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Assessment of Land Use and Land Cover Change in Southwest Mauritania, Remote Sensing and GIS Approach

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Abstract

Most countries' land use and land cover (LULC) are changing dramatically today. Most of these changes are related to the way humans and the environment interact. Various methodologies and data sources have been used in conjunction with remote sensing (RS) to categorize and map changes in LULC. This study used RS and Geographic Information System (GIS) tools to analyze LULC change and transitions from 1984 to 2022 in a tropical forested landscape in southwest Mauritania. Using a suitable and high-quality collection of Landsat satellite images. For the classification and creation of LULC maps for the selected periods, the supervised technique using a maximum likelihood classifier was used. The results indicated that there was a remarkable change in all classes of LULC, with an increase in all classes, except barren land, which had a tremendous decrease of −68.58% for the total study area. Therefore, for the total study area, an increase in agricultural land (221%), water bodies (118.46%), vegetation (57.50%), and built-up areas (14.65%) was observed. We believe that by informing policymakers, environmental managers, and the general public about the current changes, our study will help the region to establish appropriate land use rules that may lead to policy document development.

Keywords

Land-Use-Land-Cover, Remote Sensing, Geographic Information System, Maximum Likelihood Classifier, Southwest Mauritania

1. Introduction

One of the most important natural resources on the planet is land, which is also a basis for sustaining life and supporting development [1]. The concept of "land use" describes the economic or social functions related to a particular area of land. On the other hand, the types of features existing on the surface of the land are related to the land cover [2].

Major changes in LULC are currently underway in most countries of the world [3]. Most of these LULC changes have been linked to how humans and the environment interact [3] [4]. Through various methods and datasets, Remote Sensing (RS) has been used to classify and LULC changes. Landsat images, in particular, have been very useful for classifying different landscape features on a larger scale [5].

Recently, several change detection methods using RS images have been created. Different change detection methods and algorithms have been created, and their advantages and disadvantages have been discussed. The most commonly used classification algorithms are unsupervised, supervised, hybrid, and fuzzy [6].

A variety of supervised classification methods have been widely applied for the analysis of land-use change throughout the world. This technique depends on a combination of background knowledge and personal experience of the study area to a greater extent than in other areas [7]. Thus, the signatures per pixel are taken and stored in signature files using this knowledge, and the raw Digital Numbers (DN) of each pixel in the scene are thus converted into radiance values [8].

A similar technique was used to detect climate change in a closed area (RS and GIS in Support of the characterization of the climate in Mauritania: Case of the Diawling National Park (PND) and its peripheral zone) and provides accurate information on precipitation, temperature, and vegetation over the study area [9]. The study area was selected for change detection because it experiences urbanization, agricultural activities, water and soil erosion, overgrazing, and tree cutting.

Due to the accelerated agricultural development and the invasion of the aquatic species Typha australis into the study area, one of the main problems facing the same area is the rapid discharge of pesticide residues into the water courses.

The rapid growth of agricultural activities in the study area has led to several environmental problems, including various of the invasive aquatic species Typha australis, habitat fragmentation, soil erosion, and water pollution due to deforestation and pesticide wastewater discharge [9] [10] [11].

Therefore, the main objective of this research was to use GIS and RS applications to identify the extent of change in southwest Mauritania over 38 years. However, specific objectives includes: 1) identifying and delimiting the different LULC categories and the pattern of land use change in southwest Mauritania from 1984 to 2022; 2) examining the potential of integrating GIS with RS in the study of the spatial distribution of the different LULC changes; 3) determining the change in LULC categories by spatial comparison of the LULC maps produced.

2. Materials and Methods

2.1. Description of the Study Area

The study area is located in Keur Massene, southwestern Mauritania in the Senegal River delta (**Figure 1**) and is an arable area with very rich land, which allows for the growing of crops (agricultural projects). Therefore, in this area, irrigated agriculture is the main activity of the population [12]. The Islamic Republic of Mauritania is a coastal country located in northwest Africa. It lies between 15 - 27 degrees north latitude and 5 - 17 degrees west longitude, the territory covers an area of 1,030,700 square kilometres. It is bounded on the north by Western Sahara and Algeria, on the east by Mali, on the south by Mali and Senegal and on the west by the Atlantic Ocean on a coast of more than 700 kilometres [13]. The country is divided administratively into 13 regions, In Mauritania, there are generally three types of climate, which are a dry tropical climate of the Sahelo-Sudanese (characterized by 8 dry months in the extreme south of the country with rainfall greater than 400 mm per year); a sub-desert climate of the Sahelo-Saharan type in the centre of the country (characterized by high thermal amplitude and rainfall of between 200 and 400 mm per year); and a desert climate of the Saharan type in the north (characterized by rainfall of less than 200 mm/year [14].

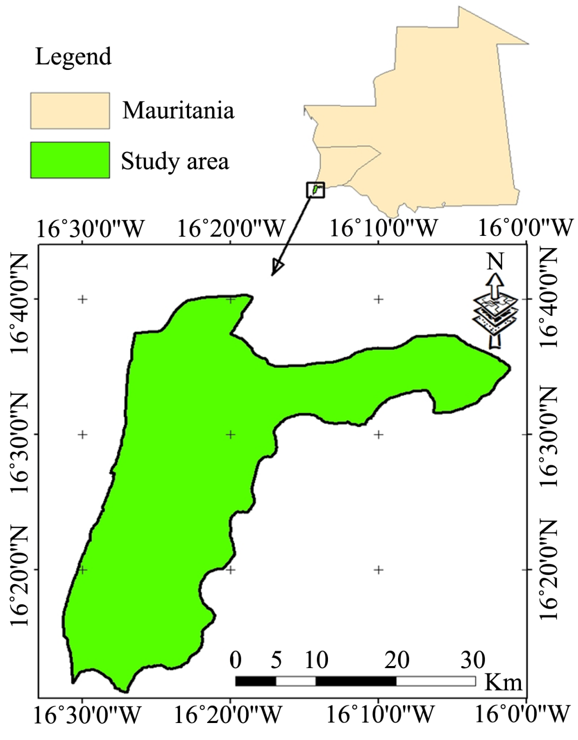

Figure 1. Map of the study area. Source: Author.

It is constituted by a three-quarters desert, which is characterized by a generally hot and dry climate marked by relatively mild winters. The average minimum temperatures are between 19˚C to 23˚C, and the maximum is between 30˚C to 23˚C. The Senegal River is the only permanent watercourse in Mauritania and is used for irrigation, transport, drinking and hydroelectric power [15]. Mauritania's soils are mostly poor in organic matter and have a high concentration of salt, with 80% of skeletal soil [12]. The most important forest resource in Mauritania in terms of density is found in the Senegal River valley and along its tributaries. It is estimated that there are 138,000 ha of protected forests and 48,000 ha of classified forests. Forests play an important role in maintaining soil fertility by shedding their leaves which contain many nutrients [16], and also help to bind soil particles with the help of plant roots. Forest cutting or deforestation in Mauritania is found in the Senegal River valley and along its tributaries, resulting in severe soil degradation. The project area is located in town and urban commune called "Keur Massene" which is in a region called "Trarza", which is a region in southwest Mauritania (**Figure 1**) with a total area of 67,800 square kilometres, surrounded by the north by the regions of Inchiri and Adrar, to the east by Brakna and to the south by Senegal River. The water resources of the Trarza region are used for a variety of purposes, from urban water supply to agriculture. About 70% of the Trarza territory has a typical Saharan climate, while the remaining 30% has a Sahara-Sahelian climate, as it is located in the transition zone between the Sahara (desert zone) and the Sahel (semi-desert or semi-arid zone). The soils of the Senegal River delta in Mauritania are salty due to the installation of the Diama dam [17].

2.2. Data Collection

Satellite image data for the LULC classification were downloaded from the United States Geological Survey (USGS) Earth Explorer website (https://earthexplorer.usgs.gov/) and are from the Landsat 8 OLI-Thermal Infrared Sensor (TIRS) dataset. The quality of the images, particularly those with little or no cloud cover, affected the selection of Landsat satellite image dates. Each Landsat image was georeferenced to the Universal Transverse Mercator Zone 28 North coordinate system and the WGS 84 datum. Landsat data sets are freely available through the USGS Earth Explorer online archive (free download worldwide). Seven spectral bands (1 - 7) with a spatial resolution of 30m make up the Landsat 8 OLI dataset. The LULC map was produced from these datasets. The downloaded data were in Geo TIFF file format. Each band of the image displays the intensity values of the research area for a certain wavelength as a greyscale image. **Table 1** shows the spectral properties of the Landsat data. Cloudy images and unwanted shadows considerably decrease the accuracy of the classification result. Therefore, high-quality cloud-free scenes were chosen in this study.

Table 1. Details of satellite data used in the research.

Year	Date of Acquisition	Path/Row	Spatial Resolution	Description
1984	04th December			Landsat 5, Thematic Mapper (TM)
2000	08th December	205/49	30 m	Landsat 7, Enhanced Thematic Mapper Plus (ETM+)
2022	04th February			Landsat 8, Operational Land Imager (OLI)

2.3. Image Pre-Processing and Classification

The classification scheme was adopted in this study. The study area was classified into five different classes. A detailed description of these classes is shown in Table 2. To create each class, texture, tone and colour were used [18]. In the image classification, these classes were assigned to the pixels.

According to [19], it is "the user develops the spectral signatures of known categories, such as urban and forest, and then the software assigns each pixel in the image to the cover type to which its signature is most comparable" and "The most commonly used method for quantitative analysis of RS image data is supervised classification" [20]. After defining Areas of Interest (AOI) named formation classes, supervised classification was used. To represent a certain class, more than one training area was used. The training sites were selected based on the combination of three band numbers that can show us the nature of the class.

2.4. Sample Selection for Training Data

The datasets were created by combining several bands of satellite images with field survey data and Google Earth data. The satellite image of the right bank of the Senegal River and the Landsat subset image was linked and synchronized using Google Earth Pro.

This procedure was used to find the distinctive features of the research area. The colour of a particular class was determined by various combinations of bands. The vegetation, woodland, crop and wetland survey used the band combination 5-4-3. The band combination 7-6-4 was used for the built-up area survey. Based on the colour of the pixels, data sets were created. By drawing polygons and placing them in an AOI (Area of Interest) layer, training locations were created in the imagery. To form each specific class, 60 polygons were brought in and placed in the signature editor. These 60 polygons were combined and given a unique class name. The signature file was then created using the signature editor file (sig format). Three signature files were developed in this study to train the three datasets (1984, 2000, and 2022). Lastly, the trained datasets were utilized in the process of supervised image classification.

Table 2. Image classification details.

No	Class name	Description
1	Water Bodies	Areas covered by water, include rivers, oceans, reservoirs, Ponds, lakes, and streams.
2	Vegetation	The vegetation types that can be found are forest, rainforest, damaged forest, marsh forest, woodland, mangrove, grassland, savannah, steppe land, agro forest, herbaceous and short Sahelian grasses.
3	Agriculture Land	Plantation, irrigated agriculture, lowland agriculture, rain fed agriculture, declining agriculture.
4	Build up Area	Land surfaced with concrete, such as low, medium and high-density roads, residential, commercial and industrial structures, educational establishments, public transport systems, open-roof concrete buildings and other man-made buildings.
5	Barren Land	All the land that is bare, *i.e.* without vegetation, uncultivated, rocky terrain, deserts, and sandy beaches near rivers and streams.

2.5. Accuracy Assessment

One of the most important final steps in the classification process is the accuracy assessment. The accuracy assessment aims to quantitatively determine how well the pixels were sampled in the appropriate land cover categories. In addition, locations that could be easily identified on the high-resolution Landsat image, Google Earth, and Google Map were the main criteria for selecting pixels for the accuracy assessment. In the classified image of the research area, a total of 70 points (locations) were formed. The reference column of the accuracy assessment cell table was filled in using the best estimate for each reference point after generating the classified images, and the accuracy of the classified images was determined using QGIS software. The evaluation of the classification accuracy is an essential step after the classification of the images.

The producer's accuracy describes the number of commission errors. For each class, omission errors occur when pixels that belong to one class are included in other classes. Another indicator characterising the omission errors is the user's accuracy.

An accuracy assessment was performed by using QGIS for 1984, 2000, and 2022 LULC maps. One of the most essential final steps in the classification process is the accuracy assessment. Its objective is to quantitatively determine how accurately the pixels have been sampled into the correct land cover categories. In addition, locations that are easily identifiable both on the high-resolution Landsat image and on Google Earth or Google Map were the focus of the selection of pixels for the accuracy assessment. A total of 70 points (locations) were created in the classified image of the study area. Google Earth, Google Map, and field visits were also used as reference sources to classify the selected points.

2.6. Land Use/Cover Change Detection

The change detection methods based on RS and GIS are popular due to their low cost and high temporal resolution. The most popular strategy for identifying changes in LULC is the post-classification comparison technique, which is based on supervised maximum likelihood classification. This approach has shown good overall classification accuracy for a range of data [21]. In order to identify where a change has occurred, the post-classification comparison approach compares the respective classes after categorising the photos. The post-classification comparison approach achieved the highest classification accuracy in a comparative analysis of several techniques.

The change detection process is the method of identifying changes in an object or phenomenon by monitoring it at various intervals [22], In this research, the intersection geoprocessing tools of ArcMap 10.8 were used to identify the change processes of LULC for the periods 1984-2000, 2000-2022, and the net change between 1984 and 2022. This method was chosen because of the ease of comparing two images from different sensors and periods [23].

This is also the method that has been used most frequently to identify changes [24], and it has the major advantage of showing "from-to" changes. However, the disadvantage of this method is that it requires two classifications and is dependent on the classification of individual images [25]. In this method, the three images of different dates are classified and labelled independently. The area of change is then calculated with an intersecting image attribute table using ArcMap 10.8. The results were presented in a table and map format.

3. Results and Discussion

3.1. Results

1) Land Use and Land Cover 1980:

The layout of the LULC map generated from the Landsat 8 dataset is shown in **Figure 3**. The land categories for the year 1984 and their statistics are presented in **Table 3**. From the results, the largest category was barren land (68667.49 ha, 66.43%), followed by vegetation (28187.61 ha, 27.27%). The other land use categories

Table 3. Extent and percentage of LULC categories of images classified.

LULC categories	1984		2000		2022	
	(ha)	(%)	(ha)	(%)	(ha)	(%)
Agriculture Land	317.76	0.31%	27478.6	26.58%	24926.3	24.11%
Vegetation	28187.61	27.27%	20645.9	19.97%	44394.3	42.95%
Water Bodies	5170.93	5.00%	10113.8	9.78%	11296.4	10.93%
Barren Land	68667.49	66.43%	39001.2	37.73%	21577.7	20.88%
Build up Area	1022.17	0.99%	6126.37	5.93%	1171.9	1.13%
Total	103,366	100%	103,366	100%	103,366	100%

were water bodies (5170.93 ha, 5% of the total area), built-up areas (1022.17 ha, 0.99% of the total area) and finally agricultural land (317.76 ha, 0.31% of the total area).

2) Land Use and Land Cover 2000:

The result of the LULCC classification for 2000 is shown in Figure 2 and summarized in Table 3. It revealed that the largest land cover class was barren land, with a total of 39001.2 ha, which is 37.73% of the entire study area. It was followed by agricultural land, which occupied a total of 27478.6 ha, which is about 26.58% of the study area. The third in this order was identified as vegetation, which was about 20645.9 ha, representing 19.97%. The fourth was water bodies, with 10113.8 ha accounting for 9.78%, and the built-up area was the least covered land class, which occupied 6126.37 ha with 5.93%.

3) Land Use and Land Cover 2022:

For 2022, the spatial distribution for LULC Change classes is shown in Table 2 and Figure 3 Results show that vegetation took the first position, occupying 44394.3 ha or 42.95% of the area, followed by agricultural land, which occupied a

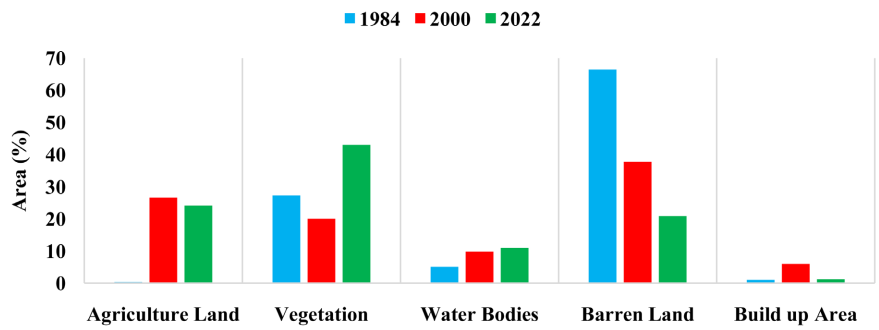

Figure 2. Area under different land use and land cover classes (1984, 2000, and 2015).

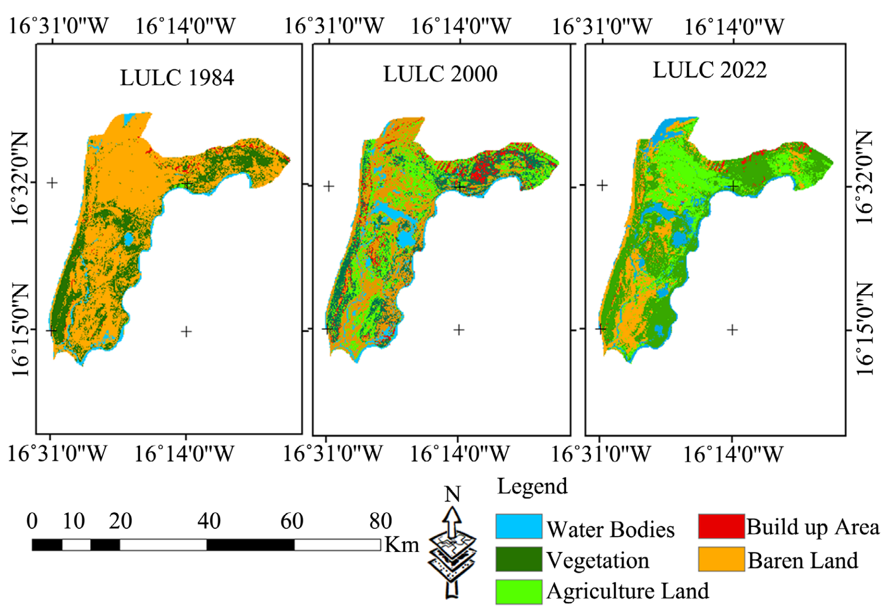

Figure 3. Maps of LULC for 1984, 2000 and 2022 in the study area.

total area of 24926.3 ha, which made up 24.11% of the study area. Barren Land occupied the third position with 21577.7 ha making up 20.88% of the entire study area. Water Bodies maintained the fourth position with 11296.4 ha representing 10.93%. Build-up Area occupied the fifth and last position with 1171.9 ha meaning 1.13%.

4) Accuracy Assessment

The 1984 LULC map had an overall kappa statistic of 0.97 and an overall accuracy of 98.60%. Producer accuracy for each class was higher than or equal to 97.9%. The user's accuracy for three classes (water bodies, built-up areas, and barren land) was 100%. The agricultural land and vegetation categories had user accuracy of 90% and 95%, respectively (Table 4). For the LULC 2000, the overall kappa statistic and overall accuracy of the LULC 2018 map were 0.82% and 86.32%, respectively (Table 5). The producer accuracy for each class was greater than 71.4%. User accuracy for all classes, except in built-up areas (60%), was greater than 80%. The overall accuracy for 2000 was lower than that for 1984, which [26] suggested could be attributed to combining images from different years due to availability requirements and cloud cover, which must be less than 10%. For 2022, the overall accuracy was 91.7%, while the producer and user accuracy ranged from 75.1 to 100% and over 80%, respectively. The Kappa coefficient was 0.88 (Table 6).

Table 4. Error matrix of the classified image 1984.

Classified Image	Reference Data					Row Total	User's Accuracy (%)
	W	V	AL	BA	BL		
Water Bodies (W)	16	0	0	0	0	**16**	100
Vegetation (V)	0	19	0	0	1	**20**	95
Agriculture Land (AL)	0	0	9	0	1	**10**	90
Build up Area (BA)	0	0	0	10	0	**10**	100
Barren Land (BL)	0	0	0	0	14	**14**	100
Column Total	**16**	**19**	**9**	**10**	**16**	**70**	**Overall Accuracy = 98.60%**
Procedure's Accuracy	100	100	100	100	97.9		**Kappa coefficient = 0.97**

Table 5. Error matrix of the classified image 2000.

Classified Image	Reference Data					Row Total	User's Accuracy (%)
	W	V	BL	AL	BA		
Water Bodies (W)	14	1	1	0	0	**16**	87.5
Vegetation (V)	0	18	0	2	0	**20**	90
Barren Land (BL)	0	1	13	0	0	**14**	92.9
Agriculture Land (AL)	0	1	0	9	0	**10**	80
Build up Area (BA)	0	2	2	0	6	**10**	60
Column Total	**14**	**23**	**16**	**11**	**6**	**70**	**Overall accuracy = 86.35%**
Procedure's Accuracy (%)	100	71.4	95	91.5	100		**Kappa coefficient 0.82**

Table 6. Error matrix of the classified image 2022.

Classified Image	Reference Data					Row Total	User's Accuracy (%)
	W	AL	V	BL	BA		
Water Bodies (W)	14	1	1	0	0	16	87.5
Agriculture Land (AL)	0	9	0	1	0	10	90
Vegetation (V)	0	0	18	2	0	20	90
Barren Land (BL)	0	0	0	14	0	14	100
Build up Area (BA)	0	0	0	2	8	10	80
Column Total	14	10	19	19	8	70	**Overall accuracy = 91.70%**
Procedure's Accuracy (%)	100	97	98.3	75.1	100		**Kappa coefficient 0.88**

The Kappa coefficients demonstrate that all the classified images were almost perfect as they ranged from 0.82 to 0.97.

3.2. Discussion

3.2.1. Change Detection in Land Use/Land Cover

As Figure 4 shows results for analysis of land use change using the supervised classification method from 1984 to 2022 showed that several soil classes (built-up area, vegetated area, water bodies, agricultural land, and bare soil) covered southwestern Mauritania in the Senegal River delta.

In general, southwestern Mauritania, along the Senegal River delta, has experienced considerable changes in land use and land cover over the past three decades, throughout its length and width. However, changes have been significant in the central part of the study area, which also supports the main cultivation of rice, and along the Senegal River, where invasive plants can thrive. The details of land use and cover change in the study area over the selected period (1984-2000-2022) are shown in Figure 4.

1) LULC Change Detection from 1984 to 2000:

Agriculture, water bodies, and built-up area all experienced increases in the first 16 years of the study period, from 1984 to 2000. For agricultural land, the change is primarily due to the period between 1990 and 2000, when the population began to shift from rain-fed crops such as maize and wheat, known as walo crops, to irrigated rice crops in the study area. In addition, at that time, agriculture, water bodies, and built-up areas occupied a significant portion of the barren land as shown in Figure 4.

2) LULC Change Detection from 2000 to 2022:

Between 2000 and 2022, vegetation increased significantly by 115.03% (2748.38 ha), followed by water bodies (11.69%, 1182.55 ha), while there was a large decrease in the built-up area by 80.87% (4954.47 ha), barren land by 44.67% (1723.50 ha), and agricultural land by 9.29% (2552.28 ha) see Figure 4.

3) Net Change Detection from 1984 to 2022:

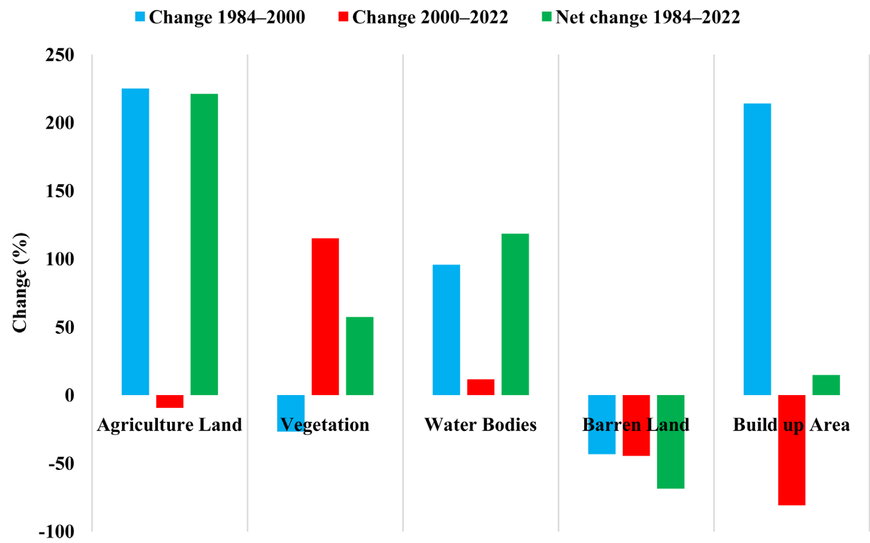

Figure 4. Area Change 1984 to 2000, 2000 to 2022, and net change from 1984 to 2022.

During the period 1984-2022, there were net increases in the area of the following areas: agricultural land (221%), water bodies (118.46%), vegetation (57.50%) and built-up areas (14.65%), while there was only one decrease in the area of barren land (−68.58%).

3.2.2. Discussion of Factors Accounting for Land Cover Change

In 1984, there was almost no land used for agriculture, and what there was appeared to be irrigated land located near the Senegal River. Over the past 38 years, there have been both positive and negative changes in the LULC categories. While the area of barren land has decreased, the area of water bodies has increased. As shown in Table 3, the agricultural land, vegetation, and barren soil categories have seen the greatest changes in the area, followed by water bodies and build up areas.

1) Water bodies:

The area of water bodies has increased by a net 6125.47 ha, from 5170.93 ha in 1984 to 11296.4 ha in 2022. The creation of the Diama Dam and the Diawling National Park in Mauritania is the reason for the increase in the area occupied by water bodies.

The Diama Dam, built on November 28, 1985, is a floating structure that opens during flood periods to maintain the regular flow of the river and closes during low-water periods to prevent a rise in salinity.

The Diawling National Park in Mauritania was created in 1991 and is located on the right bank of the lower Senegal River delta. Its primary area is more than 16,000 ha, while its surrounding area is more than 56,000 ha.

According to a study published in 2020, Diawling is the only park in the West African Marine Protected Areas Network (RAMPAO) to show an overall positive evolution of all its habitats, even though it is one of the most pressurized parks in the network. The ecosystems of this estuarine environment have thus been restored, redrawing a rich and varied landscape: at the junction between desert, ocean and river, estuaries, islands, mangrove ecosystems, inland dunes, a coastal dune, flood plains and the Senegal River are added.

2) Agriculture land:

From 317.76 ha in 1984 to 24926.3 ha in 2022, the increase in agricultural land has resulted in a net increase of 24608.54 ha. The Study Area's usable agricultural land has expanded rapidly in recent years. The expansion of Mauritania's agricultural industry has increased the area of agricultural land.

According to FAO data [27], Mauritania's agriculture has grown significantly in recent years and 1991 accounted for half of the country's grain production.

Another explanation for this increase is that businessmen have invested in the agricultural sector after realizing the benefits of agriculture, and the study area is one of the best places for agriculture.

3) Build-up area:

The area of built-up land increased by a total value of 5104.2 ha, from 1022.17 ha in 1984 to 6126.37 ha in 2000. However, it decreased to 1171.9 ha, or 3932.3 ha, in 2022. Population growth, tourism, and housing demand have all contributed to the increase in built-up land area. The study area is a rural area where people cultivated land and grazed their animals, but after the construction of the dam and park, they could not find land for their animals because the protected area was for marine ecosystems. Therefore, they moved in search of new places where their animals could graze and be thriving. That's why the area decreased. There were also problems with businessmen taking most of the land for their business, so people had to move to other lands where their animals could graze freely. The increase of invasive plants, especially typha, has also significantly impacted population movements, as this plant occupies most of the arable land and there was no solution to combat it.

4) Vegetation:

The change detection results showed a decrease in vegetation land with a net change of 7541.71 ha for 1984-2000 but an increase of 23748.4 ha for 2000-2022. The study found that built-up areas, water bodies and agricultural land have all increased as a result of vegetation loss. The reduction of vegetations is mainly caused by the expansion of cultivated land for agriculture, which is the main source of livelihood for most rural populations, especially in the study area, where the conversion of vegetation to agricultural land has been demonstrated by [11] [28].

The increase in the area of invasive plants, namely Typha, is the reason for the increase in the vegetation found in this class. Much of West Africa is host to the invasive species typha. Mauritania, Senegal, Mali and Guinea have all struggled to control typha, which causes a variety of problems. For those who depend on rivers for drinking water, crop irrigation, or fishing, it makes the banks inaccessible. Water bodies will then have developed throughout this period, allowing the plant to find a place to spread and thrive.

5) Barren land:

The net change results show a decrease in barren/other land of 47089.79 hectares between 1984 and 2022 for all periods analyzed. The decline in this category is brought on by an increase in vegetation, agricultural land, and water bodies, in addition to the park as a protected area.

4. Conclusions

The objective of this study was to analyze the changes in LULC from 1984 to 2022 in the study area using USGS remote sensing data and GIS techniques. The results indicated that there was a remarkable change in all classes of LULC, with an increase in all classes, except barren land, which had a tremendous decrease of −68.58% for the total study area. Therefore, for the total study area, an increase in agricultural land (221%), water bodies (118.46%), vegetation (57.50%), and built-up areas (14.65%) was observed.

The construction of the Diama Dam in 1986, which had many negative impacts on the study area, including the development of the Typha Australis plant, and the establishment of the Diawling National Park in 1991 to manage these impacts, are the main factors driving this change, as the available research in the study area shows, and are the causes of the changes in LULC in the study area.

The government should adopt effective strategies and procedures with the cooperation of non-governmental organisations to reduce and prevent the negative impacts of this invasive plant, Typha Australis.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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