The Pharma Innovation Journal 2022; 11(8): 783-787

www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2022; 11(8): 783-787

www.thepharmajournal.com
Received: 09-05-2022
Accepted: 12-06-2022

G Snigdha
M.Sc. (Ag.), Department of Agronomy (Water Management), PJTSAU, Rajendranagar, Telangana, India

Gumma Murali Krishna
Principal Scientist and Cluster leader, Geospatial and Big Data Sciences, International Crop Research Institute of Semi-Arid Tropics (ICRISAT), Patancheru, Telangana, India

P Panjala
Scientific Officer, Geospatial sciences and big data, International Crop Research Institute for Semi-Arid Tropics (ICRISAT), Patancheru, Telangana, India

TL Neelima
Scientist, Department of Agronomy, Water Technology Center, PJTSAU, Rajendranagar, Telangana, India

K Avil Kumar
Director, Water Technology Center, PJTSAU, Rajendranagar, Telangana, India

Corresponding Author:
G Snigdha
M.Sc. (Ag.), Department of Agronomy (Water Management), PJTSAU, Rajendranagar, Telangana, India

Mapping of rice-growing areas in Nalgonda using Sentinel-1 and Sentinel-2

G Snigdha, Gumma Murali Krishna, P Panjala, TL Neelima and K Avil Kumar

Abstract
This study established a method for mapping rice-growing areas in Nalgonda district of Telangana using SAR and Optical data. Supervised classification was executed on Sentinel-1 and 2 time series data in Google Earth Engine using a Random Forest classifier and ground reference points gathered from field survey. Results showed a total rice area of 1.55 L ha. Comparing the classification results to the ground reference data revealed that the total accuracy and Kappa coefficient obtained by RF were 92.5% and 0.89, respectively.

Keywords: Rice, Sentinel-1, Sentinel-2, random forest classification, google earth engine

1. Introduction
Remote sensing data is used to estimate crop identification, crop monitoring, acreage, and yield in real-time, accurately, and objectively. To distinguish between distinct crop types, images taken at various times during the crop growth phase are typically needed. Processing a significant volume of satellite pictures taken by numerous sensors is necessary in order to produce high resolution crop maps for vast areas (>10,000 sq. km). Large amounts of freely available satellite images can be easily accessed and processed using the cloud infrastructure offered by the Google Earth Engine (GEE). Additionally, the GEE offers a collection of cutting-edge classifiers for pixel-based categorization that may be applied to crop mapping. Since there is potential to use the GEE platform for a bigger scale (e.g., country level) and numerous sensors, the research aims to explore how effective it is for classifying multi-temporal satellite imagery for crop mapping (e.g., Sentinel-1 and Sentinel-2) [1]. During the crucial growing phase of crops, optical images are rarely available due to the cloudy and rainy weather. Therefore, it reduces the accuracy and promptness of crop area monitoring. With the benefits of all-weather, all-time, high resolution, and extensive coverage, synthetic aperture radar (SAR) has been widely employed in agricultural condition monitoring as a novel application, which offers a strong complement and support for crop identification in terms of data and technology [2]. An integrated strategy has been used in earlier research to increase classification accuracy. For example, [3] identified rice and cotton fields in India using crowd sourced ground truth data combined with Sentinel-1 and Sentinel-2 data and a deep learning classification approach. Sentinel-1 and Sentinel-2 data were combined for land cover type mapping by [4] and [5] to map wetlands in Turkey and South Africa, respectively. Sentinel-1A and Landsat-8 optical data were integrated by [6] to identify underground coal fires in China. The maize region in Hengshui, Northern China, was mapped integrating RADARSAT-2 polarimetric SAR and optical data [7].
This study employs a method for accurately mapping rice areas over the Nalgonda district of Telangana using a Sentinel-1 SAR for the exclusive temporal profile of the rice crop in VV and VH polarisation [8] compared to other crop types in the area, to identify a rice plot and Sentinel-2 optical time series for Normalized Difference Vegetation Index (NDVI) images.

2 Material and Methods
2.1 Description of the study area
The Nalgonda district lies in the southern part of the Telangana region between 16º25' N& 17º50' N and 78º40' E & 80º05' E. The average annual rainfall of the district is 751 mm, which ranges from 2.0mm in February to 171 mm in July. July is the wettest month of the year, contributing about 23% of the annual rainfall. The maximum and minimum temperatures are 40^{0}C and 17.7^{0}C respectively.

The soil comprises red soil, black soil, alkaline soil, and alluvium. The red soil constitutes 85% of the area. Black soil is found over the limestone area, in the southeast part. Alkaline soil occurs as limited patches in the central part. Alluvial soil occurs along the Alair, Musi and Kargal rivers. Major *kharif* crops include rice, cotton, bajra, green gram, red gram, castor, sesamum, jowar and groundnut. Net sown area of rice in Nalgonda in 2021 *kharif* was 1.8 L ha [14].

2.2 Data collection

2.2.1 Satellite data

A combination of radar (Sentinel-1) and optical (Sentinel-2) satellite images were used in this study. The data used is presented in Table 1. The Sentinel-1 constellation has two satellites—Sentinel-1A and Sentinel-1B, which were launched in April 2014 and April 2016, respectively. The two satellites have a combined revisit period of 6 days.

The interferometric wide (IW) swath mode, which acquires images with dual-polarization (vertical transmit, vertical receive (VV) and vertical transmit, horizontal receive (VH)), was used. A time series of monthly maximum NDVI for the months of June to October 2021, cloud-screened, was created using data from Sentinel-2 bands 4 (red wavelength) and 8 (NIR wavelength), both at 10-m spatial resolution. The cropland mask created from the supplementary data was improved in the study district using the monthly Sentinel-2 NDVI data. Normalized Difference Vegetation Index (NDVI) was calculated using Eq. (1).

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

It varies between -1 and +1, with values closer to +1 indicating high greenness.

3. Ground truth data

Field visit was planned and conducted according to the time of satellite pass. The Ground truth points were collected for mapping of rice areas using supervised classification in Google Earth Engine. A total of 160 ground reference points were collected over the Nalgonda district (Fig. 1)

3.1 Mapping of Rice growing areas

The procedure for mapping rice for *kharif* season in Nalgonda district by combining Sentinel-1 and Sentinel-2 data has been adapted as shown in Fig.2 [9]. GEE was used for satellite data processing and classification [10, 11]. The collection of Sentinel-1 of GEE provides data from a dual-polarization C-band Synthetic Aperture Radar (SAR) instrument. This collection includes the S1 Ground Range Detected (GRD) scenes, processed using the Sentinel-1 Toolbox to generate a calibrated, ortho-corrected product. VV and VH of Sentinel-1 and monthly maximum NDVI of Sentinel 2 were derived and was stacked. The stacked composite image was passed through a supervised classification by giving the training data with 160 ground reference points which were pointed in Google earth were given and random forest classifier is used.

Random Forest classifier

Random Forest is a classifier that uses multiple decision trees on different subsets of the input dataset and averages the results to increase the dataset's predictive accuracy. Instead of relying on a single decision tree, the random forest uses predictions from each tree and predicts the result based on the votes of the majority of predictions. It is based on the idea of ensemble learning, which is a method of combining various classifiers to address complex issues and enhance model performance.

3.2 Accuracy assessment of the crop map

Accuracy assessment is an essential step in the processing of remote sensing data. It determines the user's information value of the resultant data. The overall accuracy of the classified image is determined by comparing how each pixel is classified to the definite land cover conditions acquired from the ground truth data. Producer accuracy is a measure of how well real-world land cover types can be classified. The likelihood of a categorized pixel matching the land cover type of its corresponding real-world location is measured by the user's accuracy [12]. The kappa's coefficient and error matrix have become basic means of evaluation of image classification accuracy [13]. In this study, accuracy assessment is performed using ERDAS IMAGINE, where it uses error matrix.

4. Results and Discussion

4.1 Crop map

The spatial map obtained by supervised classification using random forest classification algorithm is shown in Fig 3. The rice-growing areas of the Nalgonda district were depicted on the classified map as 1.55 L ha, which was comparable to the area indicated by the government statistics of 1.8 L ha for *Kharif* season 2021[14] with the deviation of -0.16%.

The bright green colour showed the presence of rice which is mainly observed in the command areas with the Nagarjuna Sagar canal and in the areas where irrigation source is available mainly by the Krishna river in the district. The left side of the district was shown with fewer rice growing areas as there is less availability of irrigation sources.

4.2 Accuracy assessment

With the aid of error matrices, accuracy assessment was done for the classified image that was obtained using validation data. The error matrix of the Random Forest classified image achieved good accuracy in both user and producer accuracy, with a kappa coefficient of 0.894, and overall accuracy of around 92% (Table 2). Due to almost identical signatures in some regions, some other LULC which included shrubs is falsely categorized as rice crops. The result of the approach carried out in this study highlight the significance of utilising different satellite sensors' capacities to produce high temporal resolution images for mapping rice areas by obtaining more accuracy in classification.

Table 1: Satellite data and their bands used for the study

Satellite imagery	Bands	Spatial resolution	Importance
SENTINEL-1	VV and VH	5×20m	Helps to quantify the variability in the temporal dynamics of the crop
SENTINEL-2	Band4 (Red)	10m	Helps in classifying the vegetation
	Band8 (NIR)	10m	

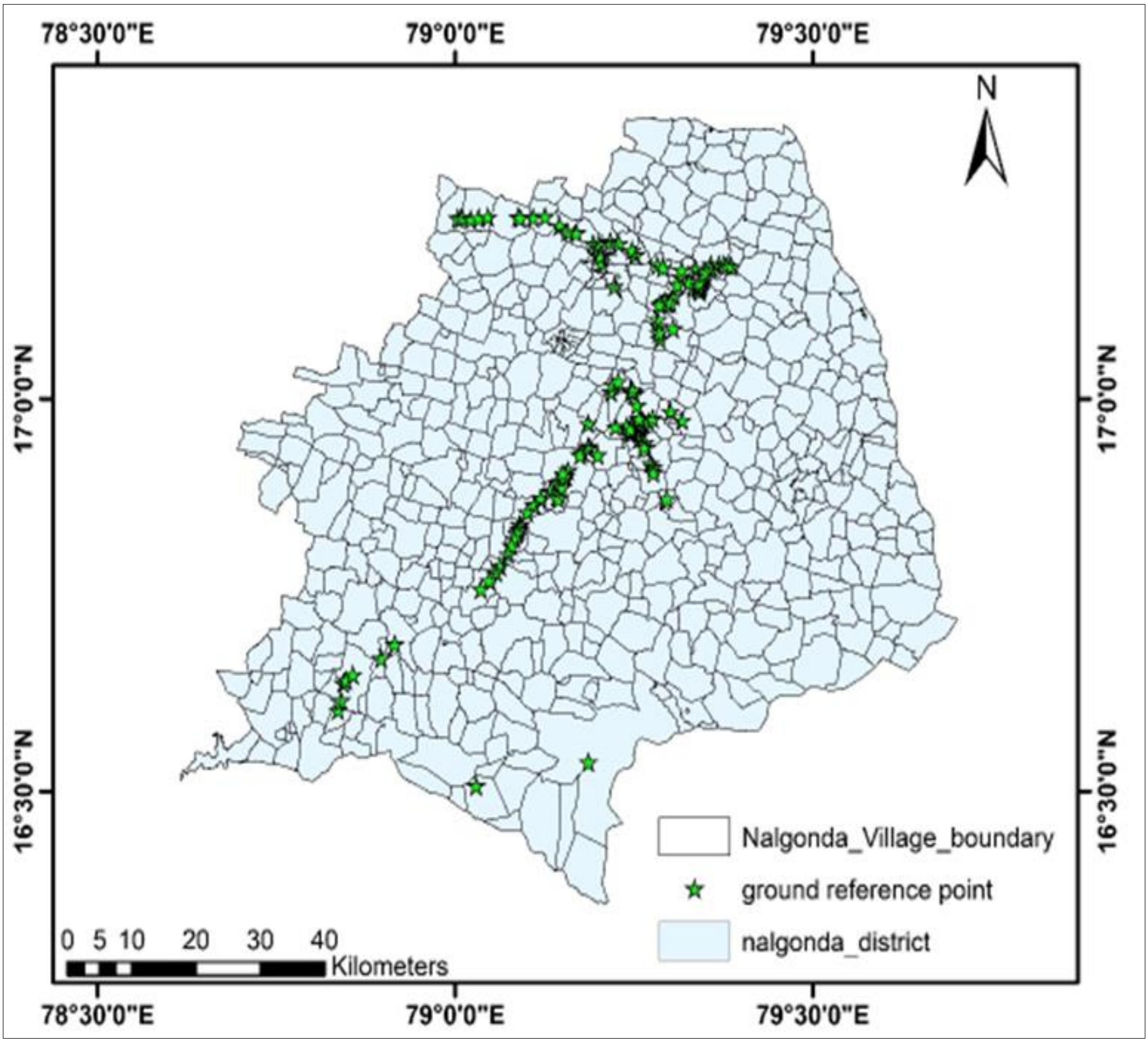

Fig 1: Ground reference points collected

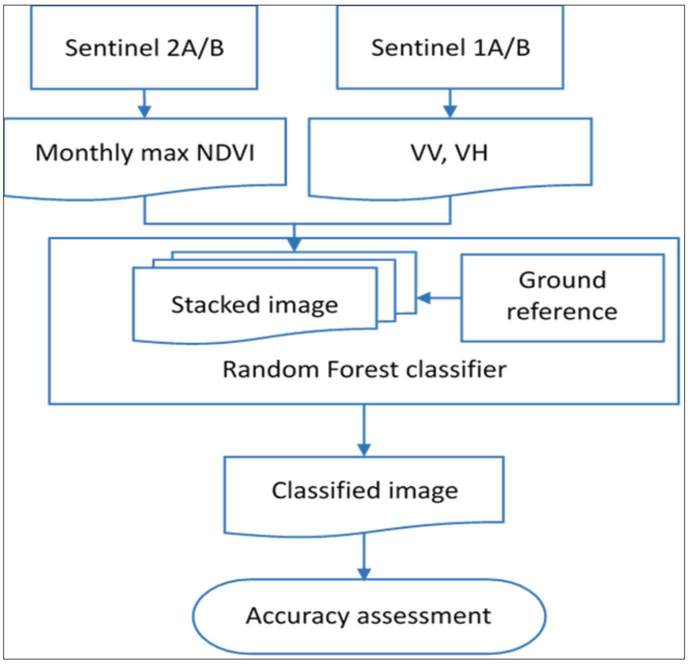

Fig 2: Schematic diagram of the methodology used for Rice classification

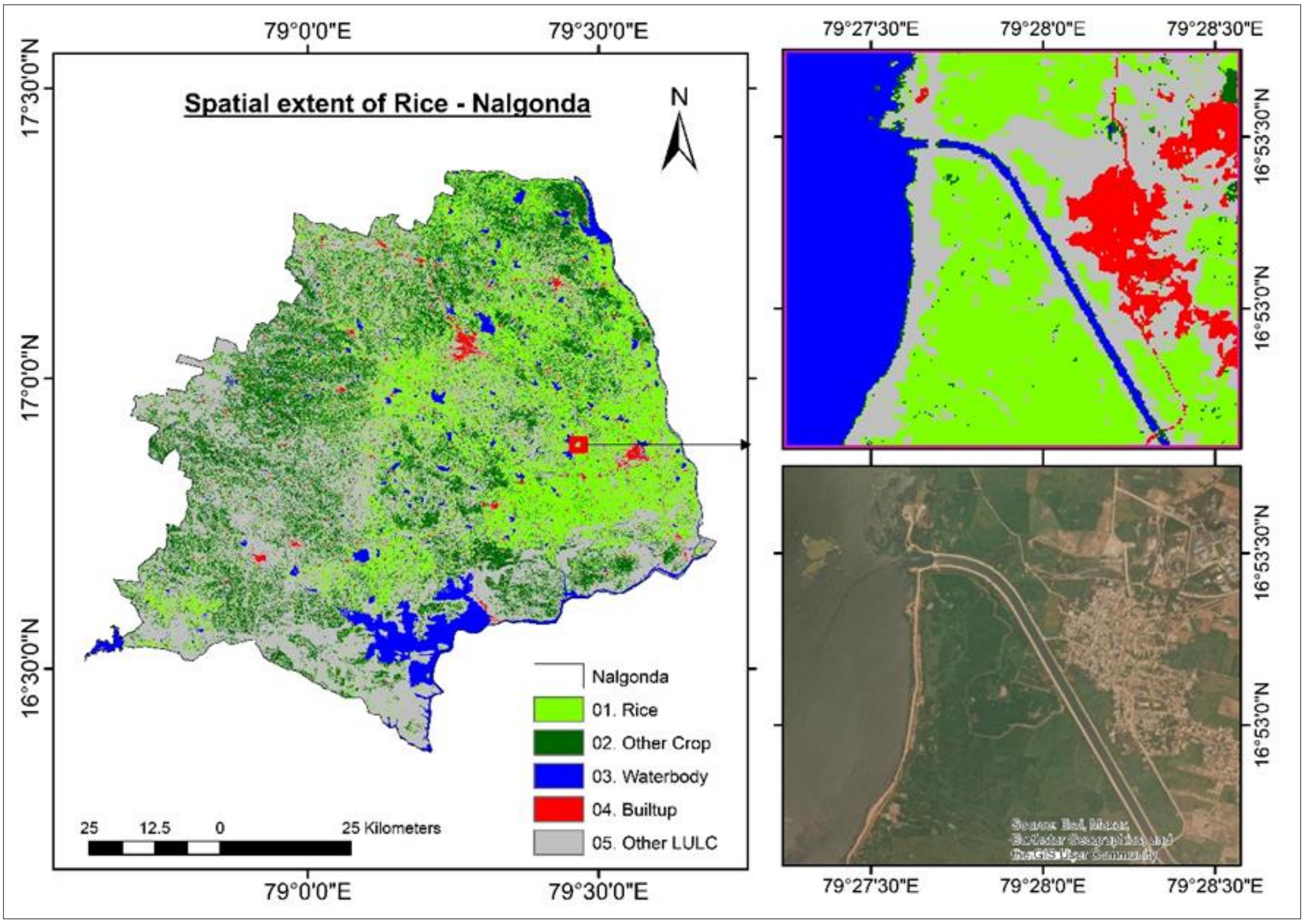

Fig 3: Spatial extent of rice in Nalgonda district in *kharif* season

Table 2: Accuracy assessment based on ground reference data

Classified data	Rice	Other crop	Water body	Builtup	Other LULC	Totals	Users
Rice	46	1	0	0	0	47	0.978
Other crop	0	12	0	0	1	13	0.923
Waterbody	0	0	11	0	0	11	0.100
Builtup	0	0	0	8	0	8	0.100
Other LULC	5	0	0	1	21	27	0.777
Totals	51	13	11	9	22	106	
	0.902	0.923	0.100	0.888	0.954	Overall	0.925
						Kappa	0.894

5. Conclusion

The present study made an approach to map the rice growing areas in Nalgonda by integrating Sentinel-1 and Sentinel-2 time series data. The SAR backscattering time series and optical NDVI of rice crop in the study area were obtained during the period between June 2021 and October 2021. The stacked image was used for supervised classification by using a Random Forest classifier. The classified map showed the overall accuracy and Kappa coefficient of 92.5% and 0.84, respectively. The result of the approach carried out in this study highlight the significance of utilising different satellite sensors' capacities to produce high temporal resolution images for mapping rice areas.

6. References

1. Shelestov A, Lavreniuk M, Kussul N, Novikov A, Skakun S. Exploring Google Earth Engine platform for big data processing: Classification of multi-temporal satellite imagery for crop mapping frontiers in Earth Science. 2017;5:17.
2. Kpienbaareh D, Sun X, Wang J, Luginaah I, Bezner Kerr R, Lupafya E, *et al*. Crop type and land cover mapping in northern Malawi using the integration of sentinel-1, sentinel-2, and planetscope satellite data. Remote Sensing. 2021;13(4):700.
3. Wang H, Zhu Y, Li W, Cao W, Tian Y. Integrating remotely sensed leaf area index and leaf nitrogen accumulation with Rice Grow model based on particle swarm optimization algorithm for rice grain yield assessment. Journal of Applied Remote Sensing. 2014;8(1):083674.
4. Kaplan G, Avdan U. Sentinel-1 and Sentinel-2 data fusion for wetlands mapping: Balikdami, Turkey. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018;XLII(3):729-734.
5. Slagter B. Tsendbazar NE, Vollrath A, Reiche J. Mapping wetland characteristics using temporally dense Sentinel-1 and Sentinel-2 data: A case study in the St. Lucia wetlands, South Africa. Int. J Appl. Earth Obs. Geoinf. 2020;86:102009.

6. Yan S, Shi K, Li Y, Liu J, Zhao H. Integration of satellite remote sensing data in underground coal fire detection: A case study of the Fukang region, Xinjiang, China. Front. Earth Sci. 2019;14:1-12.
7. Shuai G, Zhang J, Basso B, Pan Y, Zhu X, Zhu S, *et al*. Multi-temporal RADARSAT-2 polarimetric SAR for maize mapping supported by segmentations from high-resolution optical image. International Journal of Applied Earth Observation and Geo information. 2019;74:1-15.
8. Bazzi H, Baghdadi N, El Hajj M, Zribi M, Minh DHT, Ndikumana E, *et al*. Mapping paddy rice using Sentinel-1 SAR time series in Camargue, France. Remote Sensing. 2019;11(7):887.
9. Milesi C, Kukunuri M. Crop yield estimation at gram panchayat scale by integrating field, weather and satellite data with crop simulation models. Journal of the Indian Society of Remote Sensing. 2022;50(2):239-255.
10. Gumma MK, Tummala K, Dixit S, Collivignarelli F, Holecz F, Kolli RN, *et al*. Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information. Geocarto International, 2020, 1-17.
11. Panjala P, Gumma MK, Teluguntla P. Machine Learning Approaches and Sentinel-2 Data in Crop Type Mapping. In Data Science in Agriculture and Natural Resource Management. Springer, Singapore, 2022, 161-180.
12. MacLean MG, Congalton RG. Map accuracy assessment issues when using an object-oriented approach. In Proceedings of the American Society for Photogrammetry and Remote Sensing Annual Conference, Sacramento, CA, USA, 2012, 19-23.
13. Gumma MK, Kadiyala MDM, Panjala P, Ray SS, Akuraju R, Dubey S, *et al*. Assimilation of remote sensing data into crop growth model for yield estimation: A case study from India. Journal of the Indian Society of Remote Sensing. 2022;50(2):257-270.
14. https://agri.telangana.gov.in/