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Human Impacts Onland Use and Land Cover Change in Lagha Bor Catchment, Wajir County, Kenya

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Abstract

Human activities are considered one of the main contributors towards environmental changes. An assessment of the impacts of land use and land cover changes is necessary to facilitate proper planning and management of environmental resources. The objective of this study was to determine the land use and land cover change hotspots and drivers in lagha bor catchment, Wajir County in Kenya. This was achieved by use of Google Earth Engine (GEE) where archived landsat images of 1986, 1990, 2000, 2010 and 2020 were retrieved and analysed for land use land covers (LULC). The main land use considered in the study area included, dense shrubs, sparse shrubs, grassland and bare-ground. The land use and land cover change dynamics were determined through classification, change detection and analysis of Landsat imageries of 1986, 1990, 2000, 2010 and 2020 within Google Earth Engine platform. Land use and land cover change analysis showed that spare-shrubs and bare-ground cover were predominant accounting for approximately 95% of the catchment. Between 1986 and 2020, bare-ground cover increased from 35% to 45.8% while sparse shrubs decreased from 60.8% to 49%. From this, bare-ground was found to increase at the expense of sparse shrubs vegetation. Spatial-temporal trend analysis showed that hot spots which corresponded to areas under high sparse shrubs accounted for 35% while cold spots which corresponded to bare-ground cover was 43%. The hotspots were determined using optimized and emerging hot spot analysis tool in ArcGIS Pro was used in the assessment of trends. Area that experienced no pattern showed no statistically significant increase or decrease in these two land covers and accounted for about 22%. Areas recording significant changes (hot or cold spots) were observed around settlements with permanent water points.

Subject Areas

Anthropogenic Influence on Land Use and Land Cover

Keywords

Piosphere, Degradation, Land Use, Land Cover, Hot Spot, Cold Spot, Google Earth Engine

1. Introduction

Land cover patterns are rapidly changing at global, regional and local levels. The ASAL lands account for approximately 40% of the earth and support 35% of the world's population (Omoyo *et al*., 2015) [1]. Pastoralism is considered the most reliable livelihood activity in the ASAL environment and supports around 500 million people globally who rely on it for food, income, and as a store of wealth, collateral or safety net in times of needs (Liniger and Mekdaschi, 2019) [2]. With most of the global dry lands considered water scare, the livelihood system of the pastoral populations and resident community is at risk considering the human induced changes in natural resources (Kariuki *et al*., 2018) [3].

In Africa, dry lands occupy about 61% of the landmass and support about 25 million pastoralists in sub-Saharan Africa, who depend on livestock for livelihood. In Horn and East Africa, nomadic pastoralism is the predominant livelihood system in the arid and semi-arid lands (ASALs) which occupies 75% of the land area (Omoyo *et al*., 2015) [1]. In Kenya, ASAL covers 80% of the total landmass and supports approximately 25% of the population. Despite the suitability of pastoralism due to the vast ASAL areas, its productivity and sustainability are threatened by land use and land cover changes with effects on vegetation and water.

As human and livestock population continue to rise, increased demand for natural resources to meet their needs is also on the rise. This has led to increased settlements near water points and increased animal watering points in dry grazing areas (Egeru *et al*., 2015) [4]. Through settlements, humans continue to alter the vegetation cover by clearing construction grounds, use of the products for energy and construction needs as well as through introduction of alien vegetation. Accurate and timely collection of land use and land cover information is necessary for purposes of sustainable management of vegetation cover in addition to prediction of their impacts of groundwater resources (Albhaisi, *et al*., 2013) [5].

Unplanned introduction of water-based interventions in dry lands has more than often led to development of piospheres (Jawuoro *et al*., 2017) [6]. Most of the common drivers causing changes in drylands include growth in human and livestock population, expansion of urban settlements, economic and technological developments, restriction of pastoral mobility by locations near water points within high grazing areas (Lind, et al., 2020 [7]; Measho *et al*., 2020 [8]; Vehrs, 2015 [9]). The purpose of this study was to investigate the impacts of land use and land cover changes associated with increased settlements and establishment of permanent water points in the catchment to avert irreversible possible changes.

2. Material and Methods

2.1. Site Description

Lagah-bor catchment in **Figure 1** is located in Wajir County in the northern part

Figure 1. Location of study area. Source: Author (generated from SRTM DEM and ILRI datasets on international boundaries, Counties boundaries, roads, rivers and towns).

of Kenya. The catchment area is estimated at 22,370 Km^2. It drains from Moyale on the Kenya-Ethiopia border to Diff centre on the Kenya-Somalia border in South-East direction. The higher areas near Ethiopian border receive the highest rainfall of approximately 500 mm while the lower areas of Wajir and Diff represents the driest part of the catchment with an estimated rainfall of 200 - 300 mm. The average temperature is estimated at 28˚C with a maximum of 36˚C and a minimum 21˚C. The major part of the catchment is covered by sediments rocks of quaternary age. Few rock outcrops shows existence of poorly unconsolidated kunkar limestone. Ferric Luvisols, Ferralic Arenosols and Gleyic Solonetz are the most dominant soil types in the upper, middle and lower parts of the catchment respectively (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012) [10]. Thorny scattered shrubs cover most part of the catchment inter-twined with bare-ground and few acacia trees along lagha-bor river. The main livelihood activity is nomadic pastoralism.

2.2. Research Methodology

2.2.1. Land Use and Land Cover Change Classification and Detection

The land use and land cover assessment was carried out for the period 1986-2020. The choice of the period was informed by change from government water managed schemes to introduction of community management system. The shift in management affected vegetation cover with end of zoned wet or dry grazing areas to free grazing. The GEE platform which provides for both open access to datasets and cloud computing and analysis was highly relied on the assessment of land use and land cover changes in the catchment (Kumar and Mutanga, 2018) [11].

With the help of appropriate javascript codesland sat images were retrieved from the archive and clipped to the size of the study area. Cloud cover filtering, development of classifiers, undertaking supervised classification and carrying out image differencing and change analysis were all carried out within the GEE interface platform. To enable classification and change detection, training data and classifiers were developed for dense shrubs, sparse shrubs, grassland, and bare-ground land covers. This was undertaken with help of high resolution google earth embedded in the GEE platform. To ensure high level of classification, validation and accuracy assessment were done with determination of overall accuracy, user's accuracy, producer's accuracy and kappa coefficient. To achieve the most reliable outcomes, minimum accuracy threshold of 85% and 0.80 kappa values were adopted (Hütt *et al*., 2016 [12]; Mohajane *et al*., 2017 [13]).

2.2.2. Spatial and Statistical Analysis of LULCC Hotspots

The most common spatial and statistical analysis tools used include, spatial, autocorrelation, optimized hot spot analysis and emerging hot spot analysis. The current study utilized these GIS tools for the spatial and temporal analysis of land use and land cover change hot spots, patterns and trends within the ArcGIS Pro environment and setting.

1) Spatial autocorrelation

Spatial autocorrelation was carried out prior to execution of hot spot analysis in order to test data for clustering distribution pattern. The spatial distribution pattern was investigated by global Moran's I index as per Equations (2.1)-(2.3). The Moran's index define the distribution pattern as (>0) clustered, (=0) dispersed, and (<0) random. The normalised Z-score value in Moran's statistics varies from −1 to 1 where values less than 0 indicate negative correlation while values greater than 0 signifies positive correlation (Mallick *et al*., 2021) [14]. For hot spot analysis to be carried out, the global Moran's I index must yield to a clustering distribution pattern (Philippe and Karume, 2019 [15]; Shariati *et al*., 2020 [16] and Xu *et al*., 2022 [17]). The Moran's I statistical index for spatial autocorrelation is give as:

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{2.1}$$

where z_i = the deviation of the attribute for the feature i from the mean (x_i-X),

$w_{i,j}$ = the spatial weight between feature i and j

n = the total number of features

S_o = the aggregate of all the spatial weights

Z = standardization statistic of Moran's I

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2.2}$$

The z_1 score for the statistic is computed as:

$$Z_1 = \frac{I - E}{\sqrt{V}} \tag{2.3}$$

where $E = -1/(n-1)$

$$V = E(1) - E(2).$$

2) Optimized hot sport analysts

Optimized hotspot tool in ArcGIS pro was used in the assessment of hot spots and cold spot areas within the catchment. The tool makes uses of Getir-Ord Gi* statistic to reflect aggregation of high values areas as hot spots and aggregation of low value areas as cold cold-sots (Philippe and Karume, 2019 [15]; Xu, *et al*., 2022 [17]). For the formation of significant hotpots and cold-spots, the features must be surrounded by corresponding high and low values. The significant hot-spots corresponds to areas showing very high Z-score and low p-values (<0.05) while significant cold-spots define areas with very low Z-scores and small p-values < 0.05, (Philippe and Karume, 2019 [15]; Xu *et al*., 2022 [17]). The optimized hot spot analysis used in the current study applied Equations (2.4)-(2.8).

$$G^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \sum_{j=1}^{n} w_{i,j}}{n-1}}} \tag{2.4}$$

where x_j = attribute value for spatial feature j,

$w_{i,j}$ = spatial weight between feature i and j

n = total number of features

$\bar{X}$ = the mean of the area values of the type of land use neighbouring the grid cell.

S = Standard deviation of the area values of the type of land neighbourhood to the grid cell. The $\bar{X}$ and S were computed based on the following equations.

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2.5}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} \bar{X}^2} \tag{2.6}$$

3. Results and Discussion

3.1. Accuracy Assessment

The error matrix was used to evaluate the accuracy of the results from image classification process. Table 1 gives a summary of the results of the accuracy assessment while detailed information in terms of confusion matrices has been provided in **Appendix 1**. The classified images gave overall accuracies of 86.76%, 93.35%, 94.17%, 93.43% and 93.45% for the years 1986, 1990, 2000, 2010 and 2020 respectively and corresponding values of kappa coefficients as 0.803, 0.871, 0.8852, 0.8735 and 0.8714. These results showed that there was good

Table 1. Producers Accuracies (PA), Users Accuracies (UA), Overall Accuracies (OA) and kappa coefficients from image classification process.

Land cover	2020		2010		2000		1990		1986	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Dense Shrubs	85.33	64.92	96.12	79.04	90.65	64.01	92.10	69.02	83.01	52.70
Bare ground	89.60	98.39	90.70	96.68	91.76	98.23	87.79	95.53	92.79	97.70
Sparse Shrubs	96.16	95.19	96.49	94.15	96.01	96.51	96.66	94.90	78.83	93.36
Grassland	84.43	73.57	65.71	81.43	83.06	73.57	82.08	90.0	91.37	67.89
OA (%)	93.45		93.43		94.17		93.35		86.76	
kappa	0.8714		0.8735		0.8852		0.871		0.803	

agreement between the classified and reference image. The results further revealed that classification of the major land cover types namely bare ground and sparse shrubs reported high accuracies of more than 90% which confirmed that the classification process was accurate and reliable.

3.2. Spatial-Temporal Land Use and Land Cover Changes

The spatial variation of the four land cover types in Lagha-Bor catchment was displayed in Figures 2(a)-(d) for the periods 1990, 2000, 2010 and 2020 respectively. The spatial and temporal distribution of the various LULC types were calculated and a matrix prepared to quantitatively describe the changes between the various land cover types in the study area as presented in Table 2. Based on analysis in Table 2, bare ground and sparse shrubs were the predominant land covers occupying approximately 95% of the total catchment area. Sparse shrubs covered about 49% - 60% of the area, followed by bare ground which occupies

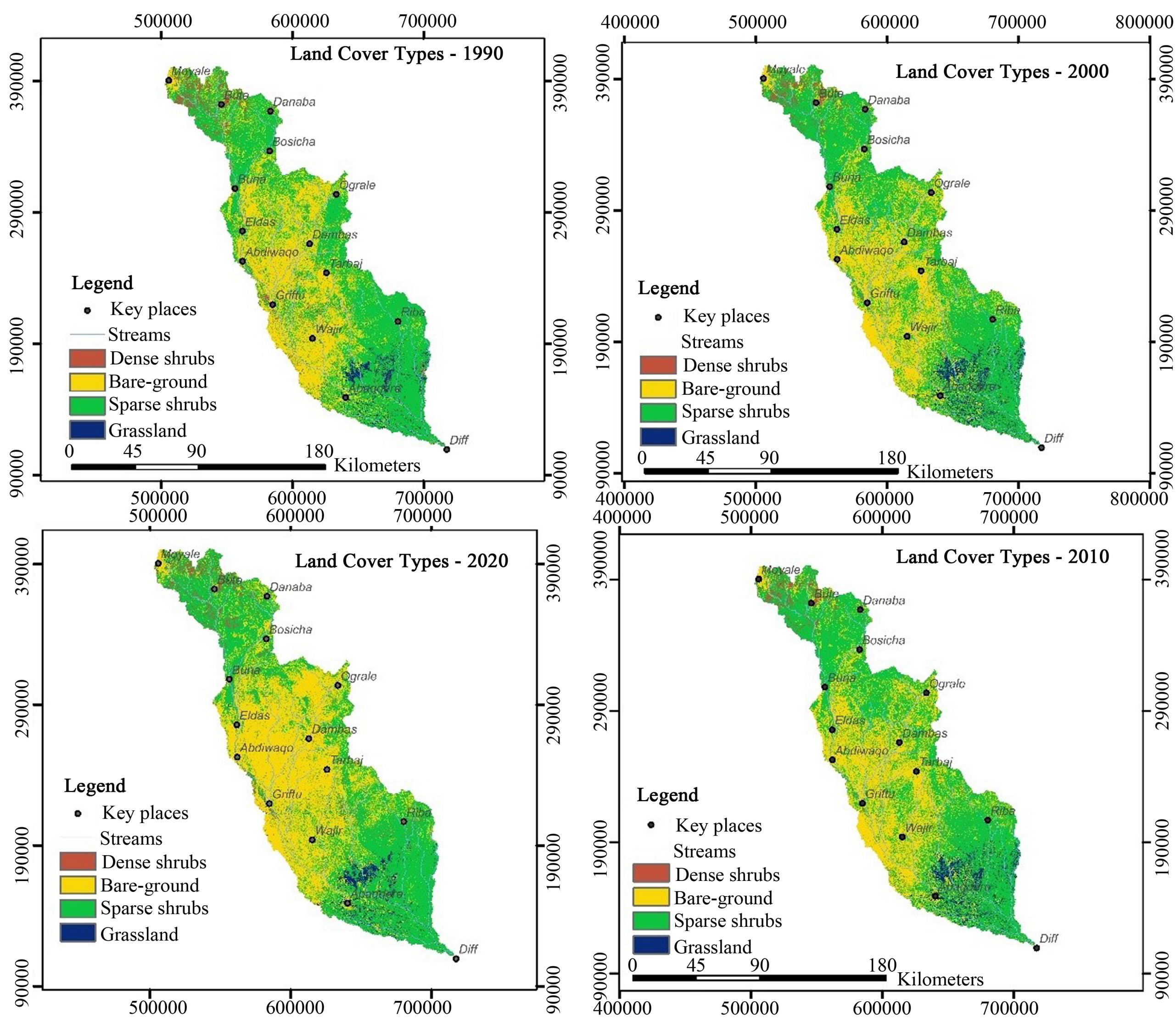


Figure 2. Land cover types for the period 1990-2020.

Table 2. Coverage by land cover type.

Land cover	Land use land cover changes									
	1986		1990		2000		2010		2020	
	Area (Km²)	Coverage (%)	Area (Km²)	Coverage (%)	Area (Km²)	Coverage (%)	Area (Km²)	Coverage (%)	Area (Km²)	Coverage (%)
Dense shrubs	585	2.6	724	3.2	573	2.5	427	1.9	602	2.6
Bare ground	7946	35.0	8791	38.7	9852	43.4	8343	36.7	10,417	45.8
Sparse shrubs	13,810	60.8	12,691	55.8	11,743	51.7	13,065	57.5	11,127	49.0
Grassland	390	1.7	525	2.3	563	2.5	896	3.9	585	2.6
Total	**22,731**	**100.0**	**22,731**	**100.0**	**22,731**	**100.0**	**22,731**	**100.0**	**22,731**	**100.0**

35% - 46%. Dense shrubs and grassland account for about 5% of the total area.

3.3. Spatial-Temporal Variations in Land Use and Land Cover

Table 2 provides details on the land use and land covers in the catchment and their respective spatial coverage as part of the total catchment area. According to results in Table 2, the area under bare ground cover maintained a steady increase from 35% to 43.3% in year 2000 before reducing to 37% in 2010 and further rising again to 46% in 2020. Though dense shrubs was observed as one of the least land cover types along with grassland, the increase in coverage area especially between 2010 to 2020 could be associated with increased establishment of prosopis juslisflora ("mathenge"). The increase was observed along the main river (Lagha-Bor) especially at flood zones as well as around main towns such as Wajir, Griftu, Buna and Eldas.

Visual inspection of the LULCC images showed that much of the change was in the central part of the catchment notably from Buna and Wajir. This was most visibly observed between the imageries of 2000 and 2010 when the increase in bare ground was highest.

3.4. Land Use and Land Cover Change Hot and Cold Spots

An autocorrelation (Moran's I index) test carried prior to execution of hot spot analysis for the land use and land cover type. The autocorrelation statistical test returned a Z-score value of 111.45 and p-value of 0.0000. With a Z-score value greater than 2.58 and a p-value of less than 0.01, the statistical test confirmed that the pattern was clustered with 99% confidence that the statistically significant hot spot and cold spot clusters were not by random chance (Philippe and Karume, 2019 [15]; Xu *et al.*, 2022 [17]).

Results of hot spot analysis relating to LULLC for the periods 1990 to 2000 and 2010 to 2020 show in Figure 3 and Figure 4 respectively. According to Figure 3, fewer and scattered hot spots and cold spots were observed. In addition, visual observation shows that there were very few hot spots and cold spots

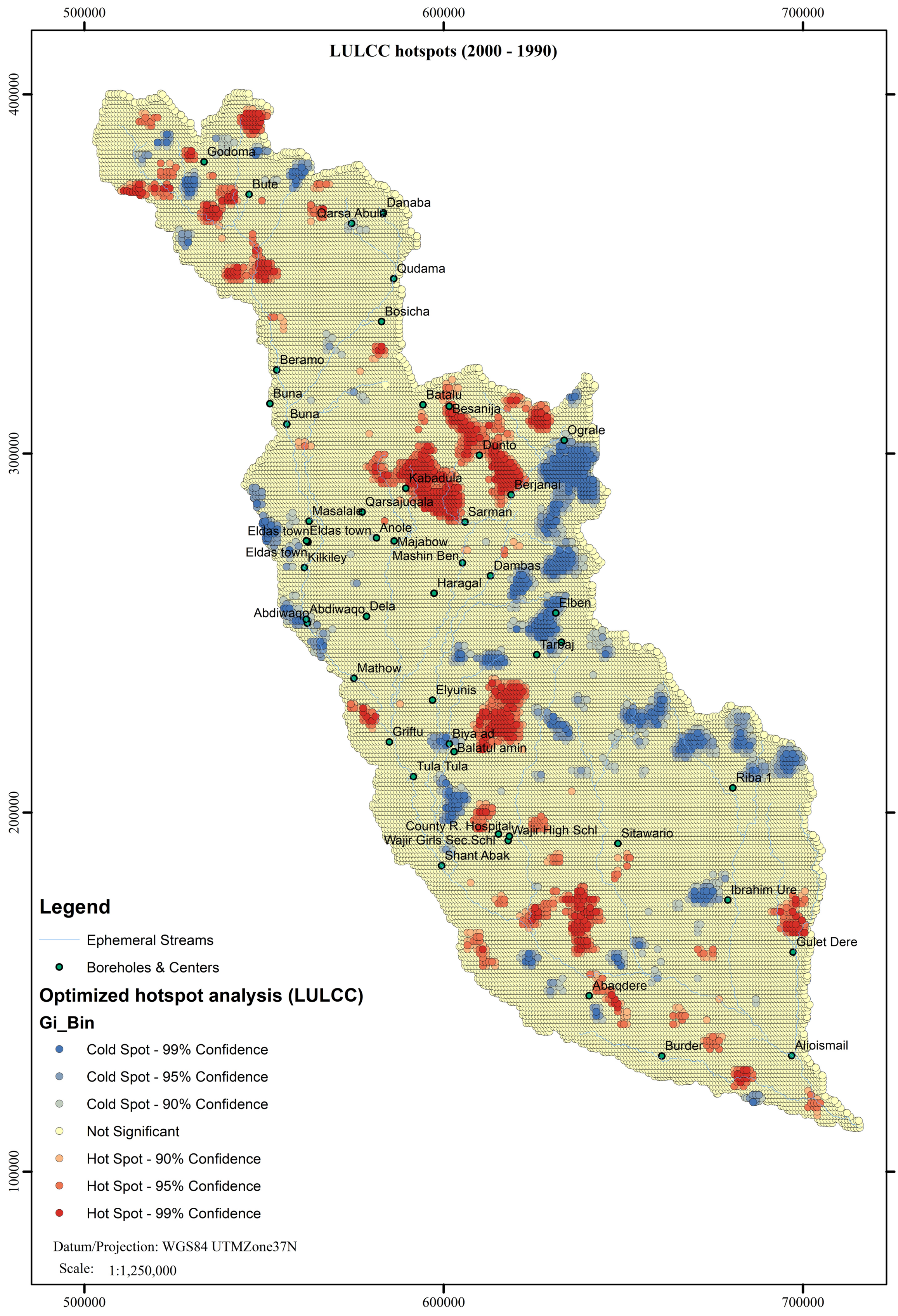


Figure 3. Land use and land cover change hot-spots and cold-spots (2000-1990).

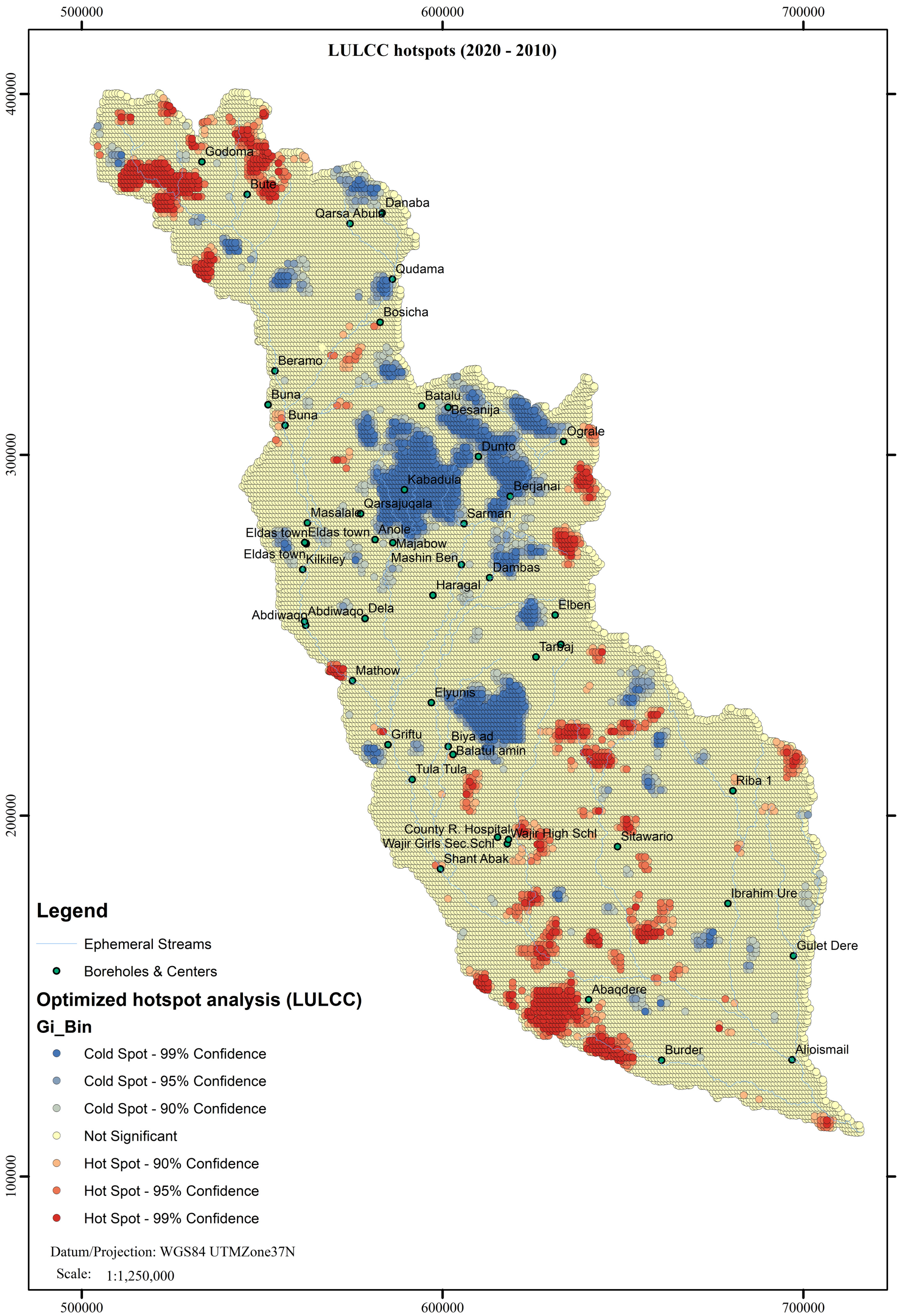


Figure 4. Land use and land cover change hot-spots and cold-spots (2020-2010).

that corresponded with settlements and watering points in the catchment. This was due to the fact that most of the settlements had not been established since most of the watering points were developed after the period 1990-2000. According to **Figure 3**, the only settlements and watering points that had been established before this period included Diff, Wajir, Dambas, Griftu, Eldas, Bute and Moyale. Most of the catchment area recorded no significant hot spots or cold spots.

However, according to **Figure 4**, which shows the hot and cold spot analysis for the period 2010-2020, most of the cold spots corresponded with the locations of established water points and settlements. The cold spots in this case corresponded to areas with statistically significant decline in sparse vegetation cover while hot spots were the areas showing statistically significant increase in vegetation cover. This showed that settlements and watering points had a negative effect on change of sparse vegetation cover. Philippe and Karume (2019) [15] reported similar findings when assessing forest cover change and deforesting in the North Kivu province, DR-Congo. Higher level of forest cover change was observed near towns and roads which point an influence from human activities.

3.5. Trends in Land Use and Land Cover Changes

Due to the spatial and isolated nature of the land use and land cover changes, emerging hot spot analysis tool in ArcGIS Pro was considered as the best approach in the assessment of the trends (Ye, *et al*., 2022) [18]. **Figure 5** shows the results of the LULCC patterns and trend analysis within the catchment from 1990 to 2020. According to **Figure 5**, persistent hot spot account for 31.24% of the total area followed by persistent cold spot at 23.32% while oscillating cold spot represented 8.12% and consecutive cold spot 6.60%. Area that experienced no pattern of change accounted for about 22.44% of the total catchment area. From this assessment, it was clear that cold spots were observed around settlements and livestock watering points.

The emergence of the persistent, consecutive and oscillating cold spots in the central part of the catchment should be an issue of concern. The cold spots in the central part of the catchment account for approximately 43% of the catchment that is affected by persistent, consecutive and oscillating decline in sparse vegetation cover. The development of these cold spots could largely be attributed to the high number of settlements and water points that negatively impact on sparse vegetation.

3.6. Factors Influencing Land Use and Land Cover Change within Hot/Cold Spots

Factors influencing land use and land cover changes were investigated by computing the area of land cover as a percentage of the total area within 1.0 Km, 2.0 Km, 3.0 Km, and 4.0 Km radius from either the settlement and/or borehole. Google Earth Engine (GEE) which has a web based computing platform was used in calculating the area under each land cover. The buffering command was

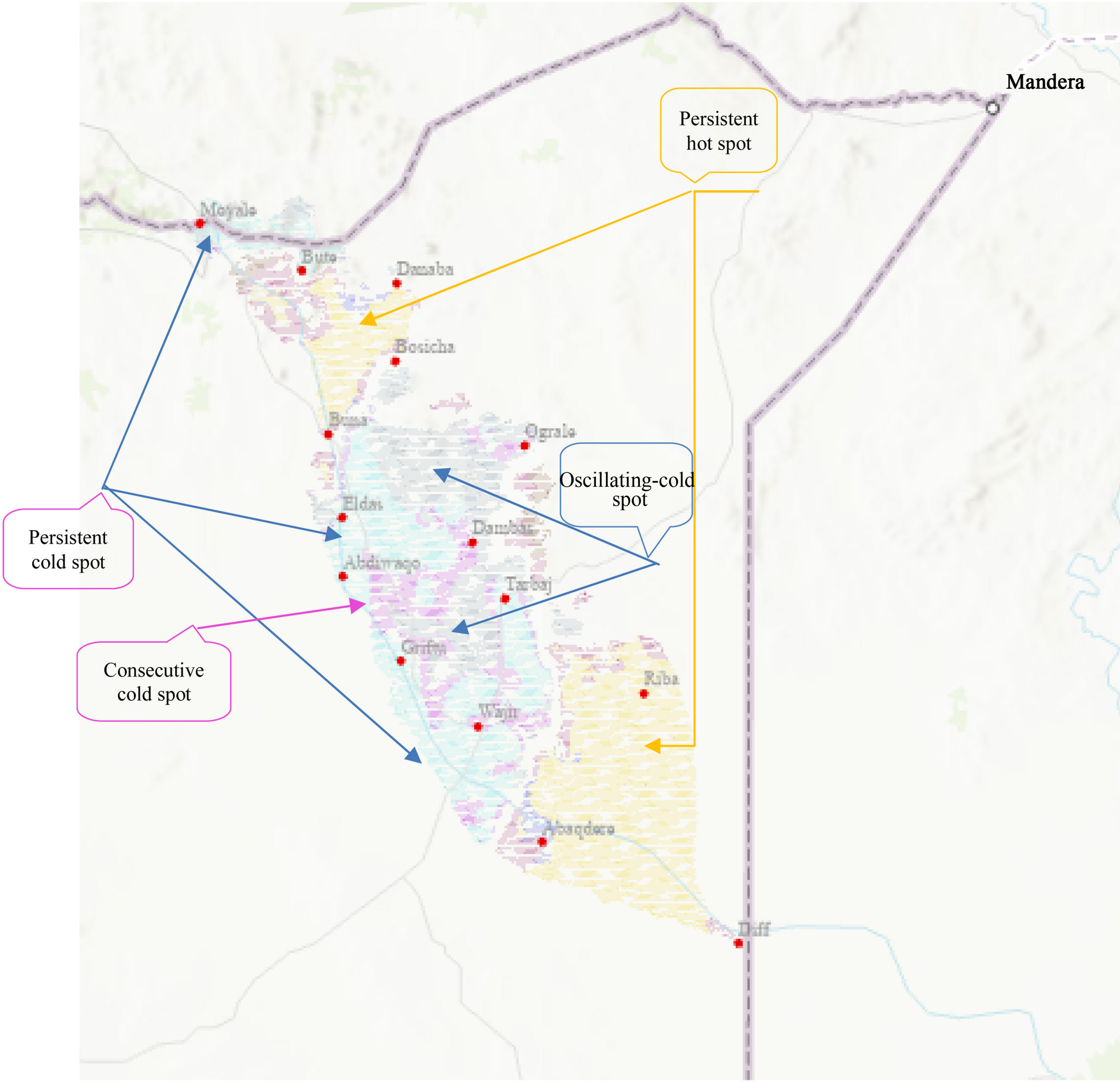


Figure 5. Predominant land use and land cover types.

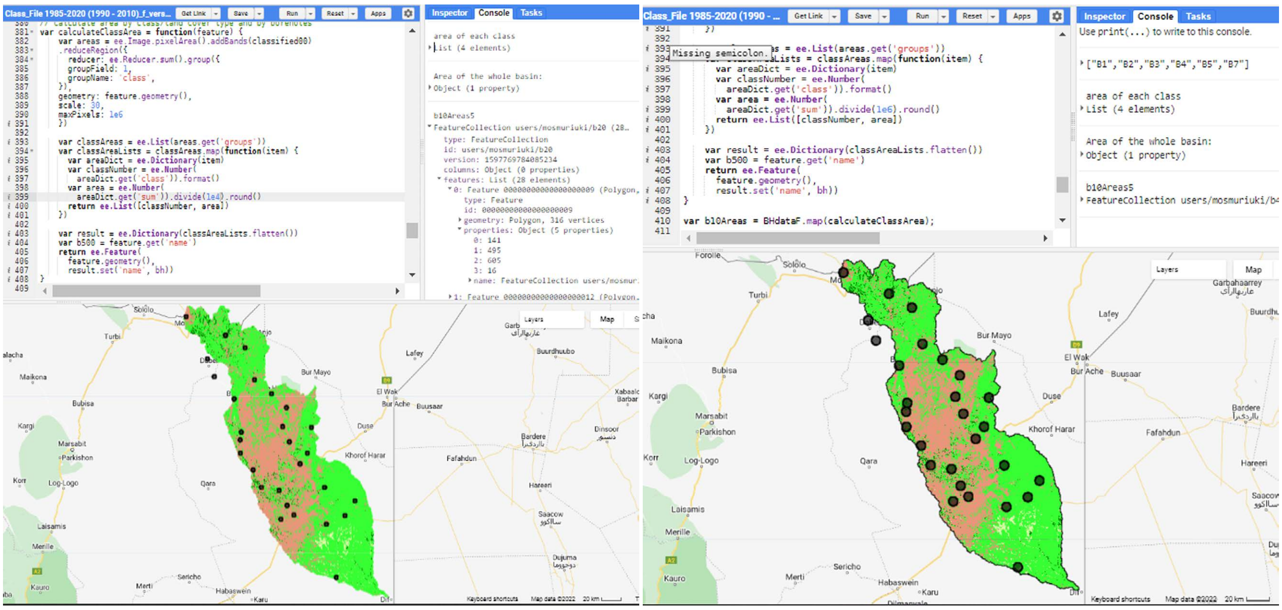
used to achieve the incremental radius from an individual point as shown in **Figure 6**.

3.6.1. Effects of Livestock Watering Points and Settlements

This was carried out by determining the change in area of various land cover types within 4 Km radius transecting from the watering points or centers radiating outwards. Some of the centers considered included Eldas and Abdiwaqo which fall within the lagha while Dambas represented water points and centers away from the lahga.

1) Effects of Eldas borehole/center

An assessment on the effects of settlement and livestock watering points for



(a) (b)

Figure 6. Land cover area within a buffer zone from a settlement/watering point.

Eldas gave the results shown in Figure 7 and Figure 8. The first borehole in Eldas was drilled in 1980s near the lagha with the main aim of supplying livestock water since there was not settlement. However, this latter attracted settlement leading to the emergence of the current Eldas town. Figure 7 and Figure 8 showed that the results of the land cover change analysis around the borehole/settlement. The results showed that 1 Km radius recorded the highest bare-ground cover and least sparse vegetation cover compared to 4 Km radius which reported the lowest level of bare-ground and highest level of vegetation cover. Between 1990 and 2020, 4 Km radius observed a reduction in sparse vegetation from 40% to 12% while the 1 Km radius observed a reduction in sparse shrubs from 30% to 7% between 1990 and 2020. In overall, this showed existence of more sparse vegetation around 4 Km radius compared to 1 Km radius due to high grazing and human related pressured around 1 Km radius as opposed to 4 Km radius. Egeru *et al.* (2015) [4] reported similar findings while carrying out an investigation on influence of livestock grazing within watering point piospheres. Heavy grazing pressure and trampling was recorded near the water points with soil bulk-density found to decrease outwards from a water point as area under bare-ground reduced.

According to Figure 8, the assessment on bare-ground land cover showed that 1 Km radius had the highest bare ground cover at 60% in 1990 before increasing to 85% in 2000 and further to 90% in 2010 and 2020. The extents of bare-ground cover reduced with distance from settlement/watering point. This could have been occasioned by reduction in sparse vegetation due to the sprawling Eldas center as well as increased pressure from human and higher livestock. Analysis of Figure 7 and Figure 8 reveals that the highest pressure on sparse shrubs due

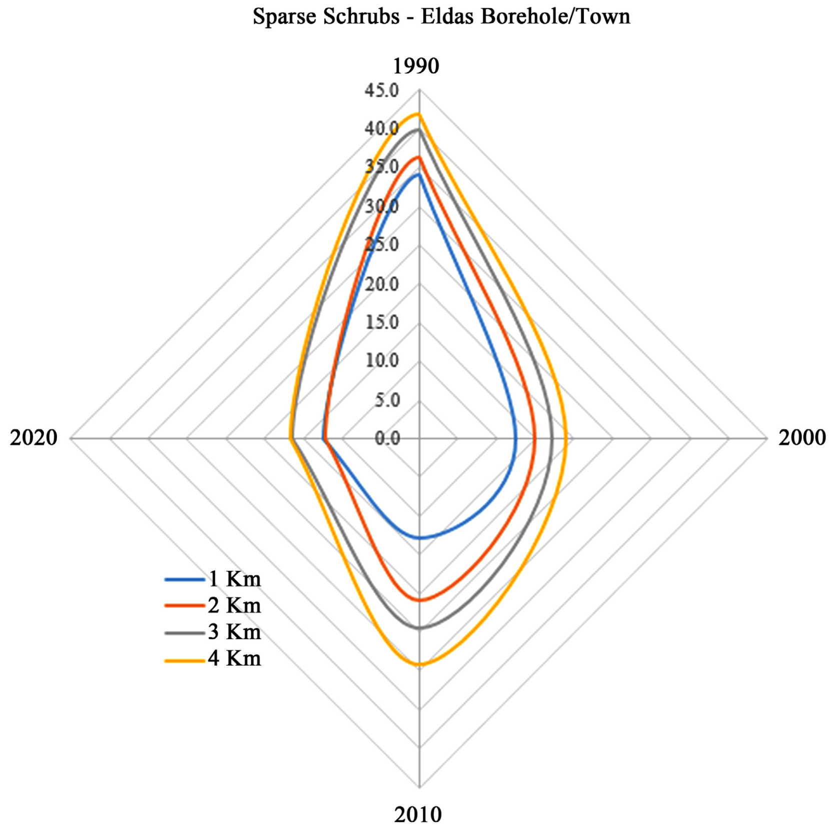


Figure 7. Percent change of sparse shrubs from 1990 to 2020 (Eldas centre).

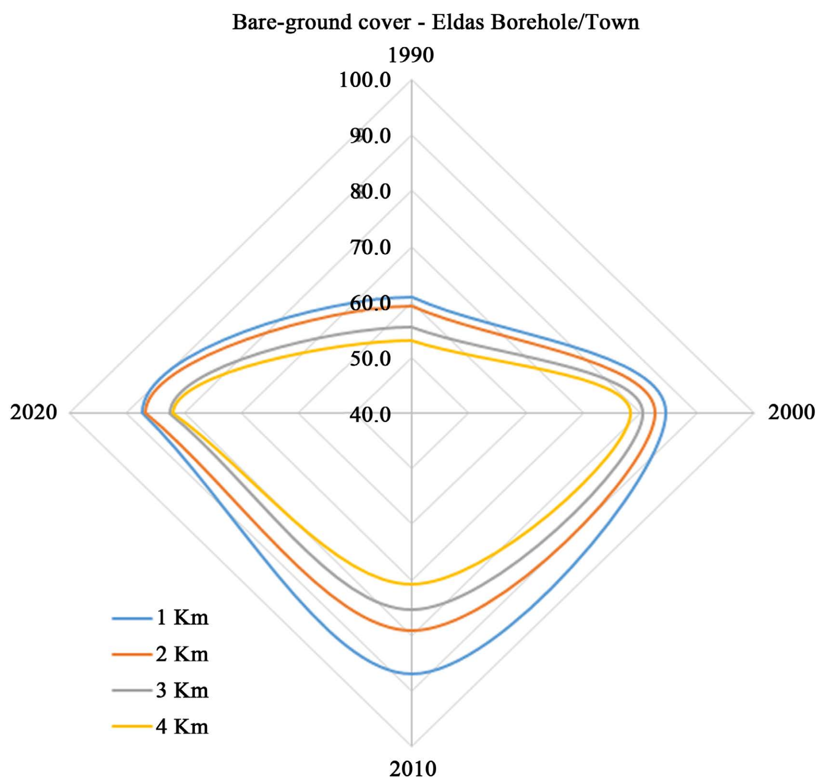


Figure 8. Percent change of bare ground cover from 1990 to 2020 (Eldas Centre).

to human activities was largely within 1 - 3 Km reducing outwards.

Similar findings were reported by Hunt *et al.* (2014) [19] and Malan *et al.*, (2018) [20] on a study carried out in Australia where the grazing impact zones were estimated to range up to 3 Km in radius from a watering point. For lagha bor catchment, interventions aimed at reducing such pressure would include extension of the livestock water pipeline and construction of watering points on both ends at 3 - 4 Km from Eldas center. To further reduce grazing pressure on either side, the watering points could be managed and operated alternately.

2) Effects of Abdiwaqo borehole/center

Figure 9 and **Figure 10** show the dynamics of sparse shrubs and bare-ground land covers at Abdiwaqo borehole and center. Among the 3 boreholes at Abdiwaqo, the first and the highest yielding borehole was drilled in 1998. This attracted permanent settlement and high presence of livestock awaiting and after watering which affected sparse vegetation. According to **Figure 9** and **Figure 10**, the sparse shrubs land cover accounts for nearly 20% while bare ground cover accounts for the largest portion at over 80%. The highest rate of change in both sparse shrubs and bare ground was observed within 1 Km and 2 Km radius reducing gradually in 3 Km and 4 Km where the intensity tapered off. Within 1 Km radius, sharp decline in sparse shrubs was observed from 15% to less than

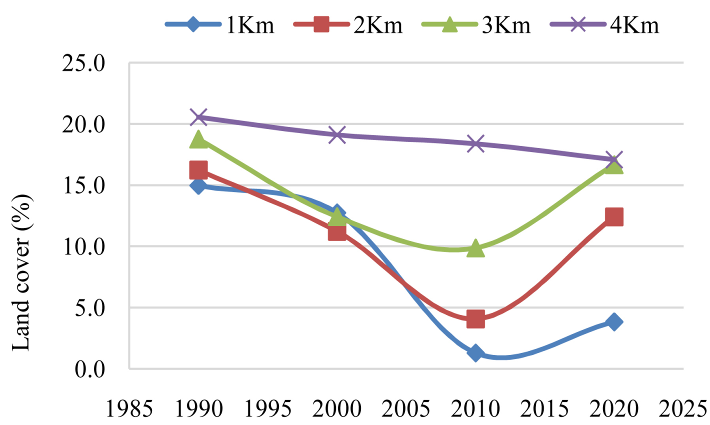


Figure 9. Level of sparse shrubs in percent from 1990 to 2020 at Abdiwaqo center.

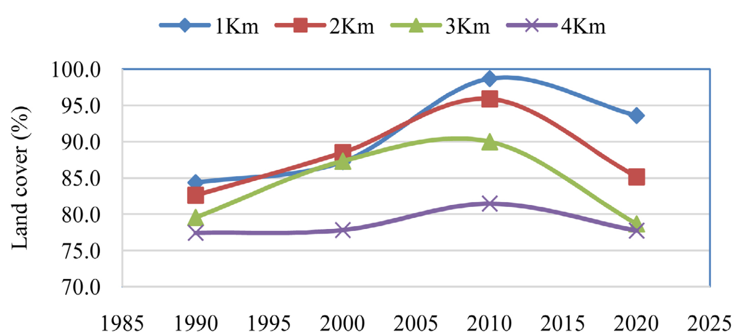


Figure 10. Level of bare ground cover in percent from 1990 to 2020 at Abdiwaqo center.

5% while bare ground increased from 84% to 94%.

The results agrees with the finding of a study in Australia by Hunt *et al.* (2014) [19] and Malan *et al.* (2018) [20] where the impact of grazing piospheres varied up to 3 Km. According to Hunt *et al.* (2014) [19] and Malan *et al.* (2018) [20], grazing impact was found to tappers off at 3 Km from a watering point. This information was useful in making a decision towards, any intervention aimed at reducing the impact of the settlement and livestock watering point. Such intervention would include closing the settlement as well as providing extending the pumping line and construction of watering points such as cattle trough at 3 - 4 Km from current point.

3) Dambas Borehole

Dambas borehole is of the water points drilled away from the main lagha bor stream. Having been drilled in 1973 with a yield of 17 m^3/hr, Dambas borehole formed one of the oldest livestock boreholes in Wajir County. Dambas center developed as a result of this permanent water point. While the water has higher salinity level at 2.7, it is considered okey for livestock but with some level of treatment for human use.

Figure 11 shows the results of an assessment carried out to determine the effects of the center and livestock borehole. This assessment deduced that bareground which accounted for about 10% in 1990 increased to 95% by year 2020 within the 1 Km. However, less impact was observed within the 2 Km radius with least impact recorded within the 3 Km and 4 Km radius. For Dambas, being in ASAL area where rainfall is both sporadic and unreliably low as well as being far from the main lagha, it is difficult for most of the vegetation in the area to recover from the land use pressures. This is the situation that could have led to the continued decline of sparse shrubs especially within the 1 Km as shown in **Figure 12**. In a related study, Shahriary *et al.* (2012) [21] arrived at similar findings where grazers in Iranian piospheres influenced the land cover through reduction of palatable species and trampling. This lead to increased grazing pressure near the watering points but the same varied inversely to distance from the watering point.

This assessment observed that interventions focusing on relieving the high

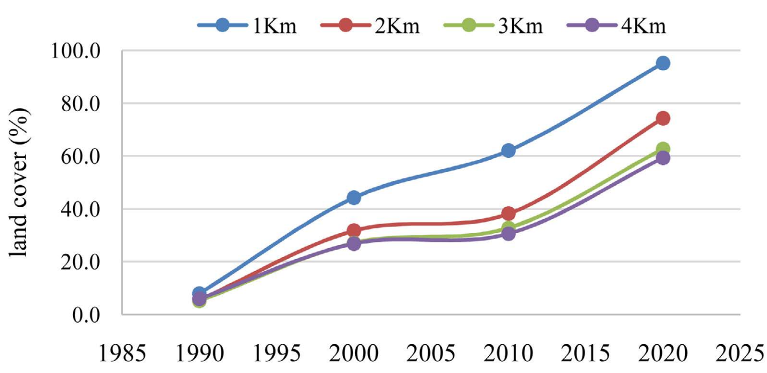


Figure 11. Percent change of bare ground cover from 1990 to 2020 (Dambas Center).

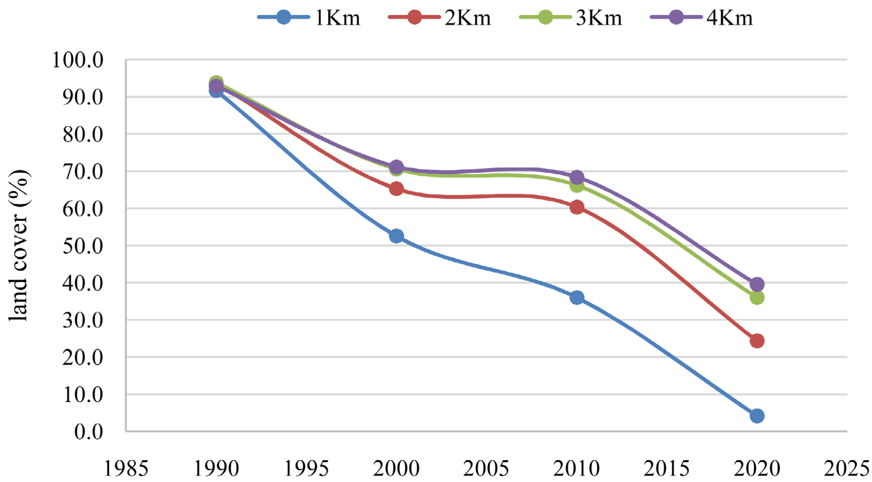


Figure 12. Percent change of sparse shrubs from 1990 to 2020 (Dambas centre).

pressures on vegetation could be achieved by setting up animal watering points at 3 - 4 Km away from the center where it is currently located. This could be done on the eastern side of Dambas considering that Haragal borehole is located 15 Km to the west. Other interventions could include improvement of groundwater recharge.

3.6.2. Effects of Urban or Settlement Development

Wajir town is the oldest and largest urban settlement both in space and population. An assessment carried out to determine the impacts of settlements revealed that sparse shrubs have been on the rise. Figure 13 showed that areas within 2 Km, 3 Km and 4 Km radius reported more shrubs than areas within 1 Km. The high level of bare-ground and low sparse shrubs within 1 Km was associated with the high urban development leaving less space compared to the sparse development going outwards. Between year 1990 and 2020, area under sparse shrubs within 1 Km increased from 45% to 75% in coverage.

As shown in Figure 14, area under bare-ground within 1 Km has reduced from 50% in 1990 to 22% in 2020. The increase in sparse shrubs and reduction of area under bare-ground could be associated with planting of related trees within the settlements as well as proliferation of Prosopis julisflora ("mathenge"). This was confirmed through observations made during ground truthing as well as discussion held with the local community leaders.

Figure 15 and Figure 16 show similar trends in reduction of bare-ground cover and an increase in area under sparse shrubs around Buna center. Area within 1 Km radius reported the highest level of bare-ground due to the increasing urbanization. Areas within 2 Km, 3 Km and 4 Km reported an increase in sparse shrubs from an average of 10% to 34%. Observations made during the field visits associated the increase to the rapidly growing Propsopis Juslisflora. While Prosopis julisflora is able to adapt and thrive under the arid and semi-arid conditions, its expansion threatens existence of the native species. For the case of Buna center which is within the periphery of the lagha bor, the growth of prosopis

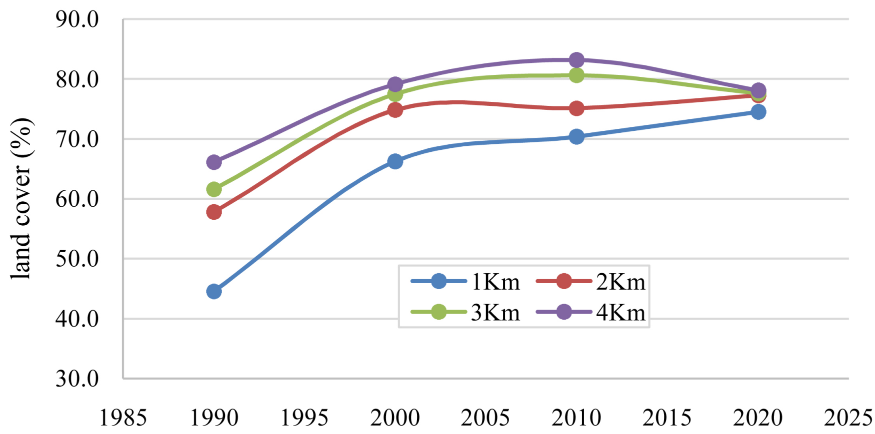


Figure 13. Percent change of sparse shrubs from 1990 to 2020 (Wajir town).

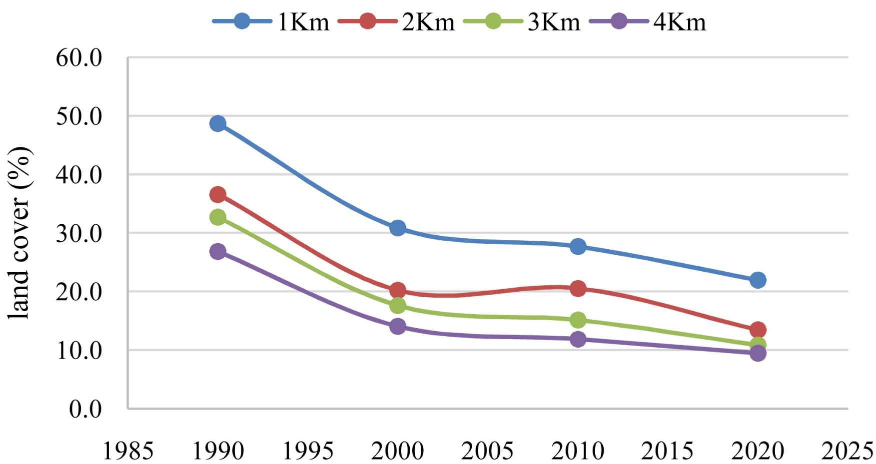


Figure 14. Percent change of bare ground cover from 1990 to 2020 (Wajir town).

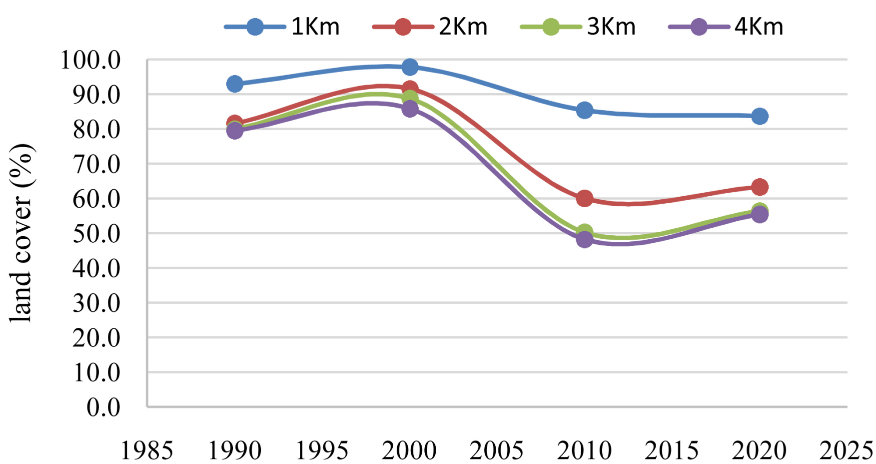


Figure 15. Percent change of bare ground cover from 1990 to 2020 (Buna centre).

needs to be contained and controlled to avert threats to native vegetation.

Around Buna center, the initial decline in sparse shrubs between 1990 and 2000 was associated with development of the center and the need to meet the

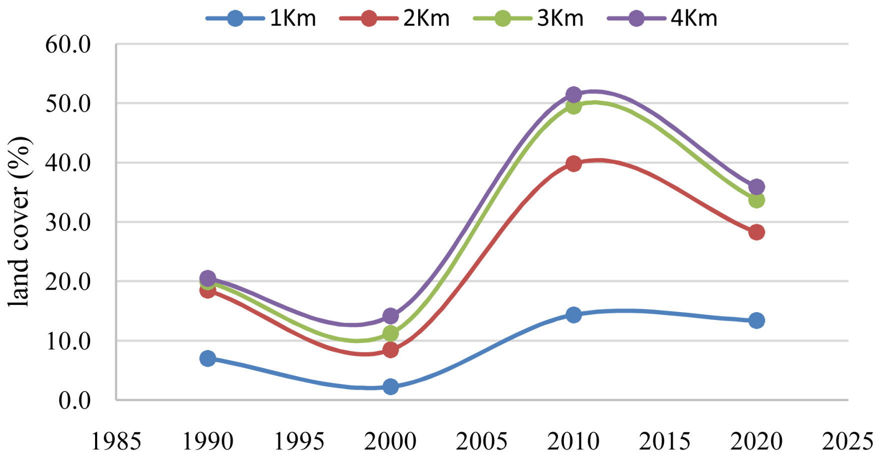


Figure 16. Percent change of sparse shrubs from 1990 to 2020 (Buna centre).

Plate 1. Rapidly growing prosopis julisflora and Bare-ground cover at Buna center.

energy and construction needs of the resident population. However, a sharp increase in vegetation cover was observed from year 2000 leading to reduction in area under bare-ground cover. This increase in vegetation cover was associated to rapid growth of prosopis julisflora which was rampant in center. Study by-Wudad and Abdulahi (2021) [22] made similar observations with expansions of propospis Julisflora due to land use land cover changes in Korahey, Somalia and eastern Ethiopia. The study reported that bare ground cover reduced substantively with high invasion of from Prosopis julisflora at the centers similar to situation shown in **Plate 1** (Buna center).

4. Conclusions

This study provided information on the scale of land use and land cover change patterns and locations of significant positive and negative changes (hot spot and cold spots) in the local setting of lagha-bor catchment which falls within an arid and semi-arid environment. The study established existence of four main land use and land cover classes' namely dense shrubs, sparse shrubs, grassland and bare ground. While sparse shrubs and bare ground were the predominant land covers accounting for over 95% of the study area, sparse shrubs have been declining while area under bare-ground cover was on the rise.

While development of permanent water points and settlements is considered important for the well-being of the community and their livestock, management failures have contributed negatively towards overgrazing and degradation. Areas recording significant changes (hot or cold spots) were observed around settlements with permanent water points. Towards this, the main factors influencing land use and land cover changes in the catchment were social and economic which included establishment of settlements driven by both population and social needs as well as technological advancement by drilling of boreholes to facilitate access to water.

A reduction in sparse shrubs covered around settlements and watering points was a result of reduction of both palatable and unpalatable vegetation. The reduction in vegetation cover and increase in bare-ground cover over time contributed towards the formation of significant hot spots and cold spots. This was confirmed during ground truthing of land use and cover change analysis and discussions with the community elders who formed part of the indigenous knowledge.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix 1: Confusion/Error Matrix

Table A1. Confusion matrix for land clover classification in year 1990.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	PA
Dense shrubs	303	45	72	19	439	69.02
Bare ground	19	1840	67	0	1926	95.53
Sparse shrubs	7	201	4542	36	4786	94.90
Grassland	0	10	18	252	280	90.00
Sum	329	2096	4699	307	7431	86.32
Users Accuracy (%)	92.10	87.79	96.66	82.08		

Overall Accuracy = 0.9335 and Kappa = 0.8710.

Table A2. Confusion matrix for land clover classification in year 2000.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	Producers Accuracy (%)
Dense shrubs	281	45	110	3	439	64.01
Bare ground	1	1892	28	5	1926	98.23
Sparse shrubs	14	119	4619	34	4786	96.51
Grassland	14	6	54	206	280	73.57
Sum	310	2062	4811	248	7183	
Users Accuracy (%)	90.65	91.76	96.01	83.06		

Overall accuracy = 94.17% and Kappa = 0.8852.

Table A3. Confusion matrix for land clover classification in year 2010.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	PA
Dense shrubs	347	20	70	2	439	79.04
Bare ground	5	1862	59	0	1926	96.68
Sparse shrubs	7	156	4506	117	4786	94.15
Grassland	2	15	35	228	280	81.43
Sum	361	2053	4670	347	7084	
UA	96.12	90.70	96.49	65.71		

Overall accuracy = 93.43% and Kappa = 0.8735.

Table A4. Confusion matrix for land clover classification in year 2020.

Prediction	Dense shrubs	Bare ground	Sparse Shrubs	Grassland	Sum	PA
Dense shrubs	285	40	107	7	439	64.92
Bare ground	2	1895	24	5	1926	98.39
Sparse Shrubs	29	175	4556	26	4786	95.19
Grassland	18	5	51	206	280	73.57
Sum	334	2115	4738	244	7431	
UA	85.33	89.6	96.16	84.43		

Overall accuracy = 93.45% and Kappa = 0.8714.