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Assessment of land use and land cover change on Gum Talha (*Acacia seyal* var. *seyal*) forest in Bahar Alarab, Sudan

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Abstract. *Younis AYI, Jonathan BN, Togun AO, Yasin EHE, Omer SO, Hamad GAI, Aissata SD. 2022. Assessment of land use and land cover change on Gum Talha (*Acacia seyal *var.* seyal*) forest in Bahar Alarab, Sudan. Biodiversitas 23: 4549-4560.* Evaluating land use and land cover change (LULC) is essential for the sustainable management of natural resources, biodiversity conservation, monitoring of food security, and research related to climate change and ecology. A better assessment of land-use changes is highly needed for further investigation due to increasingly rapid changes in LULC in response to human population growth. The emerging climatic change also has a significant effect on LULC. The objective of this study is to assess land use and land cover in Bahar Alarab, East Darfur State, Sudan, using remote sensing data obtained from satellite images. For assessing the LULC changes, Landsat images of the years 1988, 2002, and 2020 were downloaded and analyzed using QGIS 3.22.1 and ERDAS 2014 software, where supervised classification was applied with GPS point verification, change detection, matrix, and accuracy assessment. The analysis on LULC showed considerable changes during the two study periods, where 2020 had a considerable increase in forest cover in which on that year it occupied 26.44% of the area compared to 2002 and 1988 with 21.27% and 21.45%, respectively. Whereas 2002 the area was covered by a vast herbaceous vegetation (33.41%) compared to 1988 and 2002. Moreover, in 1988, shrubland decreased from 31.95% to 29.06% and 23.67% in 2020 and 2002, respectively. Sparse vegetation covered a considerable area in 2020 (23.61%) compared to 2002 and 1988 (21.65% and 17.71%, respectively). The results highlighted that there was statistically significant correlation between climate factors and LULC. Average temperature was highly positively correlated with sparse vegetation at 98.2%, while rainfall was highly negatively correlated with forest (-96.9%) and sparse vegetation (-88%), and highly positively correlated with herbaceous vegetation (83.5%). This study provides a unique understanding of LULC changes and their implications in management and conservation efforts, as well as a road map for decision makers for sustainable development of LULC in the Bahar Alarab.

Keywords: Bahar Alarab, climate change, land use, land cover, forest, matrix

INTRODUCTION

Climate change is one of the biggest threats to the sustainability of the Earth, and the risks associated with it are increasing worldwide (Shiferaw et al. 2014; Toh et al. 2018; Altea 2019; Younis et al. 2022). Effort to mitigate climate change impacts, among others, is focused on the forestry sector with the implementation of new forest and climate governance tools, and a more sustainable exploitation of forest resources (Brockhaus et al. 2021). This is fundamental since there are over 4 billion hectares of forest cover worldwide, equating to one-third of the earth's surface (Temgoua et al. 2018; Mngube et al. 2019; Nunes et al. 2022). Forests are becoming more important than ever before for balancing the earth's CO_2 supply and exchange, acting as a key link between the atmosphere, geosphere, and hydrosphere (Yagoub et al. 2015; Yahya et al. 2021). Not only important for climate change mitigation, forests also deliver other environmental benefits, including soil conservation, preservation of biodiversity and safeguard from environmental catastrophes, and provide long-term national economic benefits as well as serve as a source of livelihood for local communities (Hu et al. 2019). However, many forests globally are threatened by land use and land cover (LULC) change directly proportional to the human growth rate (Siddig et al. 2020).

With the increasing interest in the forest's resources and the impact of climate change, assessing LULC is essential for the sustainable management of natural resources (including forest), biodiversity conservation, monitoring of food security, and research related to climate change and ecology (Yagoub et al. 2017a). In particular, the increasingly rapid changes in LULC necessitate a better assessment of land use changes more than ever (Akodéwou et al. 2020). Furthermore, for the development of proper climate change impact adaptation solutions and natural resource management, the assessment of LULC in relation to climate factors will be useful (Preetha et al. 2021).

Recently, there have been changing LULC in the African region due to unsustainable development that has become an environmental interest. Combined with climate change, LULC change has likely devastating impacts on African countries. Sudan is one of the most vulnerable countries in Africa to LULC and climate change. Both factors likely affect the existence of forests in Sudan especially Gum Talha (*Acacia seyal* var. *seyal*) stands due to its sensitivity to the new climate variability (Siddig 2020). Gum Talha production is a key economic sector of Sudan due to its significant contribution to households' income generation and food security (Ibrahim et al. 2015). The LULC classes classify the importance of Gum Talha clearly appears as the main source of the economy of households of the Bahar Alarab locality, East Darfur State, Sudan in which 90% of the livelihood is associated with this commodity (Ahmed et al. 2022). The Sudan national statistics on agricultural production reported that 30% of *Acacia seyal* var. *seyal* yield in Sudan is produced in the Bahar Alarab. The Bahar Alarab locality maintains *A. seyal* trees which significantly contribute to the local rural economy as well as the national economy.

One approach to assess the aggregated magnitude and direction of LULC change is by using spatial modeling in line with remote sensing image classification (Chemura et al. 2020; Macarringue et al. 2022). This approach can quantify the change in the forest cover area, carbon storage as well as other ecosystem services (Adelisardou et al. 2021). The use of remote sensing technologies, as well as geographical spatial tools, is considered a suitable approach to assess the historical and future LULC (Alqurashi and Kumar 2013; Sharma et al. 2019). Remote sensing is used to map the extent and spatial distribution of forest and land uses based on a stable classification system for change and analysis with integration into the field data (Fichera et al. 2012; Aboelnour and Engel 2018). It is an efficient and adequate tool for monitoring and detecting changes in vegetation using multitemporal data. Images of previous dates can be compared to recent years to tangibly measure the differences in the sizes and extents of forest cover (Nzoiwu et al. 2017; Sharma et al. 2019).

The main goal of this study was to assess the impact of LULC change on *Acacia seyal* var. *seyal* forest in the Bahar Alarab locality in East Darfur State of western Sudan using remote sensing techniques. In doing so, we identified, mapped and assessed LULC in specific years of 1988, 2002, and 2020. We expected, the study would contribute directly to determining the extent of forest degradation problems in the region and how to address these problems to adapt to the changes in climate and LULC.

MATERIALS AND METHODS

Study area

The study was conducted in Bahar Alarab locality, which is in the southern part of East Darfur State of western Sudan (35 km from Ed Daein the capital of East Darfur State) (Figure 1). It covers 23,000 km^2 (Forests National Corporation [FNC] 2013), and it is part of the gum belt in Sudan with a latitude of 10°-13° N and a longitude of 25°-27° E. The Bahar Alarab locality shares borders with the Republic of South Sudan. The climate is tropical with annual rainfall ranging between 200 and 500 mm. Sandy soil is dominant in the northern and eastern parts of the state, covering approximately 70% of the total area (Elnour 2007). The soil texture classification is heavy clay in both the middle and south of the Darfur State, but in the southern part it covers approximately 30% of the area (Younis et al. 2018). Summer (dry season) starts in March and ends in May, with an average daily temperature of 40°C (Younis 2018; Younis et al. 2022). Bahar Alarab has a population of approximately 168,028 people.

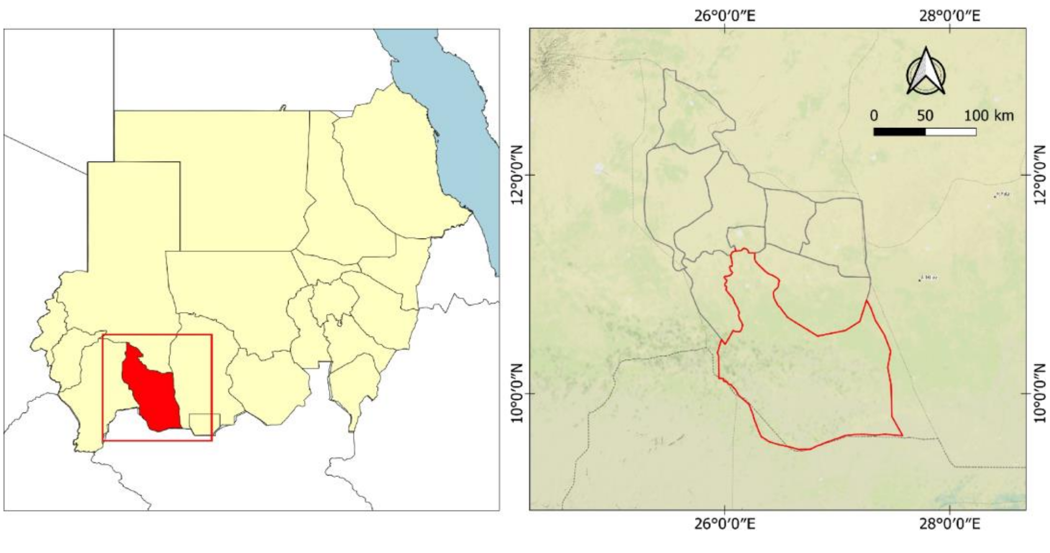

Figure 1. Map of study area showing Sudan on left. East Darfur with *Bahar Alarab* locality on right

Data acquisition and processing

To identify the LULC changes, multitemporal Landsat images were used. These images were downloaded from the United State Geological Survey (USGS) website via http://earthexplorer.usgs.gov/ at path 177 and row 53. Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI) images were downloaded for the years 1988, 2002, and 2020, respectively. Landsat images were purposively selected because of their geographical coverage and temporal availability. The available Landsat imagery with a spectral band was used in this study (Table 1). An integrated approach for data collection and analysis was used in this study (Figure 2). It was based on remote sensing data as well as other field information concerning the different land-use activities in the study area during the addressed period. Some processing techniques for the images included: (i) radiometric and geometry applied from the sources, (ii) image enhancement, (iii) image classification with supervision of natural resources in the study area, (iv) rate of change in the LULC, (v) transformations of LULC matrix, (vi) change detection of natural resources, and (vii) accuracy assessment of image classification.

In this study, information on the current and past status of forest *Acacia seyal* var. *seyal* along with other trees (Table 2) were obtained from a household survey questionnaire to provide more integrated information in line with the study objective (Younis et al. 2022). A total number of 391 questionnaires was used for smallholder pastoral and farmers residing in sampled area. More details about farmers' perceptions of past and current status of *Acacia seyal* var. *seyal* forest are available in Younis et al. (2022).

Climatic data and LULC

Climate data such as rainfall and temperature were obtained from the Ed Daein meteorological station in East Darfur State from January 1988 to December 2020. The climate condition parameters were used to understand the relationship between climate factors and LULC change in the study area. The climatic factors such as precipitation and temperature have significant relationship, and direct influence on the *Acacia seyal* var. *seyal* forest growth, yield, and livelihoods of local communities (Younis et al. 2022). The trend of average temperature and rainfall during 1988-2020 was performed using Minitab statistical software version 20.3 to generate as well as correlation analysis.

Table 1. Properties of Landsat data used in this study

Landsat data	Path/row	Zone	Date of data	Spatial resolution (m)	Band combination
L5 TM	177/53	35	Jan 10, 1988	30*30	4-3-2-1 NIR- Red - Green – Blue
L7 ETM+	177/53	35	Jan 08, 2002	30*30	4-3-2-1 NIR - Red - Green – Blue
L8 (OLI)	177/53	35	Jan 02, 2020	30*30	NIR- Red - Green – Blue

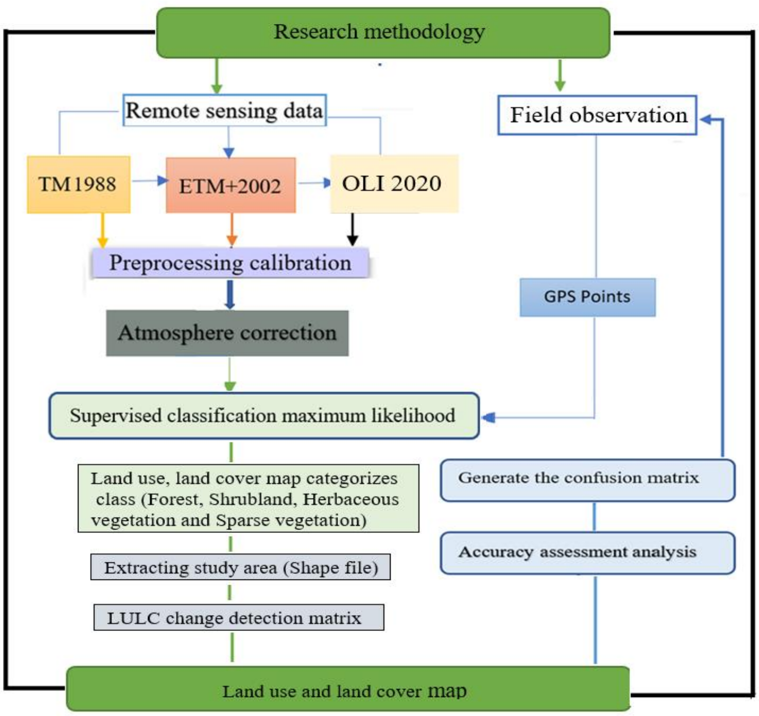

Figure 2. Schematic workflow used to analyze land use and land cover changes in the studied area

The correlation can be computed as follows:

$$r = \frac{\Sigma(x_i - \bar{x})((y_i - \bar{y})}{\Sigma(x_i - \bar{x})^2}$$

The correlation coefficient is expressed as coefficient determination measures by R square represented in the regression line. R square measures the strength and direction of the relationship between the dependent and independent variables (Sreehari and Srivastava 2018).

Data analysis

Supervised classification was performed on three satellite images for the years 1988, 2002, and 2020 to identify differences in vegetation cover in forestland. The feature classes were categorized by supervised classification according to the spectral reflectance of the electromagnetic spectrum, which has specific spectrum characteristics with the integration of a real ground survey (Khawaldah 2016; Rwanga et al. 2017). The satellite data used in this study and other information items were analyzed with ERDAS Imagine 2014, QGIS version 3.22, and ArcMap 10.7, where the images were pre-processed through radiometric and geometric correction, image enhancement, and supervised classification of LULC with the aid of remote sensing and geospatial software in combination with Microsoft Excel 2016, which was used in computing the LULC changes to show their percentages and change rates in the study area. Lastly, the accuracy assessment was systematically performed for each image; the results revealed that the overall accuracy and kappa coefficients represented for each classified image were greater than 85% for the two images. Below is a diagram explaining the applied methods.

RESULTS AND DISCUSSIONS

The status of tree cover in the study area

The farmer's perception of the status of vegetation cover in the study area in the past and current is indicated in Table 2. The results showed that *A. seyal* along with *Balanites aegyptiaca* and *Acacia nilotica* (*Acacias)* dominated the vegetation cover, while thorny and broad-leafed and non-thorny woody species were found to be more scattered. However, the current number and density of *Acacia seyal* trees in the natural stand increased from 57% to 89.8%.

From the results mentioned above, the study suggests that *Acacia seyal* tree cover showed significant increase according to farmers' perception, while *Balanites aegyptiaca* significantly decreased. Hence, these findings demonstrate that the ecological knowledge of farmers can be apprehended by changes they notice in their livelihoods.

Land use and land cover (LULC) classification

Yahya et al. (2021) mentioned that digital image classification is the process of sorting all pixels in an image into a finite number of individual classes based on the spectral information and characteristics of these pixels, which have effective significant information on relevant images for classification purposes and interpretation (Dhumal et al. 2015). The result of such processes is shown in Figure 3. The outputs of these processes were identified and categorized into four categories: (1) Forest (tree cover), (2) Shrubs land, (3) Herbaceous vegetation, and (4) Sparse vegetation. According to the FNC's report, Sudan's National Land Cover (2020) includes (i) Herbaceous; (ii) Herbaceous closed-to-sparse in terrestrial and aquatic/regularly flooded land, (iii) Shrubs: Shrubs closed-to-sparse in terrestrial and aquatic/regularly flooded land, and (iv) Sparse vegetation: Sparse closed- to-sparse in terrestrial and aquatic/regularly flooded land. Each category corresponds to a specific type of ground cover or feature to be extracted from remotely sensed data (Gómez et al. 2017). Each feature on the earth's surface records its unique signature in the satellite image; these classes' information was extracted from visual interpretation besides the prior knowledge of the study area.

The first classification data in this study was processed from Landsat5 TM with image acquisition in 1988 which indicated that the dominant land use in the study area was shrubland (31.95%), with a total area of 38,060 ha followed by herbaceous vegetation (28.89%), forest (21.45%), and sparse vegetation (17.71%) (Table 3 and Figure 3). In the second period of this study, Landsat 7 ETM+ 2002 showed that the major dominant class in the area was herbaceous vegetation (33.41%), followed by shrubland (23.67%), sparse vegetation (21.65), and forest (21.27) (Table 3 and Figure 3). Based on the results of the classification of LULC in 1988 and 2002, there was little change in forests and sparse vegetation, but there was a significant change in shrubland and herbaceous vegetation (Table 3).

Therefore, from 1988 to 2002, land cover in Bahar Alarab locality was affected by significant land use and land cover change. Vegetation cover has regressively given place to herbaceous and sparse vegetation's. Whereas, in 2020, forest cover increased in the southern part of the study area while they have regressed in the northern part. The study suggests that these findings could be explained by climate variability which influences land use systems in the study area.

Table 2. The current and past status of *Acacia seyal* var. *seyal* along with other trees in the study area (Younis et al. 2022)

Species	Farmers' observation in two periods of time			
	Past	%	Current	%
Acacia seyal (Gum Talha)	222	57	351	89.8
Balanites aegyptiaca (Laloub)	147	38	18	4.6
Acacia nilotica (Garad)	7	1.8	22	5.6
Other	15	3.5	00	00
Total	391	100	391	100

Table 3. Classification map of land use and land cover class (LULC) in the study area in 1988, 2002, and 2020

Class name	1988		2002		2020	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest	25,547	21.45	25,342	21.27	31,501	26.44
Shrubland	38,060	31.95	28,195	23.67	34,623	29.06
Herbaceous vegetation	34,420	28.89	39,800	33.41	24,877	20.88
Sparse vegetation	21,099	17.71	25,789	21.65	28,126	23.61
Total	119,128	100	119,128	100	119,128	100

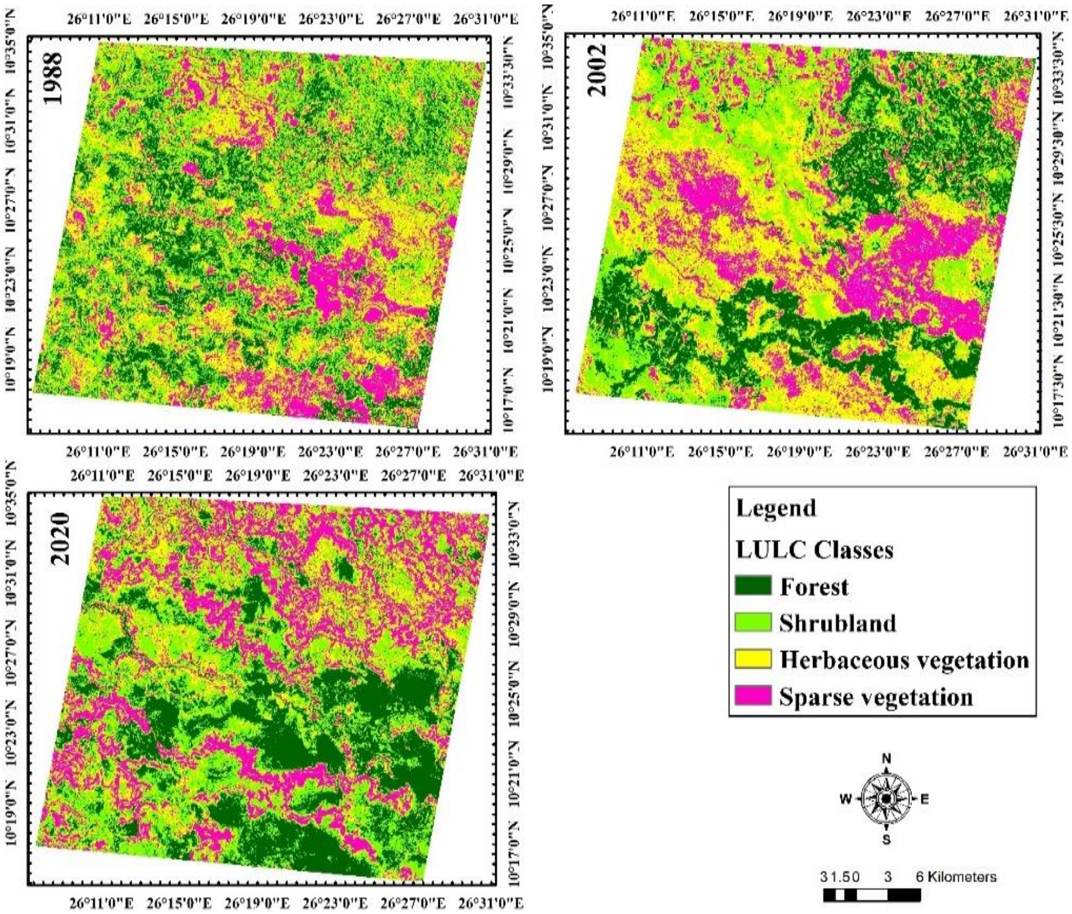

Figure 3. Classification map of land use and land cover class (LULC) in the study area in the years 1988, 2002, and 2020

The third classification of remotely sensed data in the study in 2020 was processed from Landsat8 OLI/TIRS (Table 3 and Figure 3). The results show that the shrubland was the dominant LULC (29.06%), followed by forest (26.44%), sparse vegetation (23.61%), and herbaceous vegetation (20.88%). Based on the results of the classification of LULC in 1988 and 2020, there was an increase in forests and sparse vegetation in 2020 compared to 1988, but there was a significant decrease in herbaceous vegetation and little change in shrubland between 1988 and 2020 (Table 3). Between 2002 and 2020, forest cover increased, as well as sparse vegetation during the same period; however, there was a significant decrease in herbaceous vegetation and little change in sparse vegetation (Table 3).

Climate factors and LULC

To analyze the comprehensive effect of climate and LULC on the dynamics of *Acacia seyal* var. *seyal* forest, analyzing changes in climate were related to LULC change. For this purpose, temperature data from the Bahar Alarab locality between 1988 and 2020 showed a warming trend (Younis et al. 2022). Considering the annual maximum temperature, the highest (28.9°C) and lowest (27.9°C) values were recorded in 1990 and 2009, respectively, while for the annual minimum temperature, the lowest (27.1°C) and highest (27.3°C) values were recorded in 1989 and 1996, respectively (Figure 4).

Figure 4 shows a graphical representation of the average temperature and rainfall (mm). A linear regression trend line was fitted to the graph to show the variation in temperature and rainfall (mm). Figure 4 shows that temperature increases, while rainfall decreases during 1988-2020. The trend line shows the average temperature over time and has a positive value, implying an increase in the average temperature per year. Precipitation data were computed to obtain total annual rainfall variations for the period between 1988-2020. It was observed that the annual precipitation in the *Bahar Alarab* locality varied from 100 to 800 mm, with the highest and lowest values recorded in 1997 (790 mm) and 2015 (380 mm).

In Figure 5, monthly rainfall patterns are observed to be similar in 1988 and 2002 and different for 2020. For 1988 and 2002, rainfall began to increase in April and reached the peak in August and decreased from September to November due to the dry season in the *Bahar Alarab* locality. It is observed that there was a unimodal rainfall regime in the study area irrespective of East Darfur State, Sudan. There was not much rainfall in the period from January to July, and there was very little rain in the area in the season 2020. As illustrated in Figure 6, of all three meteorological points, the recorded rainfall amount was highly concentrated in 1988 at 677 mm, decreased in 2002, and was extremely low in 2022 (40 mm). The average temperature was 28°C in 1988 and rose dramatically in 2002 to 39°C and in 2020 to 40°C.

Results of the correlation analysis established the relationship between changes in average temperature and rainfall and LULC changes. Table 4 shows that statistically significant correlations were observed between average temperature and LULC factor classification. Average temperature was highly positively correlated with sparse vegetation at 98.2%, while rainfall was highly negatively correlated with forest (-96.9%) and sparse vegetation (-88%), and highly positively correlated with herbaceous vegetation (83.5%). The LULC change is a significant driver of local climate change, and a changing climate can lead to changes in LULC and vegetation cover.

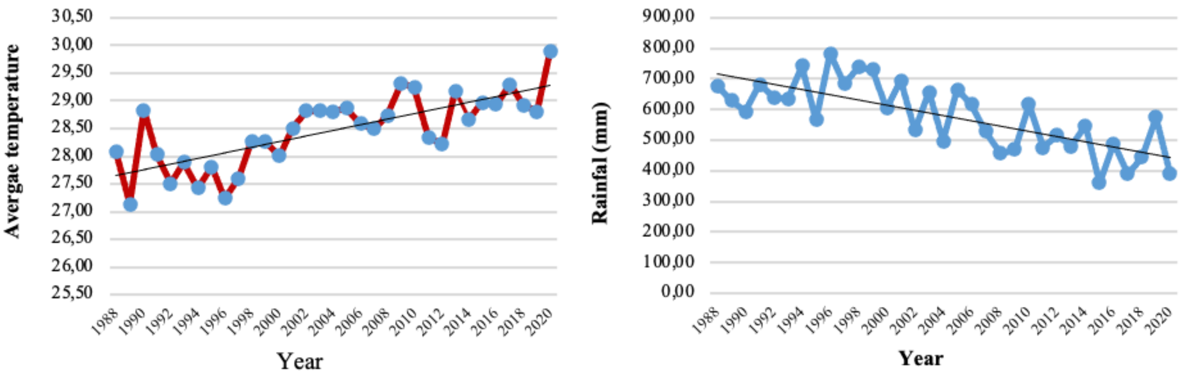

Figure 4. The trend of average temperature and rainfall during 1988-2020

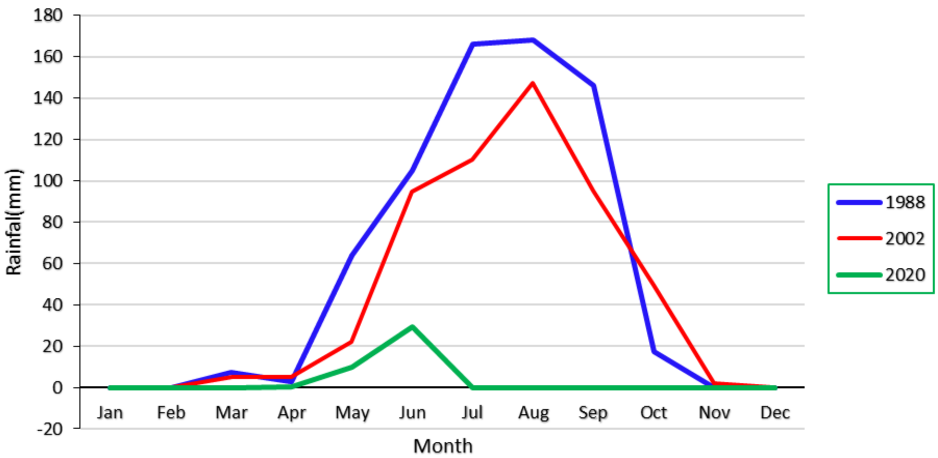

Figure 5. Monthly rainfall in 1988, 2002, and 2020

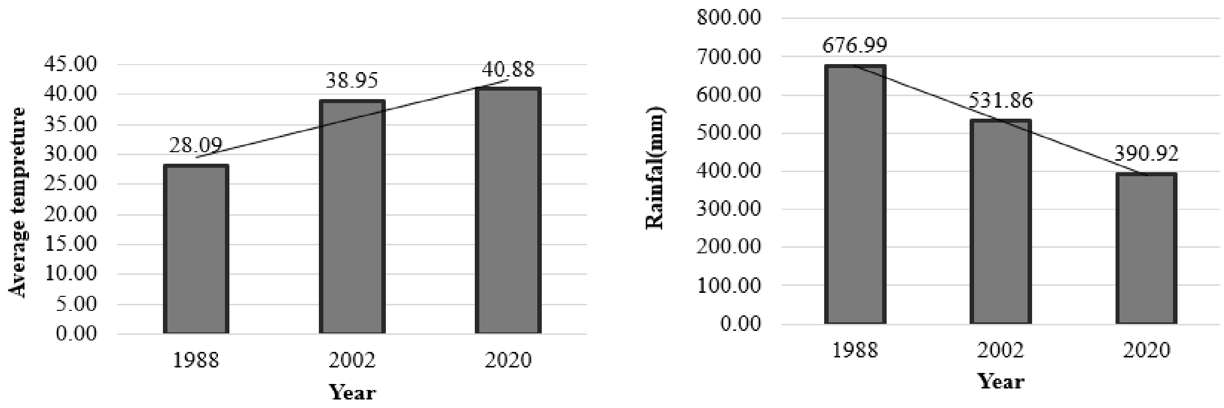

Figure 6. Average annual temperature and rainfall in 1988, 2002, and 2020

Net changes in LULC in the study area

The results indicate the change in LULC over the periods of 1988 to 2002, 2002-2020, and 1988-2020. The forest class gradually decreased by -0.17% during 1988-2002 and increased by 5.2% and 5.0% during 2002-2020 and 1988-2020, respectively, while shrubland decreased by -8.3% during 1988-2002 and increased by 5.4% during 2002-2020, respectively. Also, the herbaceous vegetation increased by 4.5% in the study area during 1988-2002 and decreased by -2.5% during 2002-2020. Furthermore, the results showed an increase in the sparse vegetation areas in the last three decades (1988-2002, 2002-2020, and 1988-2020) by 3.9%, 1.9%, and 5.9%, respectively (Table 5).

LULC change detection matrix

LULC change was dynamic in that there was deforestation as well as vegetation cover expansion resulting from natural regeneration. This dynamic reflects that land-use changes are associated with vegetation cover regeneration in abandoned lands, resulting in vegetation expansion (Awuh et al. 2018). Using the vegetation change matrix, it is possible to use cross-tabulation and show the total deforestation as well as forest expansion as a new regeneration area (Table 5). The main diagonal line of the matrix (Table 6) contains areas (ha) that have not changed during the defined period, while other cells contain areas (ha) that have changed. Vegetation change matrices for the classified LULC categories were developed to show the overall change dimensions during the period from 1988 to the 2020s. The output matrix is shown in Figures 7, 8, and 9 and in Tables 6, 7, and 8.

As shown in Figure 7 and Table 6, a total forest area of 25,547.85 ha was detected in 1988, and only 9,316.45 ha remained in the previous area in 2002, implying a total area loss of 16,233.40 ha due to conversion of forest to shrubland (5,466.53 ha), herbaceous vegetation (6,969.25 ha), and sparse vegetation (3,795.63 ha). However, the gain in forest class between 1988 and 2002 was 16,025.98 ha, resulting from the change of shrubland (10,844.71 ha), herbaceous vegetation (3,902.96 ha), and sparse vegetation (1,278.31 ha) into forest class. A total shrubland of 38,060.1 ha was detected in 1988, and only 11,377.33 ha remained in the previously shrubland area. The total shrubland area loss between 1988 and 2002 was 26,682.77 ha, resulting from conversion to forest (10,844.71 ha), herbaceous vegetation (10,289.68 ha), and sparse vegetation (5,548.383 ha). A total herbaceous vegetation area of 34,420.59 ha was detected in 1988, and only 13,921.51 ha remained from the previously herbaceous vegetation area. The total loss between 1988 and 2002 was 20,499.08 ha, resulting from herbaceous vegetation area conversion to forest area (3,902.96 ha), shrubland (8,867.22 ha), and sparse vegetation (7,728.89 ha). A total sparse vegetation area of 21,099.96 ha was detected in 1988, and only 8,716.91 ha remained from the old sparse vegetation area. The total area loss between 1988 and 2002 was 12,383.05 ha, resulting from sparse vegetation area conversion into forest area (1,278.31 ha), shrubland (2,484.70 ha), and herbaceous vegetation (8,620.04 ha).

Table 4. Correlation matrix of classification map of land use and land cover class with average temperature and rainfall for the 1988, 2002, and 2020 data points

	Forest	Shrubland	Herbaceous vegetation	Sparse vegetation	Average temperature
Shrubland	0.201	1			
Herbaceous vegetation	-0.945	-0.512	1		
Sparse vegetation	0.736	-0.515	-0.473	1	
Average temperature	0.593	-0.669	-0.296	0.982	1
Rainfall	-0.969	0.046	0.835	-0.880	-0.773

Table 5. Rate of change in land use and land cover (LULC) in the study area

Vegetation class	1988-2002		2002-2020		1988-2020	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest	-205.43	-0.17	6,159.26	5.17	5,953.84	5.00
Shrub land	-9,864.32	-8.28	6,427.55	5.39	-3,436.76	-2.88
Herbaceous vegetation	5,379.89	4.52	-14,923.1	-12.53	-9,543.26	-8.01
Sparse vegetation	4,689.89	3.94	2,336.33	1.96	7,026.19	5.90

Table 6. Transformation matrix of land use and land cover class (in hectare) during the period of 1988-2002

2002	1988				
	Forest	Shrub land	Herb. vegetation	Sparse vegetation	Total
Forest	9,316.45	10,844.71	3,902.96	1,278.31	25,342.43
Shrub land	5,466.53	11,377.33	8,867.22	2,484.70	28,195.79
Herb. vegetation	6,969.25	10,289.68	13,921.51	8,620.04	39,800.48
Sparse vegetation	3,795.63	5,548.38	7,728.89	8,716.91	25,789.81
Total	25,547.85	38,060.1	34,420.59	21,099.96	119,128.5

Note: All the values along the vertical column represent the loss from the LULC categories. The values along the horizontal row represent the gains in LULC categories. Source: Author's analysis (2021)

Table 7. Transformation matrix of land use and land cover class (in hectare) during the period of 2002-2020

2020	2002				
	Forest	Shrub land	Herb vegetation	Sparse vegetation	Total
Forest	1,750.37	4,573.52	13,978.64	11,199.17	31,501.71
Shrub land	3,609.47	7,862.81	14,672.15	8,478.90	34,623.34
Herb vegetation	6,727.48	7,262.61	6,865.794	4,021.44	24,877.33
Sparse vegetation	13,255.11	8,496.84	4,283.89	2,090.31	28,126.15
Total	25,342.43	28,195.79	39,800.48	25,789.82	119,128.5

Note: All the values along the vertical column represent the loss from the LULC categories. The values along the horizontal row represent the gains in LULC categories. Source: Author's analysis (2021)

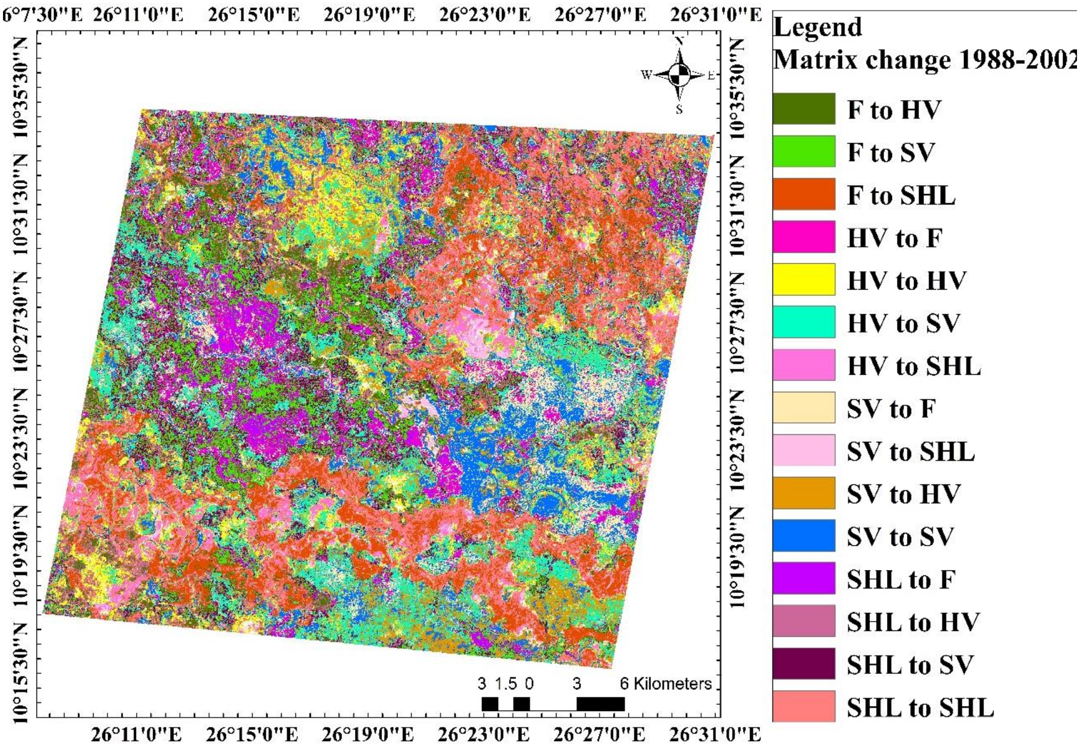

Figure 7. Spatially explicit change between LULCs in the study area during the period of 1988-2002. Where: F: Forest, HV: Herbaceous Vegetation, SV: Sparse Vegetation, and SHL: Shrub Land

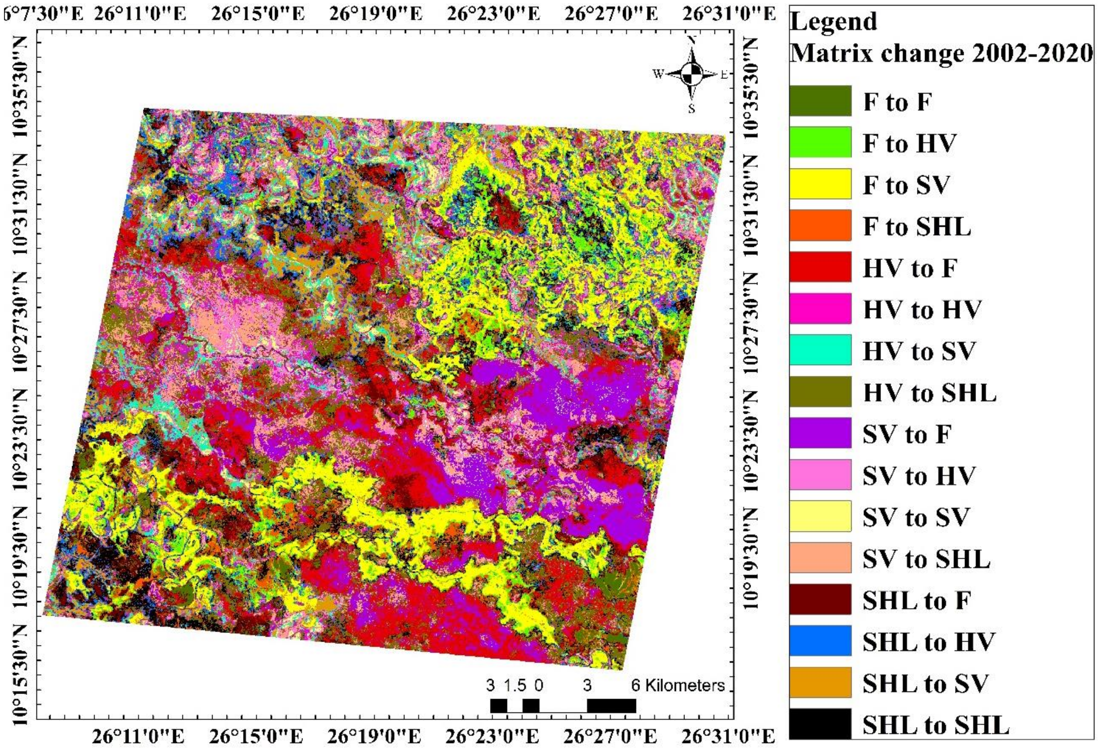

Figure 8. Spatially explicit change between LULCs in the study area during the period of 2002-2020. Where is F: Forest, HV: Herbaceous Vegetation, SV: Sparse Vegetation, and SHL: Shrub Land

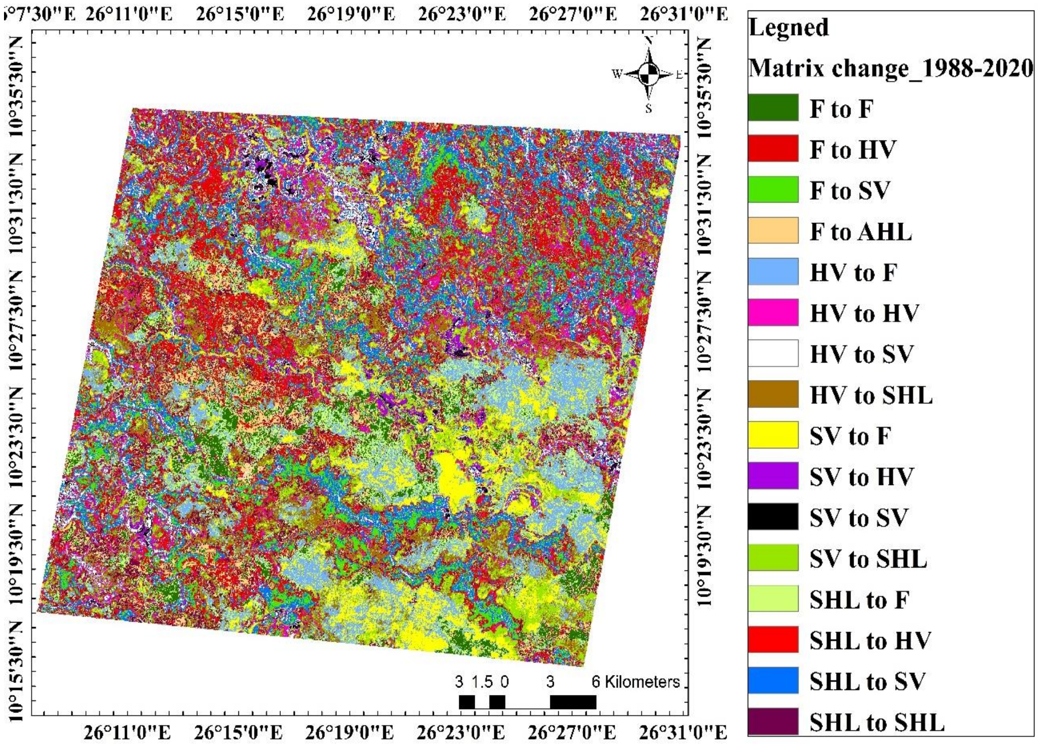

Figure 9. Spatially explicit change between LULCs in the study area during the period of 1988-2020. Where is F: Forest, HV: Herbaceous Vegetation, SV: Sparse Vegetation, and SHL: Shrub Land

Table 8. Transformation matrix of land use and land cover class (in hectare) during the period of 1988-2020

2020	1988				
	Forest	**Shrub land**	**Herb vegetation**	**Sparse vegetation**	**Total**
Forest	4,427.58	6,331.36	11,508.48	9,234.27	31,501.69
Shrub Land	5,745.45	9,148.05	12,003.32	7,726.50	34,623.34
Herb vegetation	7,253.29	8,717.16	5,829.96	3,076.90	24,877.33
Shrub vegetation	8,121.52	13,863.52	5,078.83	1,062.28	28,126.15
Total	25,547.85	38,060.10	34,420.59	21,099.96	119,128.50

Note: All the values along the vertical column represent the loss from the LULC categories. The values along the horizontal row represent the gains in LULC categories. Source: Author's analysis (2021)

A total forest area of 25,342.43 ha was detected in 2002, and only 1,750.37 ha remained as illustrated in Figure 8 and Table 7. The total loss area between 2002 and 2020 was 23,592.06 ha, resulting from forest area conversion to shrub land (3,609.47 ha), herbaceous vegetation (6,727.48 ha), and sparse vegetation (13,255.11 ha). However, the gain in the forest class between 2002 and 2020 was 29,751.37 ha, resulting from the change in shrubland (4,573.52 ha), herbaceous vegetation (13,978.64 ha), and sparse vegetation (11,199.17 ha) into the forest area. A total shrubland of 28,195.79 ha was detected in 2002, and only 7,862.81 ha remained in the old shrubland area. The total loss area between 2002 and 2020 was 20,332.98 ha, resulting from shrubland area conversion to forest area (4,573.52 ha), herbaceous vegetation (7,262.61 ha), and sparse vegetation area (8,496.84 ha). A total herbaceous vegetation area of 39,800.48 ha was detected in 2002, and only 6,865.79 ha remained of the old herbaceous vegetation area. The total loss area between 2002 and 2020 was 32,934.69 ha, resulting from herbaceous vegetation area conversion to forest area (13,978.64 ha), shrubland (14,672.15 ha), and sparse vegetation (4,283.89 ha). A total sparse vegetation area of 25,789.82 ha was detected in 2002, and only 2,090.31 ha remained in old sparse vegetation area. The total loss area between 2002 and 2020 was 23,699.51 ha, resulting from sparse vegetation area conversion to forest area (11,199.17 ha), shrubland (8,478.9 ha), and herbaceous vegetation area (4,021.44 ha).

A total forest area of 25,547.85 ha was detected in 1988, and only 4,427.58 ha remained in old forest area. The total loss area between 1988 and 2020 was 21,120.28 ha, resulting from forest area conversion to shrub land (5,745.45 ha), herbaceous vegetation (7,253.3 ha), and sparse vegetation (8,121.52 ha). However, the gain in the forest area between 1988 and 2020 was 27,074.12 ha, resulting from the change of shrubland (6,331.36 ha), herbaceous vegetation (11,508.48 ha), and sparse vegetation (9,234.27 ha) into the forest area (Figure 9 and Table 8). A total shrubland of 38,060.1 ha was detected in 1988, and only 9,148.05 ha remained in the old shrubland area. The total loss area between 1988 and 2020 was 28912.05 ha, resulting from shrubland area conversion to forest area (6,331.36 ha), herbaceous vegetation (8,717.16 ha), and sparse vegetation area (13,863.52 ha). A total herbaceous vegetation area of 34,420.59 ha was detected in 1988, and only 5,829.96 ha remained as of the old herbaceous vegetation area. The total loss area between 1988 and 2020 was 29,090.63 ha, resulting from herbaceous vegetation area conversion to forest area (11,508.48 ha), shrubland (12,003.32 ha), and sparse vegetation (5,078.83 ha). A total sparse vegetation area of 21,099.96 ha was detected in 1988, and only 1,062.28 ha remained an old sparse vegetation area. The total loss area between 1988 and 2020 was 20,037.68 ha, resulting from sparse vegetation area conversion to forest area (9,234.27 ha), shrubland (7,726.509 ha), and herbaceous vegetation area (3,076.90 ha). The results are in agreement with those reported by Arbain (2020), who found that there was very high fluctuation between increasing and decreasing forest dynamics. The increase of tree cover in 2002 compared with this of 1988 revealed the status of forest before and after reservation, which was reserved in 1993 and during that time the local communities did not depend mainly on forest land for their livelihoods. However, in 2018, the tree covers significantly decreased, which may be associated with climate change and population pressure as well as nomads. Pressures are in the forms of over exploitation and deforestation, as noticed by Sulieman (2008; 2018), in Gadarif, and Ibrahim, (2013) in South Darfur State, where climate change. Irreversibly, with increasing mixed vegetation cover during 2002 and 2018. This result reveals an over exploitation of old trees converted from dense tree cover area to scattered trees area with shrubs and grasses due to population growth and displacement. This result is Similar to the observation of Ibrahim, (2013) in Darfur, where they mapped the vegetation cover. The highest changes in UNFR cover were recorded in classes of bare land and agriculture, although the class of bare land was decreasing gradually during the study period, it still records the wide area in the forest. The class of agriculture also was increasing gradually. These changes refer to the over exploitation of forestland mainly by human induced, representing agricultural expansion, with low effects of natural causes as Sulieman (2008), found that during the study in Gadarif, the agriculture expansion is the key driver for removal of natural vegetation.

Similarly, Yahya et al. (2021) stated that the area of trees increased in 1989, 2000 and 2009 (1.65%, 2.36% and 2.51%) respectively while decreased in 2019 (1.87%). These changes in forest class may be due to many factors, like illicit felling, overgrazing, climate change, drought and agricultural expansion. etc. Shrubs lands in the study area decreased during 1989-2000 and 2009 (18%, 14.4% and 9.09%), respectively while increase in 2019 (23.1%) this was increasing in the last ten years of the study periods because rural communities still working in the hashab garden used to cultivate gum Arabic as much of them have hashab garden based of survey conducted in the study area.

In conclusion, a combination of satellite images, geospatial technology, ground inventory, and the social survey was used to assess and map the LULC and its impact on forest cover change (*Acacia seyal* var. *seyal*) in Bahar Alarab locality, East Darfur State, Sudan. The study identified the spatial and temporal patterns of LULC changes in the forest, which will help facilitate proper forest management and future rehabilitation plans. Thus, the study concludes that there were sizable LULC changes during 1988-2020 with different trends and percentages. These changes and alterations have been driven by anthropogenic activities, such as tree felling, illegal wood cutting, overgrazing, and building infrastructure, which are the main underlying factors driving LULC changes in the study area. The results highlighted that there was statistically significant correlation between climate factors and LULC. Average temperature was highly positively correlated with sparse vegetation, while rainfall was highly negatively correlated with forest and sparse vegetation, and highly positively correlated with herbaceous vegetation. This study provides a unique understanding of LULC changes and their implications in management and conservation efforts, as well as a road map for decision makers for sustainable development of LULC in the Bahar Alarab. Hence, there is a need for further research on the use of remote sensing to assess the impact of LULC changes on acacia tree growth in the Bahar Alarab locality.

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