



# A COMPARISON OF SINGLE DATE AND MULTITEMPORAL SATELLITE IMAGE FOR CROP CLASSIFICATIONS WITH MACHINE LEARNING AND CLOUD COMPUTING.

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**Abstract:** With the growing demand for food security and sustainable agricultural practices, there is an urgent need for accurate and efficient methods to assess crop development and identify potential issues affecting yield. Remote sensing plays a crucial role in timely monitoring of land, water and soil. Geospatial technology offers a suite of tools and techniques that enable remote sensing, data analysis and monitoring of agricultural landscapes at various scales. Optical Earth Observation satellite data forms the basis for crop monitoring, agriculture practices, policy making, etc. In our study we used public datasets to get crop map of a cash crop; sugarcane. Sentinel 2 satellite data were used to produce maps depicting field ranges of sugarcane crop grown in part of north Karnataka, India. Data collected for 3 years was used as a multi dated input for machine learning models in contrary with a single dated image. Dynamics nature of the crop and overlapping spectral behavior makes crop identification using single date image more challenging. Different Decision tree algorithms are used with the same set of data. Cloud computing service offered through Google Earth Engine is used for accessing satellite data and as well for computation. Near Infrared (NIR), Visible (Red, Green, Blue), Short Wave Infrared (SWIR) are the bands selected for our study. Our study revealed that using temporal images for crop identification is more complicated but resulted in good accuracies when compared with real data. Single date and multitemporal classification accuracies were compared using ground truth data as references. Multitemporal classification accuracies were more accurate than single date images for mapping sugarcane crop in this region.

**Index Terms - Sentinel 2, Decision tree, Google Earth Engine, NIR, SWIR.**

## I. INTRODUCTION

India being a land of agriculture contributed to nearly 70% of national Gross Domestic Product (GDP) in 1965 but according to fiscal year 2022 – 23 it is less than 20% which is an alarming signal towards Sustainability Development Goal (SDG) 2.0 towards Zero Hunger [1]. Survey indicates that every farmer is struggling with a different cause for poor yield which is demotivating many of them and also to even stop farming. Technology is moving at its pace and conquering over every sector in society in its own way; application of it in agriculture sector will definitely not disappoint us. By the use of modern tools and technology a farmer can not only just monitor but also can predict the yield before harvesting to check on his accounts so that shortfall and surplus of the crops can be handled in a better way [2]. Replacement of traditional methods by simple easy ways (with the use of technology) fusion with the experience and an expert involvement will be a way to strengthen agriculture in our country [3]. Geospatial technology and Machine learning/ Deep learning can be a unique set of solution to address many problems related soil, water, land etc. [4]. As a step towards the sustainability goal 2.0 (Zero Hunger); can be achieved through managing the surplus and shortage of crops effectively. A reliable predictor to identify crop regions and forecast yield will be a solution to above said issue. Conventionally crop monitoring and yield forecast is mostly done manually which is less economical and logistically cumbersome. Satellite imagery with Geospatial tools come in handy to deal with it. Cluster of Earth Observation satellites deliver Spatio temporal images. But apart from noise of Earth observation satellites; for coarse resolution images the real challenge is with a single pixel per plot being used to analyze and predict the crop, health status of crops and yield. Similar spectral behavior among the crop classes also make discrimination quite difficult. Single image to perform crop classification resulted in poor accuracy. Time series analysis on satellite images gives a clue of the vegetation pattern [5]. Distinctive phases in crop phenology which are called “Unique seasonal signatures” are the key inputs for the predictor model.

Datasets comprising temporal data over the crop calendar is a part of training the model. The start and end of crop growing season will be important. The framework developed and tested is giving a roadmap for an automatic prediction system which can be upscaled to benefit the national marketers (for pricing and shipping strategies), mill owners and insurers (for scheduling mill operations and remedial actions) and also farmers (for planning fertilization and harvesting). Many models are being developed by researchers which do predict large scale yield using satellite imagery but fine scale yields are mostly done through Unmanned Aerial Vehicles (UAVs) or Drones which becomes a costly affair for a smallholder. To address the issue a cost-effective solution to the growers can be a boon. A user interface can be done to get crop grown area, crop growth status, calculate yield and even stressed crops after an extensive testing. Hence a need to combat the above by revolutions in farming and also the preparedness for the coming uncertainties is the need of hour.

India is the 2<sup>nd</sup> largest sugarcane producer in the world next to Brazil. Sugarcane is termed as a multipurpose crop since it is used to make sugar, jaggery, khandsari, molasses, even paper [6]. Also, sugarcane is a distinguished cash crop which is called as a water guzzling crop as well. Karnataka (an Indian State) stands third to contribute sugarcane at national level after Uttar Pradesh and Maharashtra. Every year state produces not less than 40 million tons of sugarcane. Belagavi (District in Karnataka) is popularly called as Sugar Bowl of Karnataka accounting for 35% of state sugarcane production [7]. As sugarcane has been declared as an essential commodity a gap exists between the expected yield and actual yield taking the resources as constraints. In Karnataka sugarcane is a kharif crop and come in varieties such as Eksali and Adsali to differentiate as a year crop and one-half year crop respectively [8]. With Ten taluks and 21 working sugar industries Belagavi feel itself proud in producing more than one crore ton of sugarcane every year by not only benefitting the state in revenue but also central excise department [9]. Any initiative to help farmers to ease farming and also educate them on increasing their yield will be encouraging. With this as an objective an attempt is made to identify sugarcane crop grown area from satellite images with prime features extractions over a crop calendar. Initially a single dated satellite image was used to detect crop grown area but with a motive to improvise classification accuracy multi dated satellite images were used keeping same features over same learning models.

## II. WORK METHODOLOGY

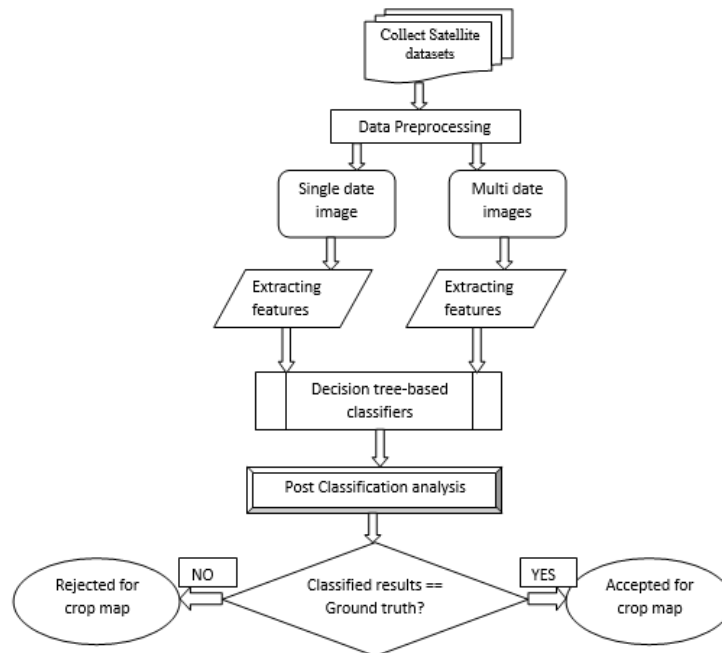
This pilot study is envisaged for the application of geospatial technology for detecting sugarcane crop grown regions in the selected study areas using remote sensing satellite imageries and Machine Learning Techniques [10]. The major objectives of the study are as follows:

1. Selection of satellite dataset spanning over the study area.
2. Study of Sugarcane Crop Phenology.
3. Feature extraction from a single satellite image.
4. Feature extraction from a multiple satellite image.
5. Comparison of single date and multi temporal accuracies.

The study area encompasses an area of 13414 sq. kms lying between the latitude of 15.852792N and longitude of 74.498703E. It lies approximately about 776m above the mean sea level. It is bounded on the North Karnataka at the foothills of the Sahyadri range (Western Ghats). The work flow used to carry the research in the area of interest is detailed in Figure 1. Initially a farm with mixed cropping in the region of interest was considered to work upon as shown in Figure 2. The ground truth was collected by field visits (current) and from a reliable source (past records from state government organization).

## III. MATERIALS AND METHODS

COPERNICUS Open Access Hub delivers various sentinel data products. Sentinel 2 multi spectral instrument data in level 1C considering cloud probability which has revisit day as 5 is used. Google Earth Engine service is used as a platform to get remote sense data and also perform cloud computing with visualization analysis tools. The public data catalogue is used for study. Plenty of datasets are available for scientific and research surveys. More than around previous 30 years of data is available for access. The Earth Engine API shown in Figure 3 is available in Python and JavaScript, making it easy to harness the power of Google's cloud for our own geospatial analysis [11]. The web-based code editor is used for fast, interactive algorithm development with instant access to petabytes of data. Among various datasets Sentinel 2 level 1C images during years 2021, 2022 and 2023 with surface reflectance were used [12]. As Google Earth Engine supports with our own boundaries, an asset for region of interest is uploaded on the Google Cloud. Specific key bands, NIR, Visible, SWIR are identified as prime inputs for training the model. Crop calendar for annual crop of sugarcane is as shown in Table 1.



**Fig. 1 : Workflow of the research performed**

The selected study site with sugarcane grown as an annual crop for past 5 years is used and is shown in the Figure 3. Cloud coverage is nullified by creating mask which masks pixel with null values. Single date image during the tillering period is used for single image analysis. The feature space is created and given to the Decision tree algorithms namely Classification And Regression Tree (CART), Random Forest and Extreme Gradient Boost and then; to validate ground truth data collected using Google Earth Pro application over the region of interest is used.

**Table 1 Growth phases of sugarcane crop (Eksali variety – annual crop)**

Sl. No	Crop Growth Phase	Schedule (ROI)
1	Germination	Feb – Mar
2	Tillering	April - June
3	Grand growth	July - Sep
4	Maturity	Oct – Dec

Same single date image was used to get band values and fed to decision trees keeping the hyperparameters same. The overall accuracy was used as an assessment tool and was calculated for single image. From same dataset images for 3 consecutive years namely 2021, 2022, 2023 were collected and the feature space with increased dimensions and size is used for the same decision trees to train. Now the classification performed was observed to be better than earlier. The overall accuracy improved over the selected study area with 3 years data given to the machine learning algorithms.



**Figure 2 : Study Area used for research [Courtesy: Google Earth Engine]**

#### IV. RESULTS AND DISCUSSIONS

Single dated image for years 2021, 2022, 2023 were given to the machine learning models and the observations were noted. Then the models were given with 45 images each for years 2021, 2022, 2023 and the inferences were noted. The classification of sugarcane crop grown regions was improved with multiple images since the key phenology which separates the sugarcane crop from other crops spectrally and structurally were captured in multi temporal datasets. The Table 2 depicts the calculated accuracies for each case. With small datasets the results obtained are convincing to carry the research ahead; to generate other crop maps, estimate yield, monitor growth status, diseased crops, nutrient deficiency, etc.

**Table 2 Accuracies of Machine Learning models with single image and multi images.**

Sl. No.	Machine Learning Algorithm	Single Date Image		Multitemporal Images	
		Training Accuracy	Overall Accuracy	Training Accuracy	Overall Accuracy
1	Extreme Gradient Boost Classifier	94.6%	78.3%	98.3%	96.4%
2	Random Forest Classifier	94.6%	72.3%	98.3%	90.1%
3	Classification And Regression Tree (CART)	94.6%	68.1%	98.3%	86.6%

The proposed model depicts acres with sugarcane grown after accurately classifying sugarcane grown regions. Results are guiding to carry forward and prepare a yield map to regional or national scale to forecast the yield very much before the actual harvest time. This not only aids growers but also mill operators. Exploration of other indices like NDVI (Normalized Difference Vegetation Index), Leaf Area Index (LAI), Green Chlorophyll Index (GCI) can be appended to sharpen the inputs given to the model to train it in a better way. The study showed that a multi temporal images gave better results than single date image. The success of the pilot study in this region will be a way forward for seamless upscaling of the same to state and national level crop grown assessment systems.

#### V. FUTURE SCOPE

Future scope can be exploration of Deep learning models and high resolution data to train the model. Any small improvisation in the model accuracy can still be a approachable way to get the optimized results at the end user. Integration of wireless sensor network, automation and learning models with a user interface will be a reality in coming years taking farming at ease and precise. Though the other data (weather, climate, meteorology etc) need to be connected to produce a full fledge support to the farmer through a stand alone application interface. An user interface with support for crop growers right from selection of crop, decision on crop calendar, fertilizer/ pesticide input, yield forecast, expert chatbots, etc. can greatly be a boon to farmers.

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#### REFERENCES

- [1] Escobar González José Luis, "Remote Sensing for Crops Identification", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-3/W6, 2019 ISPRS-GEOGLAM- ISRS Joint Int. Workshop on "Earth Observations for Agricultural Monitoring", New Delhi, India. Feb. 2019.
- [2] Senthil Kumar Swami Durai, Mary Divya Shamli, "Smart farming using Machine Learning and Deep Learning techniques", Decision Analytics Journal 3 (2022) 100041.
- [3] HU Qiong, WU Wen-bin, SONG Qian, LU Miao, CHEN Di, U Qiang-yi, TANG Hua-jun, "How do temporal and spectral features matter in crop classification in Heilongjiang Province, China?", Journal of Integrative Agriculture 2017, 16(2): 324 – 336.
- [4] Teerapat Butkhot and Pipat Reungsang, "Assessment of machine learning on sugarcane classification using Landsat- 8 and Sentinel-2 satellite imagery", Asia-Pacific Journal of Science and Technology: Vol. 26. Issue 04. Article ID.: APST-26-04-08.
- [5] Chong Luo, Beisong Qi, Huanjun Liu, Dong Guo, Lyping Lu, Qiang Fu and Yiqun Shao, "Using Time Series Sentinel-1 Images for Object-Oriented Crop Classification in Google Earth Engine", Jour.of Remote Sensing, Vol. 13, 2021, pp.561.
- [6] Md. Yeasin, Dipanwita Haldar, Suresh Kumar, Ranjit Kumar Paul and Sonaka Ghosh, "Machine Learning Techniques for Phenology Assessment of Sugarcane Using Conjunctive SAR and Optical Data", Remote Sensing Journal. Vol.14, 2022, pp.3249 - 3267.
- [7] Girish A Chavadappanavar, "Impact of COVID-19 on Sugarcane Growers and Sugar Industry-Situational Assessment in Karnataka State", International Jour. of Science and Research, Vol. 10, Issue 9, Sep 2021. ISSN: 2319-7064.

- [8] Prabhu Kadadi and Jahanara, “*Extent of Adoption of Organic Sugarcane Cultivation Practices in Belgaum District of Karnataka State*”, Int. Jour. of Innovative Science and Research Technology, Vol. 3, Issue 5, 2018.
- [9] Rahul Sreedhar, Avnish Varshney and Dhanya Madhu, “*Sugarcane crop classification using time series analysis of optical and SAR sentinel images: a deep learning approach*” Article in Remote Sensing Letters - Vol. 13, No. 8, June 2022, pp.812–821.
- [10] Megharani B. Mayani and Rajeshwari Itagi, “*Machine Learning Techniques in Land Cover Classification using Remote Sensing Data*”, International Conference on Intelligent Technologies (CONIT) Karnataka, India. June 2021.
- [11] Masoumeh Aghababaei, Ataollah Ebrahimi, Ali Asghar Naghipour, Esaeil Asadi and Jochem Verrelst, “*Vegetation Types Mapping Using Multi – Temporal Landsat Images in the Google Earth Engine Platform*”, Journal of Remote Sensing, Vol. 13, 2021, pp 4683.
- [12] J. P. Clemente, G. Fontanelli, G. G. Ovando<sup>1</sup>, Y. L. B. Roa, A. Lapini and E. Sant, “*Google Earth Engine: Application of Algorithms for Remote Sensing of Crops in Tuscany (Italy)*”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XLII-3/W12-2020, IEEE Latin American GRSS & ISPRS Remote Sensing Conference Santiago, Chile, March 2020.