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Assessing the Classification of Land Use and Land Cover Using Dual Polarization (VV, VH) Radar Data: An Analysis of the Kirkuk Governorate in Iraq

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Abstract

The purpose of this study is to investigate the performance of Sentinel-1A satellite dual-polarization radar data for land use land cover classifier in Kirkuk Governorate, northern Iraq. The area encompasses urban, agriculture and semi-arid plains with complex topography, so that traditional optical remote sensing methods are largely paralyzed by frequent dust storms and cloudiness. Two machine learning algorithms, Density Tree K-Nearest Neighbors (DT-KNN) and Random Forest (RF) were applied to enhance classification accuracy. The results indicated that the RF classifier obtained an accuracy of 98% for classification of the urban class and 99% for the DT-KNN classifier. Largely superior to DT-KNN while performance a relatively weaker for urban classes classifier, the robustness of RF to classify various land cover classes, as rocks and vegetation show, can be noted. But all of these classifiers had a problem when it came to certain categories, for example, rock areas being classified as urban land. This research shows that SAR data combined with machine learning can well remediate the lack of accurate optical data for land use and land cover classification in the spatially homogeneous regions, which are conducive for new era of smart farming and urban planning, especially in these complex terrains. It also means that there is a need for research regarding complementary models, to increase the classification accuracy in such

complex environments.

Keywords: LULC classification, SAR Data, Dual Polarization, VV, VH, DT-KNN, RF.

1. Introduction

The use of Dual-polarization radar data is one such component that helps tackle the challenge of land-use/land cover (LULC) classification in scenes like Kirkuk, Iraq(Shareef et al., 2020) (Amer et al., 2024) . Thus, having explored the research into remote sensing data for the past months I have realized that this technology provides a tremendously valuable resource to monitor environmental change, urbanization and land management. Its continuous, comprehensive coverage of the Earth's surface at these large spatial scales is critical for monitoring changes in land use and land cover over time. With the expansion of cities and shifts in farming practices and ecosystems, it is important to study these transitions (Moussaid et al., 2023). On the other hand, Optical remote sensing has been widely used for soils erosion and pollution detection however, it will face many challenges primarily in those areas resembling the northern Iraq in which frequent storms, high winds and cloud cover propensity stop optical imagery. These phenomena could negatively impact the performance of optical sensors. To address these challenging heights, synthetic aperture radar (SAR) is an effective second choice. Optical the front-quit devices that depend on daylight are visible. Synthetic aperture radar structures radiate chemical indicators and degree the go back sign (go back). This ability to operate across borders at any time of day renders synthetic aperture radar (SAR) especially valuable for monitoring changes in soil cover in areas where optical sensors are unmatched(Shao et al., 2017) , launched with the support of European Space Agency (ESA), the Sentinel-1 satellite project provides C-band SAR statistics in dual-polarization (VV and VH) modes. A closer view of the data sources for dual-polarization, showing that these can provide much more information about the irradiated area on ground level(Mohammed et al., 2024) . VV polarization is sensitive to surface roughness and urban systems, whereas VH polarization captures volume scattering, which is commonly linked with plants. SAR statistics by(Ali et al., 2024) merging each VV and VH polarizations, enables extra detailed details on land floor traits , which makes it be a helpful device for utilizing LULC sort(Ali et al., 2024).

Kirkuk, Iraq is of particular interest due to its diverse types of landscapes including urban areas, croplands, oil fields and grasslands. Both the complexities of the environment and frequent mud storms create a challenging terrain for plate style(V. F. Salahalden et al., 2024). This study utilizes two/used polarized Sentinel-1A SAR imagery in order to evaluate the dynamics of land use/land cover (LULC) types within Kirkuk province, Iraq. Thus, developed targets to boost up the picking out accuracy using moving progressive computing device studying algorithms similar to as DT-KNN and RF, extremely engaging in contemplating excessive dimensional manner generated with the help of SAR sensors(Hasan et al., 2024; Hassan et al., 2019) .

For SAR the data were pre-processed with methods including radiometric correction, noise reduction and DEM (Digital Elevation Model) based geometric corrections. The pre-processing procedures have been critical in improving the quality of the records and for measuring accurate class impacts(Hasan et al., 2021) . Using specifying strategies, this look at grants important insights into ability of SAR records for land tracking and ecological monitoring in locations wherein traditional optical information might be constrained or unreliable (Javan et al., 2025). Sentinel-1A data would be advantageous for sustainable land use practices and planning strategies in severe conditions as well such as those in Kirkuk (see e.g. (Hasan et al., 2021)).

This study attempts to bridge this gap by evaluating the potential of Sentinel-1A dual-polarized SAR data for LULC classification under diversified terrestrial domains (urban, agriculture and semi-arid plains in Kirkuk Governorate-Iraq. This work follows the growing trend of using complementary data to train ML models, which is a leap from prior studies (mostly based on either optical or single-polarization SAR) by providing richer information at VV and VH polarizations. This work primarily focused on the ability to facilitate Sentinel-1A dual-polarimetric synthetic aperture radar (SAR) data combined with state-of-the-art machine learning algorithms, such as Random Forest (RF) and Density Tree K-Nearest Neighbors (DT - KNN), in improving classification accuracy above this

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problematic region. The study thus contributes valuable knowledge about SAR-based LULC classification performance for supporting sustainable land governance and urban development monitoring in environmentally compromised areas.

2. Study Area

The study is situated in of Kirkuk governorate, placed in the northeastern part of Iraq, encompassing an area of 1,475 km². Geographically, it spans from 44°00′E to 44°50′E in longitude and 35°13′N to 36°29′N in latitude. This place became selected for its various and consultant landscape, which includes a number of land covers along with city regions, naked land, vegetation, exceptional soil kinds, water our bodies, and grasslands(V. Salahalden et al., 2024).

Kirkuk city, located inside the governorate, become selected as the focal point of the take a look at because of its strategic position among the northern mountainous regions and the flatter, greater arid areas to the south and southwest. The metropolis isn't always most effective essential because of its geographical location however also because it is wealthy in herbal assets, particularly oil and minerals(Nozad & Shareef, 2025). Additionally, Kirkuk is situated in one of the higher elevation zones in Iraq, similarly contributing to the diversity of its physical and climatic conditions. This aggregate of herbal functions makes the place a great candidate for inspecting land use and land cover modifications within the context of its precise environmental and climatic situations(Parzhen et al., 2024).

Kirkuk was selected as the study area because of its complex landscape (urban, cropped and semi-arid areas) which make this area more difficult to study using the optical RS technology. Sampling was performed randomly and systematically with incorporation of reference data over the region to represent all LULC classes. Additionally, the data sampling aligned with seasonal trends to streamline classification performance.

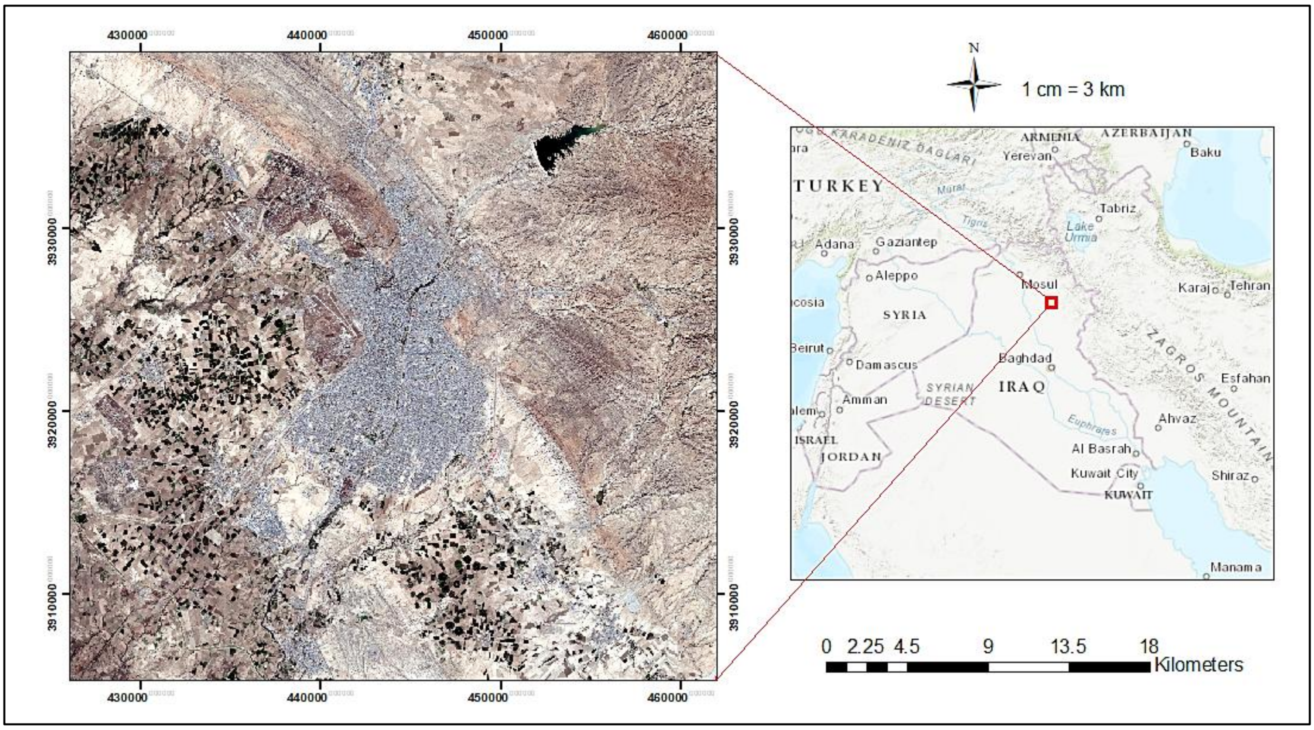

Figure (1). Area of study.

3. Description of Satellite and Reference

Sentinel-1A SAR images were used to map the wide LULC of the study area. Sentinel-1 sensors from the European Space Agency provided dual-polarized C-band SAR data in four acquisition modes (ESA 2017).

Table (1). Abstracted Metadata SAR data used in the study

Name	Value	Type	Unit	Description
Swath range	IW	ASCII	-	Swath name
The polarization	VH, and VV	ASCII	HZ	Polarization
The annotation	sla-iw-grd-vh-vv,	ASCII	-	Metadata file
Band names	Amplitude_VH	ASCII	-	Corresponding bands
First line time	03-FEB-2025 03:02:15.315244	uint32	utc	Doppler azimuth, First zero
last_line_time	03-FEB-2025 03:02:42.633541	uint32	utc	Doppler azimuth, Last zero

Satellite data used in this study is downloaded from the Copernicus Open Access Hub that provides free access to all Sentinel mission data. Two SAR datasets were obtained from Sentinel-1A and the pre-processing was performed differently(ESA, 2017). Data were radiometrically corrected by converting VH and VV polarization to radar backscatter (sigma 0), using the method of Miranda (Miranda, 2015). Geometric correction was performed to convert the slant range to a coordinate system on the ground. We also applied the Doppler correction to minimize the geometric distortions using a 30-meter resolution Digital Elevation Model (DEM) from SRTM (El Hage et al., 2022). Through applying the multi-temporal Lee filter with a 3x3 pixel window, we eliminated noise in radar images. February 2025 -- Reference data for supervised classification were collected during February 2025, and produced training/testing data for the accuracy of the classification(Fan et al., 2021). These datasets were built with GPS scopes and higher-res aerial photos. Training and examining data were derived from visually identifying nine LULC classes through Google Earth. Sampling techniques employed ensured random and representative distribution of data across the study area.

4. Methods

To achieve the goals of this study, several procedures were used to process and classify the remote sensing images. These procedures were necessary to determine suitable methods and obtain relevant information to decide upon the proper approach as shown in figure (2).

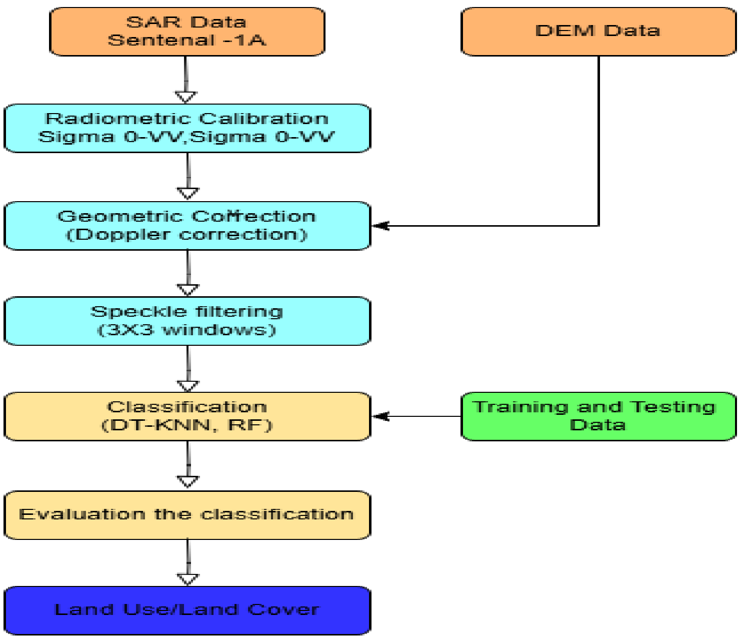

Figure (2). Flowchart of LULC mapping methodology.

4.1. LULC classification algorithms:

Numerous image classification algorithms have been employed and mentioned in the literature. These algorithms can be widely described as either supervised and unsupervised classification (Schmarje et al., 2021). In this study two types of classification algorithms were used: one to look for KD Tree KNN classifier and second is random forest in order to retrieve the performance of the diverse set of classification techniques (Lin et al., 2021).

RF is a set learning method that creates multiple trees based on irregular bootstrapped examples in the training data. The nodes are divided using the optimum split variable from a group of randomly selected variables(Salman et al., 2024). This approach is robust against over-fitting and can manage thousands of dependent and independent entering variables without any deletion of variable. The output is specified by a maximum vote for the classification tree (Chaibi et al., 2022).

However, the KD Tree KNN classifier should produce the same outcome as the slow KNN classifier while using a KD Tree to increase performance (Tiwari, 2023). A k-d tree is a space-partitioning data structure for organizing points in k-dimensional space. The k-d trees are an appropriate data structure for various applications, notably searches containing a multidimensional exploration key (e.g., nearest neighbour or range searches). The k-d trees are specific cases of binary term partitioning trees and can be shown to be a generalization of other spatial tree structures (Brown, 2022). We process the raw data (images of both sides VV and VH) and divide it into training set and testing set. Subsequently, the main parameters of the algorithms were defined (e.g., for Random Forest, number of trees: 100; and K-NN algorithm, number of neighbours = 5; distance metric). Next, the models were calibrated based on the training set and the calibrated models predicted the test set. They evaluated the models by accuracy, precision and recall. Ultimately, an LULC classification map was created based on persistence of obtained results.

5. Accuracy Assessment

Whenever working with machine learning models like RF and KNN for classification tasks, the classifier's performance is evaluated using the following performance evaluation metrics: accuracy, precision, TP, and FP (Al-Hashem et al., 2021).

5.1. Performance Metrics for KNN and RF Classifiers:

5.1.1. Accuracy:

The percentage of accurate predictions the classifier makes out of all guesses is known as accuracy. It provides a general indicator of how well the classifier can classify cases. The accuracy equation is:

$$Accuracy = (True\ Positives + True\ Negatives) / Total\ Instances \tag{1}$$

Here, True Negatives (TN) are accurately anticipated negative cases, and True Positives (TP) are accurately predicted positive examples (Al-Hashem et al., 2021).

5.1.2. Precision (KNN and RF):

The percentage of accurate positive predictions among all the classifier's positive predictions is known as precision. Reducing false positives is crucial. The precision equation is:

$$Precision = True\ Positives / (True\ Positives + False\ Positives) \tag{2}$$

where False Positives (FP) are positive cases that were predicted incorrectly, and True Positives (TP) are positive instances that were forecasted correctly (Al-Hashem et al., 2021).

5.1.3. True Positives (TP) (KNN and RF):

The number of cases that the classifier properly identified as positive is known as True Positives (TP).

5.1.4. False Positives (FP) (KNN and RF):

The number of cases that the classifier misclassified as positive is known as False Positives (FP).

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5.2. Change in Performance Metrics (Δ Accuracy, Δ Precision, Δ TP, Δ FP):

5.2.1. Δ Accuracy (Change in Accuracy):

The difference in accuracy between two models, configurations, or performance stages is denoted by Δ Accuracy. It is computed as follows:

$$\Delta Accuracy = Accuracy_{new} - Accuracy_{old} \tag{3}$$

Where: $Accuracy_{new}$ is the accuracy of the new model or configuration and $Accuracy_{old}$ is the accuracy of the old model or configuration.

5.2.2. Δ Precision (Change in Precision):

Δ Precision represents the change in Precision between two models or configurations. It is calculated as:

$$\Delta Precision = Precision_{new} - Precision_{old} \tag{4}$$

A positive value indicates an improvement in precision, meaning fewer false positives(James et al., 2023).

5.2.3. Δ TP (Change in True Positives):

Δ TP represents the change in the number of true positive predictions between two models or configurations. It is calculated as:

$$\Delta TP = TP_{new} - TP_{old} \tag{5}$$

A positive value indicates that the new model has correctly identified more positive instances.

5.2.4. Δ FP (Change in False Positives):

The difference in the quantity of false positive predictions between two models or configurations is denoted by Δ FP. It is computed as follows:

$$\Delta FP = FP_{new} - FP_{old} \tag{6}$$

The revised model has decreased false positives if the value is negative(Bakshi et al., 2021; S.F.Hasan, 2025).

6. Results and Discussion

6.1. Classification of Sentinel-1A data:

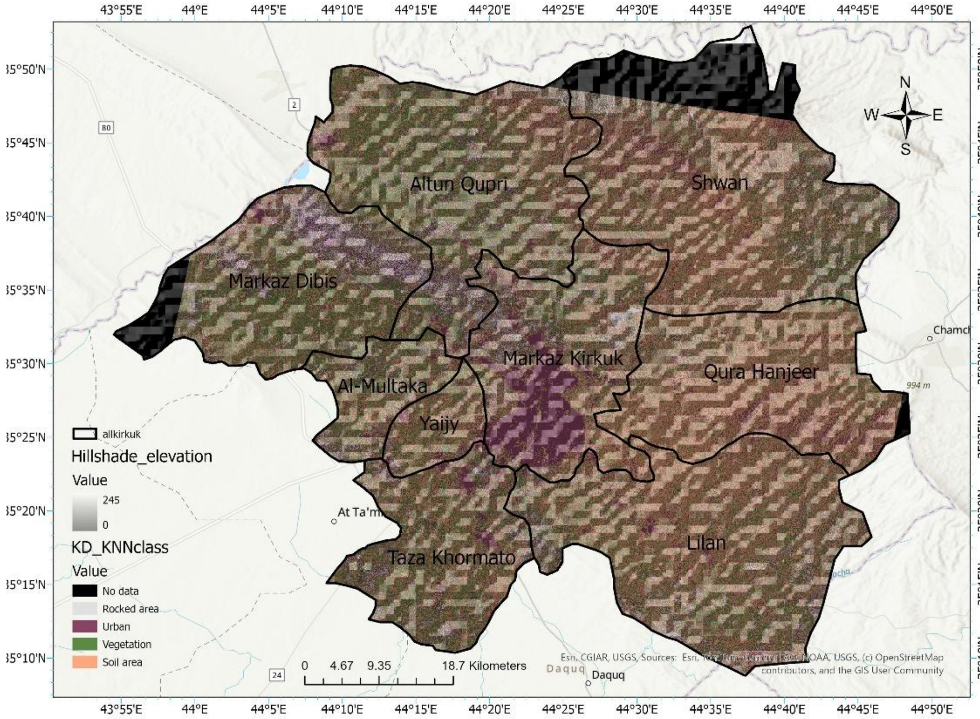

Figure (3). Classification of LULC Using KD-KNN classifier

The classification process was based on radar satellite imagery, specifically using VV and VH polarization data, for the study area. The data was utilized according to the administrative boundaries of the study area, which included the center of Kirkuk and its surrounding districts, such as Lailan, Al-Tun Kubri, as well as the sub districts of Qura Hanjeer, Taza khormato, Al-Multaqa, and Yayji, in addition to the district of Dibis and shwan. The study area was classified into three principal categories: urban areas, vegetation, and soil regions. While additional subcategories were present, only the three main classes were selected due to the primary objective of evaluating the classification method's performance based on the data type used. A digital elevation model (DEM) was employed to facilitate the classification operations on the satellite images for both classifiers, as shown in Figures 3 and 4. Figure 3 presents the land-use classification results for the city of Kirkuk using KD-KNN classifier. The features are generally distinct; however, some overlap between the categories is apparent. For instance, regions in the northern part of Kirkuk, characterized by hilly and mountainous terrain with high elevations, were mistakenly classified as urban areas. This misclassification is particularly evident in the northern part of Kirkuk. Similarly, certain agricultural areas in the southern part of the study region were incorrectly classified as soil areas.

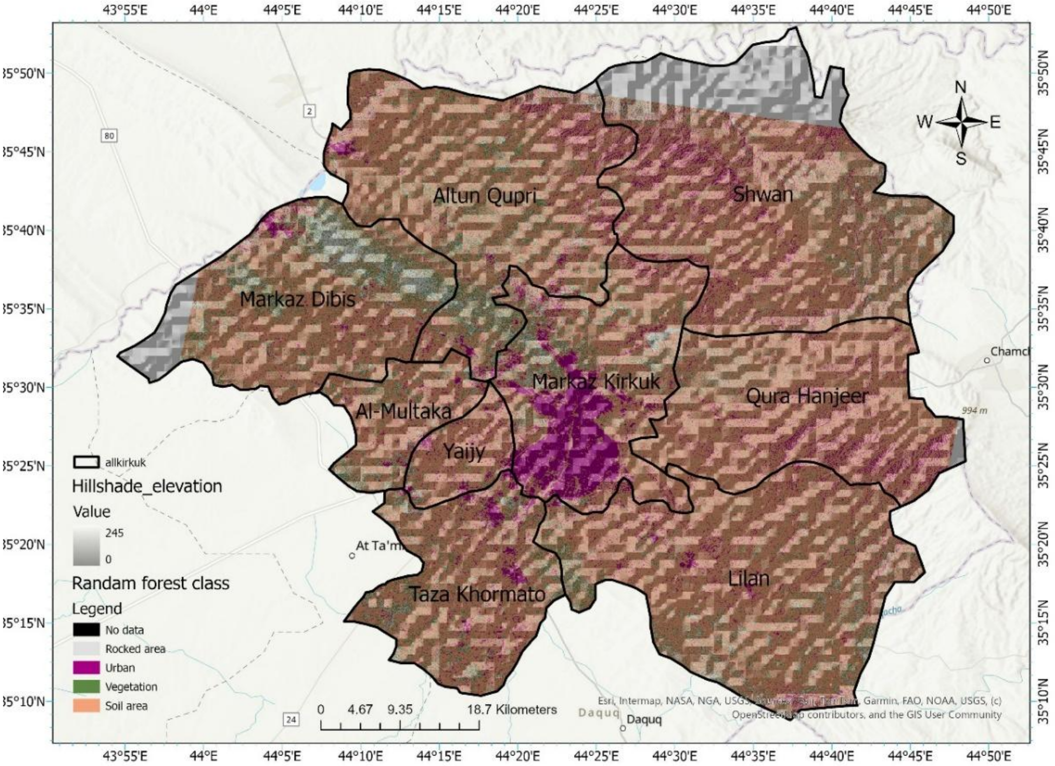

Figure (4). LULC Using RF classifier

An example of land-use types classification results using random forest classifier is shown in Figure (4). Some soil in the north-eastern and southern parts were mistakenly classified as urban zones. In addition, the northern western part of city identified as hill strip, define as vegetation or green areas. Furthermore, several study zone regions were incorrectly identified as soil regions in C-band radar satellite data. It is essential to highlight that the image classification process was carried out using both VH and VV polarization types, serving as a means to evaluate the performance of both classifiers applied to this type of radar satellite data.

6.2. Evaluation of the classification:

The primary goal of evaluating classification in C-band radar satellite images is to analyse the accuracy of classifying different land cover types using these images, focusing on improving performance and verifying the results against ground truth data. This includes examining the impact of environmental factors like terrain and weather conditions, analysing overlaps between classes, and helping to identify future applications for enhanced monitoring of land-use changes. The classification evaluation process is carried out by calculating the accuracy metrics for the classifiers used, through the analysis of class-wise performance using cross-validation techniques for classifiers such as KNN and RF, as presented in the Tables (2), (3) and (4). This includes:

1. Class-wise performance: Evaluating the accuracy for each class using cross-validation for different classifiers.
2. Overall testing metrics: Calculating overall performance metrics such as accuracy, recall, and F1-score for the classifiers used.
3. Feature importance: Determining the importance of each feature in classification based on feature importance scores for classifiers such as KNN and RF.

Table (2). Class-wise Performance (Cross Validation) for KNN and RF classifier

Class	Accuracy (KNN)	Precision (KNN)	TP (KNN)	FP (KNN)	Accuracy (RF)	Precision (RF)	TP (RF)	FP (RF)	Δ Accuracy	Δ Precision	Δ TP	Δ FP
Rock area	0.5126	0.2636	423	1177	0.7984	0.4961	510	518	0.2858	0.232	87	-659
Soil	0.8497	0.6752	631	304	0.8902	0.7125	756	305	0.0405	0.037	125	1
Urban	**0.9954**	0.9890	979	11	**0.9820**	**0.9587**	951	41	-0.0134	-0.030	-28	30
Vegetation	0.8376	0.6374	628	358	0.8622	0.6652	626	315	0.0246	0.027	-2	-43
Water	0.8571	0.6502	680	357	0.8600	0.6534	639	339	0.0029	0.003	-41	-18

Table (3). Overall Testing Metrics for KNN and RF classifier

Metric	KNN	Random Forest	Difference (RF - KNN)
CorrectPredictions	66.3800	69.6400	3.2600
Total Samples	10000	10000	-
RMSE	1.0465	1.6838	0.6373
Bias	-0.0636	-0.0440	0.0196

Table (4). Feature Importance Scores for KNN and RF classifier

Feature	TP (KNN)	TP (RF)	Accuracy (KNN)	Accuracy (RF)	Precision (KNN)	Precision (RF)	Correlation (KNN)	Correlation (RF)	Gain Ratio (KNN)	Gain Ratio (RF)
Sigma0_VH	0.7723	0.5853	0.3096	0.2341	0.5382	0.5092	0.6992	0.6651	0.4391	0.4588
Sigma0_VV	0.7679	0.5765	0.2996	0.2306	0.5585	0.528	0.6904	0.6572	0.4572	0.4783

From tables above the detailed comparative analysis includes:

1. Model Strengths:

KNN excels in Urban classification, achieving nearly perfect accuracy and precision. It's well-suited for classes with clearly defined patterns. Random Forest handles Rock area much better than KNN (accuracy jumps from 51.26% to 79.84%), suggesting its strength in dealing with complex or overlapping features.

2. Generalization:

Random Forest is more generic, as it achieves equally good performance across all classes. KNN is sensitive to variability, especially for Rock and Vegetation classes.

3. Errors and Bias:

KNN has the lower RMSE which indicates its predictions are closer to true values but not general pattern. Furthermore, Random Forest's bit lower bias (-0.0440 vs - 0.0636) suggests that is a bit better for systemic error minimization.

4. Feature Sensitivity:

RF outperforms with gain ratio and accuracy, while both rely on similar models. RF's tree-based structure might enable RF to exploit non-linear relationships that KNN cannot.

5. Application Suitability:

Urban is a class which can be separated well, therefore KNN works best in this scenario due to its high precision and low error. When it comes to generalization, Random Forest is your best bet for stable performance across a large range of land covers. If you want to take advantage of both benefits then consider ensemble or hybrid models. RF accuracy varies for the other LULC classes, which was reflected in both classification results and accuracy indices. Specifically, the RF classifier proved to be very effective in discriminating urban regions, with an overall accuracy of 0.98 for urban classes and a precision of 0.95. Its performance varied for other classes, however, with accuracy increasing for soil types (0.89) and decreasing for rock regions (0.79). Similarly, the precision scores in the vegetation and water classes revealed high class consistency as well. However, the Accuracy on K-Nearest Neighbors (KNN) was 0.99 where this method proved to take correctly metropolitan areas more often than others. Unlike RF, KNN appeared to perform poorly in other metrics, indicating it might struggle to handle more complicated or heterogeneous land cover types.

These findings identify KNN as a strong contender for high accuracy within specific categories (such as urban areas), with poor performance in other land cover classes.

areas from surrounding land covers like soil or vegetation. Small urban features, especially in rural or developing areas, may be mixed with the land type in their immediate surroundings which causes misclassification. And (3) Classifier Restrictions: Both the Random Forest and DT-KNN classifiers use the features of the radar data, for example, the backscatter intensity. Even though RF seems to be powerful in interpreting high-dimensional characteristics, both classifiers may have limited prediction capability at the mixed areas with fuzzy land cover types or where radar signature of one type is blended with that of other classes, e.g., heterogeneous environment as semi-arid plains. Additionally, it has a dependency on nearest neighbors which can create ambiguities in geographies with multiple landcovers. This would help further mitigate this issue, the paper could include error maps or sample images to observe where and how misclassification occurs. For instance, plotting a map of those urban and rock areas that are misclassified would highlight where the spatial distribution of those errors originates from. Similarly, a closer look at the feature importance of classifiers may suggest which (combinations of) features (e.g., polarization channels or geometrical patterns of the radar image) were misguiding the classification.

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7. Conclusion

The study is using dual-polarization (VV and VH) SAR along with LULC data retrieved from Sentinel-1A to inspect a good way of classifying Land use land cover on this rugged/desolate geography of Kirkuk/Iraq. This research demonstrates the potential of synthetic aperture radar (SAR) data to overcome optical sensor limitations in regions dominated by persistent dust storms or cloud formation using machine-learning classifiers, particularly random forest (RF) and density tree k-nearest neighbors (DT-KNN). SAR data pre-processing (geometric correction, removing noise and radiometric calibration) is needed to improve the quality and accuracy of classification. According to the study, the RF classifier is outperforming all comparisons with a below-2% error at classifying metropolitan areas. It also performed well with complex land-cover variables such as vegetation and rock areas. While DT-KNN was nearly perfect on old land cover (the most basic class), it did poorly on more complex classes. These results highlight the versatility of RF for a wider range of classes of LULC, and indicate that it is a more robust approach for areas with differing cover types. These results indicate that Sentinel-1A SAR data play an important role in providing accurate and consistent land cover information where optical imagery may be subject to error. These results support the utility of SAR-integrated methods in land management, urban planning and environmental monitoring in arid settings. To improve upon classification performance yet again and generate the utility of equally both classifiers across a generality of geographic spaces, future work should focus on hybrid or ensemble models which encapsulate what is beneficial about either classifier. The findings of this study showed the potential ability of Sentinel-1A dual-polarized SAR data for LULC classification in Kirkuk area, where is a complex environment but declare some important limitations for further studies should be considered. A primary limitation is that certain aspects of some land covers cannot be accurately resolved in synthetic aperture / microwave (SAR) data because of low detail resolution; e.g., urban areas and neighboring rocks or soil. SAR data includes the complementary information to optical images, however, SAR operating independently causes errors while distinguishing regions that are governed by same classes of land cover or have complex terrain [35]. These issues need further investigation to be resolved, and ensemble techniques which can take advantage of the multiple classifiers can be applied for a good increase in accuracies. Aims: Though the individual use of optical and SAR is not new, the combined effect provides redundancy in information (more than one factor can help determine the land cover types) thereby helping reduce topography/spatial resolution impact on accuracy. Furthermore, the use of high-resolution data and best-in-class machine learning (ML) algorithms can improve the classification techniques to provide better insight on land use/land cover changes in land-use stress sectors.

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