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Maize area mapping using multi-temporal Sentinel 1A SAR data in the Belagavi district of Karnataka, India

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Abstract

The study explores the integration of remote sensing technologies with ground truth data for precise estimation of maize cultivation areas in the Indian Belagavi district, Karnataka, during the *rabi* season of 2022-23. Leveraging Sentinel-1A satellite data and advanced processing techniques, the study provides insights into crop dynamics, phenology, and spatial distribution. Ground truth data collection involved 369 points covering diverse land use and land cover types. The multi-temporal Synthetic Aperture Radar (SAR) imagery underwent automated processing, extracting features crucial for maize classification. Classification accuracy assessment revealed robust performance, with 92.4% accuracy for maize and 91.1% for non-maize locations, supported by a Kappa index of 0.83. Taluk (sub- district) wise maize area estimation highlighted spatial variations, with Saudatti emerging as the leading taluk, contributing 25.74% of the total maize cultivation area. The study underscores the importance of localized agricultural planning strategies tailored to each region's agricultural landscape. Through comprehensive analysis and accurate area estimation, policymakers and stakeholders gain valuable insights for informed decision-making, ranging from optimizing input distribution to formulating targeted policies for rural development.

Abbreviations

ANLD: Adaptive Non-Local Means Denoising
dB: Temporal backscattering
GRD: Ground Range Detected
IW: Interferometric Wide
LULC: Land Use Land Cover
MTF: Multitemporal Time Series Feature
SAR: Synthetic Aperture Radar
SLC: Single Look Complex
UAVs: Unmanned aerial vehicles
VH: Vertical-Horizontal
VV: Vertical-Vertical
ergence
DAS: days after sowing
Fb: followed by

Introduction

The application of remote sensing technologies in agriculture has brought about a paradigm shift in the way agricultural activities are monitored and managed. Remote sensing encompasses a range of techniques, including satellite imagery, unmanned aerial vehicles (UAVs), and field hyperspectral measurements, which provide valuable data for various stages of the agricultural production process, from land preparation to harvesting (Ali *et al.*, 2022).

Crop area estimation serves as a fundamental tool for monitoring agricultural trends, assessing the impact of interventions, and formulating targeted policies for rural development and economic growth (Kumar *et al.*, 2017). By accurately estimating crop areas, authorities can identify regions of high productivity and potential yield gaps, allowing for the optimization of management strategies to enhance overall agricultural output (Sharma *et al.*, 2020). Furthermore, crop area estimation provides invaluable insights into changing cropping patterns, land use dynamics, and environmental sustainability, guiding long-term planning and investment decisions in the agricultural sector. By analysing historical crop area data, researchers can identify trends and patterns that inform future agricultural development strategies.

Accurate crop area estimation is vital for effective agricultural planning but is challenging due to factors such as small field sizes, diverse cropping patterns, mixed cropping systems, and prolonged sowing periods. In India, the complexity increases with staggered planting, changing cropping patterns, short-duration crops, and complex landscapes like terraced hillsides (Vogel and Bange, 1999). Maize area estimation is particularly difficult due to varying planting densities, mixed cropping, and diverse phenological stages. Traditional ground surveys are time-consuming, costly, and prone to bias. Consequently, researchers and practitioners are increasingly adopting satellite remote sensing for more precise, efficient, and scalable maize area estimation.

Satellite remote sensing offers several advantages over traditional methods for crop area estimation. Remote sensing data provides temporal, multispectral, and synoptic images of land use and land cover, allowing the classification of different crop types. High spatial and temporal resolution satellite data, combined with advanced image processing techniques, enable researchers to accurately identify and delineate agricultural fields. Furthermore, Remote Sensing data can be used to monitor crop growth, assess crop health, and predict yield potential (Pazhanivelan *et al.*, 2022). By analysing changes in vegetation indices and other biophysical parameters derived from satellite imagery, researchers can infer information about crop conditions and productivity. This information is invaluable for decision-making in agricultural management, including irrigation scheduling, fertilizer application, and pest and disease management.

Despite its many advantages, the operational use of remote sensing data for crop area assessment faces several challenges. One of the primary limitations is the small size of agricultural fields, especially in countries like India, where smallholder farming is prevalent. High-resolution remote sensing data is required to accurately identify and classify crops in these small fields. Another challenge is posed by persistent cloud cover during the rainy season, which limits the usefulness of optical imagery for agricultural applications. Synthetic Aperture Radar (SAR) data can be used to overcome this limitation, as SAR sensors are capable of penetrating cloud cover and providing information about crop structure and moisture content (Eberhardt *et al.*, 2016).

Additionally, the diversity of cropping and agronomic practices, including mixed and intercropping systems, presents challenges for crop classification and area estimation using remote sensing data. Technical issues related to the analysis and interpretation of remote sensing data also pose challenges (Mahlayeye *et al.*, 2022). These include the availability of sufficient ground truth data for calibration and validation, the computing power and storage facilities required to process large volumes of high-resolution data, and the availability of satellite data with a low temporal resolution.

Belagavi district, located in Karnataka, India, is renowned for its diverse agricultural landscape, which includes crops such as maize, sugarcane, paddy, and cotton (Kumar *et al.*, 2017). These crops thrive in the region's fertile lands and favourable climatic conditions, contributing significantly to the agricultural economy of the district. Accurate estimation of crop areas in Belagavi district is essential for agricultural planning and resource allocation. By leveraging remote sensing technologies, policymakers and stakeholders can make informed decisions regarding land use, irrigation, and input distribution, thereby ensuring sustainable production and food security (Panda *et al.*, 2018).

In the context of Belagavi district, accurate crop area estimation is crucial for understanding the dynamics of *rabi* maize cultivation. By integrating remote sensing technologies with ground truth data, authorities can effectively monitor and assess the spatial distribution and extent of maize crops. This integration allows for better management of agricultural resources, informed decision-making, and the development of targeted interventions to improve productivity. Additionally, accurate crop area estimation supports sustainable farming practices and strengthens the resilience of the agricultural sector to climate variability and other challenges.

Materials and methods

Study area

Belagavi district, located in Karnataka, spans approximately 13,415 square sq km, stretching between 14°15' to 15°15' north latitude and 74°15' to 75°15' east longitude (Fig. 1). The region falls within a hot semi-arid to sub-humid climate zone, characterized by mean annual maximum and minimum temperatures of 32.6°C and 22.2°C, respectively. Annual rainfall in the area ranges from 800 to 1400 mm, with variations across the district (Prasad *et al.* 2022). The predominant soil types in Belagavi are red sandy loam and clay loam, which offer favourable conditions for the cultivation of various crops such as maize, sugarcane, Maize, rice, black gram, and sesame. These agricultural activities are supported by the district's topography and climatic conditions (Fig. 2).

Ground truth data

Ground truth is an essential component for crop classification, either as an input for building a classification algorithm or as validation of the classification. The

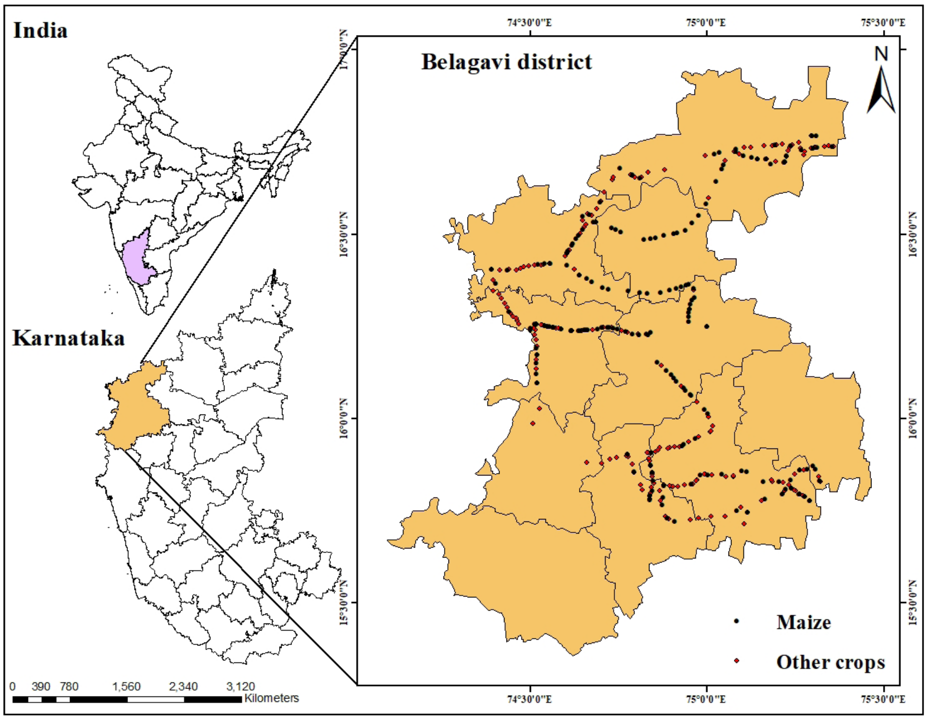

Fig. 1 - Study area map Belagavi district with Ground Truth Points

ground truth is collected with respect to land use and land cover. Typically, ground truth for crop classification includes geographical location, the village, district or state, the name of the crop, the coverage, the condition, the stage, whether it is irrigated or rainfed, the expected yield, the sowing and harvesting dates, etc. The ground truth was collected from selected sample locations spread over the entire study region, covering all types of diversity following stratified sampling methodology. Nearly 369 ground truth points (GTP) were collected including crop and non- crop points (Fig.1). The points were utilized for classification, validation and accuracy assessment.

Satellite data

Leveraging the capabilities of the Sentinel-1A satellite equipped with the C-SAR instrument ensures dependable and extensive monitoring. Utilizing SAR offers a notable advantage: it is operated at wavelengths unaffected by cloud cover or lack of illumination, facilitating continuous data collection regardless of the time of day. Sentinel-1's diverse imaging modes, including various resolutions and dual polarization, ensure comprehensive coverage and detailed observations. Ground Range Detected (GRD) and Single Look Complex (SLC) datasets from Sentinel-1A SAR, featuring VV (Vertical-Vertical) and VH (Vertical-Horizontal) polarizations in Interferometric Wide (IW) swath mode, were acquired at 12-day intervals. These datasets were deemed vital for crop identification and mapping within the study area. Data ranging from August 29, 2020, to February 25, 2021, were sourced from *https://asf.alaska.edu/datasets/daac/sentinel-1/*. This timeframe aligns with the typical maize growing season in the study region, ensuring complete coverage across all stages of crop growth.

Preprocessing

The multi-temporal space-borne Sentinel-1A SAR IW-GRD data underwent automated processing using a comprehensive processing chain developed by Holecz *et al.* (2013). This processing chain, integrated into the MAPscape software by sarmap, Switzerland, facilitated the conversion of raw data into terrain-geocoded σ^0 values. The processing involved several essential steps outlined below and depicted in Fig. 3. Firstly, strip mosaicking was performed to streamline data handling. Subsequently, co-registration aligned images with identical observation geometries in slant range geometry. A time-series speckle filtering step was then implemented to balance reflectivity variations among images. Terrain geocoding was carried out for radiometric calibration and normalization, followed by ANLD (Adaptive Non-Local Means Denoising) filtering to achieve smooth, homogeneous targets. Correction for atmospheric attenuation was executed using an interpolator. Finally, subsetting was performed to extract the rectangular study area, bounded by 14°15' to

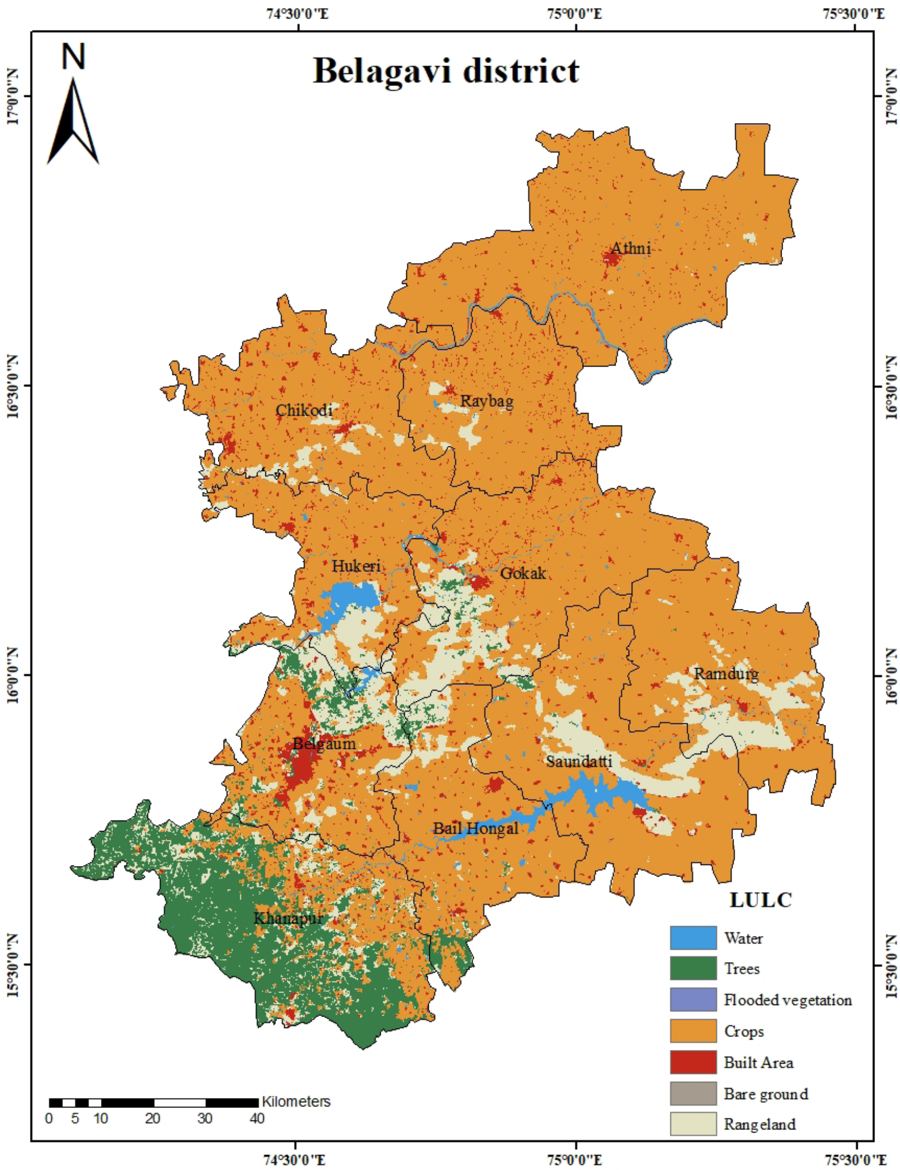

Fig. 2 - LULC analysis for rabi cropping in Belagavi District, 2022-23

15°15' north latitude and 74°15' to 75°15' east longitude, from the base map, reducing processing time for subsequent analyses.

Multi-Temporal Feature Extraction

To aid in the classification of maize crop from multi-temporal SAR data, the extraction of Multi -Temporal features was performed with VH polarization using the module of Mapscape software. The features include "Minimum, Maximum, Mean, Minimum date, Maximum date, and Span ratio". These multi-temporal characteristics were obtained by utilizing the point-based sampling tool in QGIS 2.18.20 for the ground truth locations and were specifically related to *rabi* Maize crop data.ater requirement (ha-mm)

Parameterized classification

The objective of image classification is to assign land cover categories to individual pixels based on their values. The parameterized classification method is a specialized algorithm crafted to analyze the variance and covariance of spectral response patterns for unknown pixels in the study area. This classification approach utilizes the Multi-temporal Time Series Feature (MTF) algorithm to extract features from GRD and SLC SAR images for identifying maize crop. A training polygon is created to generate a mask, specifically including the maize class, to enhance the classification performance using the σ° (sigma degree) of VH for all dates.

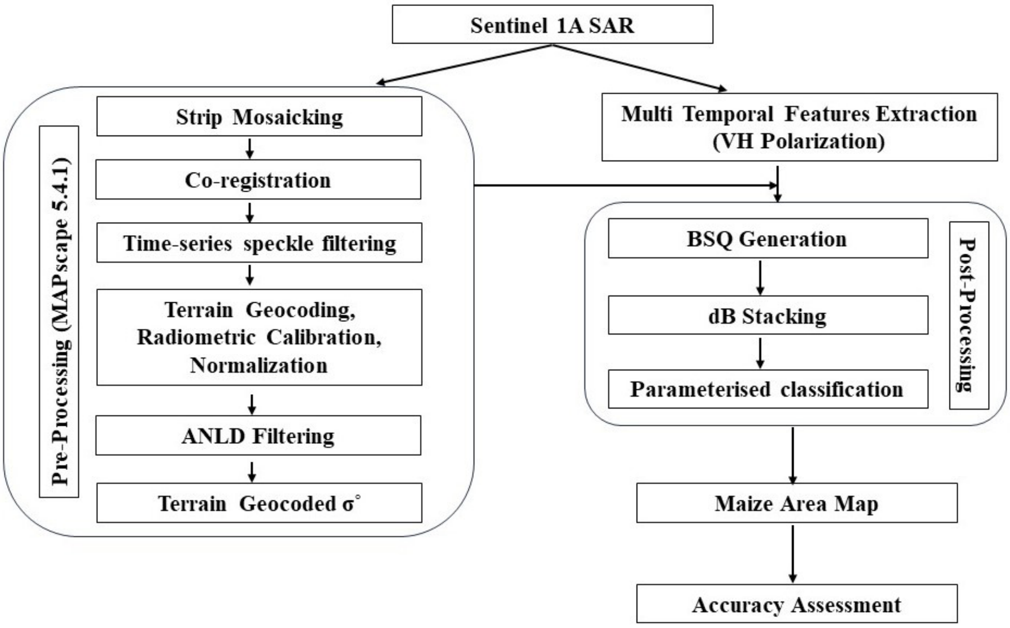

Fig. 3 - Processing of Sentinel 1A SAR satellite data for Maize area estimation

Accuracy Assessment

The evaluation of classification accuracy relies on error matrices and Kappa statistics. Each pixel's class assignment in the classified image is compared with corresponding allocations in reference data for accuracy determination. Ground reference data validate the process, compiling agreements and disagreements into an error matrix. Accuracy measures like overall, producer's, and user's accuracy are derived. Kappa coefficient, an indicator of proportional improvement over random class assignment, further assesses classification accuracy. This comprehensive approach ensures rigorous evaluation, crucial for reliable classification outcomes in various applications.

Results and Discussion

The utilization of satellite data and radar technology in agricultural monitoring will improve our ability to assess crop growth and distribution. Through temporal backscattering analysis and multi-temporal feature extraction, the study elucidates the relationship between radar backscatter values and key stages of maize phenology (Sudheer *et al.*, 2021; Kumar *et al.*, 2023). Additionally, the accuracy assessment of maize classification demonstrates the robustness of the classification

Table 1 - Date of satellite pass with mean temporal backscattering (dB) values for the maize monitoring site and crop calendar

S.No	Date of Pass	dB value	Crop Calendar for rabi Maize
D1	29.08.2022	-17.50	
D2	10.09.2022	-17.50	
D3	22.09.2022	-17.64	
D4	04.10.2022	-17.61	
D5	16.10.2022	-17.80	Sowing Window
D6	28.10.2022	-18.42	
D7	09.11.2022	-17.98	
D8	21.11.2022	-18.31	Vegetative stage
D9	03.12.2022	-17.94	
D10	15.12.2022	-17.47	50 % anthesis
D11	27.12.2022	-17.32	Grain filling
D12	08.01.2023	-17.39	
D13	01.02.2023	-17.52	50 % Dough stage
D14	13.02.2023	-17.74	
D15	25.02.2023	-18.31	Maturity/Harvest

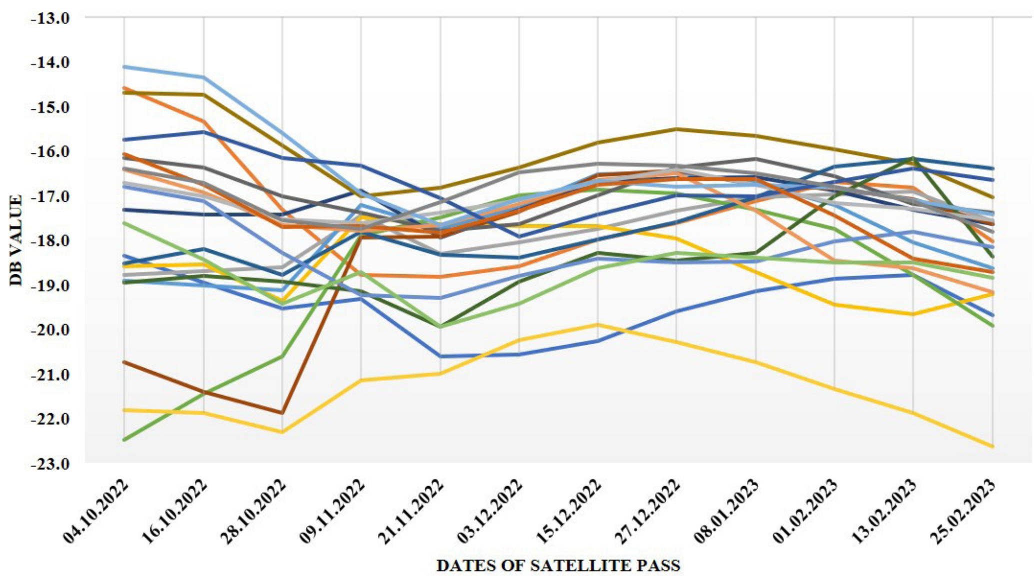

Fig. 4 - dB curves of rabi Maize at monitoring fields of Belagavi

model, essential for informed agricultural management decisions (Gupta *et al.*, 2020; Jones *et al.*, 2019). The subsequent area estimation provides valuable insights into the spatial distribution of maize cultivation, facilitating localized agricultural planning and resource allocation strategies (Sharma *et al.*, 2020; Mohanty *et al.*, 2017).

Temporal backscattering signature

The date of satellite passes along with the mean temporal backscattering (dB) values for a maize monitoring site, accompanied by the corresponding crop calendar for rabi maize cultivation is presented in Table 1. These data offer insights into the relationship between backscattering values and key stages of maize growth and development.

The temporal backscattering values exhibit fluctuations throughout the monitoring period, reflecting changes in maize phenology and crop conditions. For instance, the backscattering value at D4 (04.10.2022) during the sowing window is -17.61 dB, indicating relatively low backscatter likely due to bare soil or sparse vegetation cover. Subsequently, as the crop progresses through the vegetative stage (D6, 28.10.2022), the backscattering value increases to -18.42 dB, suggesting denser vegetation and increased biomass.

During critical stages such as 50% anthesis (D9, 03.12.2022) and grain filling (D10, 15.12.2022), the backscattering values stabilize or decrease slightly (-17.94 dB and -17.47 dB, respectively), indicating stable crop conditions and consistent vegetation cover. However, as the crop reaches maturity and harvest stage (D15, 25.02.2023), the backscattering value increases again to -18.31 dB (Fig. 4), likely due to changes in crop structure and moisture content associated with senescence and drying of the crop.

These findings are consistent with previous studies that have demonstrated the utility of radar backscattering analysis in monitoring crop growth and phenology (Satheesh *et al*. 2022 and Prakash *et al*. 2023) Radar backscatter is sensitive to variations in canopy structure, biomass, and moisture content, allowing for the detection of changes in crop development stages.

Extraction of multi-temporal features

The extraction of temporal signatures for each monitoring site enabled the generation of dB curves representing Maize fields. These curves depicted the maximum likelihood classification utilizing MTF features from C-band SAR imagery of Sentinel-1A. The MTF features, including max, min, mean, max date, min date, and span ratio, were derived from nine acquisitions during the *rabi* 2020-21 period and are summarized in Table 2. For Maize fields, the max feature (representing the maximum value) ranged from -19.83 to -15.09 at VH Polarization, while the min feature (representing the minimum value) ranged from -22.07 to -16.92, also at VH polarization (Table 2). Similarly, the mean value and span ratio for Maize fields varied from -20.97 to -15.78 and 1.04 to 3.52, respectively, at VH polarization. In the Maize fields of Belagavi district, the max date feature for VH polarization was observed on D11 (27th December, 2022) indicting peak period of crop *i.e.*, anthesis stage, while the min date feature ranged between D5

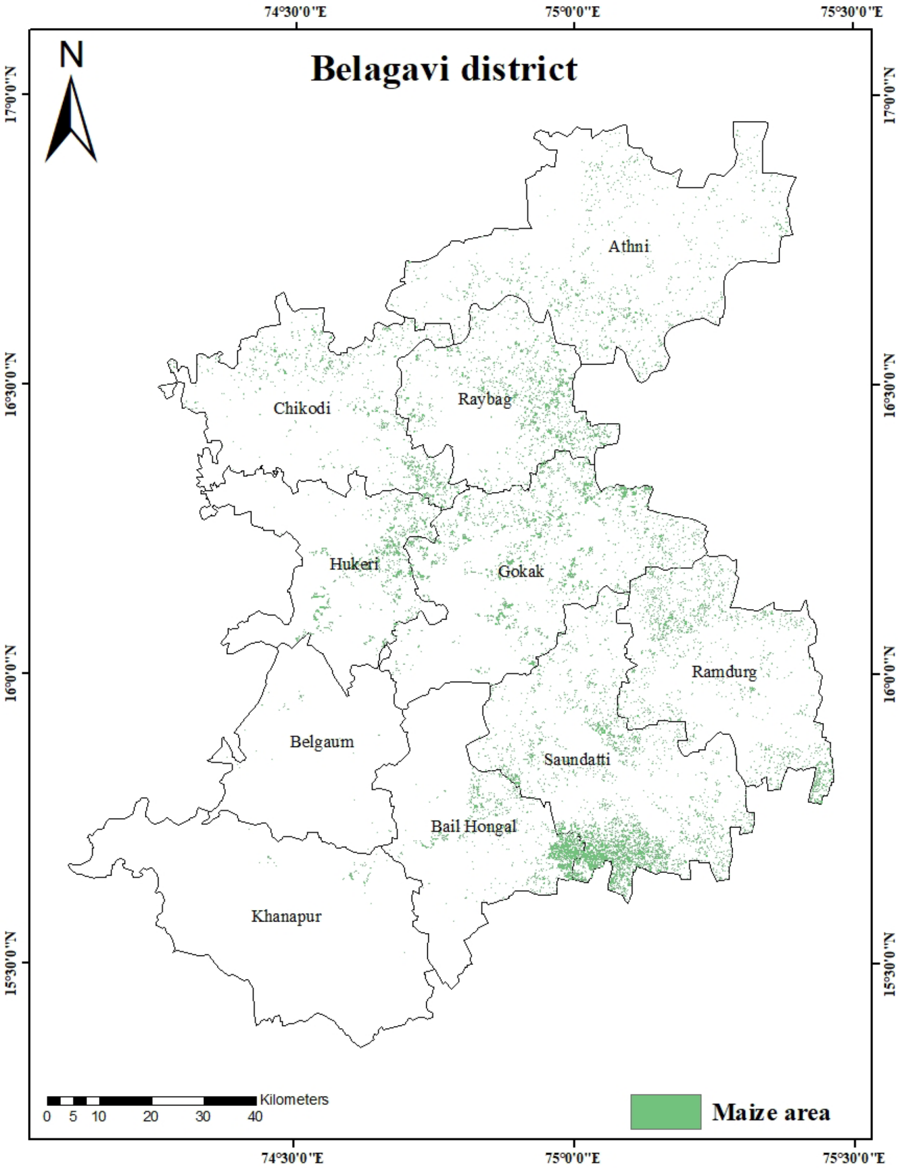

Fig. 5 - Maize area map for the rabi cropping period of 2022-23

(16th October, 2022) and D7 (09th November, 2022), with the majority of fields recording the minimum date at D6 (28th October, 2022) indicating sowing period of the crop (Table 2). Thirumeninathan *et al.* 2019 also estimated area of groundnut using Sentinel 1A SAR data extracting the MTF from C-band SAR imagery of Sentinel-1A with a higher accuracy percentage of 87.4 and kappa coefficient of 0.75.

Area estimation

The taluk-wise maize area estimation for the *rabi* season of 2022-23 in Belagavi district provides valuable insights into the spatial distribution of maize cultivation, crucial for agricultural planning and resource allocation. The analysis indicates substantial variations in maize cultivation across different taluks. Saudatti emerges as the leading taluk, accounting for the highest maize area of 14,711.50 hectares, representing approximately 25.74% of the total maize cultivation in the district (Table 4 and Fig. 5)). This finding aligns with the agricultural landscape of the region, characterized by favourable agro-climatic conditions conducive to maize cultivation (Kumar *et al.*, 2017).

Other significant contributors include Gokak, Ramdurg, and Raybag taluks, with respective maize areas of 9,873.33 hectares, 6,949.34 hectares, and 6,587.64 hectares. These taluks collectively constitute a substantial portion of the maize cultivation area, reflecting

Table 2 - **Temporal backscattering (dB) values for the satellite passing dates and VH polarisation multi temporal features for monitoring sites of Maize fields in Belagavi district during *rabi* 2022-23**

Monitoring sites	Longitude	Latitude	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	MIN	MAX	Mean	SpanR
1	75.32	15.83	-19.3	-18.8	-18.3	-18.4	-19.0	-19.5	-19.3	-20.6	-20.6	-20.3	-19.6	-19.1	-18.9	-18.8	-19.7	-20.7	-19.1	-19.8	2.0
2	75.28	15.86	-15.2	-14.7	-14.4	-14.6	-15.3	-17.3	-18.8	-18.8	-18.6	-18.0	-17.6	-17.1	-16.7	-16.8	-18.0	-18.8	-16.4	-17.7	2.7
3	75.22	15.81	-17.7	-17.7	-18.2	-18.8	-18.7	-18.6	-17.4	-18.3	-18.1	-17.7	-17.3	-17.1	-17.0	-16.9	-17.6	-18.9	-17.5	-18.5	1.0
4	75.21	15.79	-19.5	-19.5	-19.5	-18.6	-18.6	-19.4	-17.5	-17.6	-17.7	-17.7	-18.0	-18.7	-19.4	-19.7	-19.2	-18.6	-18.1	-18.3	1.1
5	75.11	15.75	-19.3	-19.1	-18.9	-18.9	-19.0	-19.1	-17.2	-17.8	-17.3	-16.5	-16.5	-16.7	-17.2	-18.1	-18.6	-18.6	-16.7	-17.7	1.8
6	75.08	15.75	-21.3	-21.1	-21.6	-22.5	-21.5	-20.6	-17.9	-17.5	-17.0	-16.9	-17.0	-17.3	-17.7	-18.8	-19.9	-20.1	-17.6	-18.2	2.7
7	74.91	15.72	-16.1	-16.2	-16.7	-17.3	-17.4	-17.4	-16.9	-18.0	-17.3	-16.7	-16.6	-16.6	-16.9	-17.3	-17.6	-18.9	-16.8	-17.7	2.1
8	74.87	15.77	-19.4	-19.9	-20.5	-20.7	-21.4	-21.9	-17.9	-17.9	-17.4	-16.5	-16.4	-16.8	-16.9	-17.1	-17.6	-20.0	-17.2	-18.6	2.8
9	74.94	16.36	-16.8	-16.5	-16.2	-16.2	-16.4	-17.0	-17.4	-17.8	-17.6	-17.0	-16.4	-16.2	-16.6	-17.2	-17.4	-18.0	-15.9	-17.2	1.8
10	74.93	16.36	-15.2	-15.0	-14.9	-14.7	-14.7	-15.9	-17.0	-16.8	-16.4	-15.8	-15.5	-15.7	-16.0	-16.3	-17.0	-16.9	-15.1	-15.8	2.0
11	75.00	16.58	-18.3	-18.9	-19.5	-18.5	-18.2	-18.8	-17.8	-18.3	-18.4	-18.0	-17.6	-17.0	-16.4	-16.2	-16.4	-19.0	-17.4	-18.4	2.0
12	75.28	15.79	-20.2	-19.5	-19.0	-19.0	-18.8	-18.9	-19.2	-19.9	-18.9	-18.3	-18.5	-18.3	-17.0	-16.2	-18.4	-20.2	-17.8	-18.8	2.4
13	75.04	15.85	-16.1	-16.3	-16.7	-16.8	-17.1	-18.3	-19.2	-19.3	-18.8	-18.4	-18.5	-18.5	-18.0	-17.8	-18.2	-19.6	-18.4	-18.6	2.3
14	74.85	15.83	-13.5	-14.8	-16.4	-16.4	-16.9	-17.7	-17.8	-17.7	-17.2	-16.6	-16.5	-17.3	-18.5	-18.6	-19.2	-17.9	-16.6	-17.3	1.3
15	74.84	15.85	-16.0	-16.4	-16.8	-16.7	-17.0	-17.5	-17.6	-17.4	-17.1	-16.7	-16.4	-16.8	-17.2	-17.3	-17.6	-18.2	-16.6	-17.3	1.7
16	75.00	16.01	-22.0	-22.1	-22.2	-21.8	-21.9	-22.3	-21.1	-21.0	-20.2	-19.9	-20.3	-20.7	-21.3	-21.9	-22.6	-22.1	-19.8	-21.0	2.2
17	74.96	16.06	-14.8	-14.3	-14.0	-14.1	-14.3	-15.6	-16.9	-17.7	-17.1	-16.7	-16.8	-16.8	-16.8	-17.1	-17.4	-17.5	-16.2	-16.2	2.9
18	74.94	16.08	-17.0	-17.2	-17.5	-17.6	-18.4	-19.4	-18.7	-19.9	-19.4	-18.6	-18.3	-18.4	-18.5	-18.5	-18.8	-20.9	-18.7	-19.8	2.2
19	75.08	16.72	-16.5	-16.4	-16.4	-15.7	-15.6	-16.2	-16.3	-17.1	-17.9	-17.4	-17.0	-17.0	-16.7	-16.4	-16.6	-17.5	-17.3	-16.9	3.5
20	75.22	16.70	-16.5	-16.3	-16.2	-16.1	-16.8	-17.7	-17.7	-17.8	-17.4	-16.8	-16.6	-16.6	-17.4	-18.4	-18.7	-17.9	-16.4	-17.1	1.4
21	75.30	16.73	-16.7	-16.7	-16.6	-16.4	-16.7	-17.5	-17.7	-17.1	-16.5	-16.3	-16.3	-16.5	-16.8	-17.1	-17.8	-18.2	-16.4	-16.9	1.8

*S.No: Indicate D1 to D15: The dates of satellite pass mentioned in Table 2, Span R: Span Ratio

the importance of these regions in maize production within the district. Conversely, taluks such as Khanapur and Belagavi exhibit relatively smaller maize cultivation areas, with 250.65 hectares and 157.73 hectares, respectively (Table 4 and Fig. 5)). Despite their limited contribution to the overall maize cultivation area, these taluks may possess unique agricultural characteristics or face constraints that warrant further investigation for targeted interventions (Sharma *et al.*, 2020).

The distribution of maize cultivation across taluks underscores the importance of localized agricultural planning and resource allocation strategies tailored to the specific needs and capabilities of each region. Remote sensing products play a crucial role in such assessments, providing reliable and spatially explicit information for informed decision-making in agriculture (Panda *et al.*, 2018).

Accuracy Assessment

The accuracy assessment conducted through a confusion matrix revealed promising results for the classification of maize and non-maize locations. The matrix presents a clear breakdown of predicted and actual classes, allowing for a comprehensive evaluation of classification performance. The accuracy of identifying maize locations was notably high, with 92.4% of actual maize points correctly classified. Similarly, the accuracy for non-maize locations stood at 91.1%, indicating robust performance across both classes (Table 3). These findings align with previous research indicating the efficacy of classification methods in agricultural mapping (Smith *et al.*, 2018).

Moreover, the reliability metrics further underscore the model's effectiveness, with an average reliability

Table 3 - **Accuracy assessment through Confusion Matrix**

		Predicted class from the map		
		Maize	**Non_Maize**	**Accuracy**
Actual class from survey	**Maize**	159	13	92.4%
	Non-Maize	17	174	91.1%
	Reliability	90.3%	93.0%	91.7%
Average accuracy				91.8%
Average reliability				91.7%
Overall accuracy				0.92
Kappa index				0.83

Table 4 - Taluk wise Maize area estimated during rabi 2022-23 of Belagavi district

S. No	Taluk	Area (ha)	Percent distribution (%)
1	Chikkodi	4651.81	8.14
2	Gokak	9873.33	17.28
3	Hukkeri	4094.86	7.17
4	Khanapur	250.65	0.44
5	Ramdurg	6949.34	12.16
6	Raybag	6587.64	11.53
7	Saudatti	14711.50	25.74
8	Athani	4742.43	8.30
9	Bail Hongal	5124.56	8.97
10	Belagavi	157.73	0.28
Total		**57143.85**	**100**

of 91.7% across both classes (Table 3). This indicates a high level of confidence in the classification results, essential for decision-making in agricultural management (Gupta *et al.*, 2020). The overall accuracy of 92% signifies the model's ability to accurately differentiate between maize and non-maize locations, crucial for applications such as yield prediction and land use planning (Jones *et al.*, 2019). Furthermore, the Kappa index of 0.83 suggests substantial agreement beyond chance, reinforcing the reliability of the classification outcomes (Congalton, 1991).

Conclusions

The integration of remote sensing technologies with ground truth data will improve agricultural monitoring and management, particularly in regions like Belagavi district, Karnataka. Through the comprehensive analysis outlined in this study, key insights into maize cultivation patterns, phenology, and area estimation have been derived. The utilization of multi-temporal SAR imagery, coupled with advanced processing techniques, has facilitated accurate crop classification and parameter extraction, enhancing our understanding of crop dynamics. The assessment of classification accuracy and area estimation further validates the reliability of the proposed methodology, offering actionable information for agricultural planning and resource allocation.

Moreover, the taluk-wise distribution of maize cultivation highlights spatial variations and underscores the importance of localized planning strategies tailored to each region's agricultural landscape. These findings provide policymakers and stakeholders with valuable insights for informed decision-making, ranging from optimizing input distribution to formulating targeted policies for rural development. Overall, this study underscores the pivotal role of remote sensing in enhancing agricultural productivity, sustainability, and resilience in the face of evolving environmental and socio-economic challenges.

Author Contributions

Conceptualization, HT and PS; Data curation, SNS and SS.; Formal analysis, HT, PS, SNS, RKP and SNK; Funding acquisition, PS and RKP; Investigation, SNK, RKP and SAP; Methodology, HT, PS and SNS; Project administration, PS, RKP and SAP; Resources, RKP, SS and VS; Software, SNS, RKP and SS.; Supervision, PS, RKP, SNK, VS and APS; Validation, HT and SNS; Visualization, SNS and SS; Writing—original draft, HT and PS; Writing—review & editing, SNS, SNK, SAP and VS. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declares that there is no conflict of interest.

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