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Estimating Net Sown Areas at Kalwakurthy Branch Canal using Multi Temporal Sentinel-2A Satellite Data

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ABSTRACT: Mapping crop areas is the first step in characterizing critical crop growing environments that help macro-level planning, leading to sustainable use of resources and improvement in drylands. Mapping of the crops at the district, regional or the national level gives an information of the change in the cropping pattern in an area and also gives the input for the various agencies such as the regional agricultural agencies, insurance agencies and geo portal boards.In the present study the attempt has been made to generate spatial distribution of the *kharif* and *rabi* area during 2015-16 in Kalwakurthy Branch Canal develop under Mahatma Gandhi Kalwakurthy Lift Irrigation Scheme (MGKLIS) which is one of the irrigation project in the Telangana State. The study utilized Sentinel-2A satellite based NDVI (Normalized Difference Vegetation Index) to extract net sown area of study site. The crop map obtained using the conditional based classification showed that the *kharif* area, *rabi* area and orchard area were estimated as 5721.54 ha, 1287.47 ha and 1627.36 ha respectively. The results indicated that the overall accuracy and Kappa coefficient achieved were 86.67% and 0.77.

Keywords: Cropping season, Crop mapping, Sentinel 2A, NDVI.

INTRODUCTION

Dryland areas are highly vulnerable because of high variability in rainfall (Misra *et al.,* 2010). Construction of the new irrigation structures ensures the water supply in dryland areas, which plays a significant role in the cropping system. Over the years, dryland agriculture's changing character and extent underline the importance of continuously monitoring croplands to ensure sustainable food production (Gumma *et al.,* 2020). Cropland mapping and monitoring are essential for estimating potential harvesting, agricultural field management (Sonobe *et al.,* 2017), food production, and sustainable natural resources management (Belgiu and Csillik 2018). Mapping of the crops at the district, regional or national level gives information on the change in the cropping pattern in an area. Also, it provides input for various agencies such as the regional agricultural agencies, insurance agencies, and geo portal boards. Crop classification and land monitoring can be estimated using many earth observation satellites (Rodriguez-Galiano *et al.,* 2012). The temporal and spatial variations in the crop area will help in improving the productivity of land and water (Neelima *et al.,* 2013). Remote sensing (e.g., satellites and drones) has made it possible to assess and monitor the extent and status of cultivated land. Remote sensing techniques are a handy and cost-effective tool for acquiring a large amount of information (Ryu *et al.,* 2011). The images from the satellite provide a valid alternative, particularly when the area needs to be estimated at the state or national level (Thenkabail *et al.,* 2010).The launch of the Sentinel -2 satellite by the European Space Agency provides free optical data with high resolution. Sentinel-2A was launched in June 2015, and Sentinel-2B, launched in March 2017, provides data at five days. For this study, conditional based classification was performed, and the approach of using temporal data. NDVI for the cropping season based on the crop calendar was used. Sentinel 2, with the higher temporal resolution availability of data, made it easier to analyze the crop condition on each 6th day, and the crop was mapped at the scale of 10-meter resolution

By keeping the above mentioned views in mind the present study was designed to examines the spatial distribution of *kharif* and r*abi* (including orchards) area under the Kalwakurthy Branch canal during 2015-16. The frequent monitoring of the cropping pattern in an area can help the irrigation engineers to schedule the irrigations which can help in calculating the water requirement for the command area.

MATERIALS AND METHODS

Location of the study site and its description. Mahatma Gandhi Kalwakurthy Lift Irrigation Scheme (MGKLIS) is one of the flagship irrigation projects in the Telangana State, which has served as a boon for drought-prone areas of Mahabubnagar, Nagarkurnool, and Wanaparthy districts since 2016. The MGKLIS is divided into two branch canals, namely the Achampet branch canal (ABC) of 90 km in length and the Kalwakurthy Branch Canal (KBC) of 160 km in length. The present study is carried out for KBC. The study area is located between 16°9'36"N to 16° 44' 54" N latitude and 78°1'18"E to 78°34' 46"E longitude. The KBC has an ayacut of 96,405 ha. It is a semi-arid region with a hot and dry climate with an annual rainfall of 600-1100 mm, and the average temperature is 35°C. The major crops grown in the study area are paddy, cotton, redgram, and groundnut. Two types of soils are predominant in the study area, namely red soils and black cotton soils

Sentinel-2 data: Sentinel-2 satellite with 10-meter resolution has a revisit period of 6-day surface reflectance from the EU Copernicus Programme is ideal for monitoring vegetation at a small scale (Xiong *et al*. 2017) was used for the study. Two tiles namely PHT and QHU covering the required region were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/).

Pre-processing of Sentinel-2Adata: ERDAS imagine software was used to pre-process and mosaic the tiles of the study area, and then stack them as a single composite. The bands Blue, Green, Red and Near Infra-Red are used for generation of the False Colour Composite (FCC) image. The shape files received from the MGKLIS Executive Engineer Office; Nagar Kurnool was used to clip the data to the study area.

Ground data collection: The field survey was carried out during 2021-22 and information regarding the crops grown during 2015-16 was collected with interaction from the farmers. The information regarding the orchards and forests was collected with the help of Google Earth Pro.

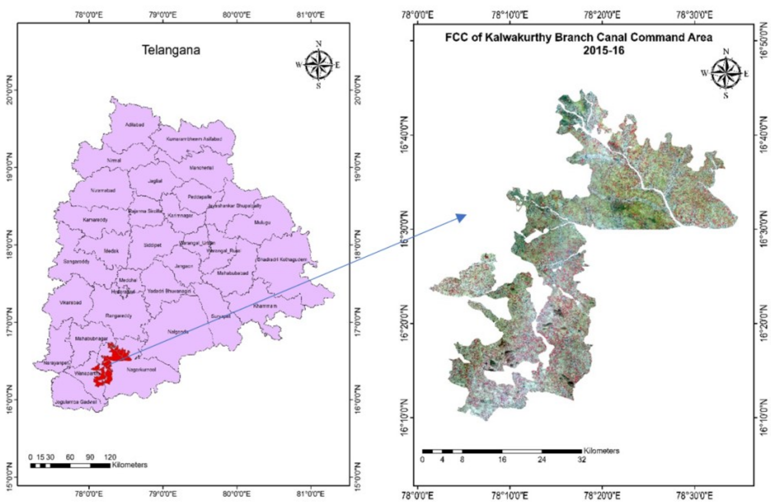

Fig. 1. Study area.

Satellite Indices: The Normalized Difference Vegetation Index (NDVI) maps were generated for the multi-date images for the year 2015-16 and the NDVI composite was prepared by layers stacking the obtained NDVI multi-date images (Jan 10th, Feb 9th, March 10th, April 18th, 2016). The layer stacked NDVI images were used for the extraction of the maximum and minimum NDVI values.

$$NDVI=\frac{NIR-RED}{NIR+RED}$$

Image Classification: Image classification aimed to separate the kharif and rabi areas using multi-date satellite images. The obtained NDVI images were layer stacked date-wise, the k-cluster algorithm of unsupervised classification was used for classification, and 300 spectral classes were generated with 200 iterations with the convergence threshold of 0.99. For these 300 classes, the zonal mean was extracted using the spatial model in the ERDAS imagine software, and this obtained zonal mean was used for the generation of the class-wise NDVI profile and for the extraction of the spectral signatures. The different classification methods give varying results that depend on factors such as the type of satellite data and the subject of the classification. The classification can also be affected by factors such as the selected spectral bands, ancillary data, and the nature of the study area (Foody and Arora 1997). Unsupervised classification is based on exploiting the inherent tendency of different classes to form separate spectral clusters in the feature space. It uses algorithms that search for natural groupings of the spectral properties of the pixels. The computer selects the class means and covariance matrix to be used in the classification. Once the data is classified into clusters, each cluster is then associated with a physical category (Deekshatulu and George Joseph 1991)

Extraction of spectral signatures: A prerequisite for classification of the crop area is to identify NDVI temporal signatures for each class of interest. The NDVI values < 0.35 indicated built-up area, water bodies and other non-vegetation areas, whereas NDVI values > 0.75 represented forest area. The NDVI values for the different crops ranged from 0.35 to 0.6.The temporal variation of crop NDVI values also makes crop lands to be easily distinguishable from other non-crop vegetation. Crops can be easily separated from other non-vegetation classes due to their higher NDVI values.

Conditional based classification for area estimation: Conditional-based classification is just another type of classifier that makes the class decision depending on using various rules. These rules were easily interpretable; thus, these classifiers are generally used to generate descriptive models. The classification uses the decision based on the NDVI values during the crop growth. The spectral signatures of the different classes were analyzed from sowing to the harvest of crops. The rules were framed based on the trends in the signatures using the model maker in the spatial editor in the ERDAS IMAGINE software. The methodology for estimating the *kharif* and *rabi* area is presented in Fig. 2.

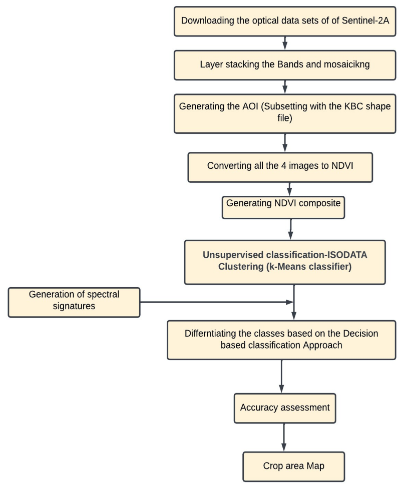

Fig. 2. Methodology used for the crop area estimation.

RESULTS AND DISCUSSION

The spatial distribution map (Fig. 4) obtained for 2015-16 using the conditional-based classification of Sentinel-2 NDVI data showed that the *kharif* area, *rabi* area and orchard area were estimated as 5721.54 ha, 1287.47 ha and 1627.36 ha respectively. The map generated from the conditional-based approach was assessed for its accuracy. Due to the scarcity of irrigation water, the *kharif* area had more cropland occupied than the *rabi* area during 2015-16, as the *kharif* area is under rainfed irrigation. The classification was carried out using the NDVI values, and the NDVI values for croplands increased a few days after sowing and attained a peak a few weeks before harvesting. After harvesting, when the land becomes fallow, the NDVI value reaches its lowest and further increases with another crop sowing. Therefore, time series NDVI of 4 months, i.e., January to April, were analyzed based on these perceptions. Each pixel was analyzed to check whether it follows this specific pattern and, if it does, then in which season it is attaining a peak value. The associated duration classes were identified and mapped based on the peaks obtained during the particular month. For the *kharif* area, the maximum NDVI value during January was 0.63; after that, it decreased for consecutive months. The *rabi* area was mainly comprised of the field crops such as paddy, maize, groundnut etc., and orchard area consist of orchards such as mango, sapota etc., The staggered planting of paddy was observed during the r*abi*. For the paddy crop, the NDVI values during January and February ranged between 0.15 to 0.2 as the crop was at the puddling and transplanting stages, respectively. When the crop reached the maximum tillering stage, the NDVI peaked during March and April, with values ranging between 0.5 to 0.6.

Consequently, the maize crop was classified during January and February with the NDVI values ranging between 0.3 to 0.45, respectively, when the crop was at knee height stage, whereas NDVI reached a peak at tasseling and silking stages during March and April with 0.6 and 0.5 NDVI. The NDVI values, which were constant for all the consecutive months and ranged between 0.45 to 0.6, were considered the orchard area. The accuracy assessment results indicated that the overall accuracy and Kappa coefficient achieved were 86.67% and 0.77, respectively.

Table 1: Minimum and Maximum NDVI Values used for Mapping the Cropped Area.

Month	10-01-2016		09-02-2016		10-03-2016		18-04-2016	
NDVI Values	Min	Max	Min	Max	Min	Max	Min	Max
Kharif	0.33	0.63	0.12	0.39	0.11	0.24	0.10	0.16
Paddy	0.17	0.27	0.13	0.22	0.17	0.58	0.34	0.55
Maize	0.22	0.40	0.18	0.44	0.36	0.61	0.33	0.52
Orchard	0.50	0.57	0.42	0.46	0.50	0.59	0.47	0.52

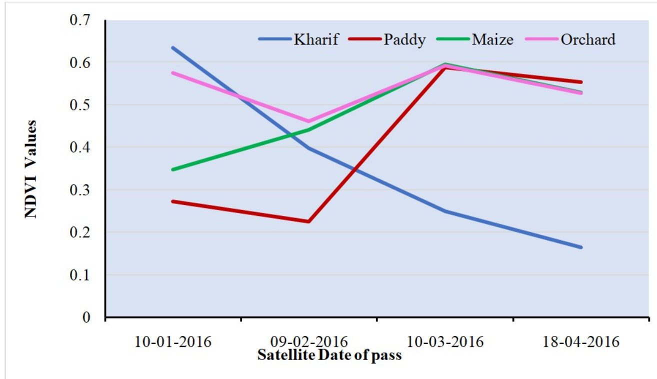

Fig. 3. Spectral Signature of different class.

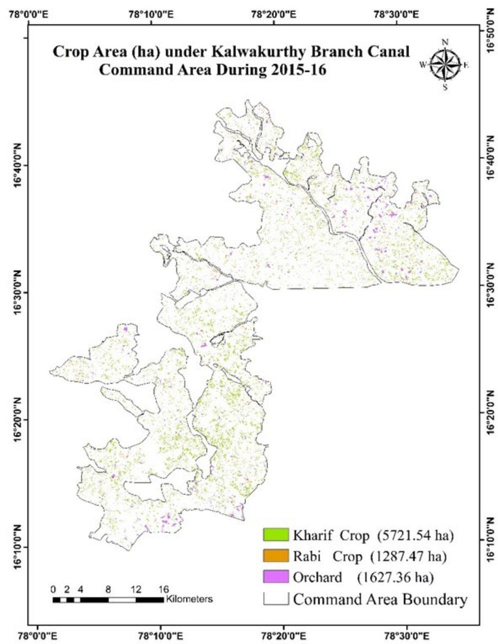

Fig. 4. Crop Map for year 2015-16 in Kalwakurthy Branch Canal Command area.

CONCLUSION

In the present study, net sown areas of 5721.54 ha (*kharif*), 1287.47 ha (*rabi)* and orchard (1627.36) were estimated over Kalwakurthy Branch Canal with an overall accuracy of 86.7%. Besides, the spatial distribution pattern of the net sown area during the Kharif and rabi seasons was also generated. The current study showcases the potentialities of high-resolution temporal images and ground data for mapping net sown area at field scale. The study has led to the development of a new method for mapping croplands using Sentinel-2 NDVI time-series and a conditional-based classification approach. The classification approach developed in the study can be applied further for regional, district, state, and country level assessment of the net sown area. The information generated in the present study could be a valuable input for the state agricultural department, various agencies such as the regional agricultural agencies, insurance agencies, and geo portal boards for micro-level planning for sustainable agriculture.

FUTURE SCOPE

There is a scope to study the performance assessment of the irrigation water for the kalwakurthy branch canal. Continuous monitoring of the crop grown under the area will help to improve the productivity of the water.

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Conflict of Interest. None.

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