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Analysis of Four Decades of Land Use and Land Cover Change in Semiarid Tunisia Using Google Earth Engine

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Abstract: Semiarid Tunisia is characterized by agricultural production that is delimited by water availability and degraded soil. This situation is exacerbated by human pressure and the negative effects of climate change. To improve the knowledge of long-term (1980 to 2020) drivers for Land Use and Land Cover (LULC) changes, we investigated the semiarid Rihana region in central Tunisia. A new approach involving Google Earth Engine (GEE) was used to map LULC using Landsat imagery and vegetative indices (NDVI, MSAVI, and EVI) by applying a Random Forest (RF) classifier. A Rapid Participatory Systemic Diagnosis (RPSD) was used to consider the relation between LULC changes and their key drivers. The methodology relied on interviews with the local population and experts. Focus groups were conducted with practicians of the Regueb Agricultural Extension Services, followed by semi-structured interviews with 52 households. Results showed the following: (1) the RF classifier in Google Earth Engine had strong performance across diverse Landsat image types resulting in overall classification accuracy of ≥0.96 and a kappa coefficient ≥0.93; (2) rainfed olive land increased four times during the study period while irrigated agriculture increased substantially during the last decade; rangeland and rainfed annual crops decreased by 58 and 88%, respectively, between 1980 and 2021; (3) drivers of LULC changes are predominately local in nature, including topography, local climate, hydrology, strategies of household, effects of the 2010 revolution, associated increasing demand for natural resources, agricultural policy, population growth, high cost of agricultural input, and economic opportunities. To summarize, changes in LULC in Rihana are an adaptive response to these various factors. The findings are important to better understand ways towards sustainable management of natural resources in arid and semiarid regions as well as efficient methods to study these processes.

Keywords: water scarcity; soil erosion; LULC; GEE; random forest; RPSD; semiarid Tunisia

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1. Introduction

Land Use and Land Cover (LULC) changes are important for identifying long-term landscape effects caused by natural processes and anthropogenic pressure [1]. These processes have important impacts on the fragile ecology of semiarid regions. Due to increasing human pressure, scarce resources in semiarid Tunisia are frequently overexploited. The pressure has been increasing in recent decades due to a higher occurrence rate of extreme climatic events such as droughts and heavy rainfall, which may force local populations to change crop systems [2]. LULC in semiarid regions has an impact on both local socioeconomic development and the environment, as well as global environmental change [3]. As a result, accurate and long-term information on LULC is a critical tool in natural resource management.

In this regard, Remote-Sensing (RS) imagery is a viable option for detecting changes at various spatial–temporal scales due to detailed resolution and widespread availability [4]. Despite the importance of using RS in long-term change detection analysis, problems arise as data volumes increase and the need to modify and homogenize images from various sensors with varying quality and periods escalates [5,6]. To overcome these problems, Google Earth Engine (GEE) can be used as a cloud-computing platform together with machine-learning algorithms for the analysis of satellite images [7–9]. This tool has recently been recognized as a potential platform for RS analysis [10,11]. Indeed, GEE is a large geospatial, cloud-based platform that provides a powerful tool to process, analyze, and visualize extensive amounts of remote-sensing data [12,13].

As mentioned above, Machine-Learning (ML) techniques can greatly help in the analysis of large data sets, such as in LULC mapping [14]. Common ML techniques include Random Forests (RF), Artificial Neural Networks (ANN), Decision Trees, and Support Vector Machines (SVM) [15,16]. Among these, RF has gained popularity for LULC mapping due to its high accuracy, which has proven to be very efficient in circumstances of large inputs of information, relatively low cost, and the need for a limited number of variables [17,18]. Furthermore, indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Soil-Adjusted Vegetation Index (MSAVI), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and the Normalized Difference Soil Index (NDSI) are effective for mapping of LULC changes [19,20].

Recent studies have demonstrated the effectiveness of using GEE within the RF classifier for automated, long-term, and accurate LULC mapping. For example, [21] utilized Landsat data, an RF classifier in the GEE platform, to map LULC in Côte d'Ivoire for the year 2020, achieving an overall accuracy of over 90%. Another study [22] employed GEE and RF classifiers to monitor annual LULC change in the Tucson Metropolitan Area from 1986 to 2020 using Landsat imagery. Their results consistently demonstrated satisfying classification accuracy, ranging from 90% to 95% for most years. The authors of [23] analyzed spatiotemporal changes in forest cover in the Ashanti region of Ghana for the years 2006, 2011, 2015, and 2020 using GEE and the two classifiers RF and SVM. The RF classifier showed an overall accuracy of 98% and a kappa index of 0.97, while SVM achieved an overall accuracy and a kappa index of 90% and 0.88, respectively. This highlights the superior performance of the RF classifier with low overfitting tendencies. The authors of [24] compared the performance of three machine-learning algorithms, SVM, RF, and CART, for LULC classification for the years 2016, 2018, and 2020. Their findings revealed that RF classifiers in the GEE platform consistently outperformed SVM and CART classifiers in terms of accuracy for both Landsat-8 and Sentinel-2 imagery.

Scholars using satellite imagery data have, to some extent, studied LULC changes in Tunisia [25]. For instance, [26] used Landsat imagery and maximum likelihood classification to examine the changes in LULC between 2007 and 2017. In another study, [27] employed the Normalized Difference Vegetation Index (NDVI) derived from the Very High-Resolution Radiometer (AVHRR) to assess the spatial and temporal patterns of land use change in North and West Africa spanning the period from 1985 to 2015. The authors of [28] focused on mapping irrigated and rainfed areas in semi-arid regions of Tunisia between 2015 and 2017 using Sentinel 1 and Sentinel 2 data. The authors of [29] analyzed vegetation dynamics over the central region of Tunisia during drought events by utilizing a multi-temporal series of NDVI derived from SPOT-VEGETATION and TERRA-MODIS satellite data. However, there has been a lack of studies conducted in Tunisia that specifically employ the GEE platform to accurately map and analyze LULC changes. Also, there is a lack of research that integrates local knowledge to understand the factors that influence farmers' land use decision making at a local scale during a long period corresponding to decades.

In view of the above, we investigated the long-term changes in LULC for a representative region in central semiarid Tunisia to improve the knowledge of possible natural and socioeconomic drivers. Hence, we assessed the decade-wise changes in LULC between 1980 and 2021 using Landsat imagery and RF classifier on the GEE platform. The NDVI, EVI, and SAVI indices were selected to characterize LULC, see, e.g., [30]. Rapid Participatory Systemic Diagnosis (RPSD) was used to clarify the relationships between LULC changes and their drivers. The objectives were the following: Firstly, to investigate whether the GEE and RF methods can provide automated, long-term, and improved accuracy of LULC mapping. Secondly, to examine the spatiotemporal patterns of LULC change in semi-arid central Tunisia. Thirdly, to identify the major natural socioeconomic drivers that influence LULC changes.

2. Study Area

The focus of this study was the Rihana region located in central Tunisia (Regueb delegation, Sidi Bouzid governorate) and one of the involved sites of the PACTE program « Climate change adaptation program for vulnerable rural territories of Tunisia» (PACTE: https://pacte.tn/) (accessed on 15 January 2019)). The Rihana region covers about 10,000 ha (Figure 1) with an annual average temperature of about 20 °C and a summer temperature that can reach 47°C. The annual rainfall is irregular, with a mean of 225 ± 129 mm (Figure 2). Rihana agriculture is characterized by small farms, often less than 10 ha, with low economic productivity. The landscape is dominated by rainfed olive production in the up- and middle stream parts and irrigated crops in the downstream plain. Rihana is among Tunisia's environmentally and socioeconomically most vulnerable territories [31]. The vulnerability is essentially characterized by degrading natural resources, such as the loss of a large part of its production potential and the overexploitation of hydro-agricultural resources and rangelands. The vulnerability is worsened by large temporal and spatial variability of rainfall, which results in alternating periods of drought, flooding, and erosion. The risk of flooding is high, and heavy rains lead to significant surface runoff, resulting in floods in almost all wadis in the region [32]. Figure 2a,b display the annual rainfall depth as well as the annual average together with mean, maximum, and minimum temperature. The data were obtained from the General Directorate of Water Resources [33] covering the period between 1980 and 2021. Historical rainfall data since 1980 show several annual extremes, e.g., the wet year 2013/2014 (395.5 mm). About ten deficit years, with a minimum of 50 mm for the year 2000/2001, occurred in the period (Figure 2).

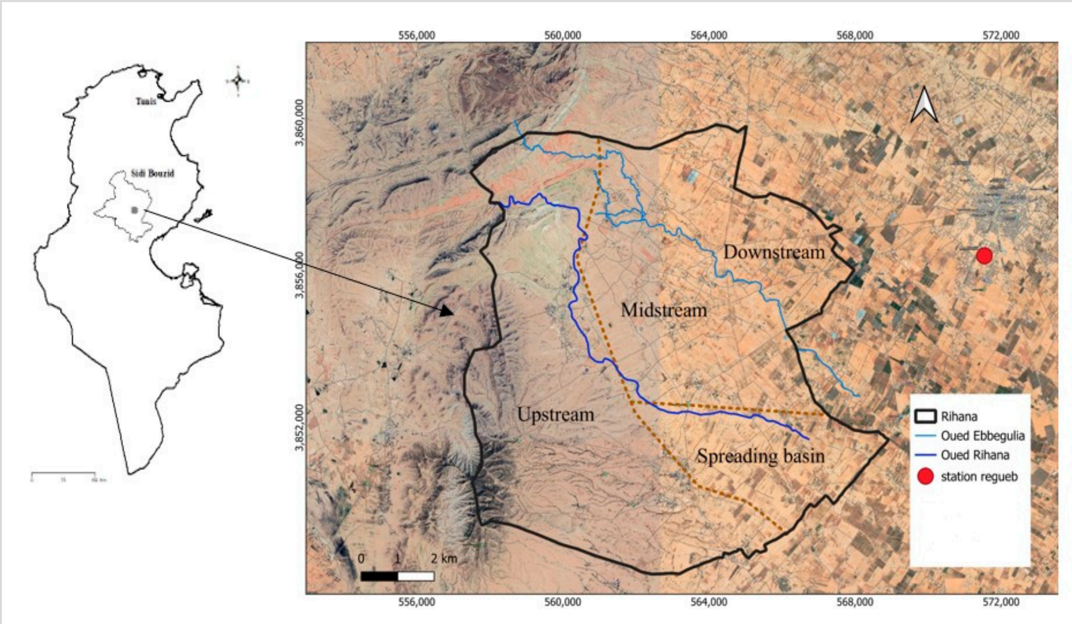

Figure 1. Geographic location of the Rihana study area in Tunisia.

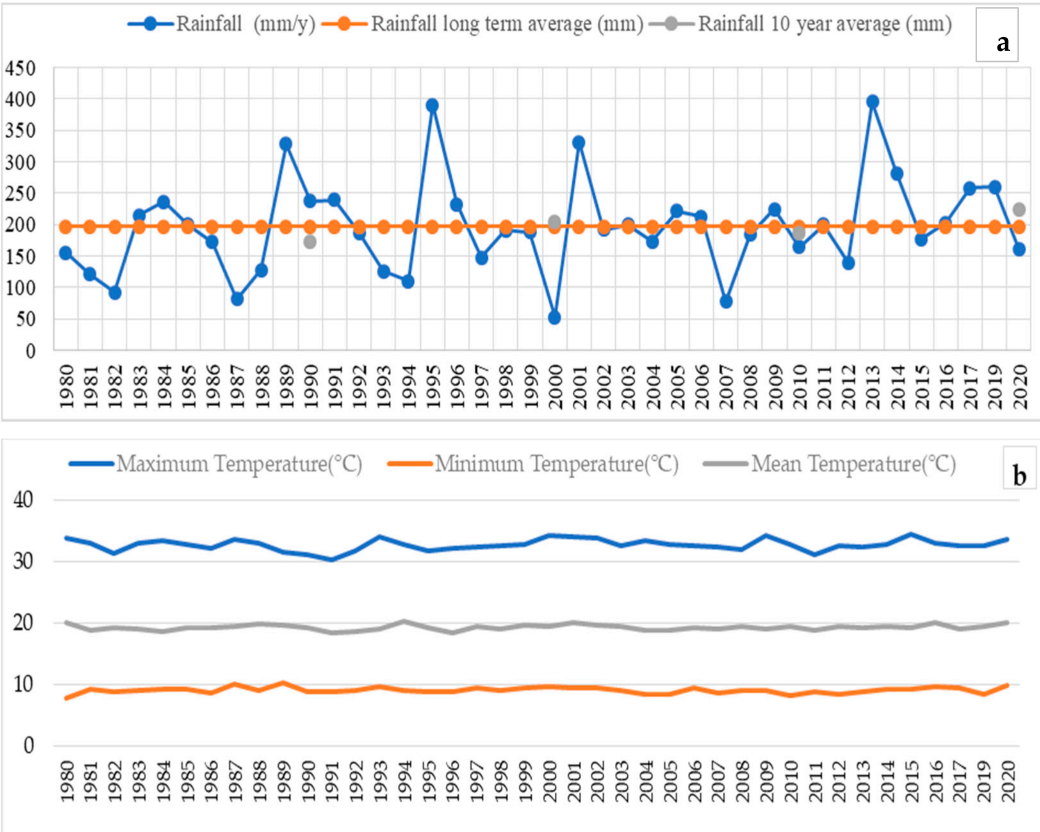

Figure 2. (**a**) Average annual rainfall; (**b**) temperature (mean, maximum, and minimum) observed at the Regueb climate station.

3. Data and Methods

3.1. Datasets

3.1.1. Satellite Imagery

Landsat 3/5/7/8 data archived by the United States Geological Survey (USGS) (http://glovis.usgs.gov/ (accessed on 15 October 2022)) for mapping LULC changes were used in this study. Table 1 presents all details of the selected images. Surface Reflectance data were utilized from Landsat-5 TM, Landsat-7 ETM+, and Landsat 8 OLI between 1 September and 31 August (hydrological year) corresponding to the years 1990, 2000, 2010, and 2020. All datasets were used and directly integrated into the GEE platform. For Landsat 3 MSS, images were corrected before being used because available corrected images for the year 1980 did not cover our area of interest.

Table 1. Used satellite imagery description.

Data Sets	Acquisition Date	Resolution (m)
USGS Landsat 3 MSS	01 September 1980/31 August 1981	60
USGS Landsat 5 Tier 1 Surface Reflectance	01 September 1990/31 August 1991	30
USGS Landsat 7 Tier 1 Surface Reflectance	01 September 2000/31 August 2001 01 September 2010/31 August 2011	30
USGS Landsat 8 Tier 1 Surface Reflectance	01 September 2020/31 August2021	30

3.1.2. Training and Validation

Training and validation are critical steps in LULC mapping. Thus, data were collected via field observations, farmer surveys, and use of Google Earth Pro. Field observations were performed in the study area during 2020 (September, October, and December) and 2021 (January, March, June, and July), where 320 polygons were selected. For 1980, 1990, 2000, and 2010, samples of polygons were collected via farmer surveys. Together with stakeholders, we identified polygons that cover the period for each LULC class. For example, field visits were performed to areas that were covered by olive trees in 1980, 1990, 2000, and 2010, and similar field visits were conducted for other classes. In general, 240 ground-truth polygons were collected. For 2010, we also used Google Earth Pro. For reference data collection, true and false color composites of Landsat imagery were used. The generated polygons were evenly distributed over the Rihana area and had a homogeneous spatial distribution. It is worth noting that former studies [34], as well as the local population, helped to define the four classes, as shown in Table 2, representing the overall land cover of the study area except for the most upstream part. The latter, which represents a nature reserve and scrubland, is considered a stable class that has not changed over the past 40 years. Table 3 displays the number of polygons for each year and LULC class, along with the average surface area.

Table 2. Description of Land Use and Land Cover classes.

LULC Category	Description
Rangeland	Grazed land characterized by natural vegetation.
Rainfed olive	Olives cultivated in solely rainfed areas.
Rainfed annual crops	Annual crops that rely on rainfall for water, specifically cereals and forage crops
Irrigated crops	Includes areas with at least one crop cycle using irrigation as a water source

Table 3. Training and validation data.

		Rangeland	Rainfed Olive	Rainfed Annual Crops	Irrigated Crops
1980 (Landsat 3)	Polygons	16	10	18	-
	Surface (pixels)	75	42	92	-
1990 (Landsat 5)	Polygons	15	7	10	-
	Surface (pixels)	233	67	89	-
2000 (Landsat 7)	Polygons	21	23	16	-
	Surface (pixels)	444	689	144	-
2010 (Landsat 7)	Polygons	23	67	8	6
	Surface (pixels)	756	2644	311	111
2020 (Landsat 8)	Polygons	92	76	6	146
	Surface (pixels)	1156	2433	233	633

3.2. Methodology

We utilized the GEE platform to classify and detect changes in LULC. The adopted approach is shown in Figure 3. Further explanation follows below.

3.2.1. Classification and Post-Processing

The input data (Landsat images) were processed using the GEE platform, as shown in Figure 3. It is preferable if the imagery used for LULC change detection contains as few clouds as possible. As a result, images were filtered with 10% cloudiness for the selected years 1990, 2000, 2010, and 2020. For 1980, images were filtered with 25%, which represents the low-cloudiness percentage available for the study area. Then, we combined each year's dataset (Landsat imagery) based on the median reducer function to produce one single image from the image collection. For the entire stack of images, a median value was used for each pixel.

To improve the classification accuracy, NDVI, MSAVI, and EVI indices were derived and calculated from all data used. The definitions for these are as follows [35]:

$$\text{NDVI} = (\text{nir} - \text{red})/(\text{nir} + \text{red}) \quad (1)$$

$$\text{MSAVI} = (2 * \text{nir} + 1 - \text{sqrt}\ ((2 * \text{nir} + 1)2 - 8 * (\text{nir} - \text{red})))/2 \quad (2)$$

$$\text{EVI} = 2.5 * (\text{nir} - \text{red})/(\text{nir} + 6.0 * \text{red} - 7.5 * \text{blue} + 1) \quad (3)$$

where nir, red, and blue represent spectral reflectance in the near-infrared, red, and blue bands, respectively.

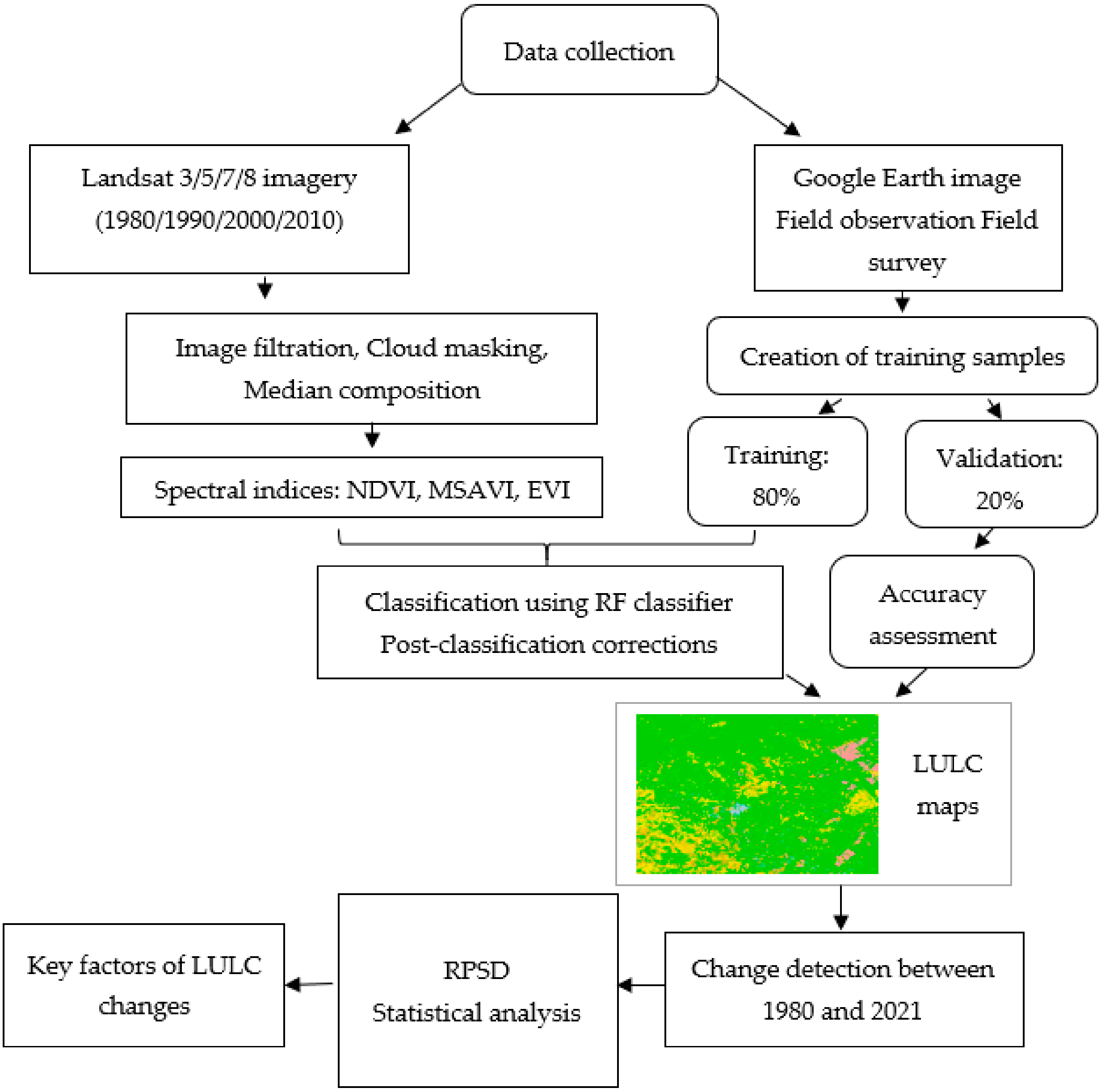

Figure 3. Description of the methodology used in this present study.

After that, and as mentioned before, we used RF machine-learning algorithm to train the classification for Landsat images. Once the classification was completed, an evaluation was carried out to determine the accuracy level of each classified image using a confusion matrix. This algorithm built on GEE depicts the relationship between ground truth and classification results [36]. We trained and validated the algorithm with 80% and 20%, respectively. To validate classification, both kappa coefficient and overall accuracy were adopted [37]. The final product was chosen based on the RF with the highest overall accuracy and kappa value. We used post-classification corrections based on the neighborhood algorithm in GEE to replace isolated pixels with surrounding values to guarantee smoother appearance of the classified results.

3.2.2. Drivers of LULC Change Based on the RPSD Methodology

To comprehend the main LULC transitions that occurred in Rihana over the past four decades and to investigate the key drivers behind these changes, a Rapid Participatory

Systemic Diagnosis (RPSD) was conducted with local farmers and experts. The RPSD is a participatory and multi-actor method. It is based on semi-open interviews with the local population, either individually or collectively, complemented by interviews with local experts. Together, it allows for the co-construction of a common understanding of the functioning and development issues of territory with local actors [34,38]. Initially, focus groups were initiated with the help of experts from the Regueb Agricultural extension for different specialties: crop production, water resources, soil resources, and water and soil conservation. During these discussions, local experts provided valuable insights and analysis of the local context of Rihana dynamics and the changing availability and use of water and soil resources. Furthermore, these groups reviewed the main changes in LULC over time. We then had detailed discussions with farmers to better understand these changes and the underlying factors that drove them in both current and historical situations. The discussions were conducted in two focus groups and via field surveys with 52 farmers. Participants were selected from various locations in Rihana, including the upstream, midstream, and downstream basin parts (Figure 4). The participating farmers had an average age of 59 years, with a majority between the ages of 41 to 64 years. Only 11% of them were below the age of 40. They owned an average farmland area of 18 ha, which is usually composed of 3 parcels. The surveyed farms were asked to list the LULC changes they had observed. In addition, participants were also asked to identify the drivers behind these changes and rank them from most to least significant. This approach allowed for a deeper understanding of the LULC dynamics and the factors contributing to them, as explained by local population and experts. During the fieldwork, a variety of tools was utilized; among them were satellite images of the region and a tablet equipped with GPS. Coordination with the local authorities and involvement of researchers, associations, and practitioners were ensured.

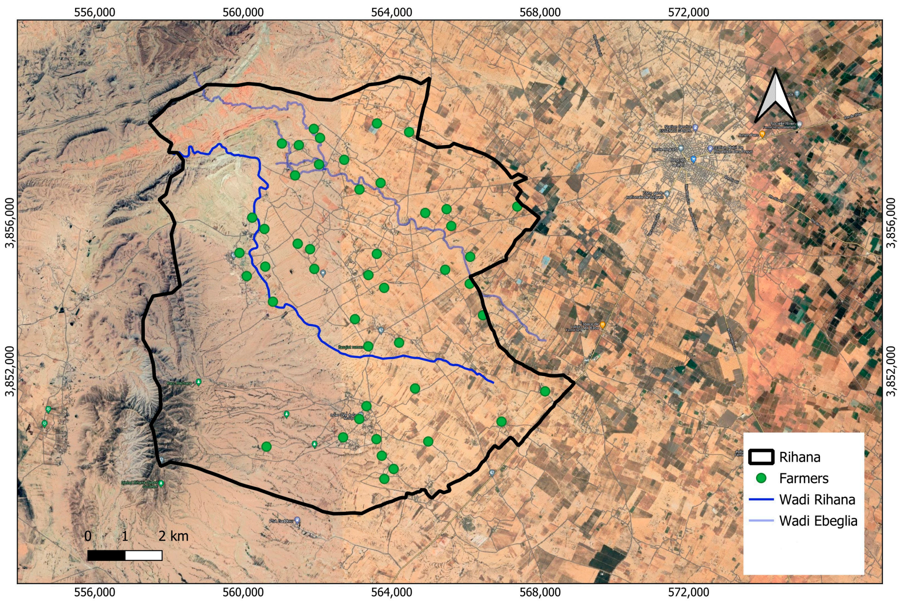

Figure 4. Geographic distribution of surveyed farms.

4. Results and Discussion

4.1. Classification Performance

An accuracy assessment was considered for the five classified maps to verify that mapped content corresponds to ground truth in the study area. The overall accuracy (OA), kappa index (K), and user and producer's accuracy were performed to identify class performance and misclassifications. Results show that the use of the RF classifier in GEE provided an OA ≥ 0.96 and a K ≥ 0.93. For Landsat 3 (1980), Landsat 5 (1990), and Landsat 7 (2000), the mean OA and K were 0.99 and 0.98, respectively. The OA for Landsat 7 (2010) and Landsat 8 (2020) was 0.96 and 0.97, respectively, with individual K equal to 0.93 and 0.95, respectively. Thus, results were generally of high quality and adequate for the subsequent analysis and change detection [39].

The classification accuracy results obtained for the different classes for every date are shown in Table 4. UA and PA did not show a big difference between rangeland and rainfed olive. They were classified with higher accuracies for all years, with producer accuracy (PA) and user accuracy (UA) ≥ 95%. For rainfed annual crops, they also showed a good performance for the first three years, unlike for 2010 (PA = 96%) and 2020 (PA = 94%). This can be explained by the confusion between rainfed annual crops and irrigated crops, which could be explained as a seasonal effect. For irrigated crops, the performance was better for the year 2020 than for 2010, with PA = 97% and 71%, respectively. The relatively lower classification shows that irrigated areas are more easily detected with Landsat 8 than with Landsat 7. Refs. [40,41] note that the low accuracy for some classes is due to the reduced samples of training that significantly affects the classification results, which is true, especially for the irrigated crops class for the year 2010.

Table 4. Accuracy assessment of the different LULC classes.

		Rangeland	**Rainfed Olive**	**Rainfed Annual Crops**	**Irrigated Crops**
1980 (Landsat 3)	PA	0.98	0.96	0.98	_
	UA	0.97	0.97	0.99	_
	OA	0.98			
	K	0.97			
1990 (Landsat 5)	PA	0.99	0.96	0.99	_
	UA	0.98	0.98	0.99	_
	OA	0.99			
	K	0.98			
2000 (Landsat 7)	PA	0.98	0.99	0.97	_
	UA	0.99	0.98	0.98	_
	OA	0.99			
	K	0.98			
2010 (Landsat 7)	PA	0.97	0.99	0.96	0.71
	UA	0.95	0.96	0.98	0.99
	OA	0.96			
	K	0.93			
2020 (Landsat 8)	PA	0.97	0.97	0.94	0.97
	UA	0.95	0.97	0.97	0.99
	OA	0.97			
	K	0.95			

PA: Producer's Accuracy, UA: User's Accuracy, OA: Overall Accuracy, K: Kappa index.

4.2. LULC Classification Analysis

Multi-temporal LULC for 1980, 1990, 2000, 2010, and 2020 are shown in Figure 5. Figure 6 shows the areal statistical distribution of LULC and their ratios for the respective period. Results indicate that in 1980, most of the study area was rangeland, and rainfall annual/cereal crops covered about 36.2% and 28.1%, respectively. Rainfed olive covered an area of 1507.7 ha (15.4%). Rangeland is distributed across the territory, with significant presence in the upstream and piedmont parts. As for rainfed annual crops, they have mainly been concentrated in the riverbed of wadi Rihana and in the spreading basin. On the other hand, in 1990, the most dominant land classes were rainfed olive and rangeland, which covered 38.8% and 30.1%, respectively. Rainfed olive cultivation was widespread across the entire study area, while rangeland was primarily concentrated in the upstream and midstream regions. The least aerial coverage was rainfed annual crops, which accounted for only 10.8%, mainly located in the spreading basin. The analysis of LULC for the year 2000 revealed that rainfed olive cultivation occupied approximately 47% of the total area, with a notable increase observed in the midstream and downstream regions. Rangeland, on the other hand, experienced a decrease and accounted for 25.8% of the area. Rainfed annual crops also decreased in various parts of the study area, except for the spreading basin, where they remained dominant, covering 6.3% of the area. In the year 2010, notable changes occurred in the LULC of Rihana. The introduction of irrigation was observed in the downstream plain, covering approximately 13.2 hectares (0.13%) of the total area. Rainfed olive cultivation continued to expand and emerged as the dominant land cover, encompassing more than 53% of the study area. Rangeland experienced a further decline, representing 22.7% of the total area, primarily in the midstream region. Rainfed annual crops witnessed a significant decrease, particularly in the spreading basin, accounting for only 3.2% of the total area. Looking at the year 2020, the most remarkable change was observed in the expansion of irrigated crop areas, which covered approximately 6.4% of the total area. Rainfed olive cultivation continued to constitute the largest proportion, although with a slight increase compared to previous years, accounting for 55%. Conversely, rangeland experienced a further decline, representing 15% of the total area. However, there was an increase in rainfed annual crops, which now accounted for 3.4% of the area.

4.3. Drivers of LULC Change

The participating local farmers provided insights into the various factors driving the changes in LULC. They reported that topography, soil type, accessibility, hydrology, local climate, population growth, individual and collective farmer strategies, socio-economic conditions of farmers, new policies, high cost of agricultural inputs, economic opportunities/financial incentives, the Jasmin revolution, and cultural factors all play significant roles in LULC dynamics in the study area. They indicated that each decade of LULC change had its unique drivers (Figures 6 and 7). Table 5 shows the main drivers of LULC changes, and their ranking as considered by the local population.

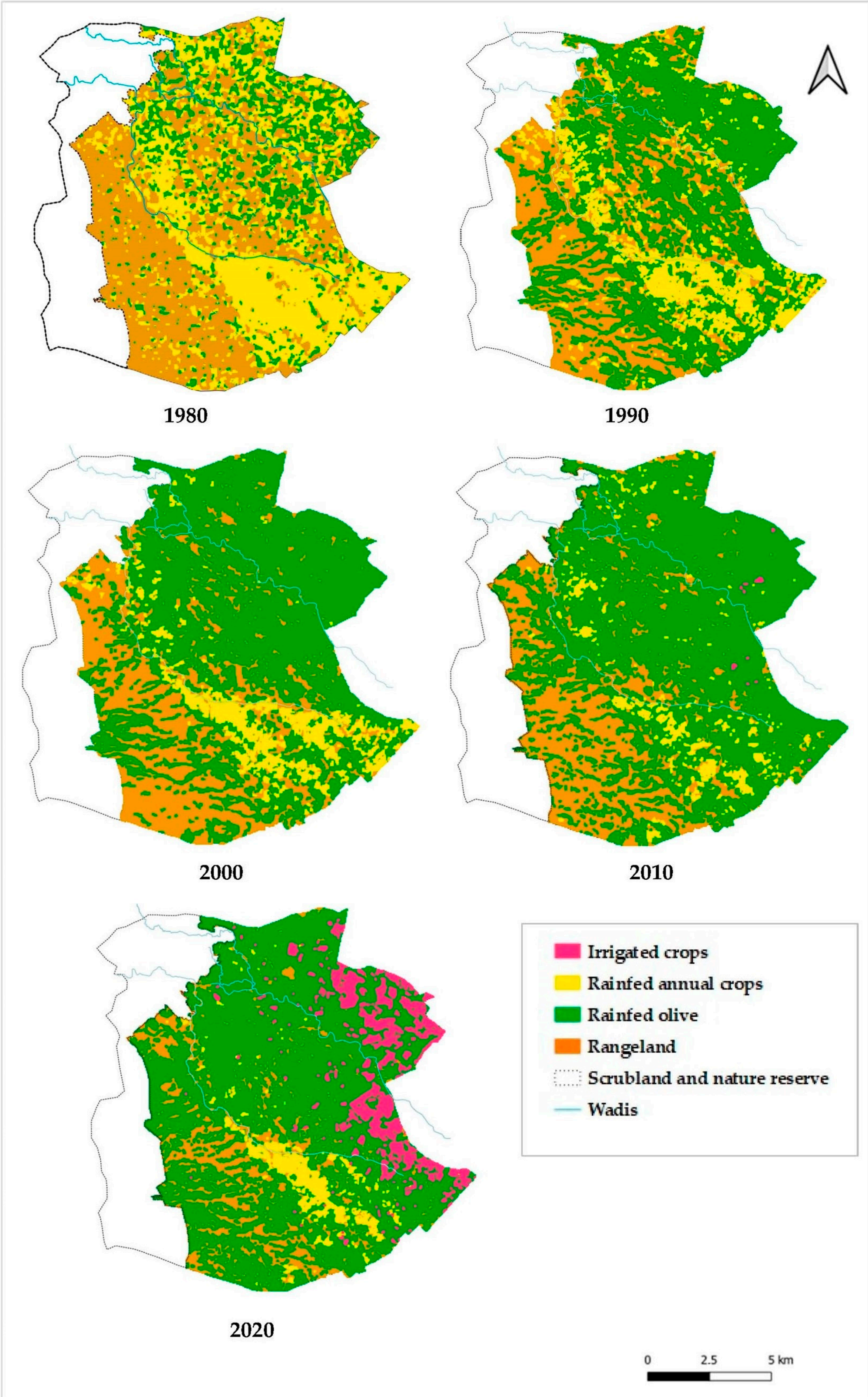

Figure 5. LULC change in Rihana for the years 1980, 1990, 2000, 2010, and 2020.

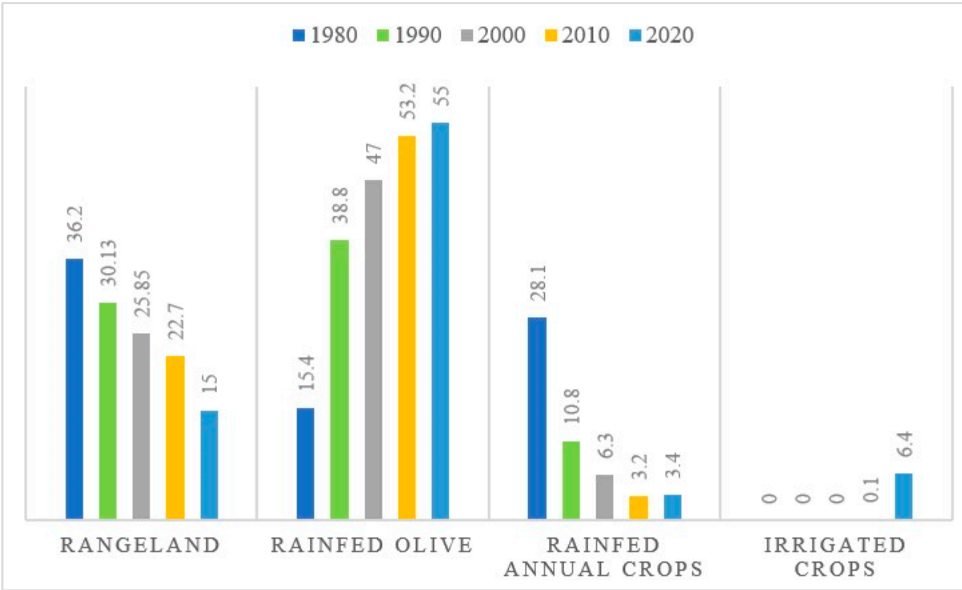

Figure 6. Successive LULC changes in Rihana from 1980 to 2020 (%).

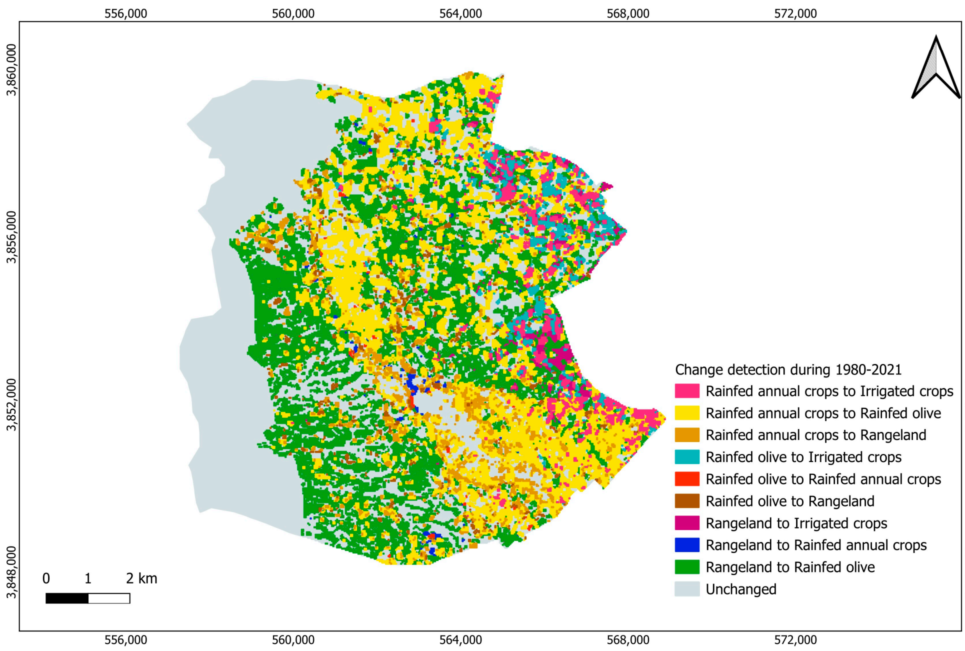

Figure 7. LULC change detection during 1980–2021.

Table 5. Drivers of LULC change and their relative ranking according to the local population.

Period	Drivers	Rank
1980–1990	Sedentarization policy	1
	Decreased sheep grazing	2
	Severe droughts	3
	Increased implementation of SWC techniques by the local population	4
	Seasonal migration	5
	Land registration operation	6

1990–2000	the implementation of the first national strategy of SWC	1
2000–2010	Severe droughts	1
	The widespread use of irrigation in Regueb	2
	Topography and soil fertility	3
	Availability of larger farms	4
2010–2020	The revolution resulting in the weak administrative control	1
	Topography and soil fertility	2
	Occurrence of larger farms	3
	Extended drought periods	4
	High cost of forage grass	5
	Increased cost of fuel and electricity	6
	Tradition of cultivating rainfed olive	7

From 1980 to 1990, major changes were observed for the rainfed annual crops and rainfed olive classes. Indeed, the annual rainfed crops experienced a massive decline in the area corresponding to 61%. This decline was a result of expanding the rainfed olive area, which increased by 152% throughout the study area. Moreover, the rangeland area, particularly in the upstream part, declined by about 17%. There were no differences among the interviewees in their responses regarding the LULC change that occurred in this period. They all indicated that there was a significant decline in rainfed annual croplands and a corresponding significant increase in rainfed olive lands. According to the local population of Rihana, the consequences of the rapid increase in the population since independence in 1956 had a significant impact on the change of LULC. This has resulted in an increase in the number of douars (small nomadic villages), with populations varying greatly from one locality to another. The main activity of this population was based on grazing sheep resulting in the large use of rangelands and cereal crops. Rainfed agriculture usually gives low yields [42]. A total of 89% of the participants indicated that the sedentarization policy led to the growth of rainfed olive crop areas between 1980 and 1990. This policy consisted of the promotion of olive and almond plantations and the creation of the first Soil and Water Conservation (SWC) techniques [43]. Consequently, the settling of nomadic populations led to a major change in their relationship with the land. The prospects of privatization made them attribute a value to the land for its own sake, whereas previously, it had only been used as a support for livestock feeding. Additionally, 60% of the interviewed local population mentioned that seasonal migration plays a significant role in the changes that occurred. These additional incomes allowed them to continue to invest in rainfed orchards and livestock. Furthermore, all farmers stressed the considerable influence of the 1987 and 1988 droughts (Figure 2). They caused the destruction of many almond trees, which were later replaced by more drought-resistant olive trees. Farmers have long developed their own SWC techniques like the mgoud and tabias for floodwater harvesting and distribution [44]. Investment in rainfed olives was favored by the operation of land registration organized by the state between 1980 and 1990. Finally, the evolution of the production system in this period is the result of the local climate, the local population strategies, and the agricultural policies [45], which were confirmed by local experts.

For the period from 1990 to 2000, results show that the rainfed olive area continued to increase by about 21%. On the other hand, rangeland and rainfed annual crops continued to decrease by 14% and 42%, respectively. The decrease in rangeland was specifically observed in the midstream part, while the decrease in the rainfed annual crops was particularly obvious in the upper areas of the downstream part. However, these crops are still cultivated in the spreading basin. All interviewees pointed out that the main driving force behind these changes is closely linked to state policies and strategies. These changes are likely to be associated with the implementation of the first national strategy of SWC in Tunisia (1990–2000). The strategy relied on different techniques of SWC designed to limit erosion and gullying. In 1990, different techniques were implemented in Rihana, such as tabias, flood spreading, and recharging wells in the wadi's upstream part. Under this strategy, the Ministry of Agriculture continued to provide Rihana farmers, landowners with which these techniques were implemented, with olive plants between 1990 and 1995. This encouraged them to plant rainfed olives that are better adapted to the soil and water availability.

During the period 2000–2010, a continuously increasing rainfed olive crop area by about 13% is observed. Rainfed annual crops experienced a massive decline of about 49%. They covered 625.2 ha of the study area in 2000 and decreased to 319 ha in 2010. The decline was primarily observed in the spreading area. Additionally, the rangelands witnessed a decrease of 12% throughout the study area. In 2010, we noticed the introduction of irrigation covering about 13.2 ha (0.13%) in the plain area. A total of 98% of the interviewees stated that these LULC changes may be primarily due to extreme climatic events observed in this specific period. Most of the territory falls under high exposure to drought, especially from 2000 to 2007 (Figure 2). The local population responded to droughts by cultivating rainfed olives. It was already mentioned [46] that drought poses the most significant threat to the socioeconomic stability of small farmers. In addition, all local experts indicated that the irrigation from drilled wells which became widespread in Regueb, motivated the local population to start the irrigation of crops. The local population situated in the plain opts for irrigation agriculture due to favorable topography, convenient access to water through wells, and the occurrence of larger farms (5 to 50 ha) compared to the upstream part. The topography of these areas is characterized by steep slopes and rocky, shallow soils and low fertility with farms that are smaller than 5 ha. Additionally, farmers consider irrigation a viable adaptation strategy to cope with the impact of climate change [47].

Considering the LULC changes between 2010 and 2020, we note the extension of the irrigated areas in the plain. They increased from 13.2 ha in 2010 to 634 ha in 2020. In addition, rainfed annual crops increased from 319 ha in 2010 to 335 ha in 2020; this trend is especially evident in the spreading basin area. During the same period, rainfed olives showed a small increase of 3.38%, particularly in the midstream part. In contrast, rangeland showed a reverse trend, decreasing by 40%. It is worth noting that since the outbreak of the Tunisian revolution in 2011, the region, as well as the country, experienced a period of transformation that induced significant environmental changes [48]. These changes are marked by the weakening of administrative control that has led to an increase in the number of illicit drillings, as reported by the experts. The local population has reported an increase in the number of illicit well drilling in Rihana, which has risen from 35 in 2019 to 70 in 2020. We also notice that the use of solar panels has recently soared in Rihana and in the semiarid region of Tunisia in general due to the increasing costs of fuel and electricity [49]. About 25% of the farmers who practice irrigation use solar panels. Additionally, another important factor reported by 90% of the interviewees is the extended drought period followed by wet years that lead to a decrease in the rangeland area (Figure 2). Moreover, 83% of the respondents mentioned that with the high cost of forage grass, they returned to cultivating rainfed annual crops for the feeding of their livestock. Furthermore, 60% of the farmers indicated that the expansion of rainfed olive lands is due to the long-standing tradition of cultivating rainfed olives, which has become an integral part of their culture and livelihoods.

Finally, it is worth noting that Sidi Bouzid, and particularly Rihana, have experienced a significant transformation regarding its agrarian system. Over the 40 past years, rainfed olive land and irrigated land increased in area by 4 times between 1980 and 2021 and 60 times between 2010 and 2021 (Figure 7). The rangeland and rainfed annual crop area decreased by 58% and 88%, respectively. It is mainly the transition from a system dominated by pastoralism based on breeding, transhumance, and rangeland to an agricultural system dominated based on irrigated and rainfed olive crops in dry conditions associated with episodic cereal cultivation and decreasing rangeland area [50]. These changes are influenced by a variety of factors, such as economic opportunities and policies, etc., but they are also highly dependent on the local context and directly linked to the livelihoods of the local population. The changes in LULC can be explained as an adaptive response to these various factors. As a result, even in small areas, there is a great diversity of agricultural situations.

5. Conclusions

Accurate and long-term LULC data are crucial for the natural resources' sustainable management in the semiarid regions of Tunisia. In this study, we started with the analysis of the LULC changes in Rihana from 1980 to 2020 using the Random Forest algorithm (RF) in Google Earth Engine (GEE) platform, along with Landsat 3, 5, 7, and 8 imageries. We characterized the dynamic LULC change using RPSD. We used time series of satellite images with an RF classifier in the GEE platform for the semiarid region. Change detection analysis enabled us to compare the spatial-temporal patterns of LULC changes. The convenience of the used approach can be considered in the future as a reference for conducting similar studies in other regions. We found that the Rihana study area has undergone major LULC changes during the past 40 years. The observed trend is an increase in rainfed olives, especially in the upstream part, and a corresponding fluctuating trend in irrigated crops in the downstream part. We noted a decrease in rangeland and annual rainfed crops over the same period. In general, the observed landscape transformations are mainly linked to local factors followed by economic opportunities and political factors. These changes increased the pressure on groundwater resources. Hence, there is a risk of a decline in rangeland and rainfed land area soon. Finally, the findings of this research have shown the necessity for raising awareness toward implementing a comprehensive assessment of human activities along with LULC management practices within the Rihana study area. Therefore, it is crucial to embrace the management and sustainability of these LULC practices, water and soil conservation measures, participatory approaches, and offering alternative livelihoods to reverse the non-desired consequences related to LULC changes in semiarid regions of Tunisia.

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