used in all the farm lands in the state. The survey is conducted every year during the Kharif, Rabi and Summer seasons. Planning and implementing agricultural interventions, such as crop insurance, crop diversification, and irrigation schemes. Assessing the impact of agricultural policies and programs. Monitoring the progress of the state's agricultural sector along with statistics. It provides point data which is used as ground truth data for remote sensing analysis. Ground truth data is information about the actual conditions on the ground, such as the type of crop being grown, the stage of growth, and the amount of irrigation being used. This data can be used to validate remote sensing data, which can improve the accuracy of the analysis. Conducting field surveys was deemed essential for this research endeavour to acquire precise spatial data pertaining to a specific crop variety. Ground-truth data were systematically gathered through a survey methodology for each agricultural plot. A modest subset of these data points was employed to establish representative spectral signatures for the accurate classification of the respective crop types. The field surveys were conducted in September for sugarcane and sorghum, while groundnut data collection took place in January. Subsequently, a comprehensive crop information form, encompassing parcel particulars and crop categorization, was diligently completed and submitted for both the Kalagi and Balabatti regions, accompanied by the appropriate photographic documentation (Crop Survey, 2020-21). After successful submission, the data was ready to use for training and testing in classification process.

Fig. 2 Crop Survey Data.

Methodology

Cadastral map with Crop Survey Details:

Cadastral map was downloaded from Department of Land Records and Survey, Govt of Karnataka (https://landrecords.karnataka.gov.in/service3/). Cadastral map is georeferenced with existing 2.5 m merged data as reference superimposed on LISS IV high resolution Satellite image and georeferenced by the use of reference as boundaries of villages from KGIS portal (https://kgis.ksrsac.in/kgis/downloads.aspx). Vectorizing the cadastral map using ArcGIS software and extracted the features like village parcel/survey polygons, water bodies, road etc. And corresponding attributes were added such as survey numbers available in the cadastral map. And more overly assigned projection to these digitized vector layers accordingly (WGS 84 datum and UTM) projection.

Crop details were collected at the village cadastral level from Crop Survey, Department of Agriculture, Government of Karnataka (https://cropsurvey.karnataka.gov.in/frmLoginEntry.aspx).Crop details and geotagging of photos were matched to the digitized vector layer accordingly to the survey numbers available in the cadastral map. The georeferencing of cadastral maps and the geotagging of crop images are complementary processes. By combining the two, it is possible to create a more accurate and comprehensive understanding of the spatial distribution of land parcels and crops. Georeferencing a cadastral map can help to identify the location of crop fields. This information can then be used to geotag crop images, which can be used to track the growth of crops, identify areas with pests or diseases, and monitor crop yields.

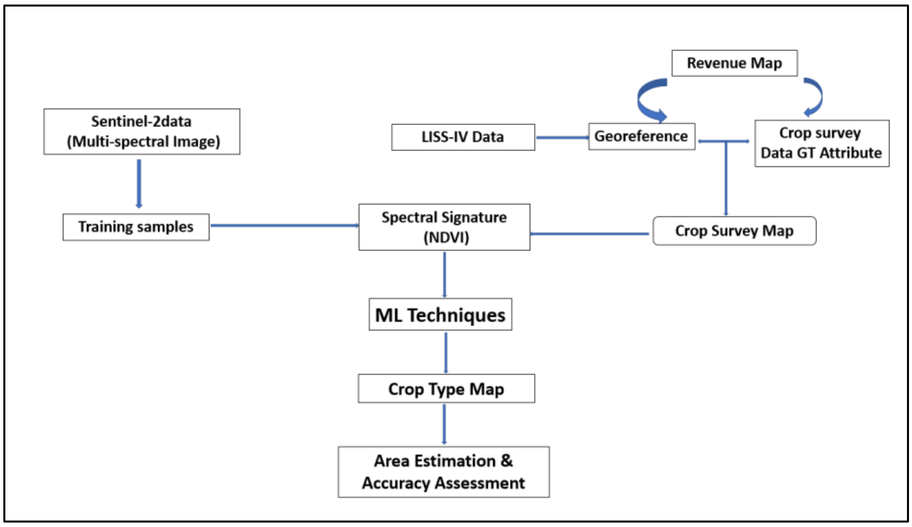

Fig. 3 Methodology Flow Chart.

Data Processing:

Sentinel-2 datasets were downloaded from Copernicus data hub (https://scihub.copernicus.eu) for the dates spanning from 02-11-2020 to 11-05-2021 representing Rabi season (Table 1). These images were already corrected for geometric and atmospheric abstractions and thus used directly for the analysis. The individual bands representing Near-Infra Red (NIR, 842 nm), Red (R, 665 nm), Green (G, 560 nm) and Blue (B, 490 nm) channels with spatial resolution of 10 meters were stacked (Singh, D et.al., 2021). Then the subset of each stack file was made using village boundary. NDVI was calculated for each stacked image to get a time-series composite of optical data (Wang, J et.al., 2020). Dates used in preparing time series data (both for optical and microwave) are given in Table 1. The time-series composites were then used for the spectral discrimination of crops. For this the average NDVI values were extracted using ground truth points also crop survey data points were randomly generated according to the Cadastral map and verified with ground data of same belt region (12-15 samples for each crop) and spectral analysis was done in temporal domain for crop type mapping using the concept of changes in spectral values in response to the phenological changes (Ofori-Ampofo, S et.al.,2021).

Table 1 *Time Series Data used for crop mapping*

Sl. No	01	02	03	04	05	06	07
Sentinel 2 Optical	02-11-2020	12-12-2020	11-01-2021	05-02-2021	27-03-2021	11-04-2021	11-05-2021

Different crop spectral signatures are found in time series data analysis. More overly three different signatures of Sugarcane identified and statistically analyses of crop phenology (NDVI) is done. Also Wheat, Sorghum and Groundnut signatures were identified during rabi season.

Spectral discrimination of crops:

The classified data produced consisted of total 1884 parcel. It included Kalagi and Balabatti village surveyed data. Time-series NDVI spectral signature as shown in (Figure 4). It is represented that, the Wheat and Sorghum are showing same spectral signature during sowing stage (i.e., November 2020). The sowing time of sugarcane varies from field to field, this spectral signature of the crop varies slightly within the sugarcane crop trait class. Here, some fields are selected which shows the similar spectral signature. Thus, groundnuts are harvested earlier than sorghum, the different spectral signature of these plants vary during the growth and harvest periods. Because the duration of Groundnut crop is 4 months and Sorghum is 5 months. The sowing time of Sugarcane is earlier than the other crops of monsoon season, and thus it gets peak NDVI values earlier than other crops during this time. Thus, sugarcane harvest occurs in December to February, and used for early prediction of related parameters such as area and yield estimation. This shows that the Groundnut and Sorghum can be discriminated by applying NDVI time-series during March and April i.e., before the end of Rabi season. Harvesting periods of sugarcane crop phenology shown in Figure (4). Here, some fields are selected which shows the similar spectral signature. Based on similar spectral signature sugarcane crop differentiated in three varieties viz, Sugarcane_1, Sugarcane_2, and Sugarcane_3. Because of the reason there is a difference in the NDVI values shows the different harvesting periods of sugarcane. Sugarcane_1 is harvested in February, Sugarcane_2 is harvested in January Whereas, Sugarcane_3 is harvested in December.

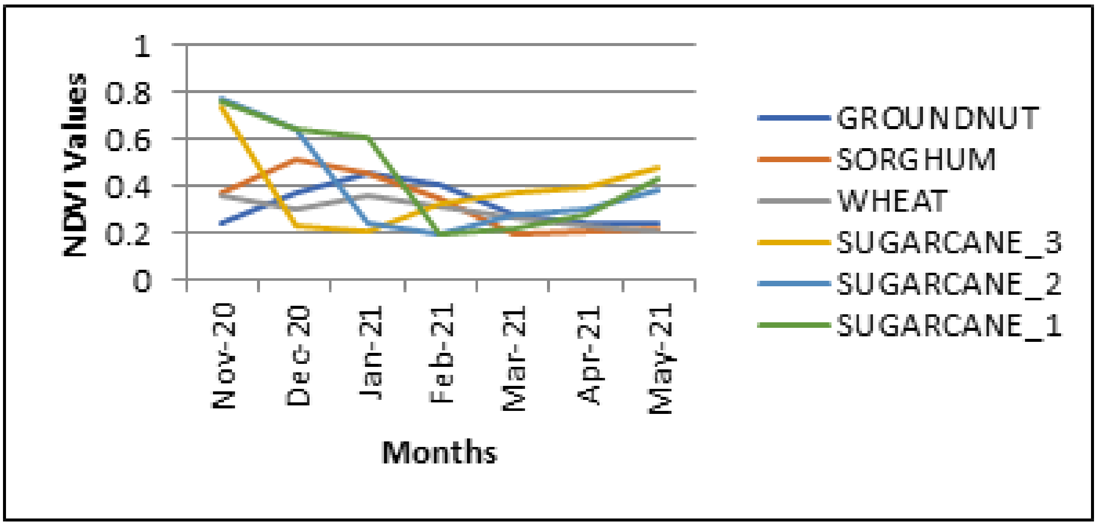

Fig. 4 Time Series NDVI 2020-21.

Accuracy Assessment: Applied an accuracy check approach where; some parcel unites were taken for the accuracy assessment except those unknown parcels taken for the classification. All the classification algorithms were assessed with various accuracy measures including PA (Eq. 1), UA (Eq. 2), OAA (Eq. 3) and Ka (Eq. 4) Table (2) (Neetu & S S Ray 2019). Where, = relative observed agreement among samples and hypothetical probability of chance agreement. Classified outputs were compared with ground truth i.e., crop survey data. This was done to check all the pixels accuracy which is first of its kind assessment. The method adopted here is new and the learning obtained from this approach suffices the purpose of identifying best algorithm for cadastral level crop type mapping. This is because all the combinations and popular algorithm were checked for all the classified unites which mean the methods are tested over whole population and results are valid for all the pixels in an image space.

Table 2 *Accuracy Analysis Equations.*

(1) Producer Accuracy (PA) = Class Specific Column Total / Class specific diagonal * 100	Eq.1
(2) User Accuracy (UA) = Class Specific Row Total / Class specific diagonal * 100	Eq.2
(3) Over All Accuracy (OAA) = Diagonal Total / Sum of all the samples * 100	Eq.3
(4) Kappa Coefficient (Kp) = $P_0 - P_e / 1 - P_e$	Eq.4

Results and Discussion

Comparative Assessment of Classifiers: A Perennial sugarcane crop, other major crops of rabi season and land use categories were classified using three popular classification algorithms (MXL, SVM and RF) by the time series of sentinel-2 data. Different classifier as different algorithms by input of the training sites and well classification as done. The error occurs at the mixed crop growth at parcel level and most at margin side due to mixed pixels. *Maximum Likelihood (MXL) Classification:* Maximum Likelihood Classification: MXL classification is one of most the popular classification techniques. Under this, the classes are identified based upon the maximum likelihood of the pixel, belonging to a particular class (Wang, J et.al., 2020). Training signatures were generated using crop survey map sites collected form crop survey. Crop signature profiles were also generated (Figure 4) and signatures were merged using signature separability and major crop classes were selected as Sugarcane, Groundnut, Sorghum and wheat, along with other classes. (Figure 5) shows the classification output of MXL classifier.

Support Vector Machine (SVM): SVM is very popular technique for solving problems in classification and regression. In support vector machines the classification problem solves through the concept of margin, which is defined as the smallest distance between the decision boundary and any of the samples. The decision boundary is chosen to be the one for which the margin is maximized. In this case margin is the perpendicular distance between the decision boundary and closest of the data points (Bishop C. M. 2006). Training signatures were generated using crop survey map sites collected form crop survey. Crop signature profiles were also generated (Figure 4) and signatures were merged using signature separability and major crop classes were selected as Sugarcane, Groundnut, Sorghum and wheat, along with other classes. (Figure 5) shows the classification output of SVM classifier.

Random Forest (RF) Classification: Random Forest is a generalized method of the decision tree. It overcomes the major drawback of the decision tree by using the concept of bagging. In bagging, multiple decision trees are constructed using a subset of training data and a subset of features for each tree and output is determined by the either considering majority vote or calculating the average of all trees. Random forest is generally faster in training and but slow in predicting ("The Random Forest Algorithm", 2019). Training signatures were generated using crop survey map sites collected form crop survey. Crop signature profiles were also generated (Figure 4) and signatures were merged using signature separability and major crop classes were selected as Sugarcane, Groundnut, Sorghum and wheat, along with other classes. (Figure 5) shows the classification output of RF classifier.

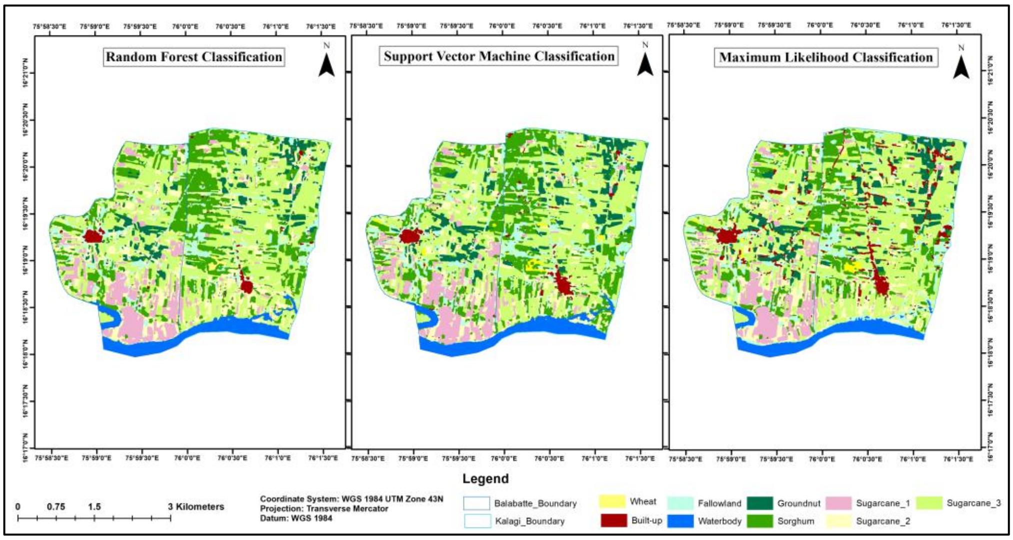

Fig. 5 Output Map of Different Classified Machine Learning Techniques.

Crop Acreage Estimation:

A long duration sugarcane and other major crops and land use categories were classified using three popular classification algorithms (MXL, SVM and RF) by the Sentine-2 time series data. Comparison of area estimation with classified outputs to crop survey data for Rabi crops. The crop acreage estimated and compared with the acreage obtained from ground survey (crop survey) data. A large variation in the acreage is observed for Sorghum crop. In Kalagi and Balabatti village sugarcane while an appropriate acreage was obtained due to similar signatures were found in the Unknown* parcels were not considered for area calculation. The area estimation of sugarcane crop is done by the analysis of Kharif and Rabi season crop survey data. The detailed area comparison of satellite-based crop acreage was done with the 100% crop survey data.

***Table 3** Comparison of classified crop area with crop survey data.*

	Sugarcane In (Acres)	*Sorghum* In (Acres)	*Groundnut* In (Acres)	*Wheat* In (Acres)
Crop Survey	1809.97	212.17	335.47	64.24
Support Vector Machine	2340.25	864.14	328.07	34.65
Random Forest	2545	838.64	267.62	37.07
Maximum Likelihood	2565.53	698.11	304.45	34.56
Classified Area (%) with known parcels	92%	79%	80%	50%

Source: Crop Survey (2020-21), Department of Agriculture, Government of Karnataka.

- Kalagi Village has a 1060.8 ac as Unknown* Parcel in the Crop Survey Data. Unknown parcels are classified as the Sugarcane, Groundnut, Sorghum.
- Balabatti village has about 773.8 ac as Unknown* Parcel in the Crop Survey Data. Unknown parcels are classified as the Sugarcane, Groundnut, Sorghum.
- Classified area in Percentage used Known* Parcels of crop survey data area in percentage with the different machine learning classified area.

Accuracy Analysis									
Confusion Matrix Based on the crop survey data									
Classification Name: Maximum Likelihood Classification									
Class Value	Built-up	Fallow land	Waterbody	Groundnut	Sorghum	Sugarcane	Wheat	Total	User_Accuracy
Built-up	8	1	0	0	1	0	0	10	0.8
Fallow land	1	4	0	0	2	2	1	10	0.4
Waterbody	0	0	9	1	0	0	0	10	0.9
Groundnut	1	1	0	7	0	1	0	10	0.7
Sorghum	0	2	0	1	16	4	1	24	0.67
Sugarcane	3	1	1	2	2	70	0	79	0.89
Wheat	0	2	0	0	1	2	5	10	0.5
Total	13	11	10	11	22	79	7	153	0
Producer_Accuracy	0.62	0.36	0.9	0.64	0.73	0.89	0.71	0	0.78
Kappa Coefficient= 0.68									
Overall Accuracy= 78%									

Accuracy Analysis									
Confusion Matrix Based on the crop survey data									
Classification Name: Support Vector Machine									
Class Value	Built-up	Fallow land	Waterbody	Groundnut	Sorghum	Sugarcane	Wheat	Total	User Accuracy
Built-up	7	2	0	0	1	0	0	10	0.7
Fallow land	0	7	0	0	1	1	1	10	0.7
Waterbody	0	0	9	0	0	1	0	10	0.9
Groundnut	0	1	0	8	0	1	0	10	0.8
Sorghum	0	2	1	1	16	3	1	24	0.67
Sugarcane	2	2	0	1	2	72	0	79	0.91
Wheat	0	2	0	0	1	2	5	10	0.5
Total	9	16	10	10	21	80	7	153	0
Producer_Accuracy	0.78	0.44	0.9	0.8	0.76	0.9	0.71	0	0.81
Kappa Coefficient= 0.72									
Overall Accuracy= 81%									

Accuracy Analysis									
Confusion Matrix Based on the crop survey data									
Classification Name: Random Forest									
Class Value	Built-up	Fallow land	Waterbody	Groundnut	Sorghum	Sugarcane	Wheat	Total	User Accuracy
Built-up	8	1	0	0	1	0	0	10	0.8
Fallow land	0	7	0	0	0	2	1	10	0.7
Waterbody	0	0	9	0	1	0	0	10	0.9
Groundnut	0	0	0	8	0	2	0	10	0.8
Sorghum	0	1	1	1	19	1	1	24	0.79
Sugarcane	1	1	0	1	3	73	0	79	0.92
Wheat	0	2	0	0	1	2	5	10	0.5
Total	9	12	10	10	25	80	7	153	0
Producer_Accuracy	0.89	0.58	0.9	0.8	0.76	0.91	0.71	0	0.84
Kappa Coefficient= 0.77									
Overall Accuracy= 84%									

Accuracy Analysis on different classification Techniques (Confusion Matrix):

Accuracy analysis is done on the basis of crop survey data at parcel level. Where, Random Forest Classifier overall accuracy (84%) is better than Support Vector Machine (72%) & Maximum Likelihood Classifier (68%). The lower accuracy is found in Maximum Likelihood

Classification that due to mixed classes found in the long duration crop & major crops at parcel level.

Conclusions

Different classification algorithms such as, MXL and SVM and RF, have been implemented in present study for the classification of crops scenario. Random Forest Classifier overall accuracy (84%) is better than Support Vector Machine (72%) & Maximum Likelihood Classifier (68%). The lower accuracy is found in Maximum Likelihood Classification that due to mixed classes found in the long duration crop & major crops at parcel level.

An approach where whole study area is covered under training and testing of ML Techniques for sugarcane crop area estimation besides its harvesting period and other associated crop area estimation at parcel level using time series data. Future work may be utilization of optical and high/ medium resolution of SAR data at parcel level for improved crop mapping.

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