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Research Article

Land Cover Change Detection in Iraq Using SVM Classification: A Remote Sensing Approach

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ABSTRACT

Land Cover and Land Use studies play an important role in regional socioeconomic development and natural resource management. They support sustainable development by tracking changes in vegetation, freshwater quantity and quality, land resources, and coastal areas. Iraq's Land Use and Land Cover Monitoring with Remote Sensing Data in the Period 2019–2023. This paper performed land use/land cover LULC type classification and time series analysis using Sentinel-2 satellite imagery for the years 2019 and 2023 to identify changes over time. Remote sensing data is used in this paper to address the challenge of detecting land cover change in Iraq through SVM classification. This goal aims to develop a fundamental method of mapping and monitoring these changes, encouraging sustainable land use practices, and achieving the United Nations Sustainable Development Goals. Land cover classes were categorized into five main types: Water, Barren, Building, Vegetation, and Rangeland. The study showed a marked increase in urbanization, and most of this occurring in previously bare soils at the edges of cities. This urbanization was primarily driven by population growth and economic development. What is beneficial for the environment can also be beneficial for us as people humanity as these findings have major implications for urban planning, green space management, and sustainable city development. It seems that there was no change to the existing barren land and buildings, which increased by 8% and 11% respectively, as noted from the data up to October 2023. However, vegetation coverage decreased by 27%, indicating a significant loss of green area. The water category was also up 9%. Results showed satisfactory accuracy assessment (OA: 93.11%) from applying a Support Vector Machine SVM for the LULC classification. The study lays the foundation for ongoing monitoring of LULC changes in Iraq.

Keywords: *Remote sensing; LULC classification Iraq environment; LULC machine learning; Geospatial Analysis SVM classifier.*

1. INTRODUCTION

Since land cover is a crucial aspect of many applications, ranging from urban planning to agricultural management and environmental conservation [1], remote sensing technologies have become increasingly powerful tools to map and assess changes in land cover. It is particularly essential in Iraq to be aware of the land cover dynamics in the country, that has experienced the complex geopolitical environment, and the influences of natural and anthropogenic factors on its natural resources [2]. This paper also addresses the issue of land cover change detection in Iraq with the Support Vector Machine classification method based on remote sensing data [3]. To learn an accurate and effective approach for mapping and monitoring land cover changes that can have a positive impact on sustainable land use and support the United Nations Sustainable Development Goals[4]. This packaging of the proposed approach exploits the strength of ML and the abundance of satellite imagery data to deliver an overview of the changing land cover in Iraq over time [5]. The trends of land use have been much altered in recent decades with rapid rate of urbanization and industrialization [3]. Being able to track these changes is essential for the sustainable use of natural resources. Satellite

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remote sensing would hold the most potential for monitoring, and for the identification of atypical land cover over large geographical areas[8]. Compared to ground surveys, satellite data offers a more efficient and rapid means of mapping and change detection of land cover, they can scan higher grounds and require relatively less resource input compared to surveying [8].Support vector machine SVM has been widely used for land cover classification based on a variety of remote sensing data over various environmental changes. In the context of this objective, SVM is one of the most attractive machine learning algorithms as it has demonstrated excellent performance in the classification of high-dimensional complex remote sensing data [7]. A previous study examines the potential of Support Vector Machine SVM classification in detecting these changes through satellite remote sensing data in Iraq [8].

2. Literature Review

The literature on land cover change detection methods involving remote sensing and machine learning techniques is significantly established. Many researchers used SVM classifiers for land cover mapping and change detection with promising results in various locations. For example:

In [2] this study presents a machine learning-based approach for mapping Land Use and Land Cover LULC in Egypt using high-resolution multi-spectral satellite imagery captured at a spatial resolution of 3 m. It employs various machine learning strategies, including Support Vector Machines, Decision Trees, Random Forests, Normal Bayes, and Artificial Neural Networks, to achieve a classification accuracy of 97.1% on a dataset of 105 geo-referenced images categorized into 8 different LULC classes. For urban land cover change detection, the study [5] uses GIS and Remote Sensing techniques, including high-resolution QuickBird satellite imagery (0.60 m), to monitor land use and land cover changes in Al-Kut city, Iraq, from 2004 to 2014. Change detection is carried out using geo-referenced images, ground control points, and ArcMap software for mapping and statistical analysis. The advantage of SVM for land cover classification was also investigated in relevant research conducted in a variety of places other than the study area, for example, in [6] evaluation of Sentinel-2 data presented for land cover/use classification, that Sentinel-2 enhances land cover/use monitoring with high-resolution data with applications in various fields, and [7] work investigated land-cover-change detection in Namyangju City, Korea based on SegNet-based semantic segmentation. SegNet achieved the highest accuracy of 91.54% compared to other models. Land-cover changes were detected between 2010 and 2012 in Namyangju city. Urbanization increased, while forest and agricultural areas decreased. The study in [8] demonstrated an SVM-based approach for time- series analysis of land cover change in Shenzhen, China from 1979 to 2022 based on the land cover map derived from multi-source urban remote sensing data based on machine learning, also provides valuable information, not only related to what contributed to the strengths and weaknesses of those SVM-based approaches using Landsat images, but also the significance of integrating multi-sensor remote sensing data for better land cover mapping. The use of machine learning for land cover classification and change detection using remote sensing data has been detailed in several related works, many of which have used SVM as their primary model, as shown above.

3. Methodology

The workflow diagram of this study can be illustrated in Fig. (1) and Algorithm 1:

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Data Acquisition: From the Sentinel-2 satellite that has a high-resolution sensor capturing at a 10-meter pixel resolution.

↓

Data Preprocessing : Performs atmospheric correction. - Applies cloud masking.
- Conducts geometric correction to ensure the data is suitable for analysis.

↓

Feature Selection : Gathers land cover reference data. - Creates a representative training dataset for the SVM classifier. - Allocates 80% of the data for training and 20% for testing.

↓

SVM Classification : - Utilizes the Support Vector Machine SVM algorithm. - Categorizes preprocessed satellite images into five land cover types: water, crops, buildings, barren land, and rangeland.

↓

Model Training : - Trains the SVM model using the collected training data.
- Optimizes the model for the study area.

↓

Accuracy Assessment : - Evaluates the performance of the SVM classification.
- Uses metrics such as overall accuracy and the Kappa coefficient.

↓

Land Cover Change Detection : - Analyzes changes in land cover by comparing SVM classification results from 2019 and 2023.

Fig.1 Workflow Diagram [9].

The SVM algorithm was applied as the task suited the high dimensional and complex data structures of remote sensing data specifically where remote sensing data was utilized [10].

Algorithm 1: Land Cover Change Detection Using SVM

Input:

- Satellite Image (multispectral raster data)
- Training Samples (labeled polygons representing known land cover classes).
- Parameters (penalty parameter **C**=100, **gamma**=0.5 , **Kernel Type**: RBF)

Output:

- Classified Land Cover Map (raster) in five classes: water, crops, barren, buildup, Rangeland.

Algorithm of SVM:

1. Loads satellite imagery into ArcGIS.
2. Collects or imports training samples for each land cover class.
3. Extracts spectral signatures from the image based on training samples.
4. Defines SVM parameters:
   - Chooses kernel function (RBF)
   - Sets penalty parameter C=100
   - gamma =0.5.
5. Trains SVM model:

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- For each pair of classes:
  - Computes the optimal hyperplane that maximizes the margin between classes
  - Solves the quadratic optimization problem
- Stores the support vectors and decision boundary

6. Classifies image:
- For each pixel in the image:
  - Extracts feature vector (e.g., spectral bands)
  - Uses the trained SVM model to assign a land cover class

7. Post-process results:
- Applies majority filtering or smoothing .
- Assesses accuracy using validation samples such as confusion matrix and kappa.

8. Exports final classified map

End

3.1 Study Area

Study area is located in the Northern part of Iraq, especially near the city of Dohuk .The area is rich in diversity in terms of landscape, including mountainous regions, agricultural fields and urban regions. This area is famous for its ancient historical places and rich cultural heritage. The GPS coordinates of study area Latitude: 36.781347° N, Longitude: 41.982362° E, and total area is 1197.732865 Km, Fig. 2 shows map of study area location[12][13].

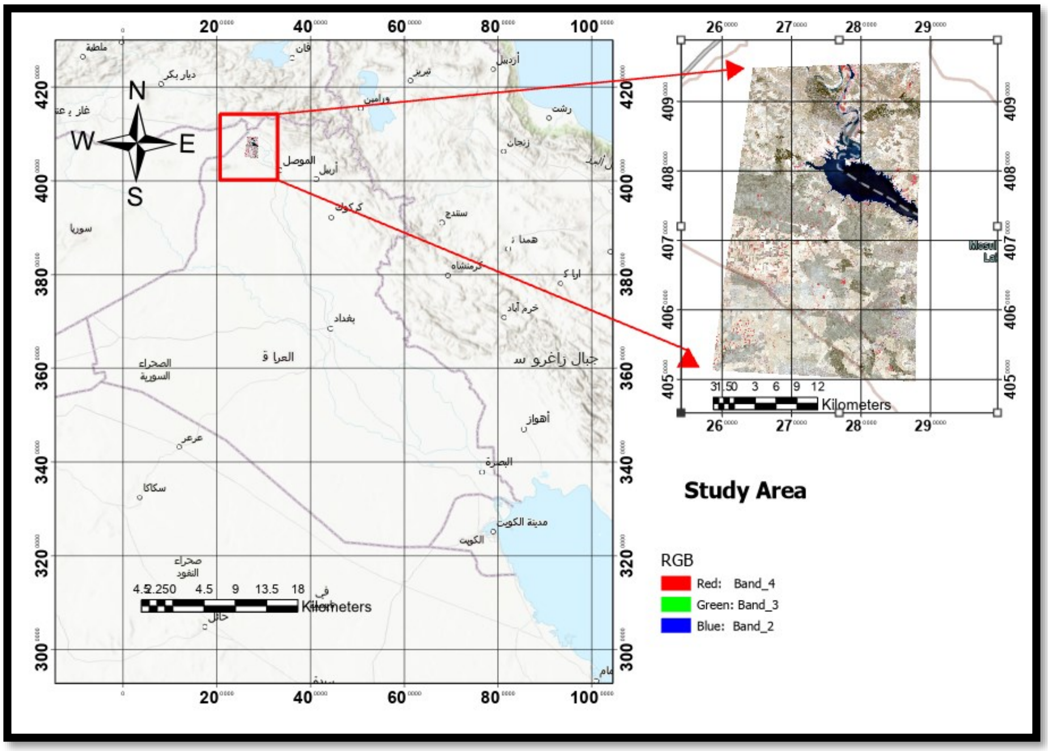

Fig. 2. Study Area in Iraq

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3.2 Dataset Collection

The dataset consists of RS imageries of study area maps from 2019 and 2023. It was extracted using Sentinel-2 from various satellite images repository like Copernicus Browser[1] [12] and Esri Land Cover[2][13], both provides access to high-resolution satellite imagery with a spatial resolution of **10 meters**. **Copernicus**, a Free and Open Access to Sentinel Satellite imagery and EU Earth observation data Satellite imaging data can help with environmental monitoring, climate research, or for emergency response. **Esri's Land Cover** Explorer utilizes high-definition satellite imagery from the Sentinel-2 mission to generate surface classification maps with a maximum resolution of 10 m [14], which can be accessed via Esri's extensive ArcGIS Living Atlas of the World.

3.3 Pre-processing

Data preprocessing is one of the most important steps of the LULC classification process since it highly affects the final results output. Preprocessing refers to the data processing done before classification to provide the maximum possible accuracy in the outcome [11]. The overall goal of data preprocessing is to enhance the data quality for improved classification results. The preprocessing steps as carried out are: **i) Atmospheric Correction**: to correct satellite images from the disturbance due to the atmosphere to get rid of both wavelength and radiance from the land surface [3]. **ii) Cloud Masking:** Detecting and masking cloudy areas of the imagery. **iii) Geometric Correction:** using ArcMap v10.7.1 to patch the geometric corrections and register the images to one coordinate by fitting WGS 1984 UTM 38 N prediction by relocating the pixels into their correct planimetric (x, y) map coordinates. **iv) Normalization:** Rescaling pixel intensity values for each sample to ensure comparability [9] [10].

3.4 SVM Classification

The Support Vector Machine algorithm is a popular supervised machine learning approach well-suited for remote sensing applications due to its ability to handle complex, high-dimensional data [11][15]. The mathematical equations of linear, polynomial, radial basis, and sigmoid kernel functions are listed below as Equations (1–4) [11].

$$k(x_i\,,y_i) = x_i^T . x^j \qquad \text{... (1)}$$

$$k(x_i y_i) = (y. x_j^T . x_j + r)^d \qquad \text{... (2)}$$

$$k(x_i y_i) = \left(e^{-y(x_i - x_j)^2}\right) \qquad \text{... (3)}$$

$$k(x_i y_i) = \tanh\,(y. x_j^T . x_j + r) \qquad \text{... (4)}$$

Where $\boldsymbol{k}$ is kernel, $\boldsymbol{j}$ is the feature, $\boldsymbol{x_i}$ are input data points, and $\boldsymbol{y_i}$ are the corresponding output data points. In polynomial kernel, $\boldsymbol{d}$ shows the degree of polynomial, whereas $\boldsymbol{r}$ in the polynomial and sigmoid function is considered as bias term. $\boldsymbol{r}$ is the gamma term that presents in all types of function except linear which describes the impact of the training range. The model will be constrained and not be able to handle the complexity of data if the value of gamma is too small and contrariwise [11][15].

The **Radial Basis Function RBF** kernel was chosen for the SVM classifier due to its effectiveness in handling **non-linear patterns** common in high-resolution remote sensing data. Unlike the linear kernel, which assumes linear separability, the RBF kernel maps input data into a higher-dimensional space, allowing for more accurate land cover classification.Key parameters were carefully tuned[16[17]:

- **C (penalty parameter)** balances classification accuracy and model complexity. A moderate value was selected to avoid overfitting.
- **Gamma (γ)** controls the influence of training samples. It was optimized to ensure clear separation between similar land cover types, such as vegetation and rangeland.

[1] https://browser.dataspace.copernicus.eu/
[2] https://livingatlas.arcgis.com/landcoverexplorer/

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3.5 Change Detection

Change detection was conducted by comparing classified images from different time periods for two years 2019 and 2023. Using Image Differencing the simplest methods where the pixel values of two images taken at different times are subtracted from each other, and that is shown in equations (5)[6].

$$D(x,y) = I_2(x,y) - I_1(x,y) \ldots (5)$$

Where:

- $I_1(x,y)$ is the pixel value at location (x,y) in the first image (earlier time).
- $I_2(x,y)$ is the pixel value at location (x,y) in the first image (later time).
- $D(x,y)$ is the pixel value at location (x,y) in the difference image.

4. Results and Discussion

The SVM classification results will be analyzed in terms of overall accuracy, and the ability to differentiate between various land cover classes that shows in Table I. The change detection analysis will reveal the magnitude, spatial patterns, and trajectories of land cover transformations in Iraq over the study period. The Support Vector Machine SVM algorithm aims to find the optimal hyperplane that separates different classes in the feature space.

TABLE I Classes' Description[3][14]

No.	*Class_name*	*Class Value*	*Description*
1.	Water	C_1	Like rivers, ponds, lakes, oceans, flooded salt plains.
2.	Crops	C_5	Human-planted/plotted cereals, grasses, and crops not at tree height; examples: corn, wheat, soy, fallow plots of structured land.
3.	Barren	C_7	Land Bare soil and land do not contain the population of people like the desert.
4.	Built-up Area	C_8	The built area can be a large or small building.
5.	RangeLand	C_11	Natural meadows and fields with sparse to no tree cover, open savanna with few to no trees, parks/golf courses/lawns, pastures.

TABLE II Land cover evaluation metrics of method in 2019

OID	Class Value	C_1	C_5	C_7	C_8	C_11	Total	U_Accuracy	Kappa
0	C_1	10	0	0	1	1	12	0.833333	0
1	C_5	0	86	0	0	15	101	0.851485	0
2	C_7	0	1	10	0	0	11	0.909091	0
3	C_8	0	7	0	9	5	21	0.428571	0
4	C_11	0	4	0	0	69	73	0.945205	0
5	Total	10	98	10	10	90	218	0	0
6	P_Accuracy	1	0.877551	1	0.9	0.766667	0	0.844037	0
7	Kappa	0	0	0	0	0	0	0	0.757904

From table II illustrates the confusion matrix, the performance of the SVM classifier in distinguishing between five land cover classes. The overall accuracy achieved is **84.4%**, with a **Kappa coefficient of 0.7579**, indicating substantial agreement beyond chance. The classifier performed well for classes **C_11**(Rangeland) and **C_7**(Barren)**,** with high user's and producer's accuracy, while **C_8**(Built-up) showed poor user's accuracy (42.86%), indicating frequent misclassification—mainly as **C_5**(Crops) and **C_11**(Rageland)**.** is defined as follows in Equations (6)(7).

[3] https://ic.imagery1.arcgis.com/arcgis/rest/services/Sentinel2_10m_LandCover/ImageServer

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TABLE III Land cover evaluation metrics of method in 2023.

OID	Class Value	C_1	C_5	C_7	C_8	C_11	Total	U_Accuracy	Kappa
0	C_1	10	2	0	0	3	15	0.666667	0
1	C_5	0	94	0	1	2	97	0.969072	0
2	C_7	0	0	10	0	1	11	0.909091	0
3	C_8	0	1	0	9	4	14	0.642857	0
4	C_11	0	1	0	0	80	81	0.987654	0
5	Total	10	98	10	10	90	218	0	0
6	P_Accuracy	1	0.959184	1	0.9	0.888889	0	0.931193	0
7	Kappa	0	0	0	0	0	0	0	0.892179

From table III shows the confusion matrix improved classification performance using the SVM model, with an ***overall accuracy*** of **93.1%** and a ***Kappa coefficient*** **of 0.892**, indicating strong agreement beyond chance. Most land cover classes, such as **C_5**, **C_7**, and **C_11**, achieved high user's and producer's accuracy (above 90%), reflecting reliable and consistent classification. Class **C_1**, however, had a lower user's accuracy of **66.7%**, suggesting it was often misclassified, particularly as **C_5** and **C_11**. is defined as follows in Equations (6)(7).

5. Evaluation Metrices:

In this study, the performance of the **Support Vector Machine SVM** classifier was evaluated using several widely accepted metrics. Below are the key evaluation metrics, their associated equations, and a description of the parameters used:

1. Overall Accuracy OA

Equation:

$$OA = \frac{TP+TN}{TP+TN+FP+FN} \text{..... Equations (6).}$$

Where:

- TP = True Positive (correctly classified positive samples)
- TN = True Negative (correctly classified negative samples)
- FP = False Positive (incorrectly classified as positive)
- FN = False Negative (incorrectly classified as negative)

Description:
Overall accuracy represents the proportion of correctly classified pixels to the total number of pixels. It provides a general idea of how well the SVM classifier performed across all classes.

$$\textbf{Overall Accuracy}=\frac{\text{Total Correct Predictions}}{\text{Total Instances}} = \frac{10+94+10+9+80}{218} = 0.931193 *100 \approx 93.11\% \text{ … in 2023}$$

2. Kappa Coefficient (κ)

Equation:

$$k = \frac{(p_o - P_e)}{(1-P_e)} \text{..... Equations (7).}$$

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Where:

- p_o = Observed agreement (Overall accuracy)
- P_e= Expected agreement by chance

Description:
The Kappa coefficient is a statistical measure of inter-rater agreement. It adjusts for chance agreement and provides a more robust evaluation of classification accuracy than Overall Accuracy alone. A value of $\kappa = 1$ indicates perfect agreement, while $\kappa = 0$ suggests no better agreement than random chance.

$$\textit{Kappa Statistic} = \frac{P_0 - P_c}{1 - P_c} \approx 89.21\% \text{ …in 2023.}$$

The discussion will focus on the implications of the findings for sustainable land management and the potential contributions to the achievement of the United Nations Sustainable Development Goals. The performance of the SVM-based approach will be compared to alternative land cover mapping and change detection methods, emphasizing the strengths and limitations of the SVM technique in this context.

The discussion will also address the challenges and uncertainties associated with the study, such as the availability and quality of training data, the influence of atmospheric and environmental conditions on the satellite imagery, and the potential sources of error in the classification and change detection analyses.

TABLE IV depicts the change of the studied land features for the period (2019-2023)

Row Labels	From Area in 2019 /m	%	To Area in 2023/m	%	Percentage change from 2023-2019
Barren	368.9174481	31%	267.5604749	31%	0%
Buildings	21.53868583	2%	85.59960983	10%	8%
Rangeland	256.4112739	21%	275.1393502	32%	11%
Crops	478.5415381	40%	110.0409764	13%	-27%
Water	72.31851537	6%	125.3465367	15%	9%
Grand Total	1197.727461	100%	**863.686948**	100%	

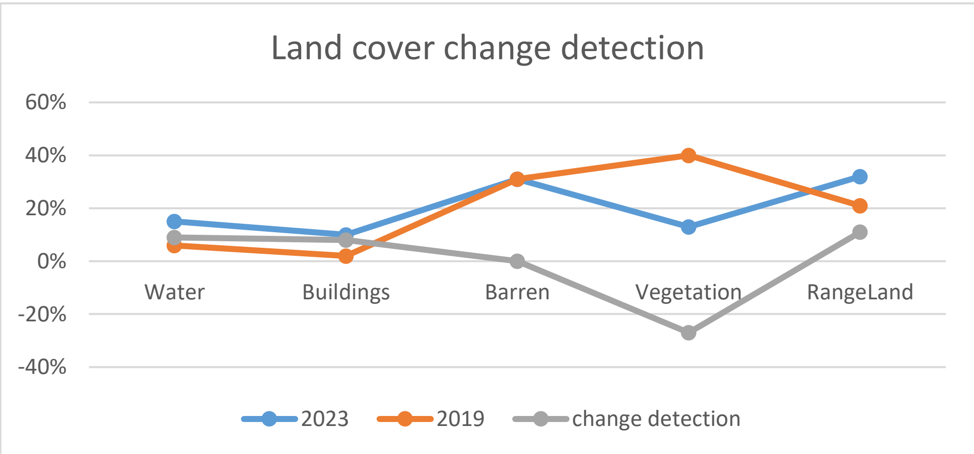

Figure (3). LULC percentages over the period 2019 and 2023

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Table (4) and figure (3) shows land use changes from 2019 and 2023, highlighting key trends and shifts in land cover categories: Water, Buildings, Barren, Vegetation and Rangeland. The data indicates that barren land experienced no change, while buildings and rangeland saw significant increases of 8% and 11% respectively. Conversely, vegetation decreased by 27%, suggesting a notable reduction in green cover. The water category also grew by 9% [18][19].

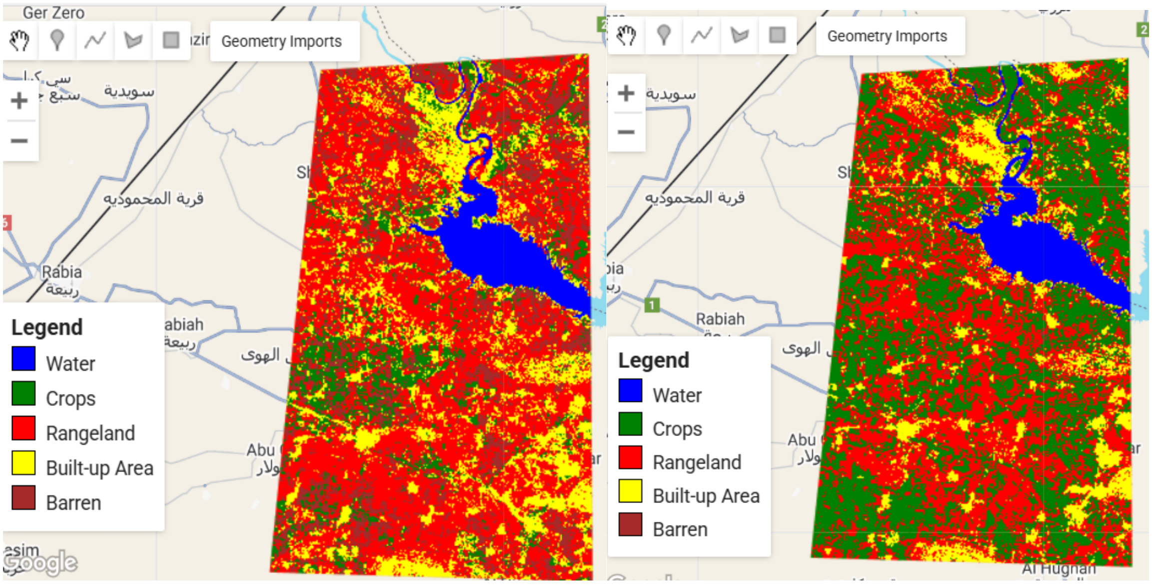

Fig.4(a) LULC changes in 2023 Fig.4(b) LULC changes in 2019

6. Conclusion

This study demonstrated the effectiveness of the Support Vector Machine SVM classifier in mapping Land Use and Land Cover LULC changes in the study area in Iraq, using high-resolution Sentinel-2 satellite imagery. The SVM algorithm successfully classified the study area into five main land cover types: Water, Barren, Building, Vegetation, and Rangeland, with satisfactory accuracy.

While the SVM classifier performed well in this context, several challenges were encountered that impacted the accuracy and robustness of the results. **Cloud cover in the Sentinel-2 imagery** presented difficulties in accurate classification, particularly in areas with frequent cloud cover, leading to **data gaps** and incomplete spectral information. Moreover, **misclassification errors** were observed, particularly in regions with complex land cover transitions, which could be attributed to the limitations of the SVM model in distinguishing certain features with high similarity.

Despite these challenges, the study highlights the ability of SVM to handle complex classification tasks, especially when working with limited training samples and high-dimensional remote sensing data. The approach was efficient in terms of processing time and produced reliable results.

Future work could explore further refinements to improve accuracy, such as incorporating cloud masking techniques, enhancing training data, or integrating other machine learning methods to address some of the misclassification issues. Additionally, exploring the potential of **deep learning models**, such as Convolutional Neural Networks CNN, could offer improved performance in handling complex spatial patterns and overcoming the limitations of traditional methods.

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