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Research Article

Crop type classification and spatial mapping in River Nile and Northern State, Sudan, using Sentinel-2 satellite data and field observation

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Abstract

Maintaining productive farmland necessitates precise crop mapping and identification. While satellite remote sensing makes it possible to generate such maps, there are still issues to resolve, such as how to choose input data and the best classifier algorithm, especially in areas with scarce field data. Accurate assessments of the land used for farming are a crucial part of national food supply and production accounting in many African countries, and to this end, remote sensing tools are being increasingly put to use. The aim of this study was to assess the potentiality of Sentinel-2 to distinguish and discriminate crop species in the study area and constraints on accurately mapping cropping patterns in the winter season in River Nile and Northern State, Sudan. The research utilized Sentinel-2 Normalized Different Vegetation Index (NDVI) at 10 m resolution, unsupervised and supervised classification method with ground sample and accuracy assessment. The results of the study found that the signatures of grain sorghum, wheat, okra, *Vicia faba*, alfalfa, corn, haricot, onion, potato, tomato, lupine, tree cover, and garlic have clear distinctions, permitting an overall accuracy of 87.38%, with trees cover, onion, wheat, potato, garlic, alfalfa, tomato, lupine and *Vicia faba* achieving more than 87% accuracy. Major mislabeling problems occurred primarily in irrigated areas for grain sorghum, okra, corn, and haricot, in wooded areas comprised of small parcels of land. The research found that high-resolution temporal images combined with ground data had potential and utility for mapping cropland at the field scale in the winter.

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Introduction

With the global population rising and essential resources such as land and water becoming increasingly scarce, the urgency to boost agricultural productivity to meet the growing food demand is more critical than ever (Feldt et al., 2020; Mahroof et al., 2021). This necessity aligns with two pivotal development objectives for the century: bolstering the reliability of food supply and adopting eco-friendly farming methods (Aryal et al., 2020; Parmentola et al., 2022). In response, recent advancements in remote sensing technology, characterized by the availability of accessible satellite data archives and innovative sensors, have significantly expanded the capability to extract detailed information on land cover and land use (LULC) (Karasov et al., 2021; Zhang and Li, 2022). This increase in data collection frequency enables the differentiation of individual crops and the assessment of their growth stages (Saiz et al., 2021; Wimberly et al., 2021).

To harness this data effectively, several studies have utilized multi-temporal imagery and vegetation indices, such as the normalized difference vegetation index (NDVI), for the classification of croplands and crop types (Kang et al., 2021; Kumar et al., 2022). This phenology-based approach aids in distinguishing areas cultivated with different crops (Zhu et al., 2021; Ashourloo et al., 2022). However, despite these advances, challenges persist in combining various types of information to accurately distinguish between crop types, often because most studies rely on data from a single remote sensing sensor (Mateo-Sanchis et al., 2019; Berger et al., 2022). Moreover, the integration of multiple data sources and the discrimination of crop types remain complex issues (Orynbaikyzy et al., 2019; Neinavaz et al., 2021). Despite these hurdles, the potential of Sentinel-2 data for agricultural applications, particularly for mapping crop types, has been widely recognized (Asam et al., 2022; Gumma et al., 2022).

The application of these technological advancements extends beyond mere agricultural productivity. In regions like the River Nile and Northern State of Sudan, where agricultural lands are prone to degradation due to factors like overuse, poor management, and the repercussions of mining operations, accurate crop type classification and spatial mapping can significantly inform sustainable land use strategies (Teucher et al., 2022; Zhang et al., 2022). This foundational step towards developing tailored agricultural interventions and land rehabilitation programs is crucial for enhancing food security and promoting sustainable land use in these vulnerable regions. Addressing the adverse effects of land degradation and mining on agricultural productivity, this study aimed to generate precise mappings of crop types through advanced satellite imagery analysis and on-the-ground observations. Such targeted interventions for land restoration and improved agricultural practices are vital for bolstering food security and sustainable land use (Luo et al., 2022; Mathenge et al., 2022). By providing detailed maps that indicate the location and type of crops grown, this research supports policymaking by enabling the development of informed agricultural practices and aiding in the accurate estimation of agricultural statistics, such as yield prediction and crop area estimation.

Overall, this research not only contributes to the scientific understanding of agricultural land use in degraded environments but also offers practical solutions for enhancing the resilience and productivity of these critical regions. Through precise crop classification and mapping, stakeholders can implement more effective strategies for soil conservation, crop selection, and land rehabilitation, thereby mitigating the impacts of degradation and mining activities and promoting sustainable development in agriculture.

This research aimed to identify and classify various crop species in the study area using NDVI and Supervised classification with ground survey data.

Materials and Methods

Study area

This research took place in the River Nile and Northern State, situated in Sudan's northern region between Latitudes 16-22 N and Longitudes 30-35 E (Ezebilo et al., 2013). The primary survey occurred in January 2021, focusing on these two states, specifically River Nile State and Northern State, as depicted in Figure 1. These areas were selected due to their high concentration of bean farms. Within these states, the study was further segmented into officially recognized localities in Sudan.

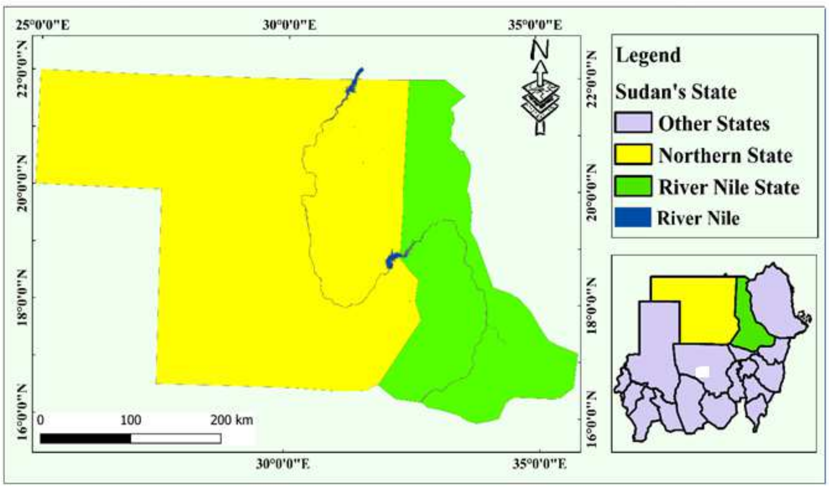

Figure 1. Location of the study area (River Nile and Northern State), Sudan.

Data collection methods

Remote sensing data

First, the coordinates of the study area were specified, and the boundary of the forest was delineated and reviewed in the Google Earth Pro Engine Platform (earthengine.google.com). Afterward, the images of the study area were downloaded. This study used Sentinel-2 products, which provide 6-day composite images at 10 m spatial resolution (bands 2, 3, 4, and 8). Sentinel-2 products include blue, green, red, near-infrared, and mid-infrared bands. Four tiles covering the required region were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/) on 04/01/2021, 06/01/2021, 08/01/2021, and 10/01/2021. The selection of images was based on the availability of free cloud cover (<10%) satellite data and the purpose of the identification and spatial mapping of different crop species on two banks of the River Nile from Hager Alasal to Wadi Halfa.

Image pre-processing

In this study, image pre-processing was carried out using QGIS free software version 3.16.10 and ArcMap software version 10.7. Initially, all bands from four image scenes were downloaded and saved as individual .tiff files. Subsequently, these individual bands were merged in a sequence from bands 2, 3, 4, and 8 using a process called virtual raster creation. During this phase, a false-color composite was also created for visualization purposes. Ultimately, a subset was extracted from the virtual raster and trimmed to match the study area's full extent precisely. This subset was then utilized to create the training dataset needed for image classification.

Normalized difference vegetation index (NDVI)

In this instance, the study utilized time-series data from Sentinel-2 and data from ground surveys collected from uniform patches. This, combined with detailed information about the cropping system and irrigation techniques, facilitated the creation of precise temporal NDVI (normalized difference vegetation index) signatures. The NDVI was calculated using the standard formula:

$$NDVI = (NIR - RED) / (NIR + RED)$$

where: NIR represents the reflectance in the near-infrared band, and RED denotes reflectance in the visible band.

Ground truth validation data

The ground truth survey in the study area took place during the winter of 2021 to validate land cover classifications, create training samples, and assess the accuracy of the classification results. While there is no specific rule for determining the number of ground truth points, at least 60 samples for each crop class are generally needed for validation (Gumma et al., 2020). In this research, 840 ground truth points were randomly generated in the QGIS software using a stratified random method. These points were then uploaded to the Google Earth Pro platform for visual analysis (refer to Figure 2). Subsequently, all the sample points were inputted into a Global Positioning System (GPS) and utilized during the field survey for validation purposes.

Image classification

Various image classification methods exist, with supervised and unsupervised classification being the most commonly utilized techniques by researchers (Saad et al., 2020). In this research, both techniques were applied to analyze imagery from Sentinel-2 (14/12/2020, 06/01/2021, 08/01/2021 and 10/01/2021). Initially, unsupervised classification was conducted to differentiate between various crop types in the study area, aiming to minimize mixed pixels among different classes and thereby enhance classification accuracy. Subsequent to this, supervised classification was undertaken. This process began with the creation of training signatures for each predefined crop type class, using polygon delineated (ROI). These signatures were based on visual interpretation (using false color composite images), prior knowledge of the area, discussions with local elders, and Google Earth's time series images. Consequently, 13 different crop classes were identified during the field survey, including okra (bamia), corn (dora shamia), lupine (tormos), haricot (fasoulia), tomato (tamatim), grain sorghum (abu sabean), garlic (toum), alfalfa (bersiem), onion, wheat, potato, tree cover, and *Vicia faba* (beans) (Table 1).

Table 1. Number of training and validation samples collected for training data of each class identification and validation.

Class name	**Training**	**Validating**
Okra	15	15
Corn	15	15
Lupine	30	30
Haricot	20	20
Tomato	30	30
Grain sorghum	15	15
Garlic	35	35
Alfalfa	30	30
Onion	60	60
Wheat	40	40
Potato	30	30
Trees cover	30	30
Vicia faba	70	70
Total	420	420

The maximum likelihood classifier (MLC) was then employed to produce the final classification output. The entirety of the remote sensing data process used in this study is depicted in Figure 2. Accuracy assessment was performed for a crop-type map by following an approach suggested by Congalton and Green (2019). User's Accuracy (UA), Producer's Accuracies (PA), Overall Accuracy (OA), and Kappa coefficients were determined.

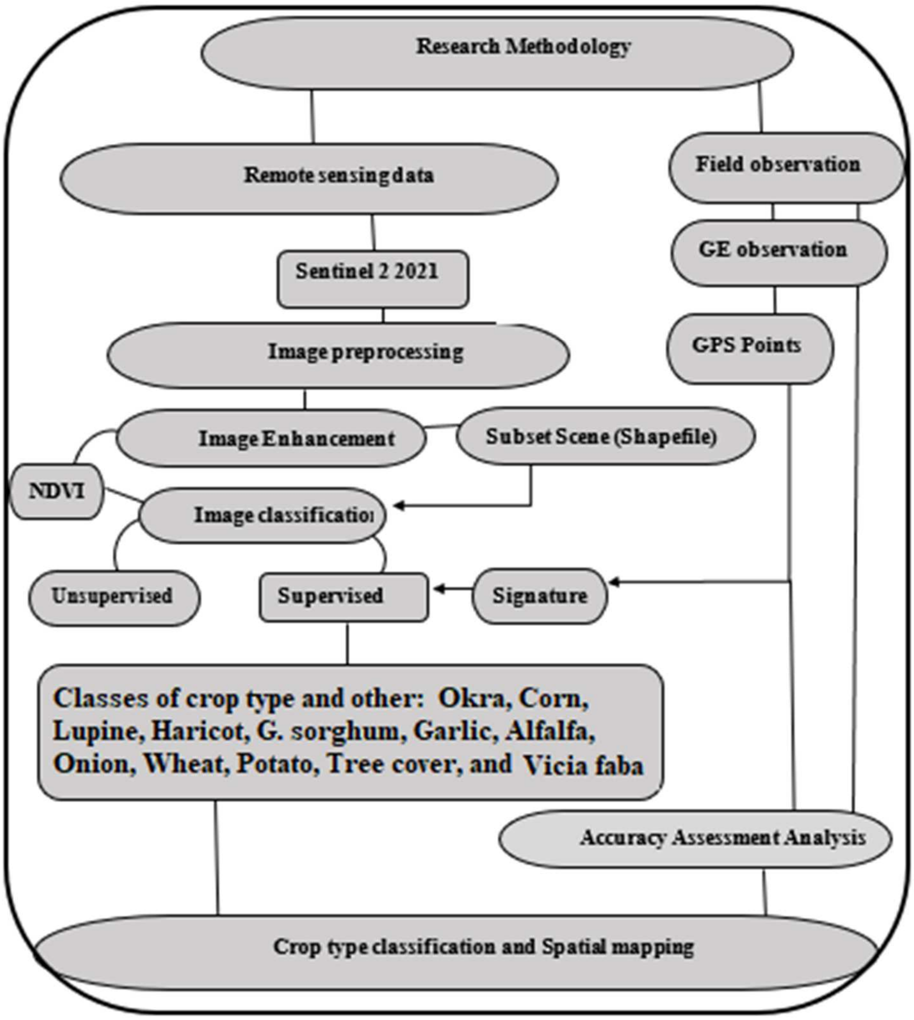

Figure 2. Flowchart of remote sensing data processing.

Results

Crop patterns in River Nile State

Figure 3 and Table 2 show the spatial distribution of crops and onion occupied the largest cropped area (35,369.15 ha) represent 32.98% of total cultivated areas and distributed in all area followed by alfalfa 9.79% (10,497.43 ha) and distributed in the middle area, garlic 9.63% (10,327.06 ha) and distributed around Atbara river and scattered area in north part, grain sorghum 6.85% (7,343.69 ha) and distributed in the middle and south part, haricot 6.21% (6,658.74 ha) and distributed in small area above Atbara river, Wheat 3.65 % (3,918.85 ha) and distributed in scatter area in the south part, *Vicia faba* 3.58% (3,838.65 ha) and distributed in small area in north part, potato 2.88% (3,085.89 ha) and distributed in small rea and scatter in middle part, tomato 2.52% (2,705.83 ha) and distributed in the south part, lupine 1.89% (2,024.5 ha) and distributed in scatter area in the south part, trees cover 1.28% (1,372.75 ha) and distributed in south part, okra 0.86% (920.44 ha) and distributed in small area and corn 0.39% (417.89 ha) which scattered in very small area of the total cultivated area.

For the distribution pattern of crop type based on River Nile localities, Figure 4 and Table 2 show that onions stand out as a dominant crop in Atbara and Berber, where they constitute 48.98% and 52.38% of the agricultural landscape, respectively. In contrast, Haricot beans are prominently cultivated in Al Matammah and Ad Damar, with significant shares of 10.59% and 12.58%, pointing to their importance as a legume crop in these areas. The presence of "Rocks and Sand" is notably high in Shendi, at 46.84%, suggesting that much of the land may be unsuitable for farming. Garlic and alfalfa are cultivated extensively in Abu Hamad, with percentages of 18.06% and 13.43%. Grain sorghum shows a notable presence in Shendi, accounting for 9.81% of the crops. Despite their smaller percentages, crops like lupine, tomato, and *Vicia faba* play a vital role in the region's agricultural diversity.

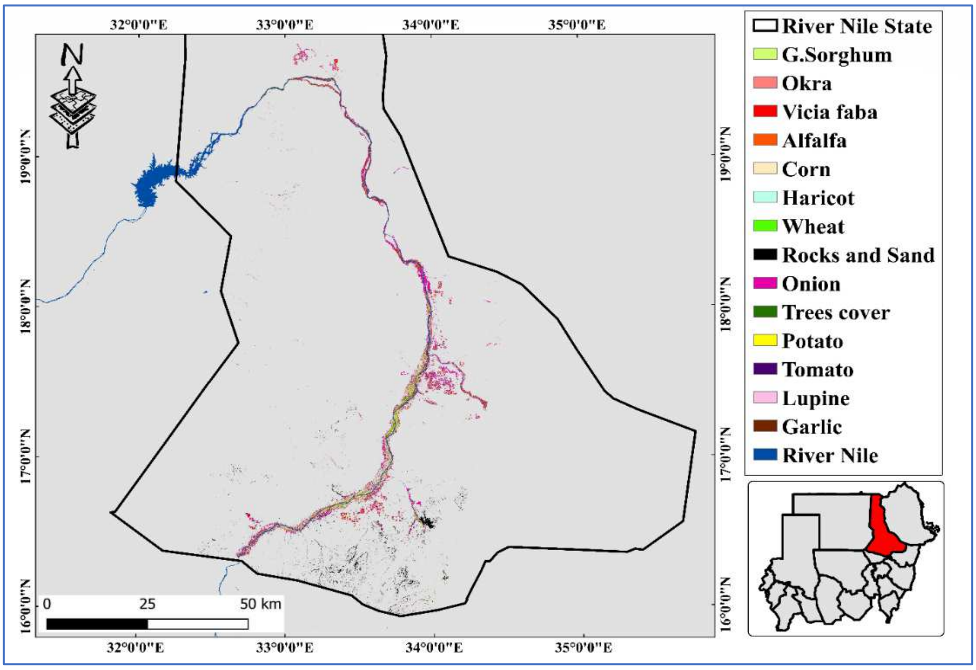

Figure 3. Spatial distribution of winter crops in River Nile State – 2021.

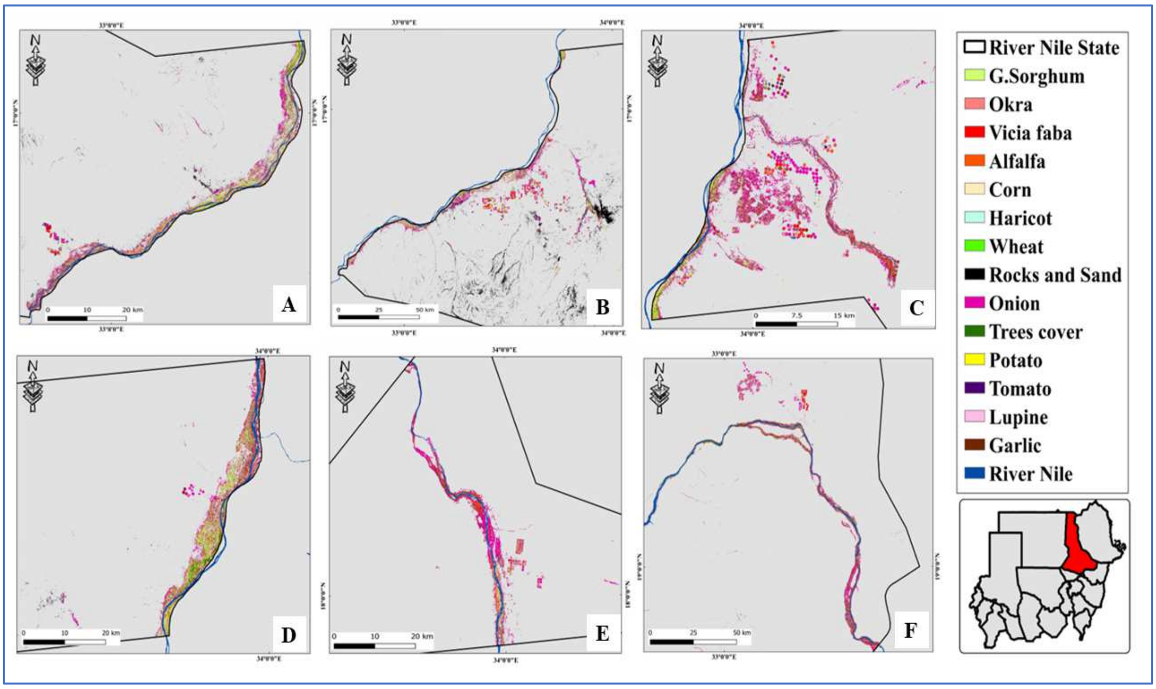

Figure 4. Spatial distribution of winter crops in River Nile State localities (A: Al Matammah; B: Shendi; C: Atbara; D: Ad Damar; E: Berber; F: Abu Hamad) – 2021.

Crop patterns in Northern State

Figures 5 and Table 3 show the spatial distribution of crops and onion occupied the largest cropped area (22,963.44 ha) represent 31.40% of total cultivated areas and distributed in the middle and south part area followed by garlic 15.50% (11,338.79 ha) and distributed in north part, trees cover 13.63% (9,967.69 ha) and distributed in the middle area and south part in the two river bank, *Vicia faba* 8.11% (5,933.75 ha) and distributed in the middle to south part, potato 6.70% (4,899.12 ha) and distributed in south part and scatter area in the middle part, wheat 5.85% (4,278.2 ha) and distributed in middle and scatter area in the south part, alfalfa 5.24% (3,828.76 ha) and distributed in small scatter area, grain sorghum 4.75% (3,474.33 ha) and distributed in the middle to south part, haricot 3.06% (2,235.73 ha) and distributed in small area and scattered, lupine 1.58% (1,157.35 ha) and distributed in scatter area in the south part, tomato 0.86 % (631.66 ha) and distributed in small area and scattered, okra 0.12% (87.77 ha) and corn 0.04% (30.54 ha) which scattered in very small area of the total cultivated area. For the distribution pattern of crop type based on Northern State localities, Figure 6 and Table 3 show that onions emerge as a dominant crop, commanding the highest cultivation percentages in Addabah (38.22%) and Merawi (36.16%), with substantial cultivation also in Dongola (30.02%) and Wadi Halfa (21.66%), respectively. Garlic and alfalfa are notably prevalent in Wadi Halfa (21.61% and 11.42%, respectively) and Dongola (18.07% for garlic). Lupine (5.64%) and haricot beans (7.41%) show a higher prevalence in Wadi Halfa. Grain sorghum presents a varied distribution, most notably in Merawi (9.11%) compared to its lowest in Wadi Halfa (2.26%). The presence of "Rocks and Sand" is more pronounced in Addabah (6.23%) and Merawi (4.82%), possibly indicating less arable land. Tree coverage is significantly higher in Addabah (28.65%) and Merawi (20.13%). Finally, *Vicia faba* (broad beans) and potato show significant percentages in Dongola (11.65%), Wadi Halfa (11.33%), and Addabah (10.52%), respectively.

Table 2. Crop area (ha) and percentage in River Nile State and percentage for each locality.

Class Name	River Nile State		% of crop patterns in the localities of River Nile State					
	Area (ha)	%	Al Matammah %	Shendi %	Atbara %	Ad Damar %	Berber %	Abu Hamad %
Okra	920.44	0.86	1.51	0.22	1.14	1.24	1.22	0.43
Corn	417.89	0.39	0.62	0.10	0.51	0.50	0.70	0.24
Lupine	2,024.50	1.89	4.13	0.60	0.85	4.47	0.69	1.50
Haricot	6,658.74	6.21	10.59	2.41	5.21	12.58	6.46	4.29
Tomato	2,705.83	2.52	5.10	0.73	2.10	3.91	2.33	2.19
G. Sorghum	7,343.69	6.85	7.73	9.81	4.88	7.58	1.23	4.61
Rocks and Sand	18,774.43	17.50	11.21	46.84	1.40	3.25	0.42	1.50
Garlic	10,327.06	9.63	7.15	2.59	16.03	12.53	12.76	18.06
Alfalfa	10,497.43	9.79	11.56	3.70	9.72	11.41	18.22	13.43
Onion	35,369.15	32.98	24.67	25.34	48.98	20.33	52.38	40.06
Wheat	3,918.85	3.65	6.12	1.81	3.28	8.09	0.95	3.26
Potato	3,085.89	2.88	4.55	2.85	1.57	5.28	0.71	1.67
Trees cover	1,372.75	1.28	1.43	0.72	0.91	3.61	0.02	2.02
Vicia faba	3,838.65	3.58	3.65	2.28	3.42	5.23	1.92	6.74
Total	107,255.30	100	100	100	100	100	100	100

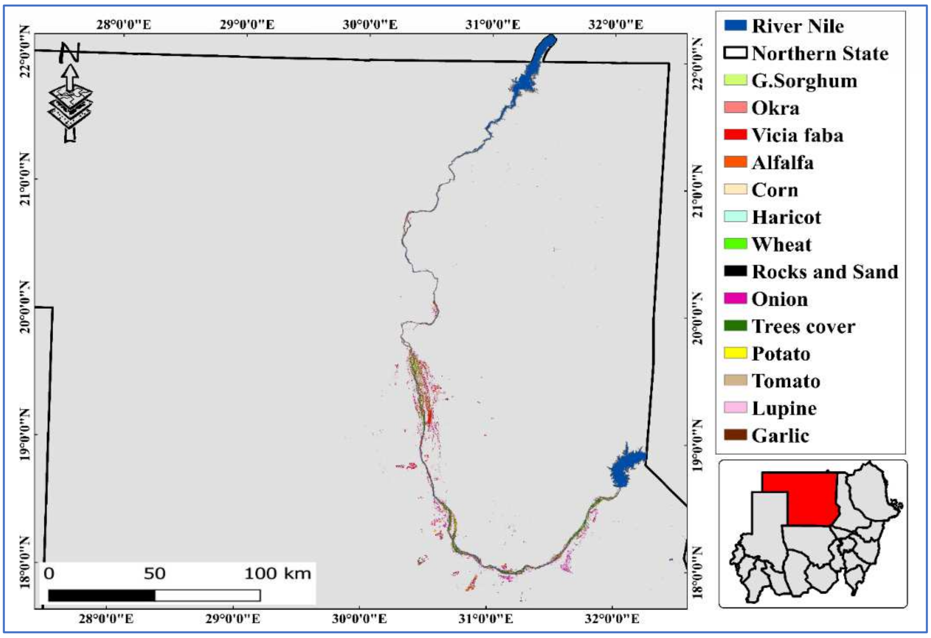

Figure 5. Spatial distribution of winter crops in Northern State – 2021.

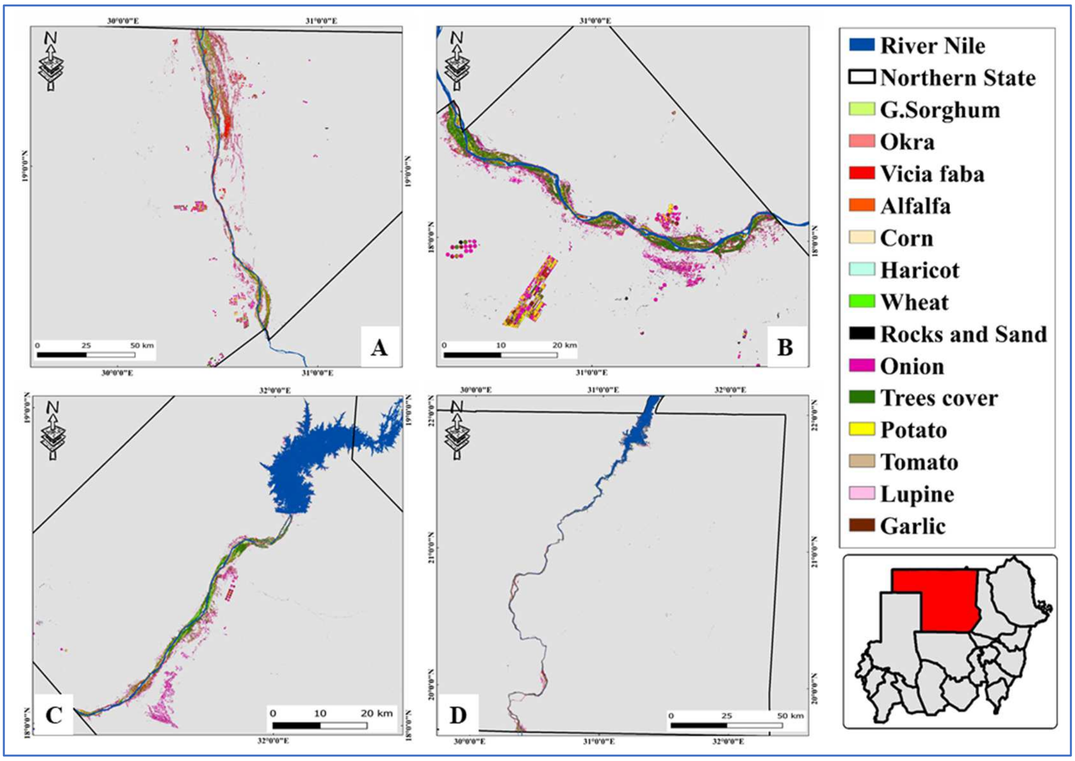

Figure 6. Spatial distribution of winter crops in Northern State localities (A: Dogola; B: Addabah; C: Merawi; D: Wadi Halfa) – 2021.

Table 3. Crop area (ha) and percentage in Northern State and percentage for each locality.

Class Name	Northern State		% of crop patterns in the localities of Northern State			
	Area (ha)	%	Dongola %	Addabah %	Merawi %	Wadi Halfa %
Okra	87.77	0.12	0.16	0.00	0.05	0.20
Corn	30.54	0.04	0.05	0.00	0.01	0.12
Lupine	1,157.35	1.58	1.39	0.06	0.64	5.64
Haricot	2,235.73	3.06	3.32	0.21	1.76	7.41
Tomato	631.66	0.86	0.94	0.01	0.17	2.62
Grain Sorghum	3,474.33	4.75	4.11	3.84	9.11	2.26
Rocks and Sand	2,310.20	3.16	2.01	6.23	4.82	1.64
Garlic	11,338.79	15.50	18.07	7.88	10.56	21.61
Alfalfa	3,828.76	5.24	5.68	1.88	2.58	11.42
Onion	22,963.44	31.40	30.02	38.22	36.16	21.66
Wheat	4,278.2	5.85	6.25	1.69	7.47	7.05
Potato	4,899.12	6.70	7.27	10.52	4.42	2.82
Trees cover	9,967.69	13.63	9.08	28.65	20.13	4.22
Vicia faba	5,933.75	8.11	11.65	0.79	2.13	11.33
Total	73,137.33	100	100	100	100	100

Comparison between River Nile and Northern State in the distribution of crop pattern

Figure 7 and Table 4 show that the total cultivated area in River Nile state is bigger than that of the Northern state (107,255.3 ha and 73,137.33 ha, respectively). However, the onion, alfalfa, grain sorghum, haricot, tomato, lupine, okra, and corn occupied large coverage percentages of cultivated area (32.98%, 9.63%, 6.85%, 6.21%, 2.52%, 1.89%, 0.86%, and 0.39%, respectively), in River Nile State more than Northern State. While the garlic, trees cover, *Vicia faba*, potato, and wheat, covering a large percentage of cultivated area (15.50%, 13.63%, 8.11%, 6.70%, and 5.85%, respectively) in Northern State more than in River Nile State.

Accuracy assessment

Table 5 shows user's and producer's accuracy for each crop in the study area. It was performed independently with 420 validation sample points. Overall accuracy for the study area was 87.38%, and the Kappa coefficient was 86.23%.

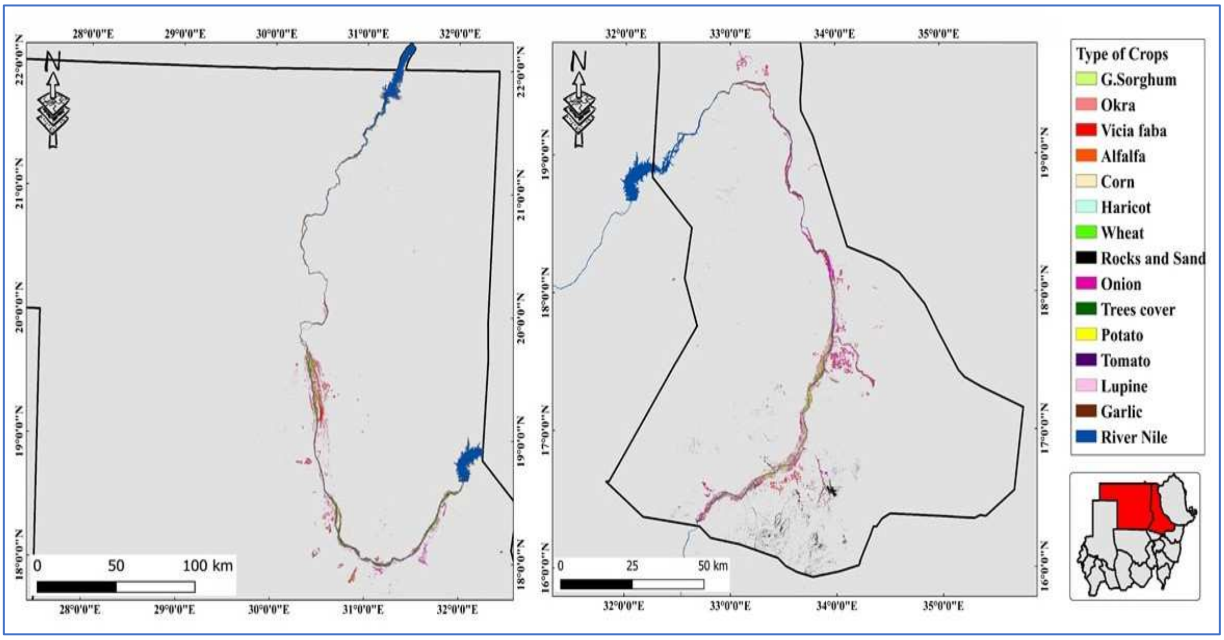

Figure 7. Comparison between Spatial distribution of winter crops in River Nile and Northern State - 2021.

Table 4. Comparison between crop area (ha) and percentage in River Nile and Northern State.

Class name	River Nile State		Northern State	
	Area (ha)	%	Area (ha)	%
Okra	920.44	0.86	87.77	0.12
Corn	417.89	0.39	30.54	0.04
Lupine	2,024.50	1.89	1,157.35	1.58
Haricot	6,658.74	6.21	2,235.73	3.06
Tomato	2,705.83	2.52	631.66	0.86
Grain Sorghum	7,343.69	6.85	3,474.33	4.75
Rocks and Sand	18,774.43	17.50	2,310.20	3.16
Garlic	10,327.06	9.63	11,338.79	15.50
Alfalfa	10,497.43	9.79	3,828.76	5.24
Onion	35,369.15	32.98	22,963.44	31.40
Wheat	3,918.85	3.65	4,278.20	5.85
Potato	3,085.89	2.88	4,899.12	6.70
Trees cover	1,372.75	1.28	9,967.69	13.63
Vicia faba	3,838.65	3.58	5,933.75	8.11
Total	107,255.30	100.00	73,137.33	100.00

Table 5. Overall accuracy with producer's accuracy and Kappa coefficient winter crop area maps.

Class name	User's Accuracy	Producer's Accuracy	Kappa Coefficient
Okra	83.33	73.53	86.23
Corn	86.67	74.29	
Lupine	83.05	89.09	
Haricot	87.50	79.55	
Tomato	85.00	86.44	
Grain sorghum	86.21	75.76	
Garlic	85.51	93.65	
Alfalfa	92.31	85.71	
Onion	83.33	92.59	
Wheat	93.75	89.29	
Potato	83.05	85.96	
Trees cover	83.33	87.72	
Vicia faba	93.53	92.20	

Discussion

The crop distribution data between River Nile State and Northern State in Sudan reveal significant insights into agricultural practices and priorities in these regions, which can be contextualized against a backdrop of existing research on agricultural trends, climate adaptability, and economic viability (Awadalla et al., 2019; Iizumi et al., 2021; Kau et al., 2023).

In River Nile State, onions dominate the cultivated area, accounting for nearly one-third of the total agriculture. This suggests a strong market demand or climatic suitability—or both—for onions in this area. Alfalfa and garlic also represent significant proportions, indicating their importance in crop rotation for soil health and as cash crops, respectively. The high percentage of rocks and sand reflects the challenges of desertification and land degradation, pressing issues in Sudan that impact agricultural productivity (Hamad and Nouri, 2011; Duarte-Correa et al., 2023).

Comparatively, the Northern State exhibits a similar pattern, with onions being the predominant crop but with a slightly lesser percentage (Saeed, 2007). This state has a higher percentage of garlic and remarkably higher tree coverage, indicating different land use priorities or environmental conservation efforts, possibly linked to agroforestry practices (Al Ameen and Emad, 2009). The presence of trees might also suggest an integration of crop and livestock farming, contributing to diversification and sustainability (Mailumo and Onuwa, 2022).

Notably, the distribution of crops like wheat, potato, and *Vicia faba* (broad beans) differs between the two states, pointing towards variations in soil types, irrigation practices, and possibly consumer preferences (Siddique et al., 2000). Wheat and potatoes, requiring more water, hint at better irrigation facilities or higher rainfall in areas where they are more prevalent (Di Paolo et al., 2015).

The significant area covered by rocks and sand in River Nile State compared to Northern State underscores the environmental challenges faced by farmers, including soil erosion and water scarcity (Altoom et al., 2023). These conditions necessitate adaptive farming techniques and the selection of crops that are resilient to such stresses (Kabbar et al., 2020).

This analysis results align with global agricultural trends towards sustainability, diversification, and the integration of environmental conservation into farming practices. The emphasis on certain crops reflects not only the adaptability of agriculture to local conditions but also the economic strategies of farmers in optimizing crop yields and meeting market demands (Tamraz and Zahida, 2022. For sustainable development and food security in these regions, understanding these patterns is crucial. It can guide agricultural policies, promote practices that enhance biodiversity and soil health, and ensure that farming remains a viable livelihood for the local population. As global environmental conditions continue to change, the insights gained from these patterns will be invaluable in adapting and sustaining agricultural practices in Sudan and similar regions worldwide.

Conclusion

This research combined ground survey information with Sentinel-2 NDVI and a supervised classification approach to create a winter cropland map. Using extensive training data, major crop extents across the two states were mapped with greater accuracy during the winter season. The research demonstrated the feasibility of using high-resolution temporal images and ground data for field-scale cropland mapping. Macro-level planning is aided by characterizing key crop growing owing environments, which can be done with the help of a map of the winter crop areas. This, in turn, leads to the sustainable use of resources and improvement in the study area. Accurate seasonal crop maps and statistics like these are crucial for determining the extent to which abiotic and biotic stresses, which already plague the region but are expected to worsen under a warming climate, have an effect on crops. However, this method is inapplicable during the autumn because of the increasing prevalence of cloud cover. The inability to generate multi-temporal NDVI spectra that can reliably distinguish between crops is a result of the lack of sufficient cloud-free Sentinel-2 data during the autumn. To accomplish this, we need to employ all-weather Synthetic Aperture Radar imagery, such as that provided by Sentinel-1.

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