



ISSN Print: 2618-060X  
 ISSN Online: 2618-0618  
 NAAS Rating (2026): 5.20  
 IJRA 2026; SP-9(10): 19-24  
[www.agronomyjournals.com](http://www.agronomyjournals.com)  
 Received: 30-07-2026  
 Accepted: 18-09-2026  
 Published: 02-10-2026

The names and affiliations of all authors are provided below, following the references.

## Integrating multi-sensor optical and SAR data with machine learning ensembles for chickpea area estimation in the Krishna zone of Andhra Pradesh

A Harshitha<sup>1</sup>, Sunil M Kumar<sup>2</sup>, AS Bharathi<sup>3</sup>, TV Sridhar<sup>4</sup>, IB Ramarao<sup>5</sup>, Y Srilatha Ch. Vani<sup>6</sup>, AK Mrudula<sup>7</sup>, AD Grace<sup>8</sup>

DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i10Sa.6760>

### ABSTRACT

This study estimated chickpea (*Cicer arietinum* L.) cultivation area using geospatial technologies by combining optical and microwave remote sensing data in the Krishna zone of Andhra Pradesh during the rabi season of 2025-2026. The study employed 143 georeferenced ground truth observations for crop classification using Landsat-9 OLI, Sentinel-2 MSI, and Sentinel-1 SAR data. Two different workflows were used to assess chickpea area estimation, a Maximum Likelihood Classification (MLC) in ENVI software and an advanced machine learning ensemble classifier that combined Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machine (GBM) algorithms applied to a 21 band multitemporal feature stack created in Google Earth Engine (GEE) and processed in R software. MLC technique estimated a total chickpea area of 87,004 ha with an overall accuracy of 88.23% ( $\kappa = 0.74$ ), the machine learning ensemble classifier significantly outperformed MLC, identifying a total area of 1,33,216 ha with a higher overall accuracy of 94.11% ( $\kappa = 0.88$ ). The multi-sensor ensemble approach significantly improved the spatial representation of chickpea distribution across the six districts of the Krishna Zone, according to a comparative analysis with Department of Agriculture (DoA) statistics. This highlights the potential of machine learning ensemble classification frameworks for reliable regional crop monitoring.

**Keywords:** Area estimation, Remote Sensing, Maximum Likelihood Classification, Ensemble Classification

### Introduction

Chickpea cultivation is increasingly adapted in the Krishna zone of Andhra Pradesh, where farmers have effectively integrated the crop into post-monsoon cropping systems. The Krishna zone accounts for a significant portion of Andhra Pradesh's chickpea cultivation favored by its deep vertisols and high residual soil moisture (Verma *et al.*, 2021) [1]. The relatively short and warm cool season window in the Krishna zone, influenced by its latitude and the moderating effect of the Bay of Bengal, increases the likelihood of terminal heat stress during the reproductive phase (Raghavendra *et al.*, 2017) [2], shortens the effective growing period and constrains yield potential compared with the longer and cooler winter seasons of the Indo-Gangetic plains.

Accurate and timely estimation of crop sown area is crucial for effective agricultural management, efficient resource allotment and informed policy planning, particularly in regions where agriculture plays a major economic role (Sud *et al.*, 2017) [3]. Traditionally, State Departments of Agriculture have depended on village level land records, girdawari surveys and data from farmers. However, these conventional approaches are limited by the constraints of statistical reliability, timeliness and spatial coverage (Ray *et al.*, 2017) [4]. Manual field inspections with coarse temporal resolution may not capture seasonal agricultural trends and farmer reports may suffer from reporting biases (FAO, 2017). To overcome these barriers and offer fast and objective knowledge, a move toward contemporary, spatially explicit remote sensing capabilities is essential. Satellite remote sensing and Geographic Information System (GIS) technologies provide reproducible, continuous land surface data that are not constrained by the logistical limitations of field surveys (Weiss *et al.*, 2020) [5]. In Andhra Pradesh, satellite imagery combined with household survey data has also been used to monitor the spatial distribution and adoption of chickpea cultivation (Gumma *et al.*, 2016) [6]. Optical sensors can supply multispectral information and spectral indices useful for delineating crop boundaries using phenological profiles and supervised classification (Karthikeyan *et al.*, 2020) [2], but their performance is restricted by cloud cover (Orynbaikyzy *et al.*, 2020) [7]. Comparative studies of rabi crops have also demonstrated improved classification performance with Sentinel-2 relative to Landsat-8, mainly due to its finer spatial resolution and additional spectral information (Paul and Kumar, 2019). Synthetic Aperture Radar (SAR) sensors are sensitive to canopy structure, soil moisture, and surface roughness (McNairn *et al.*, 2004) [8]. Furthermore, SAR sensors can penetrate clouds, thereby overcoming optical limitations and enabling ef

**Corresponding Author:**  
 A Harshitha  
 Department of Agronomy,  
 Advanced Post Graduate  
 Centre, ANGRAU, Guntur,  
 Andhra Pradesh, India

fective crop discrimination during early vegetative stages when optical contrasts are weak (Veloso *et al.*, 2017) [9]. Combining optical and SAR datasets exploits their unique spectral and structural strengths, yielding improved mapping accuracy, particularly under cloudy conditions (Adrian *et al.*, 2021) [10]. The integration of multi-temporal Sentinel-1A SAR and Landsat-8 OLI data has also been demonstrated to improve crop classification accuracy compared with single-sensor approaches (Yang *et al.*, 2018) [11]. Within this context, the present study evaluates the effectiveness of Maximum Likelihood Classification (MLC) and Machine Learning Ensemble classifiers for estimating chickpea acreage in the Krishna zone. Additionally, the study explores improvements in model performance by integrating local agricultural knowledge and finer temporal resolution during model calibration.

## Materials and Methods

The study was done during the *rabi* season 2025 in Krishna zone which is situated along the eastern coast of peninsular India bordering the Bay of Bengal. The zone encompasses six revenue districts Krishna, NTR, Guntur, Palnadu, Bapatla and Prakasam and covers approximately 47,473 km<sup>2</sup> between 14°57'00"N and 16°47'00"N latitude and 78°43'00"E and 81°54'00"E longitude, comprising 156 revenue mandals. The zone is traversed by the Krishna River and its distributary network, which form an extensive deltaic system supporting intensive agriculture across the region.

Ground truth data were collected across key chickpea growth stages to support crop area mapping. To represent regional farming heterogeneity, 143 georeferenced points were acquired during field surveys among which 58 points are for training the classification model and 85 points for validation.

### Satellite data acquisition

Landsat 9 Collection 2 Level 2 surface reflectance (30 m resolution) data from January 2026 were downloaded from USGS Earth Explorer and filtered to include only data with < 20% cloud cover. Atmospheric adjustment of bottom of atmosphere (BOA) reflectance was performed using the Land Surface Reflectance Code (LaSRC). Masking methods were used to correct the QA\_PIXEL and QA\_RADSAT bands for cloud, cloud shadow and saturated pixel contaminations. A four band subset of SWIR 1 (B6), NIR (B5), Red (B4), and Green (B3) were fetched (Wulder *et al.*, 2019) [12] to be used as input to the ENVI based Maximum Likelihood Classification procedure.

Sentinel-2 MSI Level-2A imagery acquired from Google Earth Engine (GEE) (Gorelick *et al.*, 2017) [13] was the main optical input for ensemble classification and biophysical parameters calculation. The data provides bottom-of-atmosphere (BOA) surface reflectance atmospherically corrected via the Sen2Cor processor (Main-Knorn *et al.*, 2017) [14]. Scenes were filtered by study area, date range, and a less than 30% cloud cover threshold. Using the Scene Classification Layer (SCL), pixel-level masking retained only vegetation and bare soil, while water, unclassified pixels, shadows, clouds, and cirrus were excluded alongside opaque clouds flagged by the Quality Assessment (QA) band. Band values were scaled to physical reflectance by dividing by 10,000, and the 20 m bands (B5, B6, B7, B8A, B11, B12) were resampled to a uniform 20 m grid using bilinear interpolation.

Sentinel-1 C-band synthetic aperture radar (SAR) ground range detected (GRD) imagery in interferometric wide (IW) swath mode was leveraged to provide cloud independent microwave backscatter for ensemble classifier. The data preprocessed by the European Space Agency via thermal noise removal, radiometric calibration to sigma naught ( $\sigma^0$ ) in decibels, and SRTM based terrain correction was filtered by study area, IW mode, and dual-polarization (VV+VH). Because cross-polarization is highly sensitive to crop canopy volume scattering, monthly median composites were generated exclusively for the VH band from October 2025 to March 2026. Ultimately, six

monthly VH composites at 20 m resolution were produced and integrated into a 21-band feature stack.

### Chickpea area estimation

Chickpea area estimation was done using two approaches that are maximum likelihood approach applied to Landsat 9 imagery in ENVI software and ensemble approach in R software using a 21 band multi-sensor, multi-temporal feature stack of Sentinel-1 and Sentinel-2 data from Google Earth Engine (GEE). Both approaches utilized identical ground-truth training polygons digitized in QGIS to ensure a consistent comparative baseline for mapping chickpeas within the Krishna Zone.

For MLC, Landsat 9 surface reflectance imagery from January 2026 was processed in ENVI using the Maximum Likelihood Classification (MLC) algorithm across a four-band subset (B3, B4, B5, B6) at 30 m spatial resolution. MLC operates under the assumption of a multivariate normal spectral distribution for each of the ten land cover classes, utilizing class-specific mean vectors and covariance matrices to assign pixels based on maximum posterior probability. Prior to classification, signature separability was verified using the Jeffries-Matusita distance, allowing the model's full covariance matrix to accurately model elliptical spectral distributions and effectively isolate chickpea crops from dark vertisol soil backgrounds.

The machine learning approach employed an ensemble model implemented in R, utilizing a 21-band multi-sensor feature stack constructed in Google Earth Engine at 20 m resolution. This feature stack integrated 15 Sentinel-2 spectral index bands (NDVI, EVI, LSWI, GCVI, RECI) across three phenological windows (T1-T3) to track crop canopy dynamics because crop discrimination accuracy is strongly influenced by seasonal phenological stage at the time of image acquisition (Atzberger, 2013) [15]. Temporal vegetation-index trajectories have also been used to identify chickpea and other dryland crops based on crop phenological development (Gumma *et al.*, 2020) [16]. Alongside 6 monthly median Sentinel-1 SAR VH backscatter bands (October 2025-March 2026) for cloud-independent structural insight. Three supervised classifiers, Random Forest (RF), Gradient Boosting Machine (GBM), and Support Vector Machine (SVM) were trained on a stratified dataset. The individual outputs were fused through a soft probability ensemble by averaging the per-class probability arrays of RF and GBM, complemented by a majority vote hard-label fusion scheme across all three models. Pixels falling below an ensemble confidence threshold of 0.575 were assigned to a no-class rejection category to reduce spectral ambiguity and refine chickpea area estimation.

Model performance was assessed using user's accuracy, producer's accuracy, overall accuracy and the kappa coefficient.

## Results and Discussion

Chickpea area in the Krishna zone delineated using MLC on *rabi* 2025-26 Landsat 9 composite was evaluated against Department of Agriculture (DoA) administrative statistics. The MLC model estimated a total zonal chickpea area of 87,004 ha compared to the DoA reported figure of 1,13,929 ha, resulting in a net underestimation of 26,924 ha or a 23.63% divergence. At the district level, Bapatla recorded the highest chickpea area (34,250 ha), followed by Prakasam (20,240 ha), Guntur (15,706 ha), Palnadu (13,062 ha), NTR (2,990 ha), and Krishna (756 ha). Net underestimation was most severe in Prakasam (13,230 ha) and Bapatla (6,024 ha), whereas Palnadu showed the closest agreement with DoA statistics by underestimating by only 588 ha. Conversely, Krishna district exhibited an overestimation (756 ha estimated vs. 10 ha reported), primarily caused by spectral confusion with other *rabi* pulses or residual moisture signatures. The systematic underestimation by MLC is attributed to single date optical resolution constraints, where small or irregularly shaped land-holdings smaller than one Landsat pixel footprint (0.09 ha at 30 m resolution) experience spectral dilution from adjacent land covers (Hudait *et al.*, 2022) [17].

### District wise chickpea area (ha) estimated by MLC classification in *rabi* 2025-26

| Sl. No.      | District | Normal (ha)   | DoA reported (ha) | Estimated (ha) | Difference (ha) |
|--------------|----------|---------------|-------------------|----------------|-----------------|
| 1            | Krishna  | 15            | 10                | 756            | 746             |
| 2            | NTR      | 3,857         | 7,001             | 2,990          | -4,011          |
| 3            | Guntur   | 8,121         | 19,524            | 15,706         | -3,818          |
| 4            | Palnadu  | 11,452        | 13,650            | 13,062         | -588            |
| 5            | Bapatla  | 30,792        | 40,274            | 34,250         | -6,024          |
| 6            | Prakasam | 43,687        | 33,470            | 20,240         | -13,230         |
| <b>Total</b> |          | <b>97,924</b> | <b>1,13,929</b>   | <b>87,004</b>  | <b>-26,924</b>  |

Validation of the MLC output against 85 independent ground truth points produced a producer's accuracy of 94.12% (48 out of 51 points correctly classified) for the chickpea class and 79.41% (27 out of 34 points) for the non-chickpea class. The map achieved a user's accuracy of 87.27% for chickpea and 90.00% for the non-chickpea class, indicating that roughly one in eight pixels labeled as chickpea was misclassified due to spectral overlap with fallow land or other *rabi* pulses. The overall classification accuracy for MLC reached 88.24% with a Kappa coefficient of 0.74 which is substantial agreement. While point-based sampling confirmed acceptable local classification performance, the substantial net underestimation at the regional scale highlights how point accuracy metrics fail to capture cumulative omission errors across smallholder agricultural landscapes.

To address the limitations of MLC, an ensemble model incorporating Random Forest, Gradient Boosting Machine, and Support Vector Machine was applied to a multi-temporal feature stack of optical (Sentinel-2) and SAR (Sentinel-1) data. The fusion of multi-temporal optical and microwave observations provides complementary spectral and structural information and can improve crop identification compared with individual sensor data (Zhang *et al.*, 2022) [18]. Analysis of five optical indices (NDVI, EVI, LSWI, GCVI, and RECI) across three composite dates (T1, T2, and T3) revealed distinct seasonal trajectories. NDVI and EVI provided the clearest separation between cropped and non-cropped land during early (T1) and late (T3) periods, with EVI specifically reducing background soil interference from wet vertisols at T1. LSWI tracked residual soil moisture dynamics in the vertisol profile, rising from -0.08 at T1 to 0.20 at T2 before drying

to 0.09 at T3. At peak growth (T2), chlorophyll-sensitive indices GCVI (rising to 3.65) and RECI (rising to 1.6) retained sensitivity beyond NDVI saturation, providing critical discrimination between chickpea and spectrally similar non-leguminous *rabi* crops.

the ensemble classification yielded a total estimated chickpea area of 1,33,216 ha across the Krishna zone, representing a net overestimation of 19,287 ha (16.93% divergence) relative to DoA statistics. District-wise estimates placed Prakasam with the highest area (62,275 ha), followed by Bapatla (35,371 ha), Palnadu (16,328 ha), Guntur (13,427 ha), NTR (4,113 ha), and Krishna (1,702 ha). The ensemble classifier yielded an overestimation of 28,805 ha in Prakasam and 2,678 ha in Palnadu relative to DoA records, while underestimating area in Bapatla (4,903 ha), Guntur (6,097 ha), and NTR (2,888 ha). The shift from systematic underestimation in MLC to net overestimation in ensemble machine learning reflects the greater sensitivity of multi-sensor temporal stacks in capturing fragmented smallholder crop patches. The use of time-series Sentinel-1 and Sentinel-2 data with Random Forest classification has also demonstrated the effectiveness of multi-temporal satellite observations for crop mapping under varying crop conditions (Cai *et al.*, 2019) [19]. Similar classification studies in highly fragmented agricultural systems have demonstrated the usefulness of machine-learning approaches for crop-type discrimination (Ouzemou *et al.*, 2018) [20].

### District wise chickpea area estimated by ensemble classification during the *rabi* 2025-26

#### Spatial distribution of chickpea area estimated using maximum likelihood classification during *rabi* 2025-26

| Sl. No       | District | Normal (ha)   | DoA reported area (ha) | Estimated (ha)  | Difference (ha) |
|--------------|----------|---------------|------------------------|-----------------|-----------------|
| 1            | Palnadu  | 11,452        | 13,650                 | 16,328          | 2,678           |
| 2            | Guntur   | 8,121         | 19,524                 | 13,427          | -6,097          |
| 3            | Krishna  | 15            | 10                     | 1,702           | 1,692           |
| 4            | NTR      | 3,857         | 7,001                  | 4,113           | -2,888          |
| 5            | Bapatla  | 30,792        | 40,274                 | 35,371          | -4,903          |
| 6            | Prakasam | 43,687        | 33,470                 | 62,275          | 28,805          |
| <b>Total</b> |          | <b>97,924</b> | <b>1,13,929</b>        | <b>1,33,216</b> | <b>19,287</b>   |

### Spatial distribution of chickpea area estimated using ensemble classification during *rabi* 2025-26

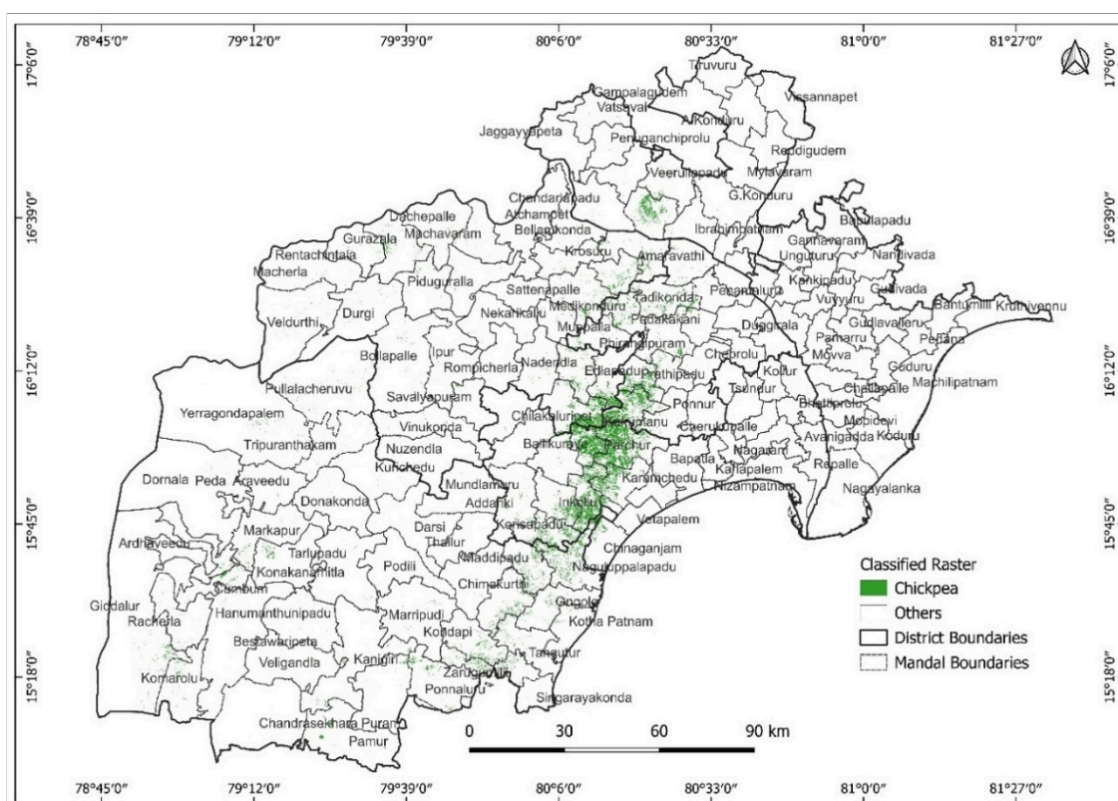
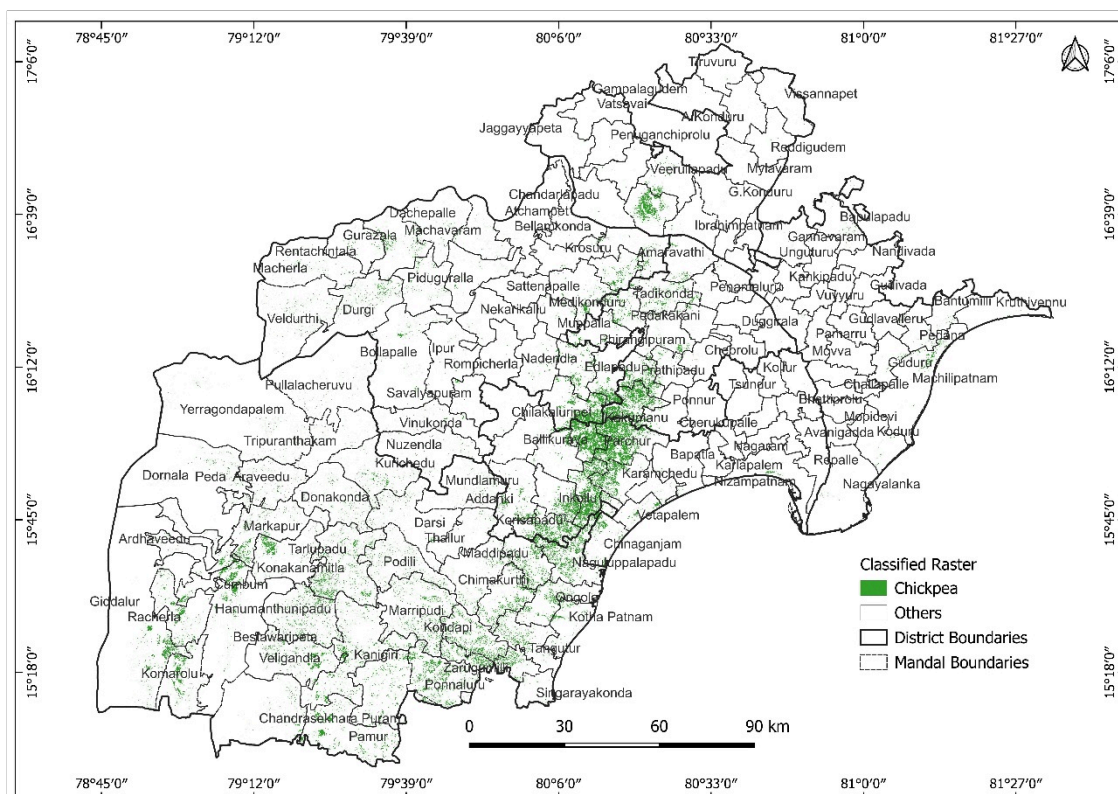
Accuracy assessment of the ensemble classification against the 85 reference points demonstrated substantial performance gains over MLC, reaching a chickpea producer's accuracy of 96.08% and a user's accuracy of 94.23%. Non-chickpea classification accuracy also improved, achieving a producer's accuracy of 93.93% and a user's accuracy of 91.17%. Overall classification accuracy reached 94.12% with a Kappa coefficient of 0.88 which is almost perfect agreement. This improvement aligns with established findings on multi-sensor, multi-classifier crop mapping, which have repeatedly shown that combining temporally dense optical and SAR observations with an ensemble of independently trained classifiers yields measurable accuracy gains over single-date, single-classifier approaches in smallholder cropping

landscapes (Kussul *et al.*, 2017; Zhong *et al.*, 2019) [21, 22]. The Kappa coefficients achieved here are broadly consistent with those reported for an SVM classifier applied to a comparable optical feature stack over the Krishna Western Delta tract of Guntur district, within the present study area, which achieved Kappa values of 0.91 and 0.93 for two other *rabi* crops grown in the same rice fallow landscape (Medida *et al.*, 2025) [23]. These results confirm that integrating multi-temporal optical and SAR data with ensemble machine learning mitigates omission errors inherent to single-date optical classifications. However, the occurrence of larger aggregated area errors alongside higher point-wise accuracy reconfirms that point-based validation metrics do not fully account for spatial over and under-counting across administrative boundaries.

## Conclusion

The integration of multi-sensor, multi-temporal remote sensing data with advanced machine learning ensemble models significantly enhances chickpea area estimation compared to MLC. By combining Sentinel-2 optical spectral indices with gSentinel-1 SAR backscatter within Google Earth Engine, the ensemble framework effectively mitigates long-standing optical remote sensing challenges, including spectral confusion with other rabi crops, dark vertisol soil background interference, and early-season cloud cover. The ensemble classifier demonstrated superior performance over MLC, achieving an overall accuracy of 94.11% ( $\kappa = 0.88$ ) compared to 88.23% ( $\kappa = 0.74$ ), alongside a marked reduction in smallholder field omission errors.

While point-based accuracy assessments confirm the high precision of the multi-sensor ensemble output, regional area comparisons against Department of Agriculture statistics highlight that MLC systematically underestimates crop extent (87,004 ha vs. 113,929 ha reported) due to spatial resolution constraints, whereas the multi-temporal ensemble offers greater sensitivity in capturing fragmented agricultural parcels (133,216 ha estimated). Ultimately, this cloud-based, multi-sensor ensemble framework provides an objective, scalable, and highly reliable methodology for operational crop monitoring, providing critical geospatial insights to support agricultural resource allocation, yield forecasting, and policy planning across regional production zones.



## References

1. Verma P, Kumar R, Solanki RK, Jadon C, Pradeep K. Chickpea (*Cicer arietinum* L.) scenario in India and South Eastern Rajasthan: A review. *International Journal of Current Microbiology and Applied Sciences*. 2021;10(1):1049-1063.
2. Karthikeyan L, Chawla I, Mishra AK. A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation and crop losses. *Journal of Hydrology*. 2020;586:124905.
3. Sud UC, Ahmad T, Gupta VK, Chandra H, Sahoo PM, Aditya K, Singh M, Biswas A. Methodology for estimation of crop area and crop yield under mixed and continuous cropping. Food and Agriculture Organization of the United Nations. 2017.
4. Ray S, Neetu. Crop area estimation with remote sensing. In Delince J (ed.) *Handbook on Remote Sensing for Agricultural Statistics*. Global Strategy to Improve Agricultural and Rural Statistics, Food and Agriculture Organization, Rome. 2017:23-45.
5. Weiss M, Jacob F, Duveiller G. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment*. 2020;236:111402.
6. Gumma MK, Devi KC, Mohammed IA, Varshney RK, Gaur P, Whitbread AM. Satellite imagery and household survey for tracking chickpea adoption in Andhra Pradesh, India. *International Journal of Remote Sensing*. 2016;37(8):1955-1972.
7. Orynbaikyzy A, Gessner U, Conrad C. Crop type classification using fusion of Sentinel-1 and Sentinel-2 data: Assessing the impact of feature selection, optical data availability and parcel sizes on the accuracies. *Remote Sensing*. 2020;12(17):2779.
8. McNairn H, Brisco B. The application of C-band polarimetric SAR for agriculture: A review. *Canadian Journal of Remote Sensing*. 2004;30(3):525-542.
9. Veloso A, Mermoz S, Bouvet A, Le Toan T, Planells M, Dejoux JF, Ceschia E. Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications. *Remote Sensing of Environment*. 2017;199:415-426.
10. Adrian J, Sagan V, Maimaitijiang M. Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2021;175:215-235.
11. Yang H, Pan B, Wu W, Tai J. Field-based rice classification in Wuhua County through integration of multi-temporal Sentinel-1A and Landsat-8 OLI data. *International Journal of Applied Earth Observation and Geoinformation*. 2018;69:226-236.
12. Wulder MA, Loveland TR, Roy DP, Crawford CJ, Masek JG, Woodcock CE, Allen RG, Anderson MC, Belward AS, Cohen WB, Dwyer J, Erb A, Gao F, Griffiths P, Helder D, Hermosilla T, Hipple JD, Hostert P, Hughes MJ, Huntington J, Johnson DM, Kennedy R, Kilic A, Li Z, Lymburner L, McCorkel J, Pahlevan N, Scambos TA, Schaaf C, Schott JR, Sheng Y, Storey J, Vermote E, Vogelmann J, White JC, Wynne RH, Zhu Z. Current status of Landsat program, science and applications. *Remote Sensing of Environment*. 2019;225:127-147.
13. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. 2017;202:18-27.
14. Main-Knorn M, Pflug B, Louis J, Debaecker V, Müller-Wilm U, Gascon F. Sen2Cor for Sentinel-2. Image and Signal Processing for Remote Sensing XXIII. *Proceedings of the International Society for Optics and Photonics*. 2017;10427:1042704.
15. Atzberger C. Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. *Remote Sensing*. 2013;5(2):949-981.
16. Gumma MK, Tummala K, Dixit S, Collivignarelli F, Holecz F, Kolli RN, Whitbread AM. Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information. *Geocarto International*. 2020;37(11):1-14.
17. Hudait A, Patel NR. Crop-type mapping and acreage estimation in smallholding plots using Sentinel-2 images and machine learning algorithms: Some comparisons. *Egyptian Journal of Remote Sensing and Space Sciences*. 2022;25:147-156.
18. Zhang H, Yuan H, Du W, Lyu X. Crop identification based on multi temporal active and passive remote sensing images. *ISPRS International Journal of Geo-Information*. 2022;11(7):388.
19. Cai Y, Lin H, Zhang M. Mapping paddy rice by the object-based random forest method using time series Sentinel-1/Sentinel-2 data. *Advances in Space Research*. 2019;64(11):2233-2244.
20. Ouzemou JE, Harti AE, Lhissou R, Moujahid AE, Bouch N, Ouazzani RE, Bachaoui EM, Ghmari AE. Crop type mapping from pansharpened Landsat-8 NDVI data: A case of a highly fragmented and intensive agricultural system. *Remote Sensing Applications: Society and Environment*. 2018;11:94-103.
21. Kussul N, Lavreniuk M, Skakun S, Shelestov A. Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*. 2017;14(5):778-782.
22. Zhong L, Hu L, Zhou H. Deep learning-based multi-temporal crop classification. *Remote Sensing of Environment*. 2019;221:430-443.
23. Medida SK, Podila PR, Sireesha G, Mrudhula KA, Ganesan PG. Identification of sowing window and sown area of maize and sorghum in rice fallows using multi-source satellite remote sensing. *Sains Tanah - Journal of Soil Science and Agroclimatology*. 2025;22(2):562-572.
24. Food and Agriculture Organization of the United Nations. Methodology for estimation of crop area and crop yield under mixed and continuous cropping. *Global Strategy to Improve Agricultural and Rural Statistics*. 2017.
25. Paul GC, Saha S, Hembram TK. Application of phenology-based algorithm and linear regression model for estimating rice cultivated areas and yield using remote sensing data in Bansloi River Basin, eastern India. *Remote Sensing Applications: Society and Environment*. 2020;19:100367.

**How to cite this article:** Harshitha A, Kumar SM, Bharathi A, Sridhar T, Ramarao I, Vani YSC, et al. Integrating multi-sensor optical and SAR data with machine learning ensembles for chickpea area estimation in the Krishna zone of Andhra Pradesh. *International Journal of Research in Agronomy*. 2026;SP-9(10):19-24. doi: <https://www.doi.org/10.33545/2618060X.2026.v9.i10Sa.6760>

## Authors

### A Harshitha

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

### Sunil M Kumar

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

### AS Bharathi

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

### TV Sridhar

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

**IB Ramarao**

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

**Y Srilatha Ch. Vani**

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

**AK Mrudula**

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India

**AD Grace**

Department of Agronomy, Advanced Post Graduate Centre, ANGRAU, Guntur, Andhra Pradesh, India