Misan Journal of Engineering Sciences ISSN: 2957-4242
Vol. 5, No. 1, 28 June 2026 ISSN-E: 2957-4250

Forecasting Potential Wheat Cultivation Zones In Zakho District, Northwest Iraq Using Remote Sensing Data And Machine Learning Techniques

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(Received 14 Dec 2025, Revised 3 April 2026, Accepted 10 April 2026)

Abstract: This research highlights the significant challenges of accurate wheat area mapping in the Zakho district of the Kurdistan region of Iraq, through the development of an accurate wheat classification and mapping system by using the integration of optical and radar imagery from Sentinel 1 and Sentinel 2 datasets, geographic information system (GIS), and machine learning algorithms. The Support Vector Machine (SVM) were used in this research to classify wheat and non-wheat areas utilizing multi-source satellite imagery, with combination of normalized difference vegetation index (NDVI) and Ratio Vegetation Index (RVI) of optical imagery, along with VV and VH polarization bands in radar data. 54 wheat farm data collected as a sample to be used as a training data for SVM method and validation to create wheat map for the study area. The results indicated that Zakho district are covered by 126,486.07 donums of wheat which is 9.2% of total area of the district in 2023. The accuracy of the classification was validated using field-collected ground truth samples, achieving an overall accuracy of 95%, and further cross-validated by comparison with official agricultural directory records. The research addressed the significance of using multiple combinations of optical and radar datasets with GIS, remote sensing and machine learning techniques to precisely map crop and agricultural farms in complex geopolitical regions. The developed maps provide accurate evidence to support the rights of farmers, promoting informed decision-making and equitable resource distribution. The outcome of this research can be used in future agricultural assessments, resulting in economic stability and sustainable development.

Keywords: Wheat mapping; remote sensing; Machine learning; Zakho district; Agricultural resource management.

1. Introduction

Wheat farming has a significant contribution to the life of farmers in Zakho district, Kurdistan region, Iraq, where the majority of the population heavily relies on agriculture, and it's the primary source of income for most local farmers. Farming, especially wheat not only contributes to the food security of the region but also significantly has an impact on the economy for the local people. The Kurdistan Regional Government (KRG) with Iraq Government in recent years created a significant supporting system for wheat farmers by purchasing wheat at prices higher than the market rate and categorizing the produce into three quality levels. However, farmers in the Zakho district faced challenges in accurately mapping wheat farming areas and ensuring fair distribution of resources. The limited purchasing quota imposed by the storage silos, which restricts the amount of wheat they can buy from farmers is one major issue. The silos have a limited quota, which severely impacted farmers by restricting the amount of wheat they can sell to silos. In 2023, wheat production in the Zakho district increased, and issues at the border with Turkey, coupled with ongoing Turkish military activities, prevented surveyors from assessing and locating all the wheat farms near the border. Consequently, the data sent to Iraq did not reflect the actual amount of wheat produced [1-3].

DOI: https://doi.org/10.61263/mjes.v5i1.247

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Remote sensing technologies such as optical and radar were have significant influence in agricultural monitoring. Optical remote sensing are related to those sensors that capture reflected energy from the Earth's surface in various spectral bands. However, due to its limitations to weather conditions and inability to penetrate clouds, optical remote sensing could be ineffective in all situations for acquiring imagery. To solve this challenge, radar remote sensing could be a great help which uses microwave signals and measure the backscatter from the Earth's surface, acquiring satellite imagery in all weather conditions. Making radar remote sensing technology useful for regions that have plenty of cloud cover or adverse weather conditions. However, recently the combination of optical and radar data contributed to the enhancement of the accuracy of crop mapping. Furthermore, the combination of both radar with optical technology to generate robust wheat maps have higher accuracy compared to using a only one of the datasets based on the contribution of Ropelewska and Jankowski (2019) [4]. The integration of remote sensing (RS) and Geographic Information Systems (GIS) commonly used recently by researchers for monitoring and assessing agriculture. Several studies highlighted the significance and effectiveness of these technologies for accurate mapping of crop types, including wheat fields. Loddo and Di Ruberto (2021) used a combination of optical and radar satellite imagery to generate an accurate wheat fields. The research showed that multi-temporal and multi-spectral data improved the accuracy of crop classification and area estimation [5]. Although, Khatri et al. (2022) used various machine learning techniques to classify wheat regions, highlighting the significant contribution of machine learnings algorithms in enhancing the precision of crop mapping [6].

The innovations in machine learning technology had the substantial influence on image classification techniques in recent years, providing the powerful tools to handle large datasets and extract valuable information in satellite imagery. Multiple researches successfully used Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN) for agricultural applications, such as accurate wheat area mapping and classifications of different crop types [7-10]. Agarwal et al. (2022) applied both SVM and K-Nearest Neighbor (KNN) machine learning classifiers to classify wheat areas using satellite imagery, and the result showed substantial accuracy of SVM algorithm [11]. Moreover, Fazel-Niari et al. (2022) utilized advanced machine learning techniques of Quadratic Discriminant Analysis (QDA) and Linear Support Vector Machine (LSVM) which showed promising accuracy for mapping wheat areas with reliable accuracy [12].

However, there are limited research locally focusing on wheat mapping in the KRI and Iraq. Abdulmajeed and Al-Ani (2022) estimated wheat yield for specific farm in Najaf Governorate, southwestern Iraq, using seven multispectral bands of Landsat 8 and Landsat 9 satellites acquired during two different time periods representing the high vegetative growth stage and the post-harvest stage [13]. The study employed Principal Component Analysis (PCA) for the change detection and maximum-likelihood method as supervised classification technique to calculate wheat production, demonstrating applicability of multi-temporal Landsat imagery for wheat yield estimation in Iraqi agricultural context. Moreover, Qader et al. (2018) combined MODIS satellite data with the official crop statistics to develop empirical regression-based model for forecasting winter wheat and barley production at governorate level across the Iraq [14]. The study used three remotely sensed indices, such as NDVI, EVI, and Net Primary Productivity (NPP), with crop phenology information. The study found that date of maximum vegetation index offered the most accurate forecast of crop production in arid and semi-arid conditions. This research represented first demonstration that crop production could be forecasted using remote sensing in Iraq, although it focused on yield prediction rather than spatial mapping of crop extent. Moreover, Al-Jasani and Al-Naji (2022) investigated impact of climatic variables on the geographical distribution of wheat crops across Iraq, emphasising that inter-annual variability in temperature and precipitation patterns significantly influences wheat production and its spatial distribution among Iraqi governorates [15]. Moreover, Azeez (2020) evaluated land suitability for wheat cultivation in Kirkuk Governorate using GIS techniques, providing spatial assessment framework for identifying most suitable agricultural lands for wheat farming based on soil characteristics and environmental factors [16]. Despite these contributions, none of existing local studies have combined optical and radar remote sensing data with machine learning algorithms for accurate spatial mapping of wheat fields in the Kurdistan Region, which

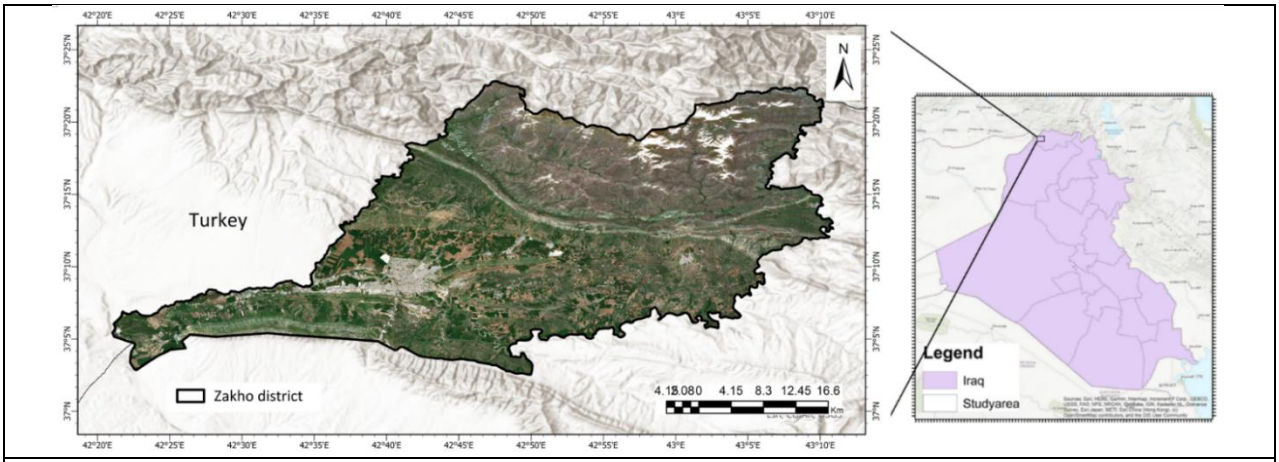
represents a significant gap that this study aims to address.

Despite growing body of literature on wheat mapping and yield estimation using remote sensing techniques, significant research gaps remain. Most existing studies in Iraq have focused on wheat yield prediction at governorate level using coarse-resolution MODIS imagery [14], land suitability assessment [16], or climatic impacts on wheat distribution [15], while none have attempted to generate accurate spatial maps of wheat fields at district level using high-resolution satellite imagery. Furthermore, integration of optical and radar remote sensing data with machine learning classification has not been previously applied for wheat mapping in the Kurdistan Region of Iraq. This study addresses these gaps by making following contributions: firstly it provides the first high-resolution wheat map for the Zakho district using the integration of Sentinel-1 radar and Sentinel-2 optical imagery with SVM classification; secondly it reveals significant discrepancy between actual wheat area identified through remote sensing and the officially surveyed area, which directly impacts the economic rights of local farmers; and finally it establishes replicable and cost-effective framework that can be adopted by local authorities and agricultural policymakers for accurate crop mapping in geopolitically complex regions where traditional field surveys are restricted.

2. Materials and methods

2.1.Study area

Zakho district, which is known for its fertile lands and high agricultural productivity, is located in Sindi Plain and lies on the Khabur River, which divided the city into two distinct parts. Zakho district lies between latitudes 37°03′ and 37°23′ N and longitudes 42°20′ and 43°10′ E. This river is a significant natural resource that contributed to the region's agricultural activities effectively. Geographically, Zakho is strategically positioned near the borders of Turkey and Syria, leading to its commercial significance enhancement (Fig. 1). It's surrounded by Turkey to the north, Syria to the west, Amadiyah district to the east, and Duhok districts to the south. Zakho is 53 kilometers away from Duhok, and 114 kilometers from Mosul. Proximity to the borders made the Zakho a critical place for cross-border trade and cultural exchange, leading to enhancement of its socio-economic dynamics [17 and 18].



Figu. 1. Location of study area (Zakho district).

The Zakho district areas is around 1,381 km2 and its population are 300,000 people as of 2021. The majority of people in Zakho are relying on agriculture. The district consisted of 107 villages and 409 farmers in 2017. The farmers cultivated 74000 donum of the land in Zakho to produce 29000 tons of wheat with 369 kg/donum. The properties of the land and the water resources provided by the Khabur River made the Zakho district a perfect place for agriculture [17 and 18].

2.2. Data collection

In this study, 54 samples were collected from wheat farms in the Zakho district, recording the exact location of the wheat farms. The collected data were visualized using GIS techniques. For more accurate mapping we used both optical and radar data to identity the wheat fields in Zakho district using SVM algorithm. The collected wheat samples were divided into 70% training data and 30% validation data to train and validate the SVM model to make insure its accuracy and reliability in distinguishing wheat fields from non-wheat areas.

Sentinel 2 significantly contributed in earth observation technology by providing high spectral and spatial resolution multispectral imagery covering entire world, which are vital for classifying different types of crops and assessing various aspects of vegetation properties. The significant bands are blue, green, red, which used for vegetation identification and true color imagery. Also red edge bands such as B5, B6, B7 and B8A are effectively used for plant health assessment and vegetation classifications (Table 1). To ensure spatial consistency across all input bands, the 20 m resolution Sentinel-2 bands were resampled to 10 m using nearest-neighbor interpolation to match the native 10 m bands (B2, B3, B4, and B8). The 60 m bands were excluded from the analysis as they are primarily designed for atmospheric correction purposes. Moreover, near infrared is commonly used band for biomass monitoring and vegetation vigor by using indices such as normalized difference vegetation index (NDVI). Water vapor band aids in the atmospheric condition corrections, however, short wave infrared bands such as B11 and B12 are used in the process of estimation of soil moisture and crop type identifications. Using the multiple bands in Sentinel 2, significantly enhance the accuracy and effectiveness of crop classification [19]. For this research, the Sentinel-1 radar bands (VV and VH polarizations) were first pre-processed and combined into a single raster layer. This radar dataset was then integrated with selected Sentinel-2 optical bands and vegetation indices to generate a composite feature map representing both spectral and backscatter information. The resulting composite dataset provided enhanced separability between wheat and non-wheat classes. Using this composite map, the Support Vector Machine (SVM) classifier was trained with ground truth samples from field surveys and applied to classify the study area, ultimately producing the final wheat distribution map.

Table 1. The used satellite data for wheat classification.

Satellite	Band	Resolution (m)	Date	Source
Sentinel 2	B2, B3, B4, B5, B6, B7, B8, B8A, B9, B11, B12	10, 20, 60	5, April, 2023	Copernicus Data Space Ecosystem, Copernics European Space Agency (ESA)
Sentinel 1	VV, VH	10	2, April 2023	Copernicus Data Space Ecosystem, Copernics European Space Agency (ESA)

2.3. Study methodology

The integration of optical and radar remote sensing data are the fundamental techniques that have been used in this research. Optical remote sensing is related to use of satellite imagery that records visible, near-infrared, and shortwave infrared bands, which is crucial for wheat fields and crop type identification [20]. However, weather conditions, particularly cloud cover are the main limitations of optical remote sensing which can be a challenge for capturing the wanted area in all weather conditions. Penetrating the clouds and providing consistent data regardless of weather conditions or time of day are the main and most significant characteristics of the Radar sensors that emit microwave signals. This data is critical not only for capturing data in all weather conditions, but it's also significant to record the structural information about the crop fields, such as surface roughness and moisture levels. The strengths combination of both optical and radar data, was the main approach of this research to develop a

comprehensive and accurate mapping of wheat farming areas [21-23]. GIS, with it's continues advancements have a significant role in enhancing the spatial analysis and generating accurate wheat fields. The GIS techniques were used in this research to manage, analyze, and visualize the spatial data achieved from field trips and satellite remote sensing.

The research process involved several sequential steps to ensure data reliability and classification accuracy. Sentinel-2 Level-2A imagery with 20 m resolution bands were resampled to 10 m using nearest-neighbour interpolation. Next step, NDVI and RVI indices were computed from the optical bands and VV/VH polarisation bands were extracted from Sentinel-1 radar imagery, with all datasets co-registered and stacked into a composite multi-layer image for SVM classification. The 54 field-collected wheat samples were verified through on-site GPS recording and visually cross-checked against high-resolution Google Earth imagery to confirm each point corresponded to actual wheat field, while samples located on field boundaries were excluded from the training dataset. The remaining verified samples were divided into training and validation subsets to train the SVM classifier. Furthermore, the total classified wheat area was cross-referenced with official agricultural directory records from Zakho. The ground truth data were used for training the support vector machine algorithm and also for validation of the result that generated from remote sensing imagery. The detailed flowchart of this study presented in Fig. 2.

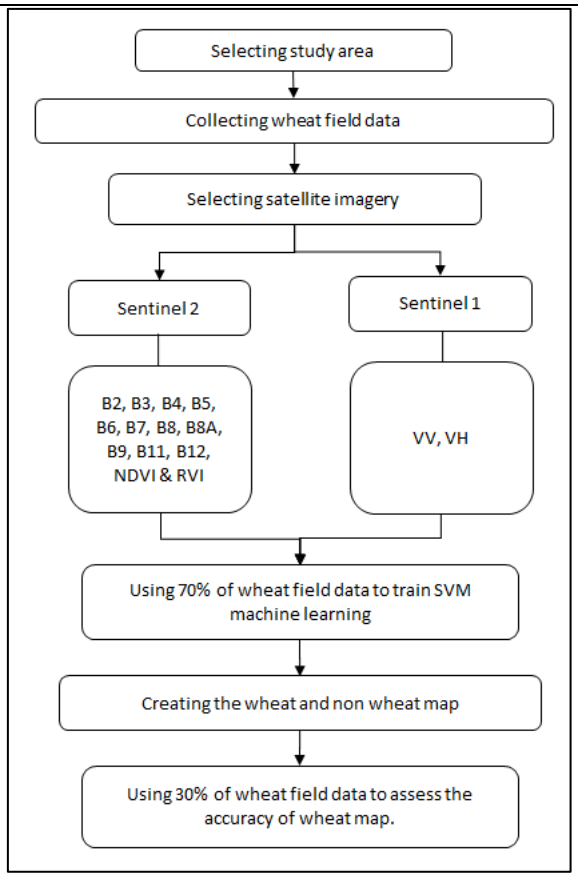


Fig. 2. Flowchart of the study methodology, illustrating the integration of Sentinel-1 and Sentinel-2 datasets with vegetation indices (NDVI and RVI) and other optical and radar bands. These inputs were combined to generate the composite dataset used in the Support Vector Machine (SVM) classification for wheat mapping in the study area.

Advanced machine learning algorithms significantly contributed in development of accuracy and effectiveness of agricultural crop classification. Support Vector Machine (SVM) were utilized as classifier for wheat identification in Zakho district. SVM [24] approach is based on the hyperplanes in a high-dimensional space, which divides the classes in an effective way to differentiate the spectral features

of wheat crops. Both radar and optical satellite imagery form Sentinel 1 and 2 were used as the base dataset to process the data and extract wheat fields using GIS and SVM. Field trip data of wheat farms were used as training points to the SVM algorithm for wheat classification, and also the generated wheat maps were validated by the ground truth data. SVM algorithm from ArcGIS Pro was applied as the primary classification technique to discriminate wheat fields from other land cover types, which employs a Radial Basis Function (RBF) kernel by default (Eq. 1 and 2). SVM is a supervised machine learning method that classifies data by constructing optimal separating hyperplanes in a multi-dimensional feature space. The input features were derived from combined Sentinel-1 radar backscatter and Sentinel-2 optical bands, including vegetation indices, which enhanced the separability of crop classes. A set of representative training samples was collected during field surveys and used as ground truth for model training, while independent validation samples were applied for accuracy assessment. By learning the spectral and backscatter characteristics of wheat compared to other crops and surfaces, the SVM produced the final wheat distribution map for the study area. The outcome of the study were compared with the existing maps of authorities to analyse the difference between each other. The popularity and accuracy in effective image classification, made SVM a comprehensive algorithms that applied in this research to generate accurate wheat mapping in Zakho district [25].

$$f(x) = \text{sign}(\Sigma_i \, \alpha_i \, y_i \, K(x_i, x) + b) \quad (1)$$

$$K(x_i, x_j) = \exp(-\gamma \, \|x_i - x_j\|^2) \quad (2)$$

Where α_i are the Lagrange multipliers, y_i are the class labels (wheat and non-wheat), $K(x_i, x)$ is the RBF kernel function, b is the bias term, and γ is the kernel width parameter that controls the influence of individual training samples.

2.3.1. Normalized Difference Vegetation Index (NDVI)

NDVI (Eq. 3) is one of the most commonly used spectral index for different types of applications which is based on optical remote sensing data, such as Landsat and Sentinel-2 satellite. NDVI is achieved by using only the red (RED) and near-infrared (NIR) bands, the formula is the following [26]:

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (3)$$

The values of NDVI is in range from -1 to 1, the higher values means healthier and more vigorous vegetation and vice versa (Fig. 3). NDVI is effective and useful in crop classification, which gives valuable information related to dense vegetation areas, offering significant insight to classify wheat fields from non-wheat areas. Having high spatial resolution and frequent revisit times, sentinel-2 is one of the effective and valuable resources which offers accurate and timely NDVI data to assess and analyse the detailed stages of wheat growth and monitoring crop health. NDVI significantly detect the changes in wheat fields which effectively helps the wheat classification in accurate and reliable way [27].

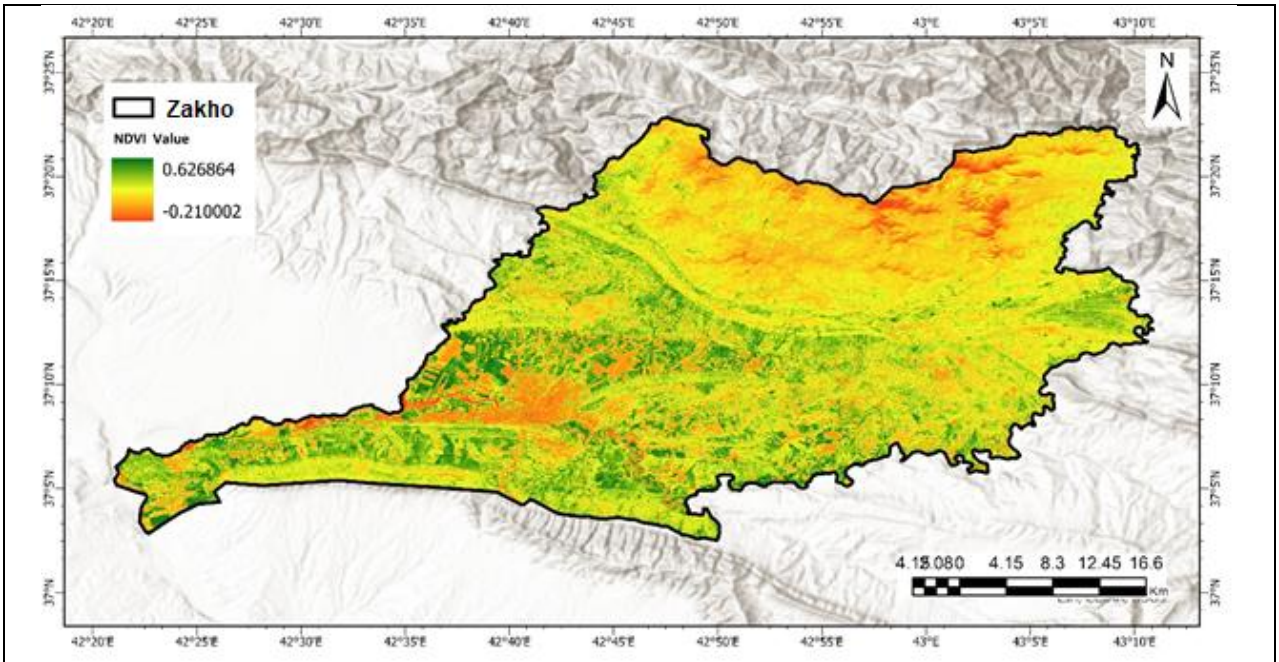


Fig. 3. NDVI map of the study area for 2023, generated from Sentinel-2 bands. The NDVI was employed as one of the key criteria in the classification process, used in combination with other optical and radar bands to support wheat discrimination. In the map, greener areas indicate higher vegetation density and vigor, while yellow to red areas represent lower vegetation cover.

2.3.2. Ratio Vegetation Index (RVI)

Another significant index that derived from Sentinel 2 imagery is the Ratio Vegetation Index (RVI), which can be achieved using the simple ratio of the reflectance in the NIR band to the RED band [28], (Fig. 4):

$$RVI = \frac{RED}{NIR} \quad (4)$$

The RVI, in some ways, is similar to NDVI but it give different information related to the conditions of the vegetation cover. RVI specifically is effective in differentiating the degree of vegetation density, which by integration with NDVI enhances the overall accuracy of crop classification [29].

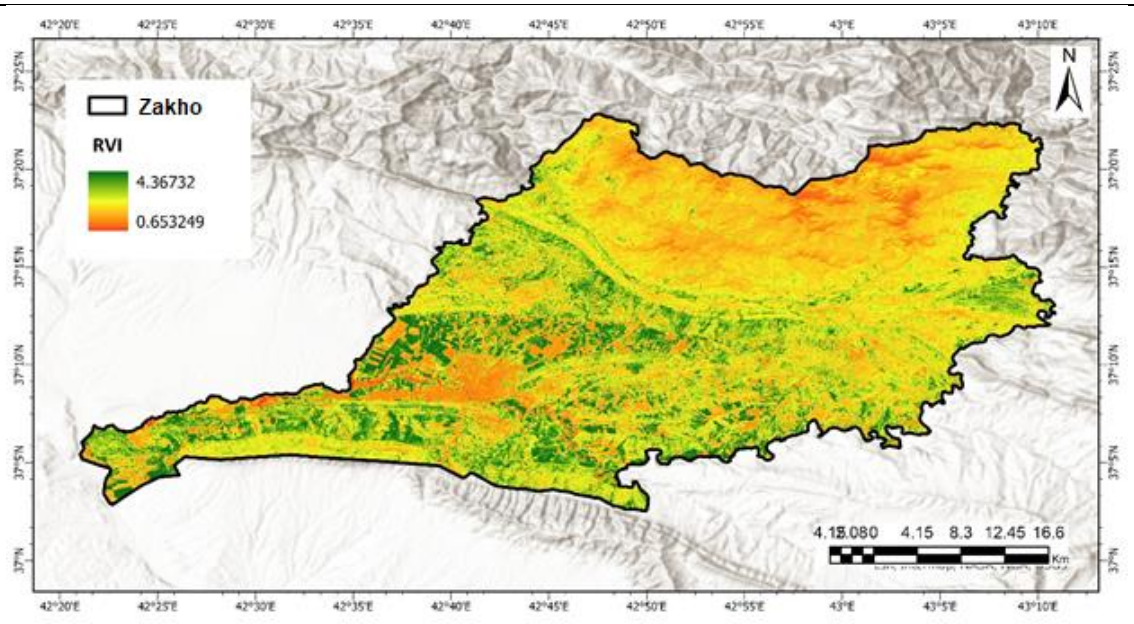


Fig. 4. Ratio Vegetation Index (RVI) map of the study area for 2023, derived from Sentinel-2 imagery using the ratio of reflectance in the red and near-infrared (NIR) bands. The RVI was integrated with NDVI, other optical indices, and Sentinel-1 radar bands as part of the composite dataset, which was then used in the classification process to improve wheat mapping accuracy.

2.3.3 VV and VH Polarimetric Data

Multiple researches used the combination of optical and radar imagery to enhance the accuracy of crop classification [30 and 31]. The recent innovations and availability of different types of data freely available, significantly improved the accuracy and reliability of crop classification. Sentinel-1 as synthetic aperture radar (SAR) provides high resolution radar satellite imagery by both Vertical-Vertical (VV) and Vertical-Horizontal (VH) polarizations, which are significant for agricultural assessments, especially for areas where optical imagery are not available. VV polarization detects the signals transmitted and received vertically, which is highly sensitive to the orientation and different types of structures of vegetation, providing valuable information for vegetation type identification and biomass analysis. However, VH polarizations means the recording the signals transmitted vertically and received horizontally, which is sensitive to the roughness and moisture content of the surface, giving significant data related to the condition of the crop types. VH is significant for wheat classification using the information recorded related to the surface roughness and moisture conditions. By using both VH and VV bands in Sentinel 1 which have 10 meter resolution, integration with NDVI, RVI form Sentinel 2 imagery, a comprehensive dataset will be created that provides valuable information related to the spectral and structural characteristics of the wheat areas. This approach significantly enhance the accuracy of wheat classification and mapping [32].

3 Results and discussions

The results of classified wheat map using SVM indicated that there are 126486.07 donum of wheat in Zakho district in 2023, which is 9.2% of total area of Study area. The dataset from directories in Zakho estimated the wheat area as 126000 donum, and the result of wheat classification in this study found it to be 126486.07 donum, which indicates the high accuracy of the approach with substantial compatibility. Also the accuracy of the wheat map were assessed by using the collected data's of wheats and the result was 95%. The evaluation of the generated map (Fig. 5) showed that the methodology that have been used in this study is effective and accurate to create wheat and non-wheat map. The outcome of this study with effective integration of optical and radar imagery significantly contribute to the challenges faced by

Zakho farmers and provide valuable information related to the wheat fields for policymakers, local authorities, and farmers.

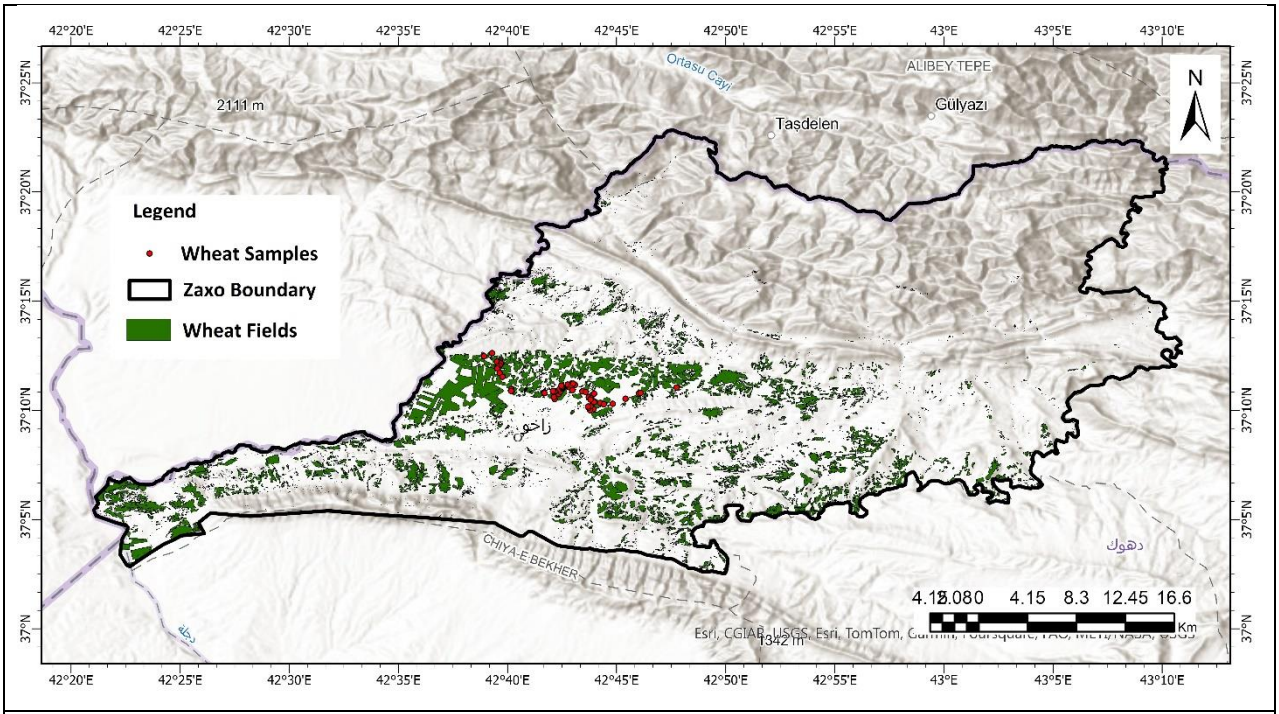


Fig. 5. patial distribution of the classified wheat fields in Zakho district, generated through Support Vector Machine (SVM) classification using integrated Sentinel-1 radar and Sentinel-2 optical datasets from the 2023 wheat growing season. The map highlights the final output of the wheat mapping process developed in this study, where other crop types and land cover classes were excluded to focus solel y on wheat.

The used methodology in this research not only offers the immediate solutions for the challenges faced by local farmers but also to develop an effective and reliable framework for future agricultural assessments and resource distribution. This approach will support sustainable development goals and the agricultural community in Zakho district, also offering significant insights for policymakers and agricultural authorities in the region.

However, despite the recent innovations in algorithms for wheat and crop classification, there are significant limitations in literature for effective and more accurate generation of crop field identification. Not having the accurate ground truth data related to the fields is one of the main limitations which significantly contribute to the reliability of the generated results. Furthermore, the existing literature focuses solely on technical aspects of remote sensing and machine learning, and there are very limited consideration of the socio-economic impacts of accurate crop mapping. More studies are needed that highlight the significant role of wheat maps on resource allocation, decision making, and the economic situations of local farmers [33].

4. Conclusion

This study achieved its primary objective of generating accurate wheat map for the Zakho district by integrating Sentinel-1 radar and Sentinel-2 optical satellite imagery with SVM machine learning classification. Classification results identified 126,486.07 donums of wheat fields in 2023, representing 9.2% of total district area, with overall accuracy of 95% validated against field-collected ground truth data. The classified wheat area closely matched official agricultural directory records of 126,000 donums, further confirming reliability of the adopted methodology. The findings demonstrate that integration of multi-source remote sensing data with GIS and machine learning techniques provides cost-effective and

reliable approach for accurate crop mapping particularly in geopolitically complex regions where traditional field surveys are restricted due to security concerns. The generated wheat maps serve evidence-based tools to support rights of Zakho farmers, promote equitable resource allocation, and inform decision-making by local authorities and policymakers. This study establishes replicable framework that can be extended to other agricultural regions in Kurdistan Region and Iraq for future crop mapping and agricultural resource management.

The implication of the outcome of this research provide valuable insights for policymakers and local administration related to agricultural resource management. The study also sheds light on the impact of inaccurate wheat mapping that have negative impact on the economy of the region. The research suggest the regular implementation of accurate crop mapping to support policy decisions and resource allocation.

5. Recommendation

Developing a standardized protocol for remote sensing, GIS, and machine learning techniques integration in agricultural assessments across the Kurdistan region would ensure consistency and reliability in future mapping efforts. More significantly, establishing a collaborative platform between local administration, agricultural authorities, and farmers could further increase transparency and fairness in resource allocation. Future research are suggested to incorporate feature importance and sensitivity analysis to quantify individual and combined contributions of each input variable, including NDVI, RVI, VV, and VH polarisation, to overall classification accuracy. This would help identify most influential features for wheat discrimination and determine whether certain inputs can be excluded without compromising classification performance, ultimately leading to more efficient and optimised classification framework for agricultural mapping in Kurdistan Region.

Moreover, future research could extend this methodology to other agricultural regions in Iraq and the broader Middle East, potentially investigating the application of deep learning algorithms for even more accurate crop classification. Crop yield estimation by developing predictive models based on the integrated remote sensing approach could provide valuable insights for agricultural planning. Furthermore, exploring the use of high-resolution drone imagery to complement satellite data could enhance small-scale farm mapping capabilities. This study not only addresses the immediate challenges faced by Zakho farmers but also establishes a scalable and reliable framework for agricultural mapping and resource management. By leveraging advanced technologies of machine learning and remote sensing techniques, it paves the way for more equitable, data-driven decision-making in agricultural policy. Ultimately, this approach contributes significantly to the sustainable development and economic stability of the region, offering a model that could be adapted and implemented in similar contexts worldwide.

Declaration of interest's: 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.

Data Availability: The data used in this research are available from the corresponding author upon reasonable request.

Author Contribution: M.M.G was responsible for data curation. K.C led the conceptualization and methodology, performed the formal analysis and visualization, and was responsible for writing the original draft, reviewing and editing the manuscript.

Funding: This research received no external funding.

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