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Change detection due to ISPAAD Programme using geospatial techniques: A case study of Dinogeng Agricultural Extension Area of Kgatleng District, Botswana

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Abstract

Dinogeng Agricultural Extension Area (DAEA), located in the south eastern part of Botswana has witnessed tremendous land use changes due to the Integrated Support Programme for Arable Agriculture Development (ISPAAD). For over a decade, crop cultivation has been relatively small both in size and population. But today, Dinogeng is one of the fastest growing agricultural areas. Therefore, it is paramount to detect the nature and magnitude of land use changes for planning purpose. Remotely Sensed data from Landsat 5 and Landsat 8 were utilized for the purpose of Land Use Land Cover (LULC) change detection. Geographical Information Systems (GIS) and Remote Sensing (RS) were used to produce LULC maps for 2006 and 2020 for assessing the severity of land degradation. In a 14-year span (2006-2020), LULC of DAEA changed markedly. Cultivated land and bare areas increased by 19.4 and 18.3 % whereas shrub land and forest areas decreased by 36.9 and 0.7 %, respectively. Supervised classification algorithms and stratified random sampling design were adopted for the accuracy assessment. The classification process produced good results with overall accuracies of 93% and 94% for the 2006 and 2020 maps, respectively. The findings could be useful to guide the development of functional land use plan for DAEA.

Keywords: Dinogeng Agricultural Extension Area; ISPAAD; LULC; GIS; RS.

1. Introduction

Suitable land for arable farming is very scarce in Botswana and the hard veld in the eastern part of the country has been the focus of interest for several years because of comparatively fertile soils. The country is a net importer of food grains due to low crop yields [1]. The causes of low crop production include unfavourable climate, poor soils and unsuitable farming methods leading to land degradation. With introduction of ISPAAD subsidy programme, population increase and failure to adopt agricultural technology by farmers, this may worsen the quality and quantity of agricultural land and its productivity in the long term. Abandoning existing farmland and searching for new agricultural fields are likely to happen and this may translate into land use changes, land use conflicts and deforestation. To address some of these problems, there is need for a study on the assessment of the impacts of the ISPAAD programme on the environment in DAEA. Dinogeng has a considerably higher number of smallholder farmers benefiting from the ISPAAD programme each year, and so chances of land degradation are very high, hence the pressing need for this study.

The primary objectives of ISPAAD are to increase grain production, promote food security at the household and national levels, commercialize through mechanization, and facilitate access to farm inputs and credit and to improve extension outreach [2]. The expected outcomes from ISPAAD include improvement of farm output and productivity through enhancement of farmers' access to inputs comprising seeds, fertilizers, draught power, credit, cluster fencing, potable water and other agricultural services.

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In Botswana, the total number of documented farmers was 31,000 in 2007/08 (before ISPAAD). The number of ISPAAD beneficiaries was 96,000 in 2008/09 when ISPAAD started. The number of beneficiaries increased to 118,000 in 2010/11. The area planted was 104,000 ha in 2007/08. The area planted increased to 298,000 ha in 2008/09 and rose to 377,000ha in 2010/11 [3]. A similar trend was observed in LULC for a study at Taung watershed in the Ramotswa Agricultural District by Moesi [4]. Shrub land decreased from 67% of the watershed in 2000 to 48% in 2020. However, there was a sharp rise in cultivated land from 18% to 38% in 2020.

The total domestic grain production during ISPAAD averaged 58,000 tons per year. Productivity remained low and continued to decline during ISPAAD [5]. The national average grain productivity was 320kg/ha of grains against an expected ISPAAD target yield of 1000kg/ha. Domestic grain production only satisfied about 10 % of national staple grain requirement. Botswana imported an average of 300,000 tons of cereal grains per year during ISPAAD [3].

Dinogeng is situated in the Kgatleng district where intensive agriculture is practised. The district has a total land area of 7600 km^2; 6.9 % of the area is used for arable farming, 13.6 % for mixed farming whilst 43.2 % is utilized for communal grazing [6]. Dinogeng covers a land area of approximately 83 km^2. According to the Ministry of Agriculture records, Dinogeng has more than 4000 arable farmers benefiting from ISPAAD programme each year.

As land becomes increasingly important and competition among alternative uses intensifies, shift in land use may be affected further by institutional and environmental constraints. It is therefore necessary for land use planners and land users to develop quantitative capabilities which can be implemented to monitor and evaluate the impact of alternative land use policies. The most important issue for the population is the threat to future production of food and other essentials by the conversion of productive lands to non-productive uses such as transformation of agricultural land use to residential, degradation of range land by overgrazing and use of other unsustainable farming methods.

This study attempts to answer the question: Has land degradation undergone a remarkable degree? Is there any significant change in vegetation clearance and bare land? This research is aimed at analyzing the spatial dimension of land use change to monitor land degradation in the study area. The main objective of the study is to assess the impacts of the ISPAAD programme on the environment in Dinogeng Agricultural Extension Area by (i) determining land use land cover (LULC) changes using GIS and RS for the period from 2006 to 2020, and (ii) assessing the pattern of and magnitude of land use changes and subsequent degradation.

2. Materials and methods

2.1. Study site description

The study area extends from 24^0 8 0′ to 24^0 35 0′S latitude and 26^0 5 0′ to $26^0$35 0′ E longitude covering an area of about 83 100 ha. The climate is semiarid with a mean annual temperature of 20.7 ^{0}C fluctuating from 13.2^{0}C to 28.2 ^{0}C. The topography is flat and undulating, with an elevation range of 901-1003m a.s.l. The communities in the study area depend on ground water for their livelihood. The soils are predominantly Luvisols and dominant soils have been reported to be sandy clay loam to sandy clay. The vegetation of the study site is dominated by shrubs with areas of woodland and savanna. Half of the area is covered by shrubs, and 7% is evergreen forest mainly along the Notwane River and other drainage lines [7]. An overview of the boundary of the study area is given in Figure 1.

2.2. LULC classifications

The different LULC classes of the study area were grouped into four for easy analysis and assessment of change detection. The LULC classification includes cultivated land, bare land, Forest land, and Shrub land. The cultivated area category includes land which is mainly used for growing food crops such as maize, sorghum, millet, beans, cowpeas, lablab, and other fodder crops. Fallow land was also grouped under cultivated. The bare land category describes the land left without vegetation cover such as eroded land due to land degradation, gravel road surface and dry pan. The forest land category includes evergreen trees mainly growing naturally in the reserved land, along the rivers and on the hills. Shrub land comprises of areas with natural pastures, grass, sparse trees and shrubs.

2.3. Image classification

Image classification was done in order to assign different spectral signatures from the LANDSAT datasets to different LULC categories or classes. This was done based on reflectance features of the different LULC types. Different colour composites were used to improve visibility of various objects on the imagery. This was supplemented by field visits together with the use of high-resolution images from Google Earth and Google Earth Pro that made it possible to establish the main land use land cover types. For each of the predetermined LULC type, training samples were selected by delineating polygons around representative sites. Spectral signatures for the respective LULC types derived from the satellite imagery were recorded by using the pixels enclosed by these polygons.

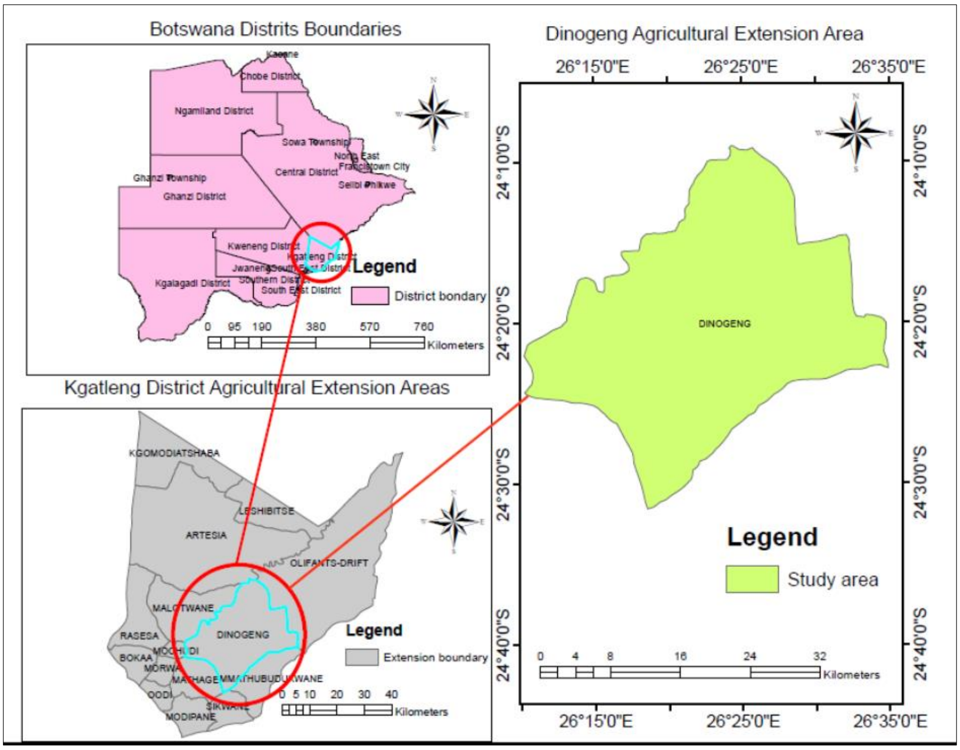

Figure 1 Location of Dinogeng in Kgatleng District, Botswana

The Geomatica focus tools were used to carry out supervised classification [8]. Training sites were created using recognizable regions of the satellite image. The training samples were then used to program the computer system to identify pixels with similar characteristics. Training site analysis was then performed to ensure correspondence between spectral classes and information classes. Running of the supervised classification was completed using the maximum likelihood classifier algorithm. The Maximum Likelihood Classification (MLC) algorithm was used as it is the most widely used and accurate of the parametric classifiers. It is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions [9]. Ground truth data were used in supervised classification, accuracy assessment and validation of the result. Furthermore, post classification filtering procedures were done to improve the overall appearance of the map.

2.4. Change detection

Post classification comparison was done for the two independently classified images in order to produce a change detection analysis. An error matrix table was obtained by using the change detection statistical tool of the post classification in ArcGIS. Finally, this classification proved to be effective because it presented the advantage of indicating the nature and magnitude of change that had taken place through pixel by pixel comparison.

2.5. Accuracy assessment

Accuracy assessment of the classified image is an important step in image classification. The quality of a thematic map from a satellite image is determined by its accuracy. Accuracy assessment was performed using the standard method of Congalton [10]. Accuracy assessment is a comparison of a classification with area of interest (AOI) or ground-truth data to evaluate how well the classification represents the real world. This was produced in a matrix table showing six different types of accuracies. However, Accuracy assessment requires that an adequate number of samples per map class be gathered when the classified results are compared with actual ground conditions. In this study, 240 sets of stratified random points were generated using GIS for the four categories against the minimum of 50 points per category recommended by Congalton and Green [11]. The process was completed by compiling an error matrix table which was used for calculation of Overall accuracy, User's accuracy, Producer's accuracy, Errors of Commission and Omission and the Cohen's Kappa coefficient. For supervised classification, the error matrix describes only how well the training pixels have been classified correctly; this is presented in the main diagonal, the columns represent the land cover classes, the rows represent the pixels classified into each class.

2.5.1. Kappa coefficient

Kappa coefficient is one of the most popular measures proposed for interpretation of the error matrix. It is a discrete multivariate technique used in accuracy assessment. The Kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Kappa coefficient is widely used because all elements in the classification error matrix, and not just the main diagonal, contribute to its calculation and because it compensates for change agreement [12].

The Kappa coefficient lies usually on a scale between 0 (no reduction in error) and 1 (complete reduction of error). The latter indicates complete agreement and is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement.

The Kappa coefficient, ***K*** was computed using the following equation:

$$K = \frac{P_o - P_c}{1 - P_c}$$

Where, Po = proportion of units which agree, = overall accuracy

Pc = proportion of units for expected chance agreement

A Kappa coefficient of 90% may be interpreted as 90% better classification than would be expected by random assignment of classes [13]. Interpretation of Kappa statistics is shown in Table 1, so a Kappa value of 90 % falls in the highly ranked statistic number (S. No) 6 rated as almost perfect [14].

Table 1 Interpretation of Kappa statistics

S. No	Kappa statistics	Strength of agreement
1	< 0.00	Poor
2	0.00 - 0.20	Slight
3	0.20 - 0.40	Fair
4	0.40 - 0.60	Moderate
5	0.60 - 0.80	Substantial
6	0.80 - 1.00	Almost perfect

Source: Rwanga and Ndambuki [14]

2.5.2. Overall accuracy

Overall Accuracy specifies the correctness of the whole classification and it was calculated by dividing the total number of the correctly classified points (addition of diagonals) to the total number of points (grand total of reference points or training pixels) [15].

User’s accuracy

The ratio between the number of correctly classified points and the classified total points of LULC class is the user's accuracy because users are concerned about what percentage of the classes have been correctly classified. The user’s accuracy was calculated by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total). This indicated the amount of misclassification or the probability that a pixel classified into a given category represented that category on the ground.

Producer's accuracy

Producer's accuracy is defined as the probability that any pixel in that category has been correctly classified. The producer's accuracy was calculated by dividing the number of diagonal elements in the error matrix with the number of training pixels in that class (the column total). This indicated the quality of the training areas.

Errors of commission and omission

Omission error is defined as the percentage of undetected change pixels in relation to the total change pixels. Commission error is defined as the percentage of pixels detected as change, but that had not changed. A changed pixel that is identified as unchanged is called a false negative or miss while a pixel that has not changed but is identified as changed is called a false positive or false alarm. True negatives are unchanged pixels that were identified as unchanged. True positives are changed pixels that were identified as changed [15]. The off-diagonal row elements represent ground truth points of a certain class which were excluded from that class during classification (viz. error of omission). On the other hand, the of-diagonal column elements represent ground truth pixels of other classes that were included in a certain classification class (viz. error of commission)

According to Bharatkar and Patel [13], a more appropriate and adopted method for this study when calculating these individual classification accuracies was as follows:

Commission error = 1 - user's accuracy or 100 - user's accuracy in percentage,

Omission error = 1 - producer's accuracy or 100 - producer's accuracy in percentage.

2.6. Determination of magnitude of change

The extent of change is a degree of expansion or reduction in the LULC size. A negative value will present a decrease in LULC size while a positive value will indicate an increase in the LULC size [16].

The magnitude of change (M) is calculated by using equation (1)

$$M = B - A \qquad \text{equation (1)}$$

The percentage of change (A) is calculated by the formula (equation (2))

$$P = \frac{B - A}{A} \times 100\% \qquad \text{equation (2)}$$

Where: M = magnitude of change

P = percentage of change

B = first date (2006)

A = Reference date (2020)

3. Results and discussion

3.1. LULC spatiotemporal variation

Cultivated lands: The cultivated land experienced an increase of 16 096 ha (19.4%) of the total area within the period from 2006 to 2020 as shown in Table 2. This result implies that the level of crop cultivation is increasing while grazing land use (shrub land) is virtually on a decrease. This means that lands meant for grazing of livestock are giving way to crop cultivation. The cultivated lands occupied an area of 16 382 ha (19.7%) in 2006 and increased to 32 478 ha (39.1%) in 2020.

Table 2 LULC change detection for the period 2006 -2020 in the DAEA

No	classes	2006		2020	
		Area (ha)	Area %	Area (ha)	Area %
1	Cultivated land	16 382	19.7	32 478	39.1
2	Bare land	9 530	11.5	24 711	29.7
3	Forest	6 011	7.2	5 434	6.5
4	Shrubs	51 194	61.6	20 495	24.7
Total		83 117	100	83 117	100

Bare lands: They include foot paths, football fields, gravel roads, dry pans and other degraded land or open spaces that vegetation could not grow on. Bare lands witnessed an increase of 15 181 ha (18.2%) within the study period. The bare surfaces covered an area of 9 530 ha (11.5%) in 2006 and increased to 24 711 ha (29.7%) in 2020.

Forest land: Forested areas are relatively stable probably due to their existence along streams and rivers and rocky surfaces where crop cultivation could not take place. Forest land occupied about 6 011 ha (7.2%) from the 2006 estimates and 5 434 ha (6.5%) in 2020.

Shrub land: The area decreased greatly by 30 699 ha (36.9%) due to the increasing demand for crop cultivation, kraal and field fencing material, fuel wood and the rapidly expanding human population. The cultivated land in the study area increased remarkably at the expense of shrub land. Shrubs covered an area of 51 194 ha (61.6%) in 2006 and decreased to 20 495 ha (24.7%) in 2020.

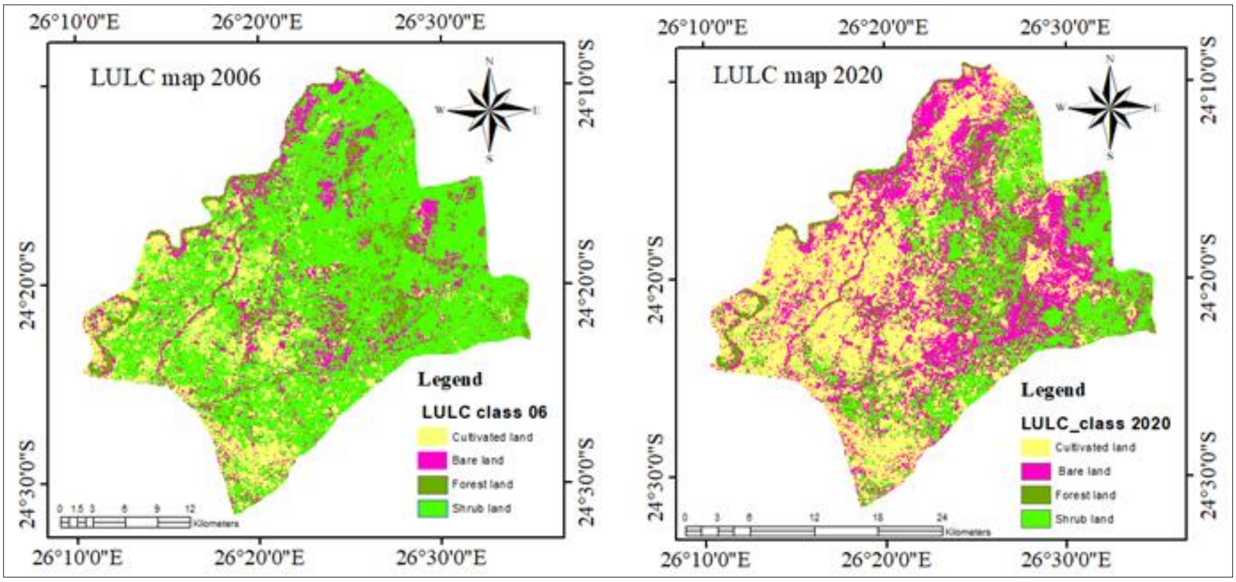

Figure 2 LULC classification maps of 2006 and 2020

3.2. LULC change detection

The results obtained after processing the two multispectral datasets of Landsat 5 and 8 for LULC change detection are displayed in Figure 2 and Table 2. Bare land and cultivated land increased by 18.3 and 19.4% of the total area, whereas forest areas and shrub land declined by 0.7 and 36.9% of the total area, respectively, over the period.

Table 3 Magnitude and percentage of change in LULC

LULC	Area in ha (A) 2006	Area in ha (B) 2020	Magnitude of change M = B - A	Percentage change P = (B - A)/A
Cultivated land	16 382	32 478	16 096	49.6
Bare land	9 530	24 711	15 181	61.4
Forest	6 011	5 434	-577	-10.6
Shrubs	51 194	20 495	-30 699	-149.8

3.3. LULC change analysis

The results of this study showed that cultivated and bare areas increased by 16 096 ha (49.6%) and 15 181 ha (61.4%), respectively. Evergreen forests decreased by 577 ha (-10.6%) whereas shrub land declined by 30 699 ha (-149.8%) over the same period. These changes, shown in Table 3, took place at the expense of other LULC classes. These LULC changes are complex and at the same time interrelated such that the expansion of one LULC type occurred at the expense of other LULC classes. The results of this study agree with those of other studies [17].

Expansion of cultivated land is related to the introduction of the ISPAAD subsidy programme by government together with increase in population. The BCA Consult [3] reported that, Botswana had a total of 31 000 arable farmers before ISPAAD started in 2007/08 but the number of ISPAAD beneficiaries increased to 96 000 in 2008/09 until it reached 118 000 in 2010/11. Furthermore, the area of land planted was 104 000 ha in 2007/08. This area increased to 298 000 ha in 2008/09 until it reached 377 000 ha in 2010/11.

The population of Kgatleng district increased from 73 507 to 91 660 in the period between 2001 and 2011 [18]. Kgatleng has an area of 7 960 km^2 and the population density of the district increased from 9.2 to 11.5 persons per km^2 in the reported period. The annual population growth rate for Kgatleng recorded between 2001 and 2011 was 2.2 percent. Due to population increase as well as positive response by farmers towards the ISPAAD programme, there was high demand for land for cultivation resulting in deforestation. The area which was initially covered by vegetation was converted into arable and bare land. Bare areas increased by 15 181 ha resulting in a sharp rise of 18.2 %.

In addition to cultivation, overgrazing is also an important cause of vegetation clearance and subsequent soil erosion. The LULC classification results show that the rate of deforestation is approximately 2.7% per year or 2, 234 ha of vegetated lands are lost annually. Removal of the topsoil negatively impacts on the agricultural productive capacity of the land resource. Uncontrolled or poorly managed grazing brings about removal of vegetation that exposes the soil to all types and processes of erosion. Land degradation has been reported to be a serious environmental problem [19], especially in the eastern parts of Botswana due to the growing human population with increased number of livestock resulting in overgrazing as well as the use of inappropriate farming techniques. Kgatleng District is relatively small and under immense pressure from different land uses [20]. Like most communal parts of Botswana, the area of study is open to both arable farming and open-access communal livestock grazing which is characterized by smallholder farmers who are also deficient in management skills of the land resources. Multiple land use involving high stocking densities of different livestock species, destruction of tree species for domestic purposes (fire wood, construction of livestock fencing and field fencing) and land clearing for arable farming was associated with the significantly low tree species density in the Mmamolongwana communal area in Zimbabwe [21].

3.4. Rate of growth and magnitude of land degradation

The rates of growth of cultivated and non-productive land use in DAEA by far outstrip population growth. This implies that the land is consumed or converted at an excessive rate against population increase.

Over a 10-year period (2001 to 2011), the annual population growth rate recorded for Mochudi, the village where DAEA farmers reside grew by 1.79 % [18] and the growth rate reduced to 1.0% from 2011 to 2022 [22] while land that was converted into cultivated land from either forest or shrubs grew by 49.6% from 2006 to 2020 and this is nearly 28 to 49 times the population growth. This implies that the per capital consumption of land for arable production has increased markedly during the study period. On the other hand, bare areas increased by 61.4% and thus almost 34 to

61 times the population growth rate. The development of land for cultivation and other uses is a direct consequence of land degradation.

3.5. Accuracy assessment

For 2006 LULC, the map results were: overall accuracy of 93%, User's accuracy of 90 - 100% and producer's accuracy of 75 - 100 %. The overall accuracy for 2020 LULC map was better with 94% whilst the other two accuracies had 88 - 100%. Results for Producer's accuracy and User's accuracy are given in Tables 4 and 5.

Although the classification process was almost perfect, a good number of pixels were excluded from bare and shrub categories, thus the areas of these classes in the classified image are to some extent underestimated. On the other hand, cultivated land in the image is to some degree not very reliable as some pixels of other categories were included in the cultivated land category. Thus, the area of cultivated land in the classified image is to some extent overestimated.

In this study, overall Kappa coefficients of 0.89 and 0.92 were obtained for the 2006 and 2020 LULC maps, respectively. These Kappa coefficients may be interpreted as 89% and 92% better classification than would be expected by random assignment of classes. Kappa statistic ranging between 80% - 100% is rated as almost perfect [14] and greater than 75% excellent [13]. The summary for the error matrices table for 2006 and 2020 is shown in Table 6.

Table 4 Error matrix for the 2006 LULC classified map

	Cultivated	Bare land	Forest	Shrub	Totals	UA	CE	Kappa
Cultivated	47	0	0	0	47	100%	0%	
Bare land	1	27	0	0	28	96%	4%	
Forest	0	0	18	0	18	100%	0%	
Shrub	15	0	0	132	147	90%	10%	
Totals	63	27	18	132	240			
PA	75%	100%	100%	100%		93%		
OE	25%	0%	0%	0%				
Kappa								0.89

Key: PA:(Producer's accuracy), UA:(User's accuracy), OE: (Omission error), CE:(Commission error)

Table 5 Error matrix for the 2020 LULC classified map

	Cultivated	Bare land	Forest	Shrub	Totals	UA	CE	Kappa
Cultivated	94	0	0	0	94	100%	0%	
Bare land	6	64	1	0	71	90%	10%	
Forest	0	0	16	0	16	100%	0%	
Shrub	7	0	0	52	59	88%	12%	
Totals	107	64	17	52	240			
PA	88%	100%	94%	100%		94%		
OE	12%	0%	6%	0%				
Kappa								0.92

Key: PA:(Producer's accuracy), UA:(User's accuracy), OE: (Omission error), CE:(Commission error)

Table 6 Error Matrix Summary Table (2006 and 2020)

			Expected				
		C	NC	Total	UA	Overall accuracy	Kappa coefficient
	C	224	14	238	0.94		
Observed	NC	16	226	242	0.93		
	Total	240	240	480			
	PA	0.93	0.94				
	Overall accuracy					0.94	
	Kappa coefficient						0.88

Key: C: Correct, NC: Not correct, UA: User's accuracy, PA: Producer's accuracy

4. Conclusion

The main objective of this study was to assess the impacts of the ISPAAD programme on the environment in Dinogeng Agricultural Extension Area. This study was set out to specifically determine LULC using GIS and RS for the period from 2006 to 2020. It was observed that vegetation and bare soil has changed remarkably. In general terms, ISPAAD has resulted into serious environmental impacts such as severe loss of natural vegetation and decline in productive capacity of the land.

In a 14-year span (2006-2020), the LULC of Dinogeng changed significantly. Expansion of cultivated land and bare land occurred at the expense of natural vegetation cover. Cultivated land and bare areas increased by 19.4 and 18.3 % of the total area whereas shrub land and forest areas decreased by 36.9 and 0.7 % of the total area, respectively. The magnitude of land that was converted into cultivated land from either forest or shrubs grew by 49.6% from 2006 to 2020 and this is nearly 28 to 49 times the population growth. On the other hand, bare areas increased by 61.4% and thus almost 34 to 61 times the population growth rate. This conspicuous change has caused an irretrievable loss of very fertile and suitable soils.

This study has shown that GIS and RS technologies are very useful and capable of detecting the changes in land use and land cover. The LULC pattern and its spatial distribution are essential for monitoring of the environmental changes and land use planning.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

We the authors of this paper hereby declare that there are no competing interests in this publication.

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