Land Use Change in Errachidia Oases Morocco using GEE and machine learning

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Abstract

Classifying land use and land cover (LULC) is essential for monitoring change and protecting the environment, especially in arid regions where ecosystems are fragile and vulnerable to climate change. This research focuses on Errachidia, an arid region in Morocco known for its natural oases, which are vital to the ecological ecosystems and the living conditions of the local population.To study changes in land use and land cover (LULC), 10-metre resolution Sentinel 2 satellite imagery was used from 2017 to 2023. Based on ground truth samples, classification was made by using Google Earth classifiers, namely Random Forest (RF), Support Vector Machine (SVM) and Cartesian Regression Trees (CART). Among these models, the Random Forest (RF) classifier outperformed the others, achieving an impressive accuracy of 94% and a kappa coefficient of 0.89, proving its strength in dealing with the challenges associated with arid environments. Looking to the future, we wanted to predict how land use would change between 2023 and 2030. Using the geemap Python package with GEE, RF and Cellular Automata-Markov (CA-Markov) were compared to predict future trends. While RF excelled in categorizing current land use with an accuracy of 93.17% and a kappa coefficient of 0.71, CA-Markov proved to have an accuracy of 93.82% and a kappa coefficient of 0.75 for long-term predictions. The predictions revealed alarming trends: The risk of desertification in Errachidia is increasing as agricultural areas decrease and desert-like sandy areas increase. The ability of the CA-Markov system to model how land changes over space and time made it particularly effective in capturing these changes. This study highlights the strengths of using GEE-RF classification and CA-Markov prediction for long-term future changes. This study underscores the efficacy of RF classification and CA-Markov in predicting long-term future changes. By identifying these changes, policymakers and land managers can take steps to combat land degradation and ensure the long-term health of these fragile ecosystems. By detecting these changes, policymakers and land managers can take steps to address land changes and ensure the long-term health of these fragile ecosystems.

1. Introduction

The observation of the Earth and monitoring the LULC have begun since the first launch of Landsat satellite at 1970. Satellite-based earth observation has been more valuable to track changes in the earth surface. The early studies focused mainly on the detection of change in the study areas of differences such as urban expansion, deforestation. With advances in sensors and data processing, satellite remote sensing has expanded its applications to diverse fields, including hydrology, agriculture, urban planing, and desertification tracking.

The main objective of remote sensing in monitoring and tracking the terrestrial environments, it has become more useful in arid and semi-arid regions, where ecosystems is fragile and land degradation processes are often fast. Remote sensing technology gives the ability to capture a large-scale spatial at regular time intervals up to weekly and monthly observation, providing the researchers and decision-makers to observe changes in vast areas over time.

Among these technologies, Sentinel-2 imagery offers high resolution data (10m)(Brown et al., 2022) suitable for capturing details of land surfaces, particularly in diverse use case, also short revisiting cycles (Boumahdi et al., 2025). To classify LULC from satellite imagery, machine learning classifiers such as Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART) were used with differents tools such as MATLAB, WEKA, Genstat (Thamilselvan and Sathiaseelan, 2015). On the other hand, over the last decade many classifier integrated in Google Earth Engine(GEE) which facilitates using data and classifier simultaneously (Lee et al., 2024)(Zhao et al., 2024).

Understanding the past and present of land changes is very important, proactive land management requires early anticipation of land-use change. In order to tackle these issues, models have gained attention such as Cellular Automata-Markov (CA-Markov) (Mondal et al., 2020) and RF have gained attention.

The main of this study is analyzing and predicting LULC changes in the Errachidia Region from 2017 to 2030 using high resolution open source satellite imagery(Sentinel-2) and integrated classifiers(RF, SVM, CART) in GEE platform. Several studies have shown the effectiveness of predicting with CA-Markov prediction for land change modeling (Mondal et al., 2020) (Tahir et al., 2025)

In order to achieve these objectives, the following tasks have been undertaken: collect data for major land cover classes; preprocess and analyze Sentinel-2 imagery within the GEE environment, calculate NDVI, NDWI, NBDI indices, implement and compare machine learning classifiers; and generate predictive LULC maps for future planning purposes.

2. STUDY AREA AND DATASET

2.1 Study area

The study area is Errachidia province, located in the sought Est of Morocco in the Draa Tafilalet region (latitude 31° 45’ 0.00” N, longitude 4° 30’ 0.00” W) Figure 1, known by its arid climate. This Province known by it oases as the ZIZ Oases is the largest one worldwide. The oases palms dattes is the main important sources of income. That is the reason that oases lands management is very important for the region. The study area

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cover five land use classes which are water surface, vegetation, urban, sand, barren land.

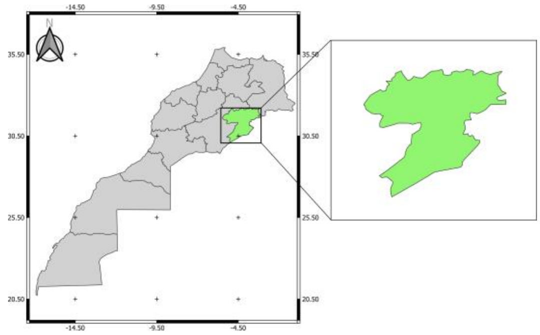

Figure 1. Study Area.

2.2 Dataset

In the present research study, Sentinel 2A MSI used for classifiying LULC accessed from Copernicus Open Access Hub (https://scihub.copernicus.eu/) and imported to GEE or by using GEE platform (https://earthengine.google.com/), it provide a medium spatial re´solution (10m) and include 13 spectral bands, four bands at 10 meters and six bands at 20 meters, while the last three bands are at 60 meters see table 1.

Table 1. Spectral bands used for LULC classification

Band	Description	Spatial Re´solution(m)
B1	Aerosols	60
B2	Blue	10
B3	Green	10
B4	Red	10
B5	Red Edge 1	20
B6	Red Edge 2	20
B7	Red Edge 3	20
B8	NIR	10
B8A	Red Edge 4	20
B9	Water vapor	60
B11	SWIR 1	20
B12	SWIR 2	20
SCL	Scene Classification Map	20

3. Methodology

3.1 Workflow

The workflow followed in this study is presented in Figure 2. The aim is to assess the accuracy of integrated GEE classifier using medium resolution satellite imagery, also the comparing RF and CAM capabilities on the land-use/land-cover prediction accuracy in oases areas. In principle , GEE offers free access to sentinel 2A data for any region and time period via its API.

3.2 Classification

Supervised classification for LULC mapping follows a structured a process. This process begins with visualisation of satellite imagery to understand the spatial distribution of each land cover type. The last step followed with representing training and testing samples for each class. A suitable classification algorithm(RF, SVM, CART) selected and applied to the satellite

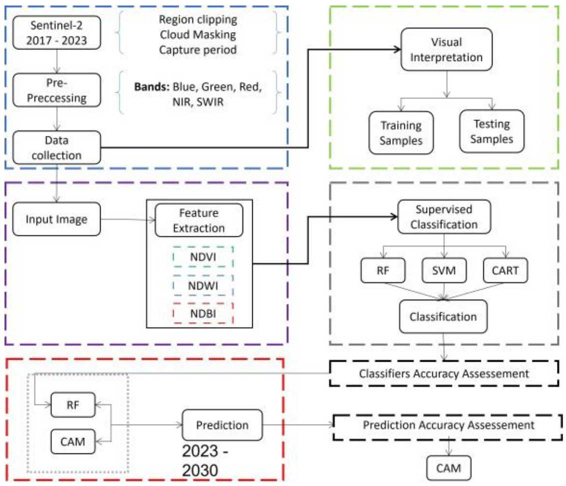

Figure 2. workflow applied in this study.

imagery to produce a classified lulc map. As final step, an accuracy assessment of the classification is carried out using performace metrics.

Table 2. Vegetation, Built up, and water indices used for LULC classification

Index	Formula
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR-Red}{NIR+Red}$
Normalized Difference Built-up Index (NDBI)	$\frac{SWIR-NIR}{SWIR+NIR}$
Normalized Difference Water Index (NDWI)	$\frac{NIR-SWIR}{NIR+SWIR}$

4. Results and Discussion

The current paper evaluates the performance of three machine learning techniques: CART, SVM, and RF, for the LULC classification of Errachdia Oases. In this study, three indices (i.e., NDVI, NDWI, and NDBI) were computed from Sentine 2A data. These algorithms were applied for the classification of four classes including water, built up, vegetation, sand , and barren land . The LULC maps from 2017 to 2023 of the performed model (RF) of the study area are shown in Figure 4. Figure 5 present the transition of different classes in three periods, between 2017 and 2019, 2019 and 2021, 2021 and 2023, it present a hug change in sand and barren classes while the other are less changed.

RF and CAM are very accurate in prediction, Figure 6 shows the matching of the origin lulc Map and the predicted. This prediction accuracy is about 93.17% for RF and 93.82% for CAM, confirming that CAM outperforms RF, especially for long future predictions.

The GEE platform offers significant advantages over traditional satellite data processing tools, global-scale data access, and easier processing tools. It provides free access to a wide range of pre-processed satellite datasets, including Landsat, Sentinel and others imagery, all stored and managed in the cloud. GEE enables the processing of large-scale remote sensing datasets, providing the capture for inaccessible areas with high efficiency

	0	1	2	3	4
0	131208	0	1600	1912	45016.54
1	485	0	125161.7	27737.98	1211976
2	770.463	0	2624935	44740	705534.5
3	37	0	1631	30818304	7189387
4	8487.8	0	582668.9	9326013	2.59E+08

CAM

	0	1	2	3	4
0	0	1245	5614	1234	62350.42
1	0	227007.8	193416.8	22640.8	921514.6
2	0	4787.357	2464657	74135	830930.1
3	0	2412	3322	27859163	10144366
4	0	92362.81	864421.3	8070953	2.6E+08

RF

Figure 3. The confusion matrix for RF and CAM .

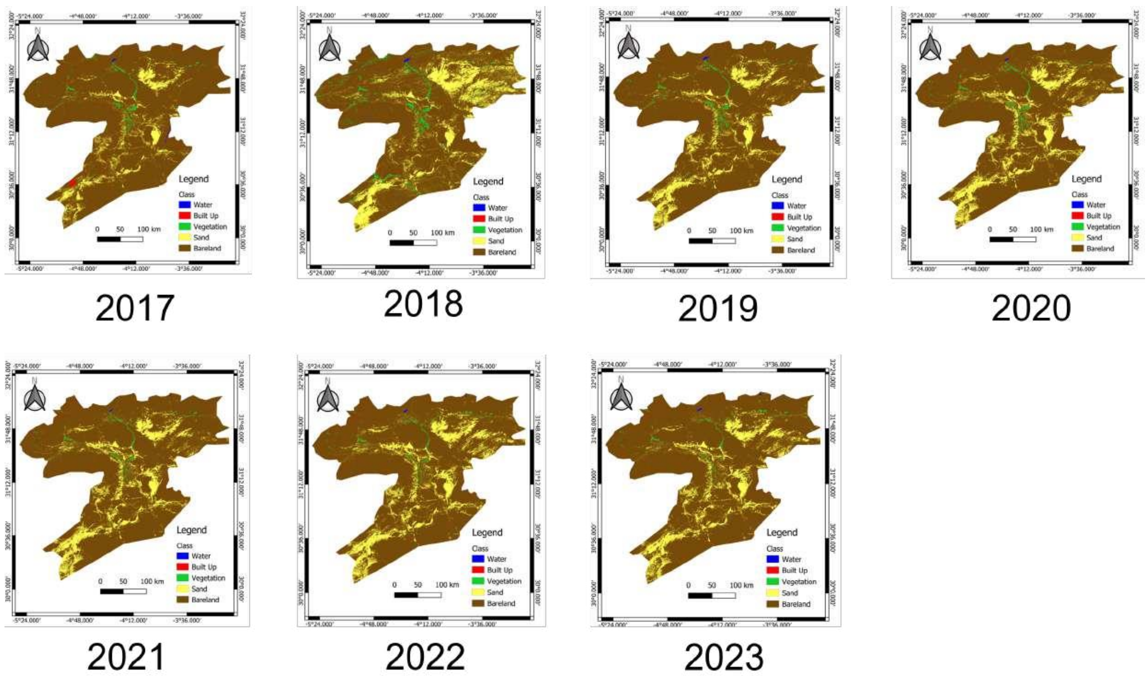

Figure 4. RF classification results.

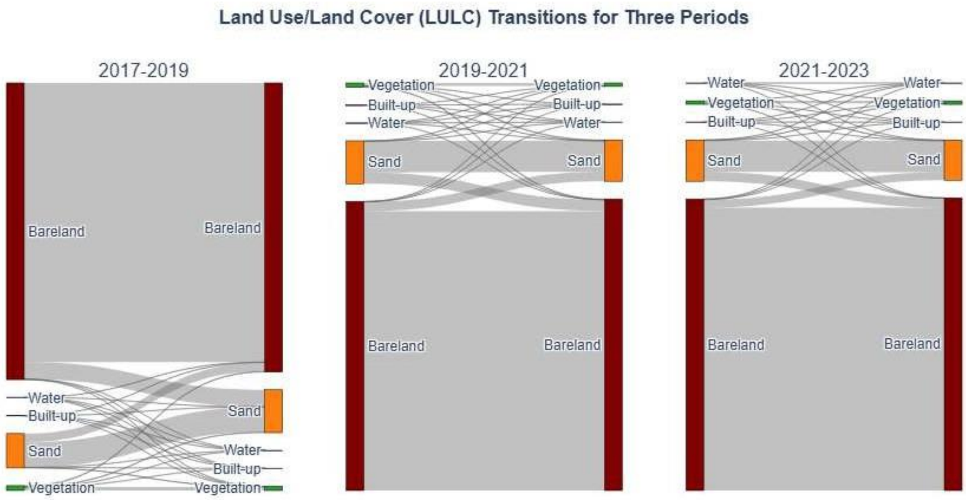

Figure 5. LULC transitions from 2017 to 2023.

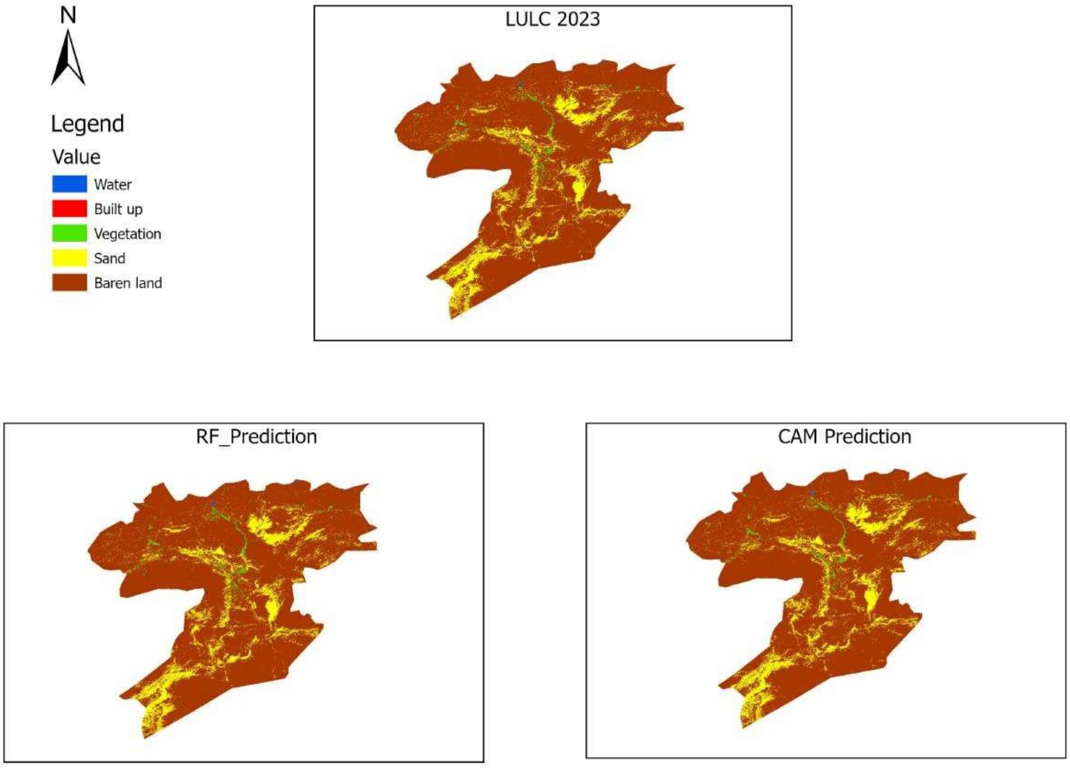

Figure 6. Comparison of RF and CAM prediction to the origin LULC MAP.

and computational speed. For these reasons, GEE recommanded to be the primary platform in this research.

5. Conclusion

The main objective of this study was to develop an automated workflow for land use/land cover classification in oases areas using Sentinel-2 imagery within GEE, based on integrated machine learning algorithms. Instead of comparing different algorithms, this research focused on the practical application and performance of the Random Forest (RF) algorithm, which is readily available in GEE. Future research could extend this work by predicting for 2030 and add improve detection of dynamic land cover types. In addition, comparing other machine learning approaches within the GEE environment or incorporating external high-resolution data sources may improve classification performance and tracking desertification mouvement.

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