E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
www.agronomyjournals.com
2025; SP-8(1): 350-358
Received: 02-10-2024
Accepted: 10-11-2024

Sellaperumal Pazhanivelan
Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India

NS Sudarmanian
Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India

S Satheesh
Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India

KP Ragunath
Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India

Corresponding Author:
Sellaperumal Pazhanivelan
Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India

Spatial sorghum yield forecasting: Integrating remote sensing data and DSSAT simulation model in Belagavi

Sellaperumal Pazhanivelan, NS Sudarmanian, S Satheesh and KP Ragunath

DOI: https://doi.org/10.33545/2618060X.2025.v8.i1Sf.2434

Abstract
Effective sorghum yield prediction plays a pivotal role in sustainable agricultural planning and food security. This research explores the integration of Sentinel-1A synthetic aperture radar (SAR) data and the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model to map sorghum yield spatially in Belagavi district, Karnataka, India. The study processed SAR backscatter to delineate crop areas, achieving an overall classification accuracy of 85.2% with a kappa index of 0.70, demonstrating the utility of SAR for consistent monitoring under diverse weather conditions. Leaf Area Index (LAI) derived from backscatter was integrated with DSSAT outputs to estimate spatial yield, validated against Crop Cutting Experiment (CCE) data. The results showed an agreement of 85.4% between observed and predicted yields, confirming the robustness of this approach for precision agriculture. Future work will aim to refine model parameters and leverage advanced machine learning for enhanced adaptability to climate impacts.

Keywords: SAR, sorghum, yield prediction, crop simulation model, remote sensing and backscattering value

1. Introduction
Accurate and scalable agricultural yield estimation is a cornerstone of modern precision agriculture. It supports effective resource management, informed decision-making, and strategic policy development to address the growing challenges of food security and environmental sustainability. While traditional yield estimation methods, such as ground surveys and manual sampling, provide accurate results at local scales, they are often labor-intensive, time-consuming, and lack spatial coverage. The advent of remote sensing technologies and crop simulation models has revolutionized agricultural monitoring by providing efficient, scalable, and timely solutions for estimating crop yields over large regions.

Remote sensing offers invaluable geospatial data for monitoring vegetation dynamics, crop health, and yield potential (Karmakar *et al.*, 2024) [8]. Optical remote sensing, relying on sensors that capture reflectance in the visible and near-infrared (NIR) bands, has been extensively used to derive vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI). These indices are strongly correlated with crop health, leaf area index (LAI), and biomass. Studies such as Ma *et al*. (2022) [10] have demonstrated the integration of optical remote sensing data with crop growth models, such as SAFY, for precise wheat yield estimation. Despite its advantages, optical remote sensing is highly susceptible to atmospheric interference, particularly cloud cover, which limits its effectiveness in regions with persistent cloudy weather during critical crop growth stages (Wu *et al*., 2023) [19].

In contrast, microwave remote sensing, specifically Synthetic Aperture Radar (SAR), provides an all-weather monitoring capability, unaffected by cloud cover or time of day. SAR data is sensitive to biophysical parameters such as surface roughness, soil moisture, and vegetation structure, making it particularly effective for crop area mapping and growth monitoring in challenging weather conditions (Subbarao *et al*., 2021) [15]. Yang *et al*. (2021) [20] emphasized the effectiveness of integrating SAR data with crop growth models for biomass yield prediction in sorghum, demonstrating its reliability and robustness under diverse agro-climatic conditions. Furthermore, Gumma *et al.* (2022) [6] highlighted the successful use of SAR data in combination with crop simulation models for large-scale yield estimation in India, showcasing its potential to address spatial variability in crop performance.

The integration of SAR data with crop simulation models combines the strengths of remote sensing and biophysical modeling. Crop growth models, such as DSSAT-CERES, simulate crop development based on site-specific parameters, including soil properties, weather, and management practices (Chen & Tao 2022) [2]. These models provide detailed insights into crop performance and yield potential but require accurate spatial inputs for improved predictions (Torre *et al.*, 2021) [4]. Remote sensing data serves as a critical input for calibrating and validating these models, enhancing their spatial precision and predictive accuracy.

This study focuses on integrating Sentinel-1 SAR data with the DSSAT-CERES crop simulation model to estimate spatial yields of Rabi sorghum in Belagavi district, Karnataka, India. Sorghum, a staple cereal crop in semi-arid regions, plays a vital role in food and fodder security. Belagavi district, with its diverse agro-climatic zones and extensive sorghum cultivation, presents an ideal case for applying advanced remote sensing and modeling techniques. The specific objectives of the study are to map sorghum cultivation areas, derive spatial LAI and yield estimates, and validate predictions using field-level Crop Cutting Experiment (CCE) data.

2. Materials and Methods

2.1 Study Area

This research was conducted in the Belagavi district of Karnataka, India, a region known for its extensive Rabi sorghum cultivation. Belagavi covers approximately 13,415 square kilometers and is situated between latitudes 15°23'N to 16°58'N and longitudes 74°5'E to 75°28'E (Fig. 1). The district features a semi-arid climate with hot summers and mild winters. The average annual rainfall varies between 600 mm and 800 mm, primarily received during the southwest monsoon from June to September. The soils are predominantly black cotton soils with good water retention capacity, making them suitable for sorghum cultivation. Belagavi's agricultural landscape is characterized by rainfed farming systems, with sorghum being one of the principal crops grown during the Rabi season.

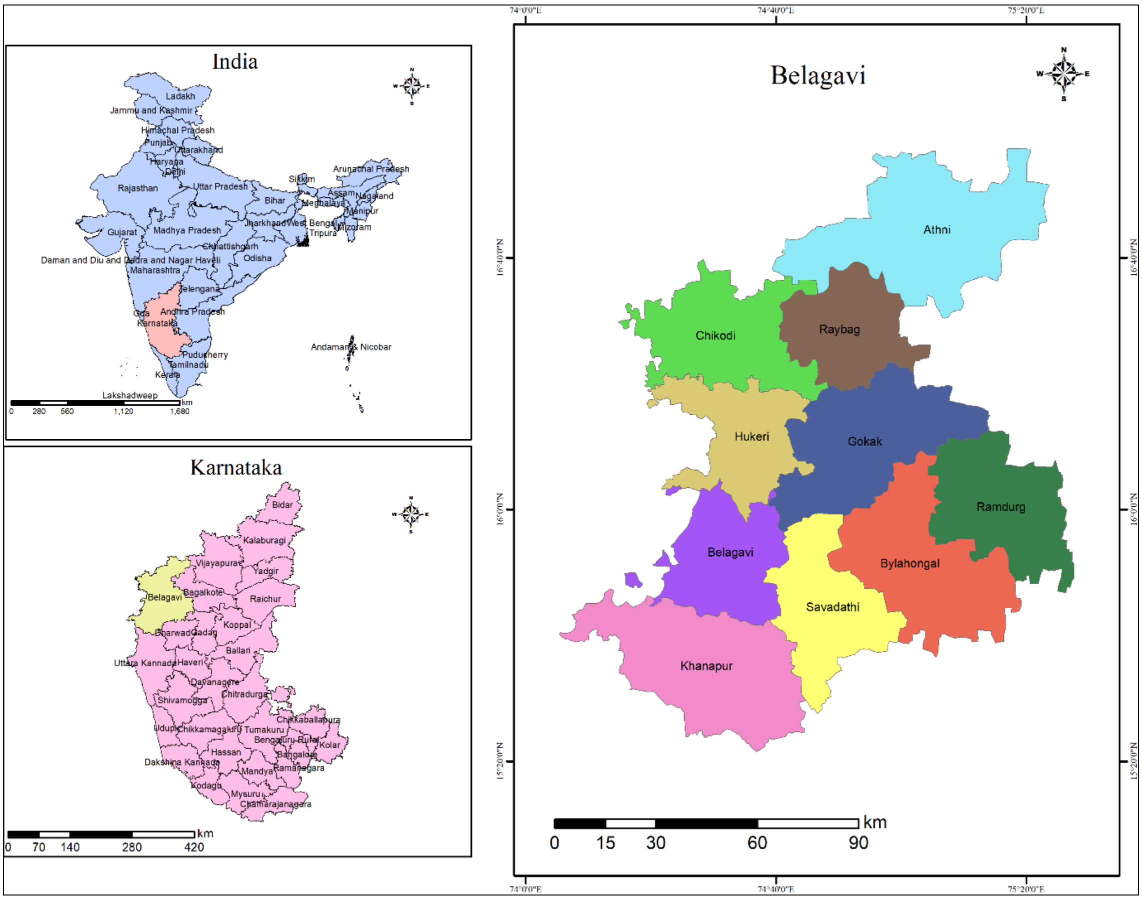

Fig 1: Location of the Stude Area

2.2 Satellite Data

Sentinel-1 SAR data, obtained from the European Space Agency (ESA), was used for this study due to its ability to capture all-weather, day-and-night backscatter information. The satellite operates in the C-band and offers dual polarization (VH and VV) data, which are sensitive to soil moisture and vegetation structure. The study utilized Interferometric Wide Swath (IW) mode Ground Range Detected (GRD) products acquired during the Rabi season from October 2022 to March 2023. These data were collected at 12-day intervals, enabling temporal analysis of crop growth stages. Table 1 provides detail information about Sentinel 1A satellite.

Table 1: Details of Sentinel 1A (IW-GRD) data

S. No	Parameters	Characteristics
1.	Pixel value	Magnitude detected
2.	Coordinate system	Ground range
3.	Polarization options	Single (VV or HH) or Dual (HH+HV or VV+VH)
4.	Look overlap (range, azimuth)	0.250, 0.000
5.	Resolution (range x azimuth in meters)	20.4 x 21.7
6.	Bits per pixel	16
7.	Pixel spacing (range x azimuth in meters)	10 x 10
8.	Radiometric resolution	1.7 dB
9.	Incidence angle (degree)	32.9
10.	Ground range coverage (km)	251.8
11.	Equivalent Number of Looks (ENL)	4.4
12.	Absolute location accuracy (m)	7
13.	Number of looks (range x azimuth)	5 x 1
14.	Azimuth look bandwidth (Hz)	327
15.	Range look bandwidth (Hz)	14.1

Source: (De Zan and Guarnieri, 2006) [5]

2.3 SAR Data Preprocessing
The Sentinel-1 SAR data were preprocessed using Mapscape software and other geospatial tools to ensure accurate analysis. Key preprocessing steps included:

- **Strip Mosaicking:** Individual SAR image frames from the same orbit and acquisition date were mosaicked to generate continuous strips, facilitating seamless data management and processing.
- **Co-registration:** Multi-temporal images were geometrically aligned using co-registration, which is a prerequisite for effective time-series analysis and speckle filtering (Raman *et al*., 2019) [14].
- **Time-Series Speckle Filtering:** A multi-temporal filter by De Grandi *et al*. (1997) [3] was applied to reduce speckle noise while preserving the reflectivity of stable objects.
- **Terrain Geocoding and Radiometric Calibration:** Digital Elevation Model (DEM) data were used to convert the SAR data into geocoded σ° values in a cartographic reference system. Radiometric normalization was applied to correct for range and angle dependencies (Ramalingam *et al*., 2019; Venkatesan *et al*., 2019; Karthikkumar *et al*., 2019) [13, 18, 9]
- **ANLD Filtering and Atmospheric Correction:** Adaptive Non-Local Means filtering (ANLD) was employed to smooth homogeneous areas and enhance feature boundaries. Corrections for atmospheric attenuation due to water vapor and heavy rainfall were applied using temporal signature anomaly detection techniques (Aspert *et al*., 2007) [1].

2.4 Crop Area Mapping
SAR backscatter data were classified into crop and non-crop categories using a rule-based classification approach based on temporal signatures (Fig. 2). Site-specific parameters, such as minimum and maximum backscatter values, were derived for sorghum fields. These parameters guided the classification process, and the results were validated using ground truth data collected from stratified random sampling points across the study area. Accuracy metrics, including overall accuracy and the kappa coefficient, were calculated to assess the reliability of the classification.

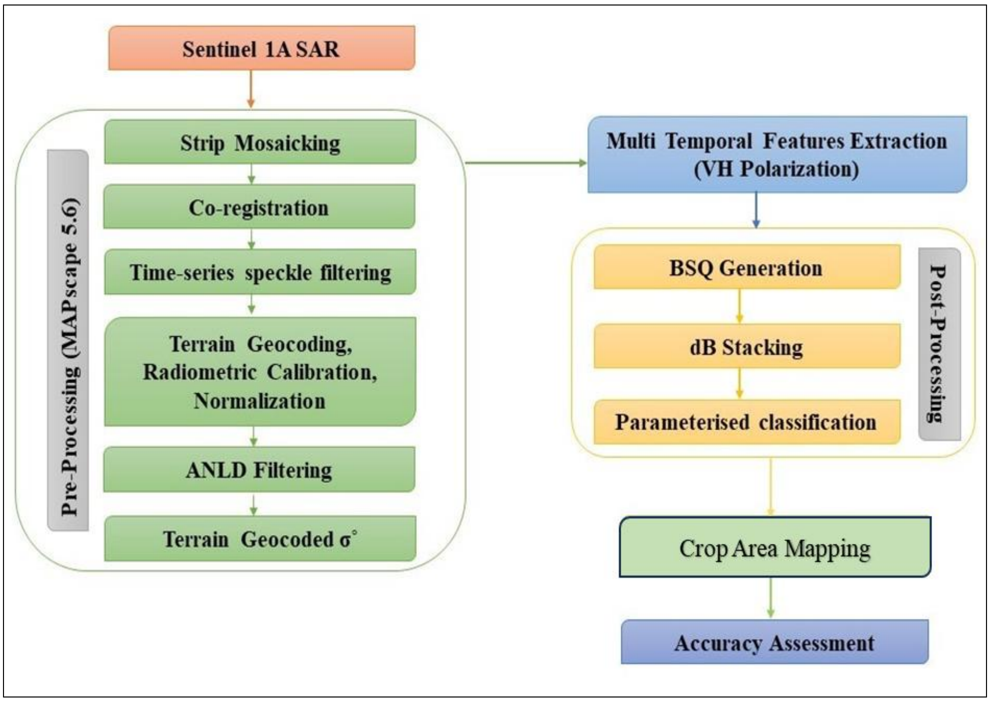

Fig. 2: Methodology for crop area mapping

2.5 DSSAT-CERES Crop Simulation Model
The DSSAT-CERES Sorghum model was used to simulate crop growth and yield under specific environmental conditions (Fig. 3). Key input data included:

- **Weather Data:** Daily maximum and minimum temperatures, solar radiation, and rainfall, sourced from local meteorological stations.
- **Soil Data:** Soil texture, organic carbon content, and moisture availability were derived from local soil surveys.
- **Crop Management Data:** Information on planting dates, row spacing, fertilizer application, and irrigation schedules was collected through field surveys.

The model was calibrated using observed field data and validated with Crop Cutting Experiment (CCE) yields collected from representative locations in the study area.

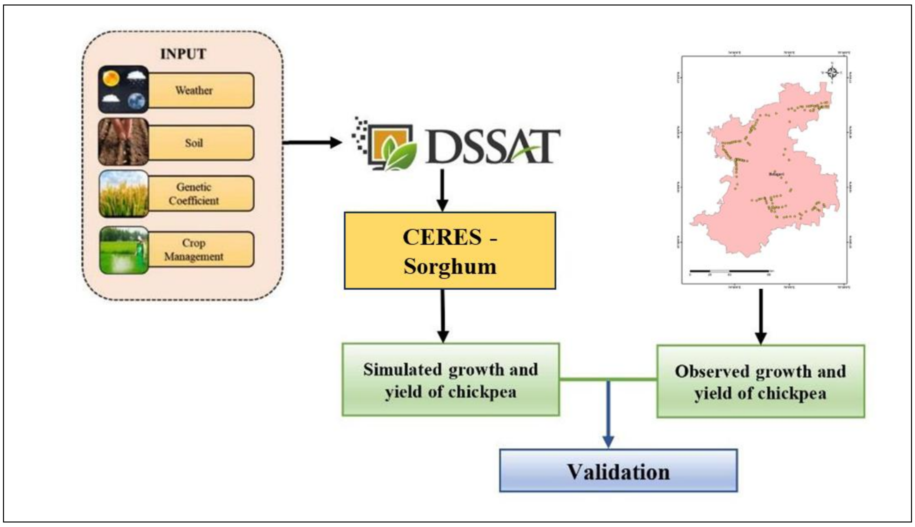

Fig. 3: Schematic diagram illustrating the methodology of the DSSAT CERES-Sorghum crop simulation model

2.6 Leaf Area Index (LAI) Estimation
LAI values were derived from SAR backscatter data using a regression model developed by correlating field-measured LAI with SAR backscatter values. These spatially estimated LAI values served as critical inputs for the DSSAT-CERES model to simulate sorghum growth and yields across the district.

2.7 Yield Estimation and Validation
Spatial yield estimation was conducted by integrating SAR-derived LAI with DSSAT-simulated yields (Fig 4). The results were validated using CCE data collected at 30 representative locations across the district. Statistical metrics, including Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), and percentage agreement, were used to evaluate the accuracy of the predictions.

2.8 Statistical Analysis
The reliability of the classified sorghum area and yield estimates was assessed using accuracy metrics such as overall classification accuracy, kappa coefficient, RMSE, and NRMSE. Agreement percentages were calculated to quantify the degree of similarity between observed and predicted values.

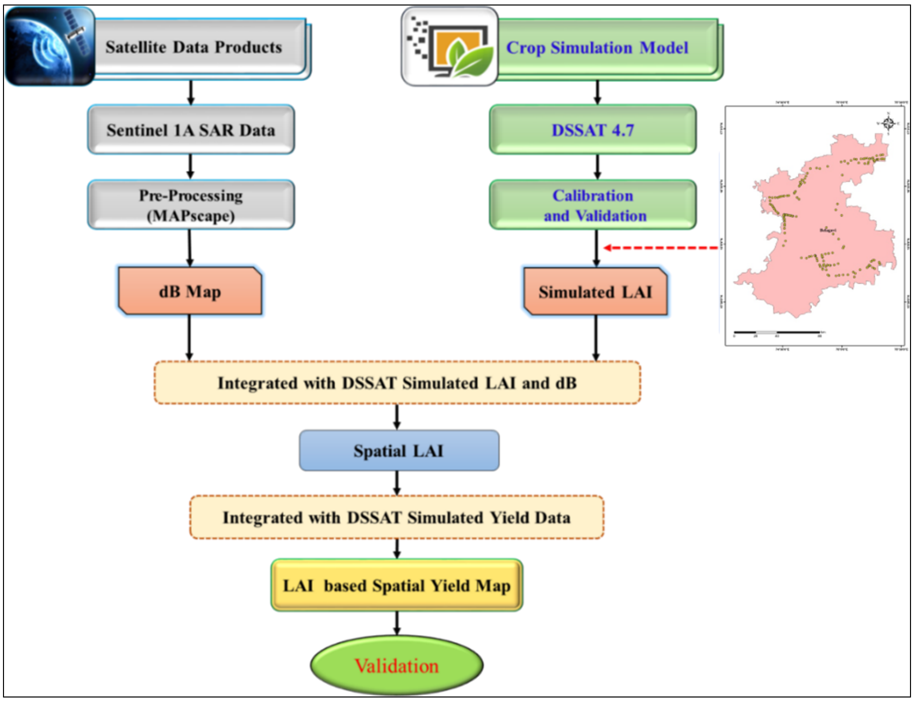

Fig. 4: A schematic representation of crop yield estimation integrating SAR satellite-derived products with the DSSAT crop simulation model

3. Results and Discussion

3.1 Sorghum Area Estimation

The classified Rabi sorghum area in Belagavi district, Karnataka, was estimated to be 141,756 hectares during the Rabi season of 2023 (Table 2). The analysis revealed significant spatial variability in sorghum cultivation across the district. Among the ten administrative blocks, Gokak recorded the highest sorghum area at 26,743 hectares, followed by Athni and Raybag, with 25,737 and 17,933 hectares, respectively. These regions benefit from favorable agro-climatic conditions and relatively higher soil fertility, supporting extensive sorghum cultivation. Conversely, blocks such as Khanapur (1,309 hectares) and Belgaum (4,941 hectares) had comparatively lower sorghum cultivation, potentially due to their focus on alternative crops or limitations in irrigation infrastructure.

The spatial distribution of sorghum cultivation areas was visually represented in a Fig. 5 thematic map, highlighting the variability across blocks. Such detailed spatial information can support targeted agricultural interventions, such as optimized resource allocation, strategic irrigation planning, and adaptive crop management practices, especially in high-producing regions like Gokak and Athni. These insights align with findings from Yang *et al.* (2021) [20], who highlighted the utility of remote sensing for spatially explicit biomass mapping, aiding precision agriculture. Crop area mapping using SAR data is unaffected by cloud cover and rainfall, enabling image acquisition both day and night (Kannan *et al.*, 2021; Poompavai *et al.*, 2024) [7, 12].

Table 2: Block-wise Crop area statistics

S. No	Block Name	Area (ha)
1.	Athni	25737
2.	Bail Hongal	9161
3.	Belgaum	4941
4.	Chikodi	14282
5.	Gokak	26743
6.	Hukeri	12376
7.	Khanapur	1309
8.	Ramdurg	12917
9.	Raybag	17933
10.	Saundatti	16356
Total		141756

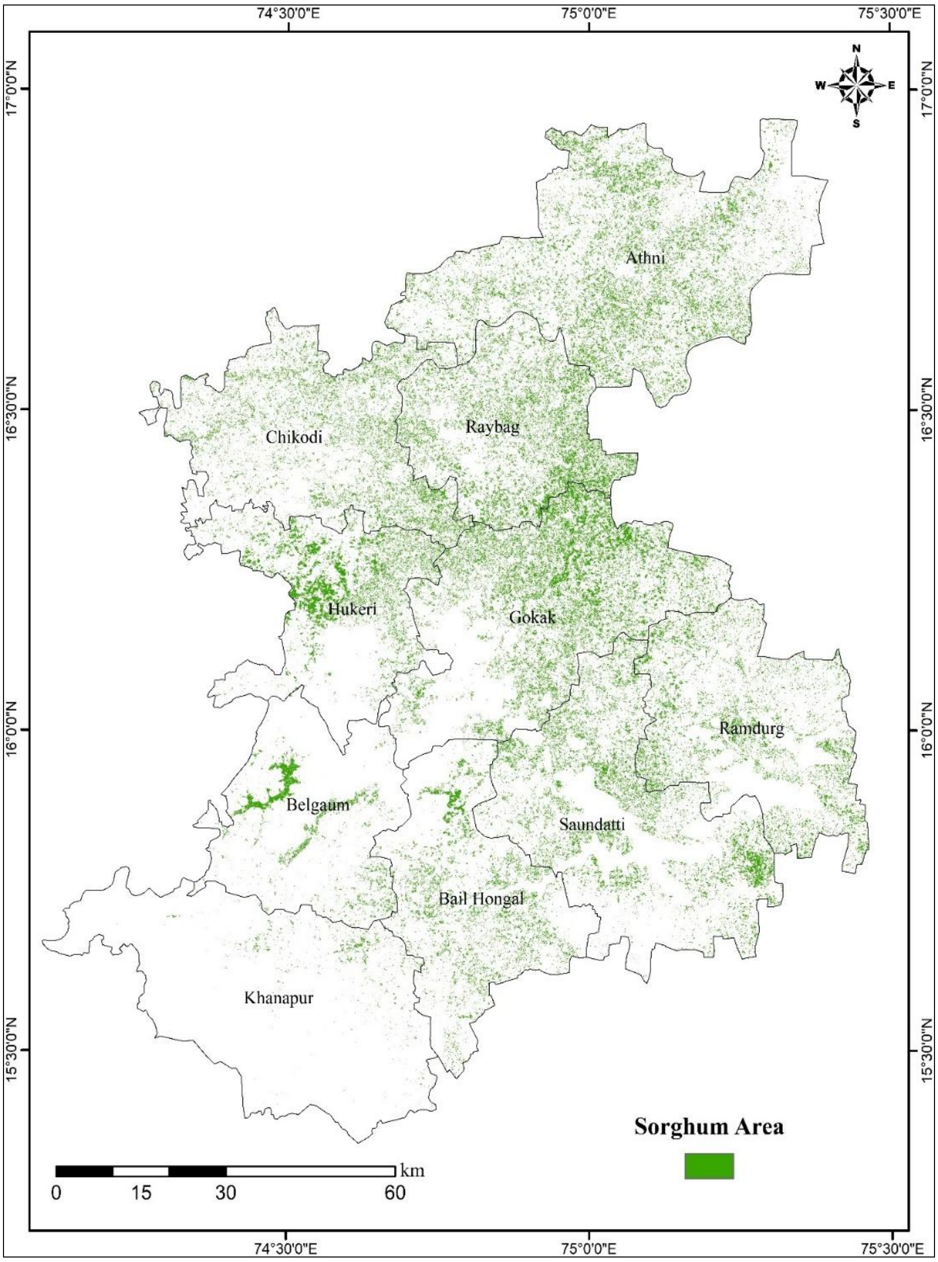

Fig. 5: Sorghum crop area map

3.2 Accuracy assessment of crop area

The reliability of the sorghum area map was assessed using ground truth data collected through stratified random sampling. A total of 169 points, including 82 from sorghum fields and 87 from non-sorghum fields, were used for validation (Table 3). The overall classification accuracy was 85.2%, with a kappa coefficient of 0.70, reflecting good agreement between the classified map and the ground truth data.

The average reliability of the classification was calculated to be 85.2%. These results underscore the effectiveness of integrating Sentinel-1 SAR data with a rule-based parameterized classification approach for crop mapping (Pazhanivelan *et al*., 2022, Thirumeninathan *et al*., 2024) [11, 16].

Table 3: Accuracy assessment of sorghum crop area

Actual class from survey	Predicted class from the map			
	Class	**Sorghum**	**Non-Sorghum**	**Accuracy (%)**
	Sorghum	70	12	85.4%
	Non-Sorghum	13	74	85.1%
	Reliability	84.3%	86.0%	85.2%
Average accuracy		85.20%		
Average reliability		85.20%		
Overall accuracy		85.2%	Good Accuracy	
Kappa index		0.70	Good Accuracy	

3.3 Estimation of Leaf Area Index

The spatial Leaf Area Index for Rabi sorghum in Belagavi district was developed by integrating Sentinel-1 SAR backscatter values with DSSAT-simulated LAI values. A regression model was established to correlate field-measured LAI with SAR-derived backscatter (σ°) values. The resulting spatial LAI map revealed significant variations in LAI across the district, reflecting differences in crop health and growth stages among blocks (Fig. 6).

The LAI ranged from 0.8 to 4.2, with the highest values observed in blocks such as Gokak and Athni, where favorable agro-climatic conditions and better management practices were prevalent. In contrast, blocks like Khanapur and Belgaum recorded lower LAI values, likely due to less favorable conditions or lower inputs. This spatial variability in LAI underscores the importance of site-specific crop management strategies to optimize sorghum productivity.

The accuracy of LAI estimation was validated against field data, with high agreement percentages across the study area. These results align with previous studies, such as Yang *et al*. (2021) [20] and Ma *et al*. (2022) [10], which demonstrated the efficacy of combining SAR data with crop simulation models for reliable LAI estimation in sorghum and wheat, respectively.

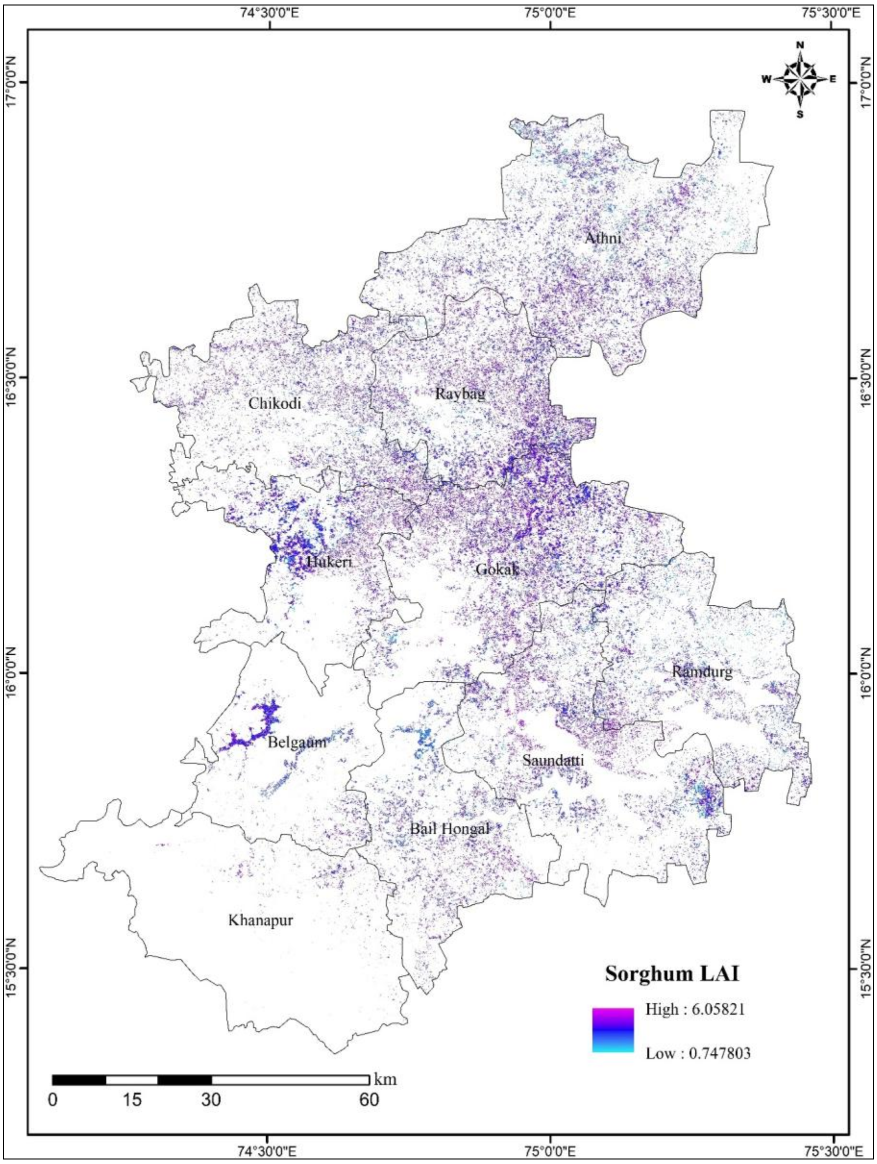

Fig. 6: Spatial Leaf Area Index for Belagavi district

3.4 Sorghum Yield Estimation

The spatial yield of Rabi sorghum was estimated by integrating the DSSAT-CERES Sorghum model with Sentinel-1 SAR-derived LAI values. The DSSAT model simulated yields based on soil, weather, and crop management inputs, while SAR-derived LAI values provided spatially explicit observations to calibrate the model. Figure 7 shows spatial yield across Belagavi district.

The estimated average yield 1028 kg/ha across Belagavi district. Blocks with higher yields, such as Gokak and Athni, corresponded to areas with higher LAI values, reflecting better crop health and favorable growing conditions. The yield estimates were validated using Crop Cutting Experiment (CCE) data collected from 30 representative locations across the district (Table 5). The validation revealed a strong agreement of 85.4% between predicted and observed yields, with an RMSE of 92.5 kg/ha and a Normalized RMSE (NRMSE) of 8.6%. These metrics indicate a high level of accuracy in yield prediction, demonstrating the reliability of integrating SAR data with the DSSAT-CERES model.

The results align with findings by Gumma *et al*. (2022) [6], who reported similar levels of agreement when combining remote sensing data with crop growth models for yield estimation in India. Additionally, the spatial yield map generated in this study provides actionable insights for precision agriculture, enabling farmers and policymakers to identify high- and low-productivity areas for targeted interventions.

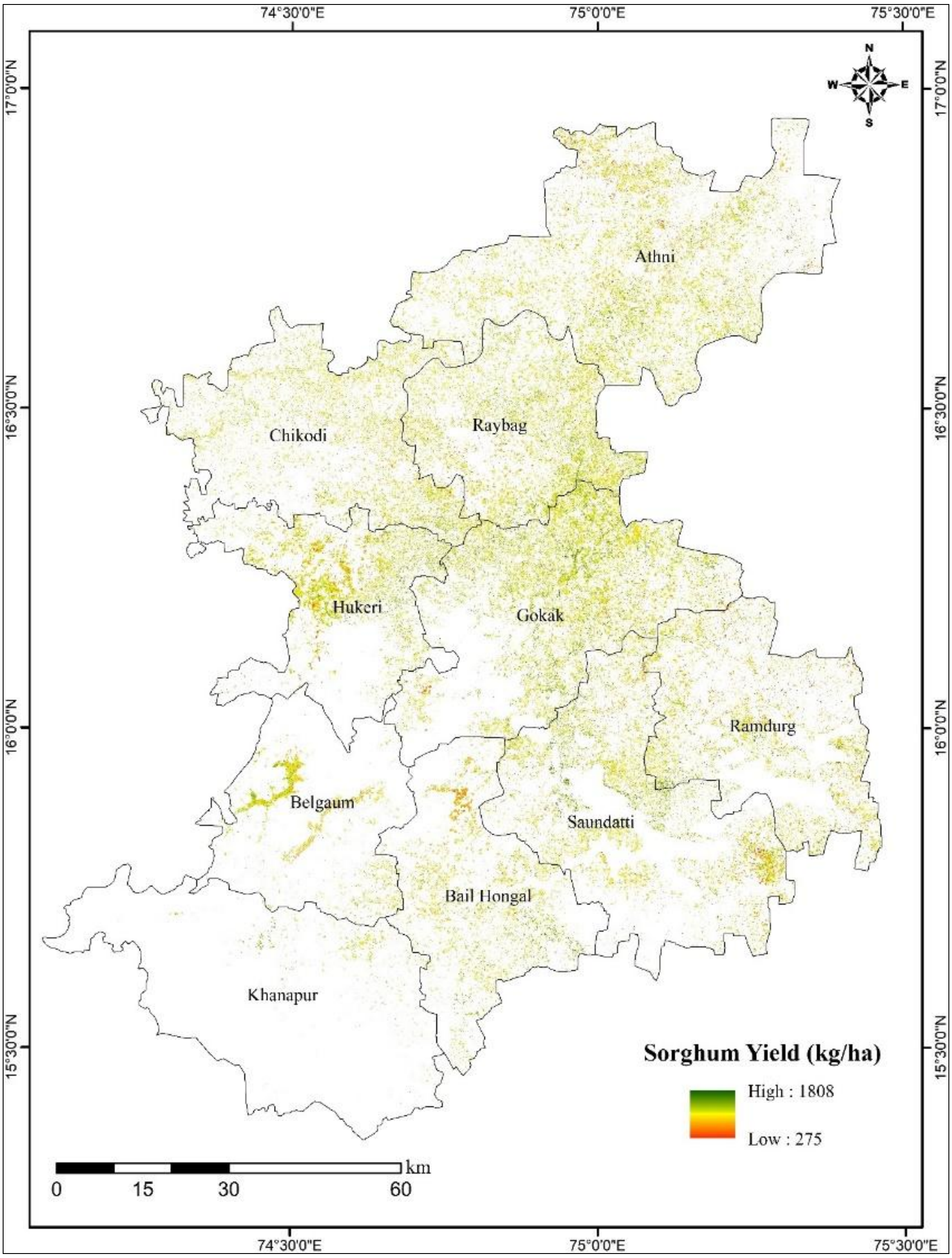

Fig. 7: Spatial yield for Belagavi district

Table 5: The Table shows agreement between Remote Sensing yield and Observed yield

S .No	Longitude	Latitude	Remote Sensing Yield (kg/ha)	CCE (kg/ha)	Agreement (%)
1	15.99485	75.13859	1145	1480	77.4
2	16.2105	74.59584	1485	1275	83.5
3	15.71664	74.92572	865	950	91.1
4	15.71686	74.93779	926	910	98.2
5	15.72686	74.93767	845	800	94.4
6	15.9297	74.82475	921	950	96.9
7	15.92547	74.80901	614	580	94.1
8	15.93266	74.81438	453	326	61.0
9	15.77061	74.64319	765	850	90.0
10	15.78462	74.64774	856	950	90.1
11	15.77361	74.64076	1121	1450	77.3
12	16.35244	74.50611	1121	1310	85.6
13	16.22001	74.59898	1235	1490	82.9
14	16.35229	74.50072	1058	1240	85.3
15	15.7596	74.65035	854	720	81.4
16	16.35892	74.50651	1017	800	72.9
17	15.87995	74.68652	1005	900	88.3
18	15.88215	74.67919	988	1130	87.4
19	15.87603	74.67892	988	1170	84.4
20	15.86901	74.79382	987	1260	78.3
21	15.85763	74.79295	785	610	71.3
22	15.86667	74.77582	985	978	99.3
23	15.717	75.19993	1329	1550	85.7
24	16.00864	75.03388	962	1280	75.2
25	15.72766	75.18973	1069	1295	82.5
26	15.70572	75.19919	1485	1210	77.3
27	15.7705	74.6507	1485	1318	87.3
28	15.77148	74.64009	1365	1320	96.6
29	15.78343	74.64443	987	870	86.6
30	16.10932	75.15255	1140	1130	99.1
Agreement					85.4

4. Conclusion

This study demonstrated the integration of Sentinel-1 SAR data with the DSSAT-CERES crop simulation model for spatial estimation of Leaf Area Index (LAI) and yield of Rabi sorghum in Belagavi district, Karnataka. The spatial sorghum average yield 1028 kg/ha, with the highest yields in Gokak and Athni blocks, highlighting optimal growing conditions. The classification accuracy of sorghum areas was 85.2%, with a kappa coefficient of 0.70, validating SAR data's reliability for crop mapping in semi-arid regions. Integrating SAR-derived LAI with DSSAT simulations achieved 85.4% agreement between predicted and observed yields, demonstrating the synergy of remote sensing and modeling.

The all-weather capability of SAR ensured consistent data acquisition, critical for agricultural monitoring in regions with variable climates. The spatial maps generated provide actionable insights for precision agriculture, enabling targeted interventions to optimize productivity and resource use. Future efforts should focus on integrating optical and SAR data, advanced machine learning techniques, and multi-crop models to further enhance prediction accuracy. This approach supports sustainable agriculture and food security, particularly in resource-limited semi-arid regions.

Acknowledgement

We thank the Mahalanobis National Crop Forecast Centre (MNCFC) for providing funding to support this research.

Competing Interests

Authors have declared that no competing interests exist.

5. References

1. Aspert F, Bach-Cuadra M, Cantone A, Holecz F, Thiran JP. Time-varying segmentation for mapping of land cover changes. Proc ENVISAT Symp; 2007. p. 23-27.
2. Chen Y, Tao F. Potential of remote sensing data-crop model assimilation and seasonal weather forecasts for early-season crop yield forecasting over a large area. Field Crops Res 2022;276:108398.
3. De Grandi GF, Leysen M, Lee JS, Schuler D. Radar reflectivity estimation using multiple SAR scenes of the same target: Technique and applications. IGARSS'97 IEEE Int Geosci Remote Sens Symp Proc Remote Sens-Sci Vision Sustain Dev. 1997;2:1047-1050. IEEE.
4. dela Torre DMG, Gao J, Macinnis-Ng C. Remote sensing-based estimation of rice yields using various models: A critical review. Geo-Spatial Inf Sci. 2021;24(4):580-603.
5. De Zan F, Guarnieri AM. TOPSAR: Terrain observation by progressive scans. IEEE Trans Geosci Remote Sens. 2006;44(9):2352-2360.
6. Gumma MK, Kadiyala MDM, Panjala P, Ray SS, Akuraju VR, Dubey S, *et al*. Assimilation of remote sensing data into crop growth model for yield estimation: A case study from India. J Indian Soc Remote Sens. 2022;50(2):257-270. https://doi.org/10.1007/s12524-021-01425-2
7. Kannan S, Kaliaperumal R, Pazhanivelan S, Kumaraperumal R, Sivakumar K. Rice area estimation using Sentinel 1A SAR data in Cauvery Delta Region. Int J Curr Microbiol Appl Sci. 2021;10(2):848-853.
8. Karmakar P, Teng SW, Murshed M, Pang S, Li Y, Lin H. Crop monitoring by multimodal remote sensing: A review. Remote Sens Appl Soc Environ. 2024;33:101093.

9. Karthikkumar A, Pazhanivelan S, Jagadeeswaran R, Ragunath K, Kumaraperumal R. Generating banana area map using VV and VH polarized radar satellite image. Madras Agric J. 2019;106(1-6):1-6.
10. Ma C, Liu M, Ding F, Li C, Cui Y, Chen W, *et al*. Wheat growth monitoring and yield estimation based on remote sensing data assimilation into the SAFY crop growth model. Sci Rep. 2022;12(1):5473. https://doi.org/10.1038/s41598-022-09475-w
11. Pazhanivelan S, Geethalakshmi V, Tamilmounika R, Sudarmanian NS, Kaliaperumal R, Ramalingam K, *et al*. Spatial rice yield estimation using multiple linear regression analysis, semi-physical approach, and assimilating SAR satellite derived products with DSSAT crop simulation model. Agronomy. 2022;12(9):2008. https://doi.org/10.3390/agronomy12092008
12. Poompavai V, Kumar NM, Hebbar R, GN NK. Early season crop acreage estimation for pigeon pea using SAR data: A case study of Kalaburagi District, Karnataka. J Geomatics. 2024;18(2):24-31.
13. Ramalingam K, Ramathilagam AB, Murugesan P. Area estimation of cotton and maize crops in Perambalur district of Tamil Nadu using multi-date Sentinel-1A SAR data and optical data. Int Arch Photogramm Remote Sens Spatial Inf Sci. 2019;42:137-140.
14. Raman MG, Kaliaperumal R, Pazhanivelan S, Kannan B. Rice area estimation using parameterized classification of Sentinel-1A SAR data. Int Arch Photogramm Remote Sens Spatial Inf Sci. 2019;42:141-147.
15. Subbarao NVT, Mani JK, Shrivastava A, Srinivas K, Varghese AO. Acreage estimation of kharif rice crop using Sentinel-1 temporal SAR data. Spat Inf Res. 2021;29:495-505.
16. Thirumeninathan S, Pazhanivelan S, Mohan R, Pouchepparadjou A, Sudarmanian NS, Ragunath K, *et al*. Integrating S1A microwave remote sensing and DSSAT CROPGRO simulation model for groundnut area and yield estimation. Eur J Agron. 2024;161:127348.
17. Veloso A, Mermoz S, Bouvet A, Le Toan T, Planells M, Dejoux JF, *et al*. Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications. Remote Sens Environ. 2017;199:415-426. https://doi.org/10.1016/j.rse.2017.07.015
18. Venkatesan M, Pazhanivelan S, Sudarmanian N. Multi-temporal feature extraction for precise maize area mapping using time-series Sentinel-1A SAR data. Int Arch Photogramm Remote Sens Spatial Inf Sci. 2019;42:169-173.
19. Wu B, Zhang M, Zeng H, Tian F, Potgieter AB, Qin X, *et al*. Challenges and opportunities in remote sensing-based crop monitoring: A review. Natl Sci Rev. 2023;10(4):nwac290.
20. Yang KW, Chapman S, Carpenter N, Hammer G, McLean G, Zheng B, *et al*. Integrating crop growth models with remote sensing for predicting biomass yield of sorghum. in silico Plants. 2021;3(1):diab001. https://doi.org/10.1093/insilicoplants/diab001