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Identification of sowing window and sown area of maize and sorghum in rice fallows using multi-source satellite remote sensing

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ABSTRACT

Identifying the start of sowing in rice fallows is challenging due to its typical low land agro-ecosystem. Tracking the spatio-temporal shifts that take place during the transition from a wet to dry ecosystem, identifying crops, assessing their extent, and identifying optimal planting periods are vital information for researchers and planners. This study aimed at determining the crop sown area and sowing window of maize and sorghum crops planted in rice fallows during the Rabi 2020-2021 season in the Krishna Western delta of Guntur district, Andhra Pradesh. Optical cloud-free satellite images of Landsat-8 and Sentinel-2 were downloaded and using band ratios NDVI and NDWI was derived. A Threshold based algorithm was developed to detect the crop sowing window. The total area sown was determined using the SVM algorithm. The threshold-based algorithm is well-suited for identifying the sowing windows. The sowing window in the second fortnight of January had the largest area for both crops compared to other sowing windows. The detected sowing windows exhibited a deviation of up to two satellite acquisition intervals. The estimated area using SVM algorithm for maize and sorghum was 29,518 ha and 65,417 ha, respectively. The threshold-based algorithm overestimated the maize and sorghum crops as compared to SVM. This study established the superior performance of the Support Vector Machine (SVM) algorithm for crop classification. Statistical validation confirmed that the SVM model achieved significantly higher accuracy in distinguishing both maize and sorghum from other land covers compared to the threshold-based algorithm, which exhibited a greater tendency for misclassification.

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1. INTRODUCTION

The selection of crops for rice fallows was determined by a variety of factors, particularly the ability of crops to thrive under the unique challenges posed by the agro-ecosystem of rice-fallow areas. One of the key challenges in these systems is the presence of crop residues, and early ground cover, which, while essential for moisture conservation, can also impede crop establishment (Kumar et al., 2025). Thus, the success of crops in such environments depends on their ability to establish effectively despite these residues, and their capacity to benefit from moisture conservation, rapid growth, and early maturity (Peramaiyan et al., 2023). Traditionally, pulses were favoured for cultivation in rice fallows due to their suitability in these environments. However, in recent years, various biotic stresses, such as increased pest and disease pressure, and abiotic factors, such as pre-harvest sprouting, have reduced the profitability of pulse crops in rice fallows. These issues have been compounded by difficulties in crop establishment, often exacerbated by high soil moisture and the persistence of crop residues, making these systems less viable for farmers (Chapke et al., 2017; Chowdhury et al., 2020). As a result, farmers have been increasingly shifting toward more robust crops such as maize and sorghum.

Maize, in particular, has gained popularity in the rice-fallow system, especially in areas where water is available for irrigation. This shift towards maize cultivation is driven by

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several factors that include the ability to efficiently utilize residual nutrients left in the rice soil, thereby increasing its yield potential (Sarangi, Singh, Srivastava, et al., 2020). Additionally, maize has a relatively high tolerance to moderate salt stress and low electrical conductivity, making it more adaptable to the soil conditions found in rice fallows (Sarangi, Singh, Kumar, et al., 2020). This adaptability makes maize a viable option for farmers who are seeking to maximize yield in suboptimal conditions. Similarly, Sorghum, with its low water requirements and ability to tolerate terminal moisture stress, has emerged as a preferred crop in regions that experience drought-like conditions towards the end of the growing season (Liaqat et al., 2024).

The rise of maize and sorghum in rice fallows during the rabi season can also be attributed to their high profitability compared to the traditional rice fallow black gram and green gram. In regions like Andhra Pradesh, maize and sorghum are cultivated extensively during the rabi season, with the Guntur district alone accounting for a significant portion of the total sown area—23% for maize and 34% for sorghum (Directorate of Economics and Statistics, 2020). In this context, the Krishna Western delta, located within the Guntur district, plays a particularly important role, as it contributes to more than 85% of the total maize and sorghum cultivation in the district during the rabi season. Given the economic importance of these crops, understanding the sowing window—the period when sowing is optimal for crop growth—is crucial for maximizing yields. By identifying the sowing window, farmers can optimize their irrigation schedules, nutrient management practices, and other critical resources. This also enables agricultural planners and policymakers to better support farmers through improved advice on crop selection, resource management, and yield forecasting.

The importance of accurately identifying sowing windows in rice fallows has led to the use of various remote sensing techniques, which offer a more efficient and cost-effective alternative to traditional ground-based methods. Vegetation indices derived from remote sensing data, such as the Normalized Difference Vegetation Index (NDVI) and Land Surface Water Index (LSWI), have proven valuable for identifying crop sowing periods. For instance, NDVI time series have been utilized to track the phenological stages of wheat (Zhang et al., 2025), drought monitoring (Suud & Kusbianto, 2024), while integrated NDVI and LSWI approaches have been employed to pinpoint rice planting windows (Gutierrez et al., 2019). Satellite-based vegetation indices like NDVI are widely recognized for their effectiveness in tracking crop (Olivares Campos et al., 2021), and its development and physiological status. By detecting temporal variations in canopy reflectance and greenness, these indices facilitate the identification of sowing periods and enable monitoring of crop growth over time. This approach has proven particularly valuable in assessing seasonal cropping dynamics across diverse agricultural landscapes (Medida et al., 2023; Rolle et al., 2022). Similarly, LSWI has been employed to monitor soil moisture and determine the timing of sowing in water-dependent crops. In addition to these indices, other methods, such as the Modified Bare Soil Index (MBSI), have been utilized to distinguish fallow lands from actively cropped areas. These methods, along with the use of multi-satellite data, enable researchers to better understand the dynamics of rice-fallow systems and identify transitions between different crop stages, such as from rice-to-rice fallow (Chandna & Mondal, 2020; Gu et al., 2022). Such transitions are critical to understanding the sowing windows for subsequent crops like maize and sorghum. Identifying these transitions accurately is essential for timely crop management decisions, including determining the best time for sowing, irrigation, and fertilization (Naik et al., 2020).

Beyond crop identification, the ability to estimate crop areas reliably is also crucial for agricultural planning. In the past, crop area estimation was typically done using ground surveys, which are time-consuming and expensive. However, remote sensing offers a more practical and scalable approach to estimating crop areas over large regions. Studies have shown that remote sensing-based crop area estimation is not only cost-effective but also provides highly accurate data on crop coverage and its changes over time (Gumma et al., 2015; Ray & Neetu, 2017). One of the most commonly used machine learning algorithms for this purpose is the Support Vector Machine (SVM), which has proven to be highly effective in classifying complex, multi-dimensional data. The SVM algorithm has been successfully applied in remote sensing to map crops, estimate crop areas over larger areas (Zhong et al., 2019). This algorithm's ability to handle high-dimensional datasets and deliver accurate results makes it particularly valuable in precision agriculture.

Given the significant role of maize and sorghum in rice fallows, this study seeks to employ geospatial tools, to detect sowing windows and estimate the cropped areas for these two crops in the Krishna Western delta. This study aims to develop a dependable approach for identifying sowing periods and estimating crop-sown areas using time-series optical satellite data from Landsat-8 and Sentinel-2. While many remote-sensing studies rely solely on either threshold-based techniques or machine-learning models, their performance is rarely compared in rice-fallow regions, where mixed cropping patterns and frequent cloud cover make crop detection difficult. To address this gap, the study evaluates both a threshold-based algorithm and a Support Vector Machine (SVM) classifier for the same task, allowing a clearer understanding of how each method responds to the complexities of rice-fallow landscapes. The results aim to offer farmers and planners more timely and accurate information on sowing activity and crop distribution, supporting better decisions related to resource use, management, and yield planning.

2. MATERIAL AND METHODS

2.1. Study area

The Krishna Western Delta region, located in the Guntur district of Andhra Pradesh, India, spans an area of approximately 17,626 km^2. Geographically, it lies between 16° 52′ 35″ to 15° 70′ 92″ of northern latitude and 80° 22′ 98″ to 80° 90′ 37″ of eastern longitude (Fig. 1). The soils in the study area are deltaic alluvial with a moderate to heavy texture. Rice is cultivated as the predominant crop during the kharif season, while maize and sorghum are largely grown during the rabi season. Additionally, rice fallow pulses such as black gram and green gram are cultivated to a lesser extent. The rainfall distribution in the study area exhibits a bimodal pattern. Of the normal annual rainfall of 889 mm, approximately 524.6 mm occurs during the southwest monsoon period (June to September), while 231.0 mm is received during the post-monsoon period (October to December). The remaining 133.4 mm of rainfall is distributed over the rest of the year.

2.2. Data collection

Cloud-free optical data from Landsat-8 and Sentinel-2 were downloaded from the USGS Earth Explorer database (Table 1). The data was harmonized to ensure consistency in spatial resolution of 10 m.

2.3. Vegetation indices and sowing window detection

To monitor seasonal changes and crop dynamics, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were calculated using the harmonised Landsat-8 and sentinel-2 satellite data. The NDVI used to track the end of the rice crop season, the transition from aquatic conditions to dry soil, and the start of the maize and sorghum cropping season and NDWI was used to assess soil condition transformations and shifting water dynamics.

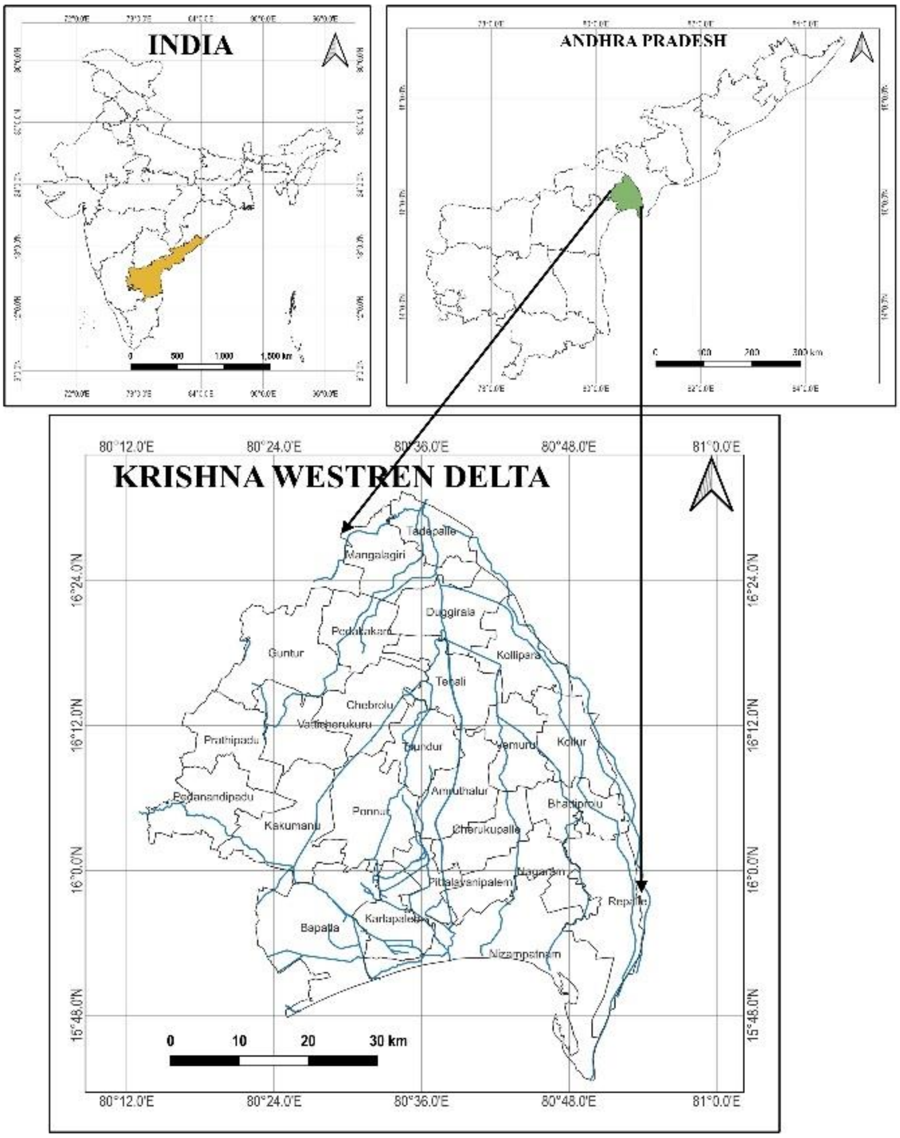

Figure 1. Study area

Table 1. Cloud free optical satellite data used in the study

S. No	Satellite data used	Date of acquisition	Satellite data used	Date of acquisition
1	Landsat 08	27-10-2020	Sentinel 2A	01-11-2020
2	Landsat 08	14-12-2020	Sentinel 2A	21-11-2020
3	Landsat 08	16-02-2021	Sentinel 2B	06-12-2020
4	Landsat 08	12-03-2021	Sentinel 2B	25-01-2021
5	Landsat 08	20-03-2021	Sentinel 2B	04-02-2021
6	Landsat 08	24-04-2021	Sentinel 2A	01-03-2021

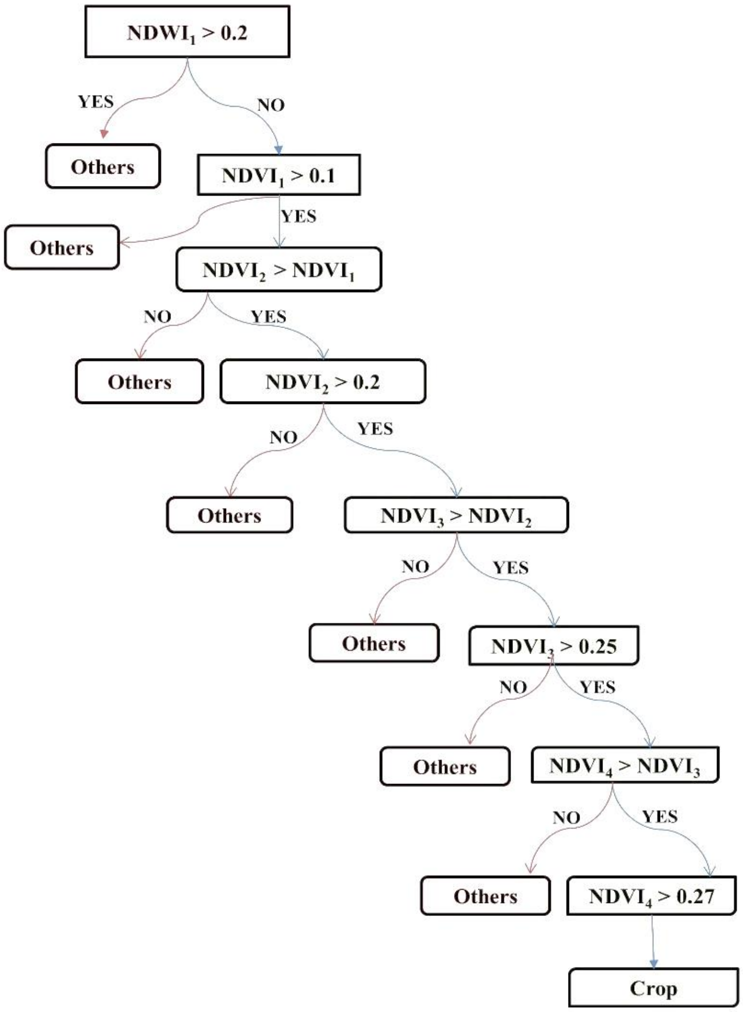

Figure 2. Logical Algorithm to delineate the sowing window of Maize and sorghum crops

A logical algorithm was developed using temporal NDVI and NDWI data to identify the beginning of the cropping season, accounting for various field preparation techniques. After rice harvest, farmers plant maize and sorghum, either through traditional land preparation or zero tillage methods. In the developed threhold based algorithm (Fig. 2), is grounded in analyzing the distinct developmental pattern of these crops during the inital stages of crop growth using four image acqusations from the assumed sowing date (designated $NDVI_1$ to $NDVI_4$) to verfy the pixels wehther the crop was sown or not. The initial step verifies that sufficient vegetation is present at the start ($NDVI_1 > 0.2$) and that the crop is in an active growth phase shortly after ($NDVI_2 > NDVI_1$). Subsequently, the analysis checks that the vegetation cover remains established ($NDVI_2 > 0.2$) before progressing to confirm a period of vigorous growth, marked by a further rise in the index ($NDVI_3 > NDVI_2$) exceeding a specific threshold ($NDVI_3 > 0.25$). The final stage seperates the maize and sorghum from crops like greengram, pulses and others, where the crop must show sustained growth ($NDVI_4 > NDVI_3$) and reach its vegetation density ($NDVI_4 > 0.27$). A pixel is conclusively classified as maize or sorghum, with its sowing date tied to the first acquisition, only if it successfully meets every one of these criteria. This stringent step-wise filtering effectively isolates the target crops from other land cover types. To compensate for inconsistent data gaps caused by frequent cloud cover in the tropical coastal study area, the algorithm incorporates two flexible threshold rules. These rules adjust the required NDVI values based on the actual time elapsed between satellite passes, ensuring the model remains accurate even with irregular image availability. The first condition modifies the NDVI threshold for the third acquisition ($NDVI_3$). If the time difference between $NDVI_2$ and $NDVI_3$ is less than 16 days, the threshold remains at 0.25. However, if this interval is between 16 and 30 days due to cloud cover, the threshold is increased to 0.27 to accommodate expected vegetation development over the period. Similarly, the second condition adjusts the threshold for the fourth acquisition ($NDVI_4$). A time difference of less than 16 days between $NDVI_3$ and $NDVI_4$ retains a threshold of 0.27. If the interval is between 16 and 30 days, the threshold is raised to 0.30, reflecting the continued maturation of the crop canopy.

2.4. Cropped area estimation

The Sentinel-2 satellite data acquired in March 2020 was extracted, and 8A, 8, 7, 6, 5, 4, 3, and 2 bands were resampled to a 10 m spatial resolution. The resultant bands were custom reprojected, mosaicked, and clipped up to the extent of the study area. The ground truth observations (Fig 3) of 118 numbers collected during the field trips on the 45th and 72nd days after sowing (DAS).

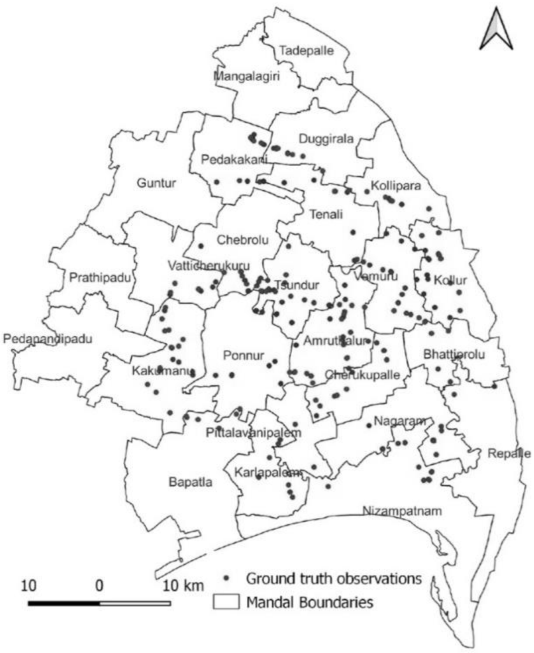

Figure 3. Ground truth observations collected during the crop growth period

The support vector machine (SVM) learning technique was used to classify the rater using a training data set in ENVI software. The accuracy assessment was conducted using the second ground truth observation data, and the kappa index was calculated. A post-classification sieving followed by masking of non-agricultural areas using a land use map to better represent the surroundings. Using the zonal histogram technique of QGIS software, crop area was calculated for each administrative boundary.

2.5. Accuracy assessment

The accuracy of the classified satellite imagery was evaluated through a systematic accuracy assessment procedure. Initially, a set of reference samples, commonly known as ground-truth data, was collected from the study area. These samples were independently compared with the corresponding classified pixels in the imagery. Subsequently, an error matrix—also referred to as a confusion matrix was constructed, summarizing the agreement between the classified results and the reference data across all classes. Standard accuracy metrics such as overall accuracy, user's accuracy, producer's accuracy, and the kappa coefficient were computed from this matrix. Overall accuracy represents the proportion of correctly classified samples to the total number of reference samples, while user's and producer's accuracies provide class-specific reliability and completeness, respectively. The kappa coefficient further quantifies the degree of agreement, accounting for the possibility of random classification.

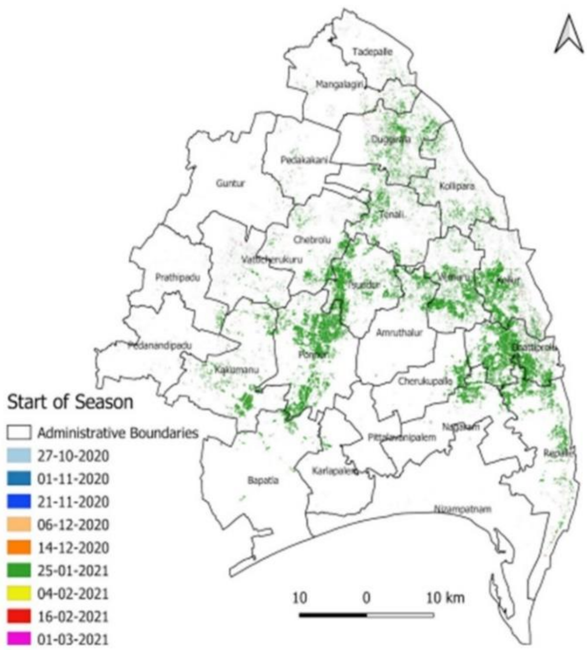

Figure 4. Sowing windows of maize crop during *rabi* 2020-2021 cropping season

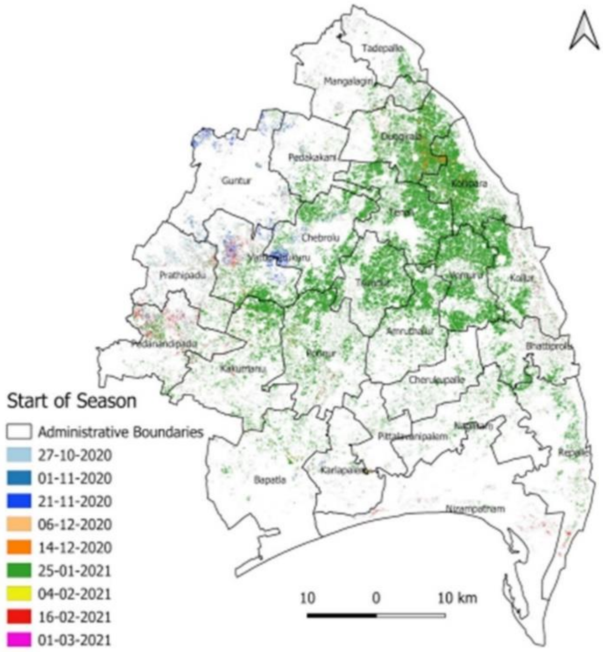

Figure 5. Sowing windows of Sorghum crop during *rabi* 2020-2021 cropping season

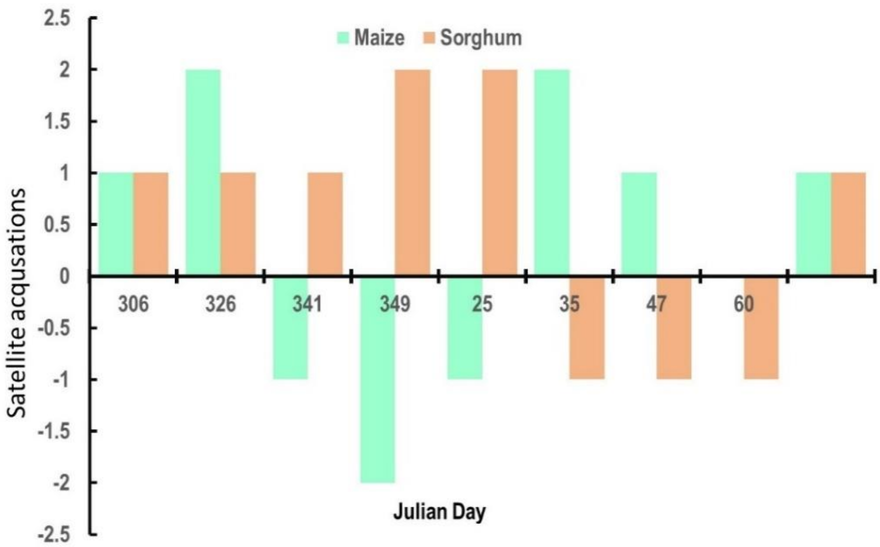

Figure 6. Maximum deviation in identifying the sowing window

3. RESULTS

3.1. Sowing window analysis

The timing of maize sowing was determined through a logical algorithm applied to satellite imagery collected between late October 2020 and early March 2021 (Fig. 4). In the upland areas of Guntur, Prathipadu, Peda Kakani and Mangalagiri mandals where rice was not cultivated as the the kharif crop, maize planting was minimal and primarily occurred before mid-December of 2020. In contrast, rice fallow fields saw maize sown from early December through late February, with the highest activity in the latter half of January. Certain tail-end command areas—including Vatticherukuru, Repalle, Nizampatnam, Bhattiprolu, Kollipara, Kolluru, Pedanandipadu, Prattipadu, and Duggirala—showed a concentration of sowing during the first half of February.

Threshold-based classification (Fig. 5) indicated that sorghum was mostly sown before mid-December in non-rice soils, particularly in Guntur, Vatticherukuru, Prattipadu, Pedanandipadu, and Pedakakani. In rice fallows, the sowing period for sorghum extended from early December to late February, peaking in the second half of January. These results are consistent with established patterns of crop management in similar agro-ecological zones.

Variation in the detected sowing windows was observed, with deviations up to two satellite acquisition intervals (Fig. 6). This discrepancy was mainly attributed to weed emergence during the transition from wet to dry soil conditions, though the affected areas were limited. Increasing the frequency of satellite observations is expected to improve the precision of sowing window detection. The algorithm's performance was assessed using the kappa index, which reached 0.82, indicating substantial agreement. Early January was marked by persistent cloud cover and fog, which affected the clarity of optical satellite observations.

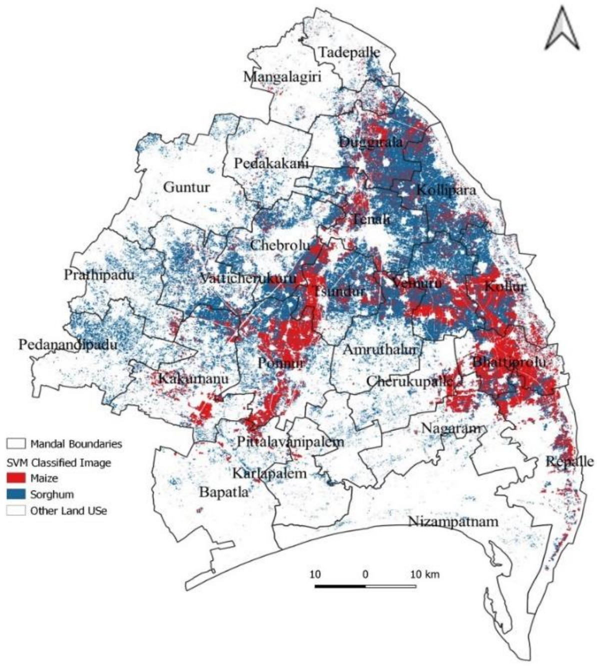

Figure 7. Spatial distribution of maize and sorghum crops during the *rabi* 2020-2021 cropping season

Table 2. Mandal-wise comparison of maize and sorghum area estimates derived from SVM and threshold based classification algorithms.

S. No	Mandal Name	SVM algorithm		Threshold based algorithm	
		Maize	Sorghum	Maize	Sorghum
1	Amruthalur	802	3080	870	2898
2	Bapatla	451	1050	490	982
3	Bhattiprolu	4237	1747	4832	1684
4	Chebrolu	1074	4421	1250	4528
5	Cherukupalle	514	875	480	820
6	Duggirala	1937	5365	2150	5420
7	Guntur	40	1300	18	1450
8	Kakumanu	1457	3361	1620	3450
9	Karlapalem	67	428	85	471
10	Kollipara	1187	5722	1069	5827
11	Kollur	2926	3454	2895	3351
12	Mangalagiri	393	1121	420	1254
13	Nagaram	841	862	759	782
14	Nizampatnam	8	400	25	364
15	Pedakakani	151	1194	142	1494
16	Pedanandipadu	51	2658	39	2564
17	Pittalavanipalem	3	443	17	511
18	Ponnur	4244	4414	4056	4621
19	Prathipadu	148	1976	168	2341
20	Repalle	2334	1705	2154	1853
21	Tadepalle	127	639	132	710
22	Tenali	1384	5535	1265	5820
23	Tsundur	2326	4371	2390	4465
24	Vatticherukuru	399	3744	387	3942
25	Vemuru	2419	5551	2510	5680
	Total	**29518**	**65417**	**30223**	**67282**

3.2. Estimation of crop area:

During the 2020–21 rabi season, the estimated maize sown area using SVM algorithm was 29,518 hectares, which is below the five-year average of 37,204 hectares (Fig. 7 & Table 2). Maize was present across all mandals, with the largest areas in Bhattiprolu (4,237 ha), Ponnur (4,244 ha), and Kollur (2,926 ha). The smallest maize areas were found in Pittalavanipalem (3 ha) and Nizampatnam (8 ha). In tail-end canal command areas such as Pittalavanipalem, Nizampatnam, and Karlapalem, delayed harvest of the preceding kharif crop and the prevalence of light-textured soils contributed to the limited adoption of maize.

Sorghum covered 65,417 ha (Table 2), significantly exceeding the normal area of 25,174 ha, with the highest concentrations in Kollipara (5,722 ha), Vemuru (5,551 ha), and Duggirala (5,565 ha). Nizampatnam recorded the lowest sorghum area at 400 hectares. The support vector machine (SVM) algorithm effectively distinguished maize and sorghum from other land cover types, achieving kappa indices of 0.91 and 0.93 (Tables 3 & 4), respectively, which indicates a high level of classification accuracy. The difference in crop area estimates between the SVM and threshold-based methods was approximately 7%, likely due to differences in algorithm parameterization.

4. DISCUSSION

The findings from this research revealed that maize sowing predominantly occurred between early December and late February, with the peak sowing activity observed in late January, particularly in rice fallow areas. In contrast, sorghum exhibited a similar sowing window, predominantly between early December and late February, with peak activity observed in the second half of January. These findings align with established crop management patterns in regions with comparable agro-ecological conditions (Gumma et al., 2016; Srivastava et al., 2023). Moreover, the research indicated a significant variation in the area cultivated with maize and sorghum, with maize cultivation being lower than the five-year average, while sorghum cultivation exceeded expectations for the 2020–2021 rabi season.

The sowing windows for both maize and sorghum were strongly influenced by the delayed sowing and harvesting of kharif rice, which is a major crop in the region. The delay in harvesting rice, which is followed by a required period of soil drying to prepare the seedbed, creates a bottleneck for subsequent crops like maize and sorghum. This delay is further exacerbated by low winter temperatures, which slow down soil drying, causing a postponement in sowing activities. The delayed sowing of maize, particularly in the first half of February, is influenced by the risk of terminal moisture stress and elevated temperatures during the reproductive phase. If sowing occurs too late, maize is more vulnerable to environmental stresses such as water shortages and higher temperatures, both of which can negatively impact crop yield (Bamboriya et al., 2025). Thus, despite the challenges in acquiring cloud-free satellite data in early January, the phenological evidence from the region suggests that January remains the optimal sowing period for maize. This observation aligns with previous research, indicating that sowing in early January is critical to avoiding yield losses caused by environmental stresses (Srivastava et al., 2023).

In addition to climatic factors, soil conditions played a crucial role in determining the sowing windows for maize and sorghum. The study found that sorghum sowing was concentrated in areas with medium to light-textured soils, which are more favorable for early sowing. These soil types allow for quicker drying and better seedbed preparation, which are key for early sowing. In contrast, heavier soils, commonly found in areas with more water retention, were - less conducive to timely sowing. Additionally, the study observed that farmers in the region tend to delay sowing sorghum due to the presence of long-duration kharif paddy varieties. The cultivation of these varieties occupies the land for a longer period, preventing the timely sowing of sorghum and other crops. Furthermore, the prevalence of tail-end canal command areas, where water availability can be delayed, also contributed to delayed sowing in these regions. These tail-end areas are often characterized by delayed rice harvests and the presence of lighter soils, both of which restrict the adoption of maize and sorghum cultivation in those areas. The limited adoption of maize in areas like Pittalavanipalem and Nizampatnam, as noted in the study, is a direct consequence of these agronomic and soil-related challenges. Similar findings have been observed in other agricultural studies, which indicate that delayed sowing is often linked to soil and water availability issues (Babu & Padmalatha, 2023).

Table 3. Accuracy assessment of the binary maize versus non-maize classification using SVM algorithm

Reference data	Maize	Others	Total	User's accuracy (%)
Maize	35	2	37	94.6
Others	2	79	81	97.5
Total	37	81	118	
Producers' accuracy (%)	94.6	97.5		
Kappa Coeffcient = 0.91				

Table 4. Accuracy assessment of the binary sorghum versus non-sorghum classification using SVM algorithm

Reference data	Maize	Others	Total	User's accuracy (%)
Maize	42	2	44	95.5
Others	2	72	74	97.3
Total	44	74	118	
Producers' accuracy (%)	95.5	97.3		
Kappa Coeffcient = 0.89				

Another important aspect of this study is the estimation of crop area, which was significantly influenced by the sowing window and the availability of resources. The area of maize sown in the 2020–2021 rabi season was found to be considerably lower than the five-year average, primarily due to the delayed sowing window. The limited sowing time results in a shorter growing season, which reduces the total area sown with maize. On the other hand, sorghum cultivation exceeded the average for the region. The greater flexibility of sorghum, particularly in terms of its adaptability to a variety of soil conditions and its tolerance to drought, explains its broader cultivation in the region. Sorghum is known for its ability to thrive under relatively harsh conditions, making it a viable option for farmers, especially in areas where maize may not perform well due to adverse environmental conditions. This finding supports earlier studies that emphasize the resilience of sorghum in tropical and semi-arid regions (Gao et al., 2021). The higher concentration of sorghum in areas such as Kollipara, Vemuru, and Duggirala is indicative of regions where soil and water conditions were more favorable for its cultivation.

The support vector machine (SVM) algorithm, used for classification in this study, demonstrated a high degree of accuracy in distinguishing maize and sorghum from other land cover types. The kappa indices of 0.91 for maize and 0.93 for sorghum indicate that the SVM algorithm was highly effective in identifying crop areas. These findings confirm the growing utility of machine learning techniques, particularly SVM, in agricultural remote sensing applications. The slight discrepancy (approximately 7%) observed between the SVM and threshold-based methods can likely be attributed to the differences in parameterization and the inherent characteristics of each algorithm. Although the SVM approach proved more accurate in crop classification, the threshold-based method remained a reliable tool for delineating sowing windows in smallholder systems, where crops are often planted in heterogeneous landscapes. These results underscore the value of combining machine learning algorithms with more traditional threshold-based methods to improve the precision of crop monitoring systems in complex agricultural settings.

When comparing the threshold-based method using NDWI and NDVI with the SVM classifier, a variation in the estimated sown area across mandals is observed. Such a discrepancy is not unexpected, given that these methods are based on very different principles. The thresholding approach relies on fixed spectral cut-offs, which may struggle to capture the full spatial heterogeneity of rice-fallow fields. On the other hand, SVM is more flexible and can model non-linear and subtle spectral differences, but its accuracy is strongly influenced by the quality and representativeness of its training data especially in heterogeneous fragmented landscapes (Moumni & Lahrouni, 2021).

Furthermore, real-world factors such as soil moisture gradients, uneven residue retention after harvest, and staggered sowing dates across mandals can alter the spectral response of inter-sown crops. These differences in phenology and ground conditions might lead each method to interpret the same area differently. Importantly, the deviation between methods falls within a reasonable uncertainty range for remote sensing based crop area estimation. Thematic map uncertainty is a well-known issue in remote sensing, driven by mixed pixels, classifier limitations, and spatial sampling (Olofsson et al., 2014). Under these circumstances, both the threshold-based and SVM-based estimates can be considered complementary and operationally reliable. However, this study has some limitations that should be acknowledged. One of the primary limitations was the cloud cover in early January, which reduced the availability of cloud-free satellite imagery. This, in turn, compromised the accuracy of sowing window identification for both maize and sorghum during that period. While the study utilized a reasonable temporal resolution of satellite data, the accuracy of sowing window detection could be improved with higher spatial and temporal resolution imagery. Furthermore, while ground truth data was collected during the 45th and 72nd days after sowing, this limited the ability to capture the full range of temporal variability in sowing windows across the entire study area. More frequent field observations would help improve the robustness of the algorithm, allowing for a more detailed assessment of sowing patterns. Additionally, the study's algorithm, while effective for maize and sorghum, could benefit from further validation across different agro-ecological zones and seasons to determine its generalizability and applicability in other regions. Higher-resolution satellite imagery and more frequent satellite observations would improve the precision of both sowing window detection and crop area estimation, as small-scale variations in sowing times and crop areas were not fully captured with the available data.

5. CONCLUSION

The present study successfully identified the sowing windows for maize and sorghum in the Krishna Western Delta using satellite imagery and logical algorithms. The results revealed that maize sowing predominantly took place from early December to late February, with peak sowing observed in late January, especially in rice fallow areas. Sorghum sowing followed a similar trend, with peak activity in mid to late January. The timing of sowing was significantly influenced by factors such as the delayed harvest of kharif rice, the need for soil drying, and low winter temperatures, which notably affected maize sowing. Sorghum, being more adaptable to varying soil conditions, exhibited a more flexible sowing window. The application of the SVM algorithm for crop classification showed that maize cultivation was below average, while sorghum exceeded expected areas. Despite challenges like cloud cover and limited temporal resolution of ground truth data, this study highlights the potential of remote sensing and machine learning techniques to provide accurate and timely crop monitoring. The findings offer valuable insights for enhancing agricultural management and decision-making in similar agro-ecological regions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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