



Crop acreage and yield mapping of groundnut crop in erstwhile Mahabubnagar District using RS and GIS

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ABSTRACT

An investigation was carried in the erstwhile Mahabubnagar district of Telangana during *rabi* 2019-20 aiming the estimation of groundnut crop acreage and yield. The crop area was estimated using the satellite images of Landsat-8-OLI sensor from September to February covering the entire crop growth period by performing an unsupervised image classification technique with 300 classes, 300 iterations and a convergence threshold of 0.99. The groundnut yield was estimated by developing the regression equation using crop-cut yield data and NDVI values of the corresponding GPS locations. The crop area was estimated to be 57,865 ha with producer's and user's accuracy of 100 and 90% respectively, and a relative deviation of 28.6% when compared with actual ground estimates of the Department of agriculture. The crop yields were estimated with an R^2 value of 0.71 and a correlation coefficient of 0.87.

Introduction

The groundnut crop is mostly cultivated under rainfed conditions of all the districts of Telangana, mainly concentrated in Mahabubnagar, Warangal and Nalgonda districts (Agriculture at glance, 2014). Mahabubnagar district of Telangana accounts for 60.0% of the total area of the Groundnut crop. Mahabubnagar is mainly a drought prone area which suits the growing climatic conditions of groundnut. In Mahabubnagar district of Telangana, the annual average production of groundnut crop during 2013-14 was 220 thousand tons and annual average yield per hectare during the same period was 1751 kg/ha (Shruthi *et al.*, 2017). The crop statistics shows that during the year 2019-20, the crop area extended to 0.91 lakh ha in Telangana state with 0.83 lakh ha alone in Southern Telangana Zone (Rabi 2019-20, Pre-harvest price forecast of Groundnut, 2020). Groundnut production for the year 2019-20 was 2.90 lakh mt during rabi 2019-20 (Agriculture Action

Plan, 2019-20). Recent developments in aerospace survey technology, digital image processing, modelling of crop production process, and geographic information systems has created promising opportunities for upgrading the agriculture statistical systems. Remote sensing data can greatly contribute to the monitoring of earth's surface features by providing timely, synoptic, cost efficient and repetitive information about the earth's surface (Justice *et al.*, 2002). Crop inventory related applications comprise of identification/discrimination of crop covers and acreage estimation, predicting crop yield and crop growth condition assessment and cropping system analysis (Kingra *et al.*, 2016). The present study was taken up aiming the groundnut crop area and yield estimation in the groundnut belt in erstwhile Mahabubnagar district of Telangana using remote sensing and GIS techniques during the *rabi* season of 2019-20.

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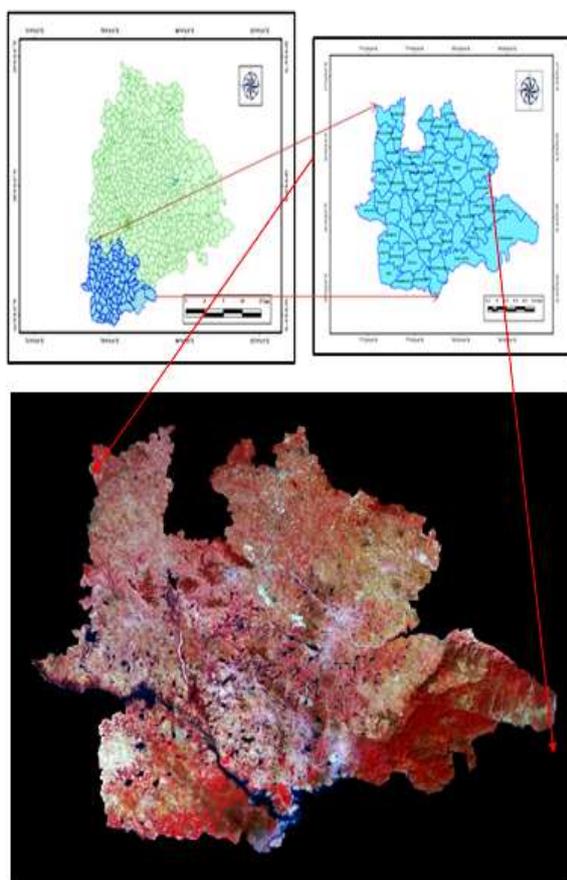
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Material and Methods

Study area

The present research was conducted in the erstwhile Mahabubnagar district of Telangana (Figure 1). Mahabubnagar district is one of the western districts of Telangana and lies between 15°55' to 17°20' Northern latitudes and 77°15' to 79°15' Eastern longitudes. The total area of the district is 18,432 Sq. km and ranks 2nd position contributing to 6.70% of the total geographical area of the state. The average normal rainfall in the district is 604 mm and most of it is received during the south-west monsoon. The rainfall was hardly 64.0 per cent of the state average (940 mm). The year-to-year variation in the actual rainfall showed that there were more dry spells during the cropping season. The predominant soil is the chalka dubba which is about 70.0% of the total area and the water holding capacity is low (District census handbook, Mahabubnagar, 2011).



**Figure 1: Geographical map of the study area
Satellite data**

In this study the freely downloadable, false colour composite satellite images from Landsat-8 OLI sensor were acquired from earthexplorer.usgs.gov.in website to classify the study area. In order to study the crop from sowing to harvesting, multi-temporal, cloud free satellite images from September to February were collected for digital image processing. NDVI values were computed for the satellite data for assessing the area under vegetation. NDVI is calculated as a ratio difference between measured canopy reflectance in the red and near infrared bands respectively (Nageswara *et al.*, 2005).

Digital image processing

The satellite image processing, generation of training sites, acreage estimation and yield estimation was carried out in ERDAS 2018 imagine analysis software.

Area estimation

The satellite images were pre-processed using top of atmosphere corrections for the conversion of radiance images into reflectance images (Figure 2) which were further layer stacked band-wise and mosaic subset images were created using the vector images of the study area. These images were used for generation of NDVI images and then layer stacked into a single image. The multi-date NDVI layer stack image was used for the generation of monthly maximum NDVI composite image. NDVI thresholding is a standard technique which includes calculating of minimum and maximum NDVI values with variance to identify NDVI threshold value of cultivated areas in order to create a mask for cultivated areas and isolate these areas from the other land cover types (Abdelraouf *et al.*, 2018). NDVI thresholding was performed in spatial model maker in ERDAS imagine software with NDVI values > 0.40 and < 0.70 considering as vegetation to form the vegetation mask (Figure 3). The NDVI values < 0.40 indicates the built-up area, water bodies and other land cover types and the NDVI values > 0.70 indicates the forest area. For the vegetation mask, forest mask was applied and the crop mask was generated. The ground control points collected during the survey were superimposed on the 6 date NDVI layerstack image and drawing the area of interest for each GCP, training signatures were generated using the signature editor tool in ERDAS imagine software as presented.

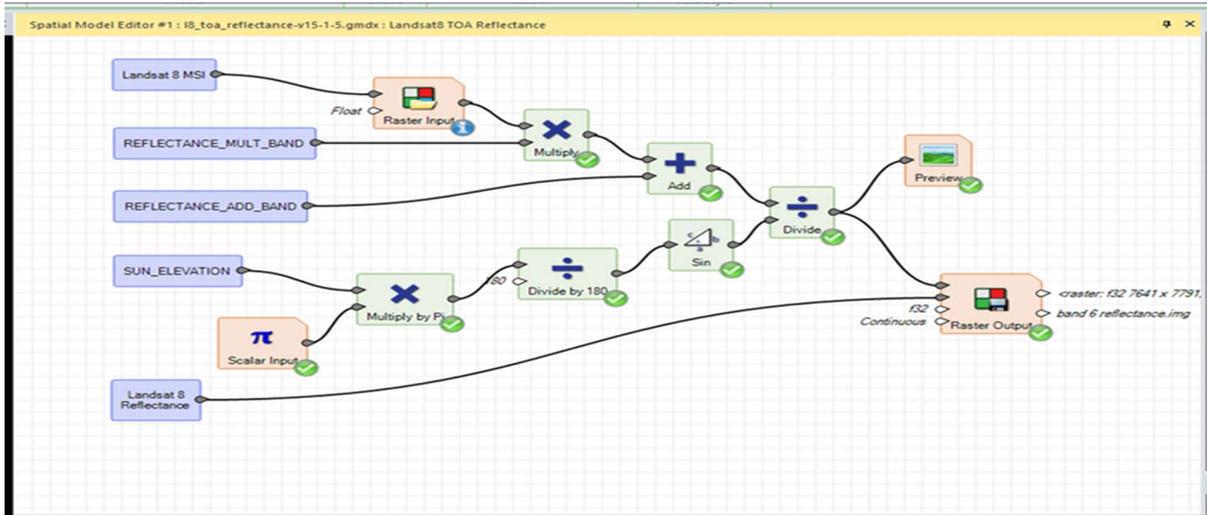


Figure 2: Spatial model used for atmospheric corrections in satellite images

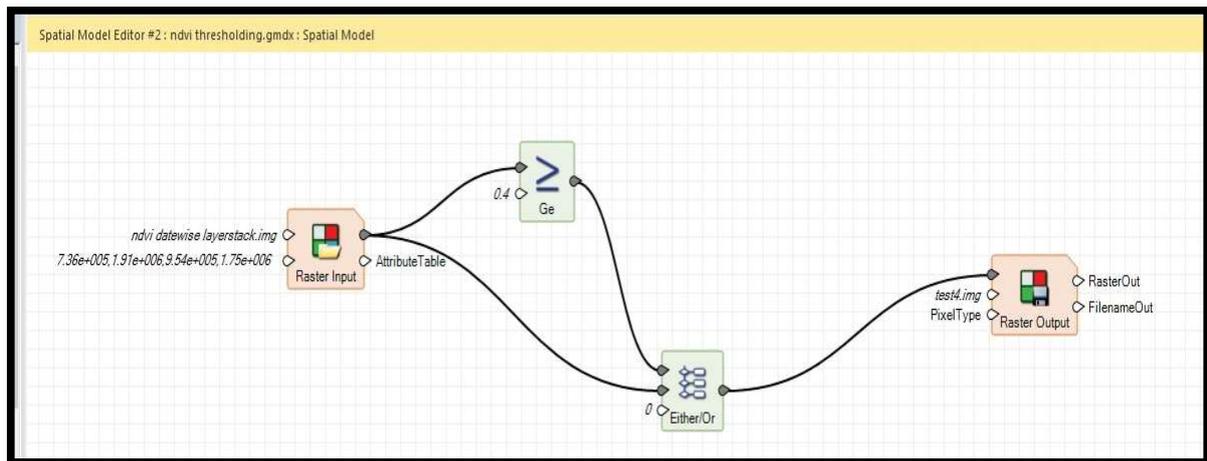


Figure 3: Spatial model used for calculating NDVI threshold

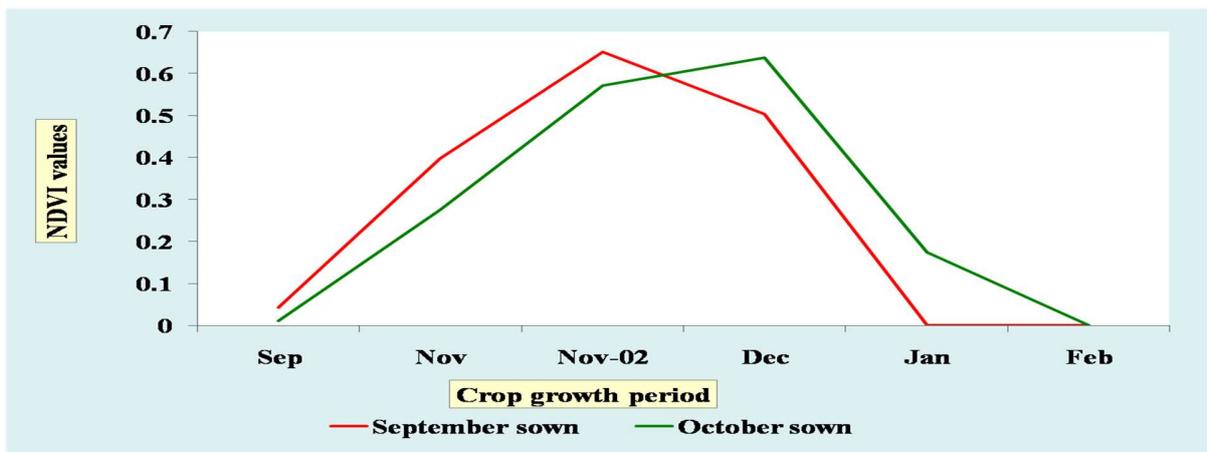


Figure 4: Typical spectral crop growth profile of groundnut crop

From the generated training signatures, by extracting the maximum, minimum, mean and standard deviation statistics, spectral growth profile curves of groundnut crop were generated (Figure 4). Unsupervised classification methods were applied in order to efficiently process a large number of unlabeled samples in remote sensing images (Zhe Ma *et al.*, 2020). Image classification was done using the crop mask and by adopting unsupervised classification technique based on K-cluster algorithm generating 300 spectral classes with 300 iterations and a convergence threshold of 0.90. From the 300 classes generated, the groundnut crop classes were segregated using the spectral signature graphs obtained from the monthly maximum NDVI composite images by overlaying the ground control points collected during the survey. Thus, only groundnut class was isolated for area estimation by manually assigning each class to groundnut by carefully studying the spectral curve from the generated spectral signatures and eliminating all other classes. The area under groundnut crop was then computed to arrive to the estimated area.

Accuracy assessment

Accuracy assessment plays a key role in remote sensing studies for assessing the results. A confusion matrix or error matrix contains information about actual and predicted classifications done by a classification system. The pixel that has been categorized from the image was compared to the same site in the field (Ayyanna *et al.*, 2018). Classification error matrix for the assessment of crop area estimates was prepared as it is one of the most common means of expressing classification accuracy, which compares the relationship between known reference data and the corresponding results of an automated classification which means the variation in total number of crop pixels and the number of correctly classified pixels. From the above information producer's accuracy and user's accuracy were calculated and the overall classification accuracy was computed by dividing the number of correctly classified pixels by total number of reference pixels.

Yield estimation

For yield estimation, ground truth was collected by conducting the crop cut experiments in 3x3 m² area in the selected farmers fields. For extraction of

maximum NDVI values, seasonal maximum NDVI image was generated using the model maker tool by employing maximum function to the 6-date NDVI layer stack image. Then using the seasonal maximum NDVI values and the crop cut yield data of the corresponding GCP locations, a regression equation (Figure 6) was developed and the yield model thus generated was used to estimate the yields of groundnut. A simple curve was drawn between predicted and observed yields to understand how close the curve fits the data as mentioned in Figure 8. Groundnut yield map generated through remote sensing was validated using Root Mean Square Error (RMSE) and coefficient of determination (r^2) of multiple regression statistical techniques.

Results and Discussion

The area under groundnut crop was estimated by generating the crop mask implementing unsupervised classification technique for image classification and then crop area was estimated. From the above procedure, the groundnut crop coverage for the erstwhile Mahabubnagar district was computed to be 57,865 hectares. The spatial distribution map (Figure 5) of groundnut for erstwhile Mahabubnagar district has shown maximum extent of the crop in Nagarkurnool and Wanaparthy divisions (high potential zone). In this zone, the crop has been observed under cultivation both as homogenous and discrete patches at places. The groundnut crop in rest of the divisions (Narayanpet, Gadwal and Mahabubnagar) of the district was found mostly scattered and in sparse patches. Confusion matrices were used to assess the accuracy of the crop area estimation as they compare the relationship between the ground data as the reference data and the "corresponding" results of the unsupervised classification techniques (Table 1). From the results of accuracy assessment, it was observed that groundnut crop area was estimated with 100% producer's and 90.0% user's accuracy. This indicated that the scrubs omitted in the producer's category were included in the user's category resulting in a misclassification of 10.0%. The spatial distribution map of maize crop of the Mahabubnagar district of Telangana generated through unsupervised classification using Landsat-8 and Sentinel data was classified similarly with a producer's accuracy and user's accuracy of 96%

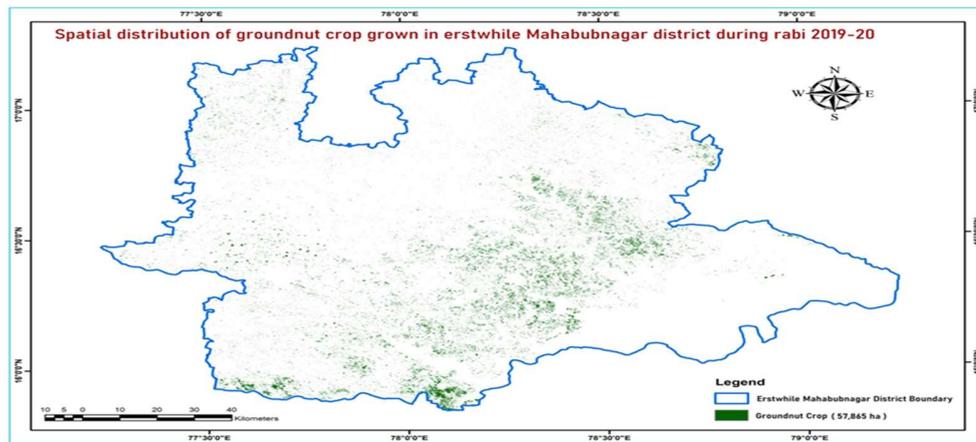


Figure 5: Spatial distribution (hectares) map of groundnut crop acreage obtained through unsupervised classification

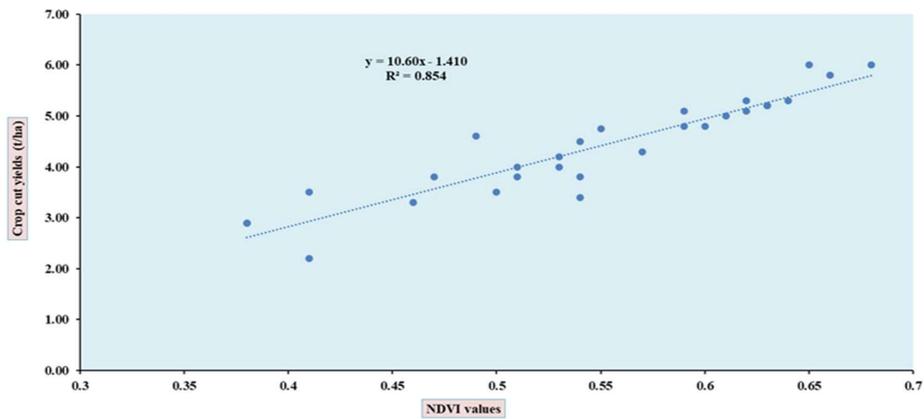


Figure 6: Yield model for estimating groundnut crop yield

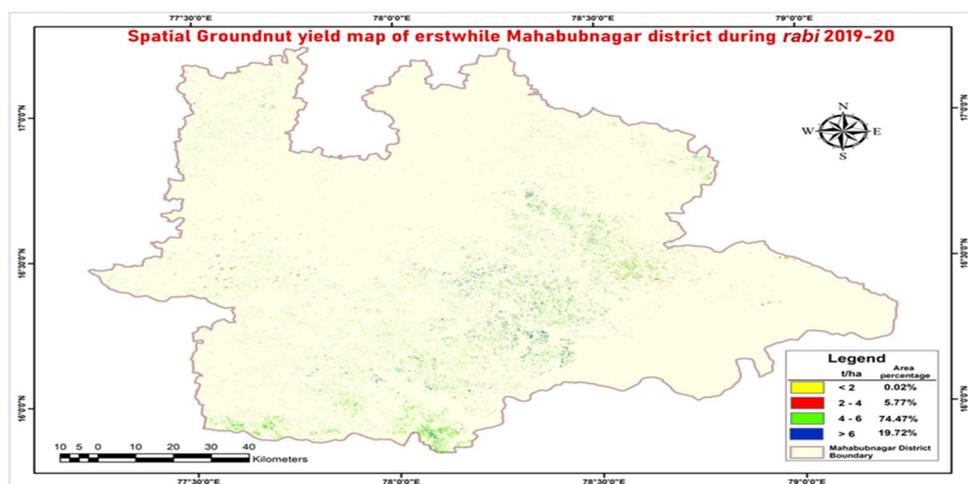


Figure 7: Spatial distribution map depicting the estimated groundnut crop yield

Table 1: Classification accuracy of groundnut crop acreage by unsupervised classification

Classified Data	Non groundnut class	Groundnut class	Row total
Non groundnut class	2	0	2
Groundnut class	0	18	18
Column Total	2	18	20
Producer's accuracy	100 per cent		
User's accuracy	90.0 per cent		

and 86% respectively (Gumma *et al.*, 2021). A similar study conducted in Andhra Pradesh for the delineation of vegetation class, non-vegetation class and water bodies also classified with vegetation class using unsupervised classification with a producer's accuracy and user's accuracy of 96% and 87% respectively (Sreelekha and Reddy, 2019).

Mixed signatures of scrubs with the crop at peak growth stage during November and December months for both September and October sown crops resulted in misclassification. Extensive rains during September and October months had resulted in excessive growth of scrubs along with the crop, thus duplicating the spectral signatures. For unsupervised classification, though the chance of error may decrease by using a lower number of information classes, the chances of pixel misclassification may actually increase in areas where multiple land cover types transit into each other, where there is a large number of instances of mixed pixels (Mukherjee and Mukherjee, 2009) or in cases where a feature may be spectrally similar to those of a different land cover type, such as the confused classes identified by Hung and Wu (2005). The remotely sensed crop area under groundnut crop was compared with ground estimates of state department of agriculture to find the deviation in remotely sensed estimates by computing the relative deviation (RD) percentage. The remote sensing estimate of groundnut acreage for the erstwhile Mahabubnagar district has been computed as 57,865 hectares with a relative deviation of 28.6% from the DOA estimates. Mixing of soil reflectance values with the crop reflectance during initial growth, non availability of cloud free data during peak growth stage and mixing of scrub with the post vegetative growth stages has led to misclassification of the crop. Also, cultivation of the crop in discrete patches owing to small and marginal fields in the

study area, and the crop being short statured was misclassified as scrub in most of the regions which might have resulted in less estimation of the cultivated area in the groundnut belt. Further, it may be noted that the remote sensing area estimates were for Mahabubnagar district, while the DOA estimates were obtained from newly formed districts of re-organised erstwhile Mahabubnagar district wherein, couple of *mandals* having groundnut crop cover were added from erstwhile Rangareddy district. Hence, area estimates obtained from the Department of Agriculture were higher than the remote sensing estimates. Also, area estimates of the district could only be obtained during the study. If it were for *mandal* estimates, that accuracy could be precise.

Yield estimation

The crop yield was mainly estimated using NDVI. The NDVI values for groundnut crop ranged from 0.38 to 0.68, with a mean value of 0.55 which represent the maximum greenness value for each groundnut pixel. The groundnut yield estimation was carried out by using the ground information collected by conducting the crop cut experiments in a 3x3 m² area of selected farmer's fields in the erstwhile Mahabubnagar district of Telangana and developing the regression equation from the maximum NDVI values and the crop cut yields. The crop cut yields ranged from 1.67 to 6.67 t/ha with an average value of 4.71 t/ha. The yield estimated through the regression equation for the entire study area was categorized into four categories as <2.00 t/ha, 2.10-4.00 t/ha, 4.10-6.00 t/ha and >6.00 t/ha constituting 0.02, 5.77, 74.5 and 19.7% of the groundnut area respectively as mentioned in Figure 7. With the above-mentioned categories, yield map was generated in ERDAS imagine software. The average production of groundnut in the Mahbubnagar was found to be 2.19 lakh tons.

Validation of remotely sensed yield estimates

The yield prediction model estimated groundnut yield with a significant variability of 85.0% ($R^2=0.85$). The satellite based similar study estimates reported total soybean production as 22 lakh tons with an average productivity of 844 kg/ha when compared to ground truth at an overall accuracy of 80.7% showing the reliability of RS based crop inventory (Maurya, 2011). The regression yield model was validated using measured yield collected from the crop cut

experiment plots and the predicted yields derived from the satellite image. The observed /measured yield from CCE plots ranged from 2.20-6.00 t/ha. On the other side, predicted yield for groundnut ranged from 4.06-6.81 t/ha. The predicted yield deviated

from the observed /measured yield ranging from 0.07-1.92 t/ha with a mean value of 1.57 t/ha. A simple curve was drawn between predicted and observed yields to understand how close the curve fits the data which showed a strong positive

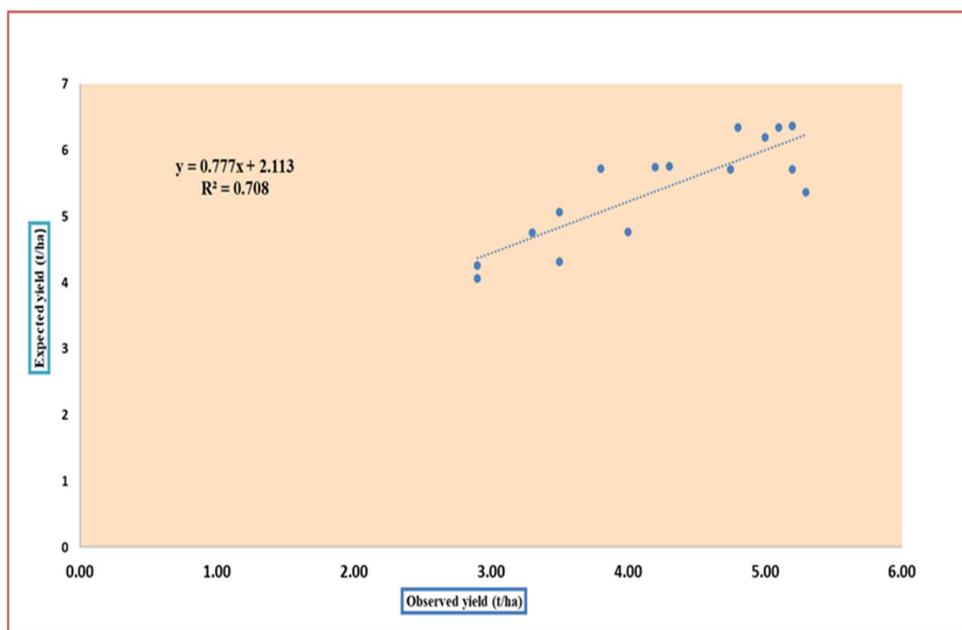


Figure 8: Scattered diagram plotted for the determination of correlation coefficient for validating the yield model

correlation of observed and predicted yields with R^2 value of 0.71 and the correlation coefficient of 0.87. The yield estimation of sugarcane crop under FASAL programme using the Landsat and Resourcesat data also arrived at a correlation coefficient value of 0.60 which may be attributed to lack of capturing ability of variation found in the sowing dates of the crop across the country (Sharma *et al.*, 2019). A significant correlation ($r^2 = 0.82$) between the groundnut pod yield with that of the corresponding NDVI values was also reported at 115 dryland locations at Queensland during 2004-07. The measurement of infrared reflectance from groundnut crop canopies via multispectral satellite imagery was observed to be an effective method for identifying the spatial variability in crop vigour, as well as producing high correlations with groundnut yield ($r^2=0.91$) and poor maturity ($r^2=0.67$) (Andrew *et al.*, 2007). The root mean square error (RMSE) was used to validate the performance of regression yield model (Miles and Shelvin, 2001) and measures

dispersion of the observations from the true values (Longley *et al.*, 2005). The smaller the RMSE value, higher is the accuracy of the predicted values (Watson and Teelucksingh, 2002). The RMSE value for the yield estimates in the present study was found to be 1.25 which indicates that the predicted yields deviated from the observed yields by 1.25 t/ha.

Conclusion

The groundnut crop acreage estimation using multi-date NDVI images from Landsat-8 OLI sensor by adopting K-cluster algorithm technique in unsupervised image classification has realized the groundnut area of 57,865 ha during *rabi*, 2019-20 for the erstwhile Mahabubnagar district with producer's and user's accuracy of 100 and 90.0%, respectively. The remote sensing crop area estimates deferred from the estimates (81,095 ha) of the State Department of Agriculture, Government of Telangana with a relative deviation of 28.64%. The estimated crop yield was categorized into four

classes viz., < 2 t ha⁻¹, 2 to 4 t/ha, 4 to 6 t/ha and > 6 t/ha contributed from 0.02, 5.77, 74.5 and 19.7% of the study area, respectively. The crop cut yields in the study area ranged from 1.67 to 6.67 t/ha. The NDVI values for groundnut ranged from 0.38 to 0.68 representing maximum greenness for each groundnut pixel. The yield model generated based on crop cut yield data and NDVI values, predicted

the crop yield with a good correlation at r^2 of 0.708 and correlation coefficient of 0.869. The predicted yields deviated from the observed yields with RMSE of 1.25 t/ha.

Conflict of interest

The authors declare that they have no conflict of interest.

References

- Abdelraouf, M.A., Mohamed, A.A., Mohamed, A.E. & Nasser, H.S. (2018). Comparative analysis of some winter crop area estimation using Landsat-8 and sentinel-2 satellite imagery. *Asian Journal of Agriculture and Biology*, 6 (2), 189-197.
- Agriculture action plan. (2019-20). Department of Telangana. 1-328. www.agri.telangana.gov.in
- Agriculture at a Glance. (2014). Government of India. Ministry of Agriculture. Department of Agriculture & Cooperation, Directorate of Economics & Statistics.
- Andrew, R., Graeme, W. & Stuart, P. (2007). Remote Sensing Applications in Peanuts: The assessment of crop maturity, yield, disease, irrigation efficiency and best management practices using temporal images. University of Western Australia (eds.) - Proceedings of "5th Australian Controlled Traffic and Precision Agriculture Conference", University of Western Australia, Perth, 16-18 July, 2007. University of Western Australia, 188-196.
- A.K. Bhandari, A. Kumar. (2012). Feature Extraction using Normalized Difference Vegetation Index (NDVI): A Case Study of Jabalpur City. Proceedings of "Communication, Computing & Security. *Procedia Technology*", Volume 6, pp. 612–621.
- Ayyanna., Polisgowdar, B.S., Ayyanagowdar, M.S., Dandekar, A.T., Yadahalli, G.S. & Bellakki, M.A. (2018). Accuracy Assessment of Supervised and Unsupervised Classification using Landsat-8 Imagery of D-7 Shahapur Branch Canal of UKP Command Area Karnataka, India. *International Journal of Current Microbiology and Applied Science*, 7 (7), 205-216.
- District census handbook – Mahabubnagar. (2011). Directorate of Census Operations, Andhra Pradesh. Series-29, 1-600.
- Gumma, M.K., Kadiyala, M.D.M., Panjala, P., Ray, S.S., Akuraju, V.R., Dubey, S., Smith, A.P., Das, R. & Whitbread, A.M. (2021). 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*. DOI:[10.1007/s12524-021-01341-6](https://doi.org/10.1007/s12524-021-01341-6).
- Hung, M.C., & Wu, Y.H. (2005). Mapping and visualizing the Great Salt Lake, landscape dynamics using multi-temporal satellite images, *International Journal of Remote Sensing*, 1972-1996.
- Justice, C.O., Townshend, J.R.G., Vermata, E.F., Masuoka, E., Wolfe, R.E., Saleons, N., Ray, D.P. & Morissette, J.T. (2002). An overview of MODIS Land data processing and product status, *Remote Sensing Environment*, 83, 3-15.
- Kingra, P.K., Majumder, D. & Singh, S.P. (2016). Application of remote sensing and GIS in agriculture and natural resource management under changing climatic conditions. *Agricultural Research Journal*, 53 (3), 295-302.
- Longley, P.A., Goodchild, M.F., Maguire, D.J. & Rhind, D.W. (2005). *Geographical information systems and science*. 2nd edition of *Manual of Geographical Information Systems*, Chichester: John Wiley and sons, 1, 1-26.
- Miles, J. & Shevlin, M. (2001). *Applying regression & correlation: A guide for students and researchers*. Sage Publications, London, United Kingdom.
- Mukherjee, S. & Mukherjee, P. (2009). Assessment and composition of classification techniques for forest inventory estimation: A case study using IRS-1D imagery. *International Journal of Geoinformatics*, 5 (2), 63-73.
- Nageswara, P.P.R., Shobha, S.V., Ramesh, K.S. & Somashekhar, R.K. (2005). Satellite -based assessment of Agricultural drought in Karnataka State. *Journal of the Indian society of remote sensing*, 33 (3), 429-434.
- Rabi 2019-20, Pre-harvest price forecast for groundnut, 2020. Government of India. <http://pjtsau.edu.in>.
- Season and Crop Coverage Report, Rabi. (2018-19). Commissionerate of Agriculture, Department of Agriculture, Government of Telangana, 1-16.
- Sharafi, M.A. (2000). Crop inventory and production forecasting using remote sensing and agrometeorological models: the case of major agricultural commodities in Hamadan province, Iran. *International Archives of Photogrammetry and Remote Sensing*, XXXIII (B7), 1364-1372.

- Sharma, N., Saxena, S., Dubey, S., Choudhary, K., Sehgal, S. & Ray, S.S. (2019). Analysis of sugarcane acreage and yield estimates derived from remote sensing data and other hybrid approaches under FASAL project. In the proceedings of “*The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*”, ISPRS-GEOLAM-ISRS Joint Int. Workshop on “*Earth Observations for Agricultural Monitoring*”, 18-20 February 2019, New Delhi, India, XLII-3/W6, 157-163.
- Shruthi, G., Dayakar Rao, B., Latika Devi & Jolly Masih. 2017. Analysis of area, production and productivity of groundnut crop in Telangana. *Agricultural Science Digest*, 37 (2), 151-153.
- Sreelekha, M. & Reddy, S.N. (2019). Accuracy Assessment of Supervised and Unsupervised Classification using NOAA Data in Andhra Pradesh Region. *International Journal of Engineering Research & Technology*, 8 (12), 60-64.
- Watson, P.K. & Teelucksingh, S.S. (2002). A practical introduction to econometric methods: Classical and modern. The University of the West Indies Press, Barbados, Jamaica, West Indies, 1-323.
- Zhe Ma., Zhe Liu1., Yuanyuan Zhao., Lin Zhang., Diyou Liu., Tianwei Ren., Xiaodong Zhang, & Shaoming Li. (2020). An Unsupervised Crop Classification Method Based on Principal Components Isometric Binning. *International Journal of Geo-information*, 9 (648), 1-24.
- Zonal Annual Report, Southern Telangana Zone, (2017-18). Regional Agricultural Research Station, Palem. 5-6.
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