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Monitoring the Extent of Reclamation of Small Scale Mining Areas Using Artificial Neural Networks

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Abstract

Small scale mining is mainly widespread in developing and underdeveloped countries. Although it is a source of livelihood for several people, it causes environmental degradation. Reclamation is needed to restore mined areas to an acceptable condition. This study uses ANN to monitor reclamation activities in small scale mining area. Landsat satellite images of study area (2007, 2011 and 2016), ground truth data and ESRI shapefile of the study area were used for the analyses. Two ANN classification methods, Unsupervised Self − Organized Mapping (SOM) and Supervised Multilayer Perceptron (MLP), were used for the classification of the satellite images. Normalized Difference Vegetation Index (NDVI) change maps were generated in order to help confirm where actual change had occurred and to what extent it had occurred. The results show disturbance and revegetation in the study area between 2007 and 2016. The Barelands/mined areas class increased by 60.4% and a decrease in the vegetation class by 18.7% from 2007 to 2011. There was revegetation from 2011 to 2016 with the Barelands/Mined Area decreasing by 51.7% and the vegetation increasing by 3.9%. The study shows an increase in the settlement class by 87.3%. The research concludes that the application of ANN be strongly encouraged for image classification and mine reclamation monitoring in the

country due to the size and quality of training data, network architecture, and training parameters as well as the ability to improve the accuracy and fine tune information obtained from individual classes as compared to other classification methods.

Keywords: Environmental science, Geography

1. Introduction

Small scale mining is mainly widespread in developing and underdeveloped countries. It causes environmental degradation even though it serves as a source of livelihood for several people (Mihaye, 2013). Reclamation is needed therefore, to restore mined areas to an acceptable condition. Existing research on small-scale mining, reclamation and artificial neural networks have placed emphasis on environmental and livelihood effects of small − scale mining (Ontoyin and Agyemang, 2014), the effect of small-scale mining on soil physical properties (Mensah et al., 2014), using tasseled cap transformation, at-brightness temperature and K-means algorithm to monitor coal surface mining and reclamation (Alden, 2009), artificial neural networks for soil analysis (Amato et al., 2015). Artificial neural networks (ANN) are also being used recently for soil analysis, land use/land cover analysis, wildfire detection (Miller et al., 2003) etc. and can therefore be used for reclamation monitoring (Anon, 2015a). This study investigates how artificial neural networks can be used to monitor reclamation activities in small scale mining areas and specifically, to assess the damage caused by small scale mining activities and assess the extent to which reclamation has occurred.

1.1. Small scale mining and mine reclamation

Small-scale mining in Ghana is usually referred to as using traditional methods to extract precious minerals particularly gold and diamonds. In developing countries, it is an activity mainly driven by poverty (Owusu and Dwomoh, 2012). It is a practice that consists of undeveloped ways of extracting minerals, extreme manual processes, hazardous working conditions all which constantly affect human and environmental health negatively.

There are two types of small-scale gold miners in Ghana, namely the licensed or legal small-scale gold mining units and unlicensed or illegal small-scale gold mining units (Kessey and Arko, 2013).

Mine reclamation is the process of restoring land that has been mined, back to a natural or economically usable state. Mine reclamation creates useful and improved landscapes ranging from the restoration of productive ecosystems to the production of industrial resources. Modern mine reclamation minimizes and mitigates the

environmental effects of mining (Anon, 2015b). For sustainability to be achieved, the mining industry should consider merging enhanced socioeconomic growth, development and improved environmental protection (Hilson and Murck, 2000).

1.2. Review and comparison of current techniques commonly used for image classification

Various researches have reviewed and compared current unsupervised, supervised satellite image classification methods as well as the combination of both with respect to classification accuracy and kappa coefficients. "In digital image classification the conventional statistical approaches for image classification use only the gray values. Different advanced techniques in image classification like Artificial Neural Networks, Support Vector Machines, Fuzzy measures, Genetic Algorithms and Fuzzy Support Vector Machines are being developed for image classification." (Seetha et al. 2008). They go ahead to compare the different classification techniques with regards to their benefits, limitations and various parameters. Tables 1 and 2 below show these comparisons.

1.3. Artificial neural networks (ANN) for image classification and monitoring reclamation activities

Various classifications of data obtained via remote sensing have resulted in Land-Use/land-cover (LU/LC) maps for several applications such as urban planning,

Table 1. Benefits and limitations of the various classification methods.

Classification method	Benefits	Limitations
Support vector machine	• Models nonlinear class boundaries • Over fitting is unlikely to occur • Computational complexity reduced to quadratic optimization problem • Easy to control complexity of decision rule and frequency of error	• Training is slow compared to Bayes and Decision trees • Difficult to determine optimal parameters when training data is not linearly separable • Difficult to understand structure of algorithm
Fuzzy logic	• Different stochastic relationships can be identified to describe properties	• Priori knowledge is very important to get good results • Precise solutions are not obtained if the direction of decision is not clear
Genetic algorithm	• Can be used in feature classification and feature selection • Primarily used in optimization always finds a "good" solution (not always the best solution) • Can handle large, complex, non-differentiable and multimodal spaces • Efficient search method for a complex problem space • Good at refining irrelevant and noisy features selected for classification	• Computation or development of scoring function is nontrivial • Not the most efficient method to find some optima, rather than global • Complications involved in the representation of training/output data

Source: Seetha et al. (2008).

Table 2. Comparative analysis of the different image classification techniques with respect to various parameters.

Parameter	Support vector machines	Fuzzy logic	Genetic algorithms
Type of approach	Non-parametric with binary classifier	Stochastic	Large time series data
Non-linear decision boundaries	Efficient when the data have more input variables	Depends on prior knowledge for decision boundaries	Depends on the direction of decision
Training speed	Training data size, kernel parameter, class separability	Iterative application of the fuzzy integral	Refining irrelevant and noise genes
Accuracy	Depends on selection of optimal hyper plane	Selection of cutting threshold	Selection of genes
General performance	Kernel parameter	Fused fuzzy integral	Feature selection

Source: Seetha et al. (2008).

characterizing agricultural crops, and classifying forest ecosystems (Yuan et al., 2009). ANN's are among the most notable classification approaches even though there are other modes of classification to accomplish such tasks (Yuan et al., 2009). ANN's emanated from such research whose development has been extensively used in remote sensing for a while, mainly for image classification (Tso and Mather, 2009).

ANN approaches are advantageous over statistical classification methods in that they are non-parametric and need little or no knowledge of the distribution model of input data. Other advantages of ANNs include parallel computation, estimating non-linear relationships between the input data and desired outputs and capability of fast generalization (Tso and Mather, 2009). Previous studies on multispectral image classification have confirmed a better classification accuracy performance from ANNs than traditional classification methods (Yuan et al., 2009).

A number of fundamental neural network architectures including counter-propagation networks and Hopfield networks can be used for image classification but this study focused on Multilayer Perceptron (MLP)-Supervised Classification) and Self-Organized Mapping (SOM)-Unsupervised Classification.

The SOM Network automatically detects the relationships within the set of input patterns. This property can be used to convert images from higher dimensions to a two-dimensional feature space using learning vector quantization to train and classify the image (Kangas et al., 1990). The input and output neurones in a SOM are respectively known as the sensory cortex and the mapping cortex, which are parallel to the functions in the brain. The number of neurones in the input and output layers define a SOM network. The number of input neurones is the same as the number of input features. But then, there are no specified rules about the number of output neurones (Tso and Mather, 2009). One of the benefits of the SOM is the ability to handle categorical data.

MLP is a supervised method based on the back-propagation learning algorithm. This network is composed of an input layer, an output layer, and one intermediary hidden layer at least (there can be more than one intermediary layer). Other variables are nodes in the input layer, while final classes result as neurons in the output layer (Freire et al., 2009).

The research will contribute to narrowing the gap in understanding how artificial neural networks (ANN) can be used to monitor the extent of reclamation in small-scale mining areas since it has not been done in this part of the world. The lessons could help researchers and professionals in the industry to learn more about ANN and how to use its principle for image classification in other areas besides monitoring reclamation activities.

2. Materials and Methods

2.1. Data

Landsat satellite images for this research (2007, 2011 and 2016) were downloaded from the United States Geological Survey (USGS) website (see Table 3). Licenses for small scale mining begun to be issued from the year 2006. Small scale mining peaked between 2010 and 2011. Currently, licenses for prospecting and mining in small scales have been suspended to address the issues of illegal mining and to also restructure and streamline the policies regarding small scale mining. This has led to a significant improvement in the regrowth of vegetation as well as the improvement in turbidity of water bodies. Also, according to the 2012 Ghana Report, the Minerals Commission (Ghana) in 2011, granted 66 prospecting licenses, 53.5% increase on 2010 and the highest in prospecting licenses for the past 20 years. The choice of the years 2007, 2011 and 2016 have been informed by these reasons. ESRI Shapefiles of Tarkwa and its environs were obtained from the Minerals Commission, Accra, Ghana. Ground training data made up of GPS coordinates of potential LU/LC classes which will assist in the Supervised MLP classification were gathered from various communities within Tarkwa and its environs. Some of the communities the ground training data was gathered from are Mile 8, Nsuta, Tarkwa Banso, Nkamponase, New Atuabo and Domeabra. Below is a table showing details of the Landsat data used.

2.2. Study area

Tarkwa was chosen because of the centre of focus of the research- the presence of small scale mining activities, willing provision of data by the Minerals Commission (Ghana) and the Environmental Protection Agency (EPA), familiarity of the area and easy access to the communities. Tarkwa is the capital of the Tarkwa-Nsuaem Municipal Assembly which is located in the Western Region of Ghana. Tarkwa has a

Table 3. Landsat data used for classification.

	Acquisition date	Satellite	Spatial resolution	Sensors	Number of bands
2007	13th January, 2007	Landsat 7	30 m	ETM +	8
2011	29th March, 2011	Landsat 7	30 m	ETM +	8
2016	6th January, 2016	Landsat 7	30 m	ETM +	8

history of almost a century of gold mining and has the highest concentration of mines in a single district in Ghana, with all the new mines operating open-pit.

Economic activities rely on the availability of natural resources in the area. The inhabitants of the area had subsistence and commercial farming as their main economic activities until recently when mining took over as the main economic activity. An example is shown in Fig. 1. Tarkwa possesses the most mining companies in the country. This includes the only manganese mine. Half of the large-scale mines in Ghana are located in the Tarkwa area, producing a significant proportion of the country's gold output. In addition, there are over 70 registered, small-scale mining companies together with over 200 galamsey operators are in the area. About 30 local and foreign companies are involved in mineral prospecting in the area. 8 major companies operating in the area use the open-pit method of mining Fig. 2 shows the location of Tarkwa.

2.3. Methods

Two Artificial Neural Network (ANN) classification methods, Unsupervised Self-Organized Mapping (SOM) and Supervised Multilayer Perceptron (MLP), were used in this research to classify the Landsat satellite images. Landsat images for 2007, 2011 and 2016 were used for the analysis. ArcMap was used for the mask extraction and in the creation of the resultant maps. The IDRISI Taiga Software (Clark Labs) was used to perform the Artificial Neural Network classifications including the image segmentation and training. The Quantum GIS Software was

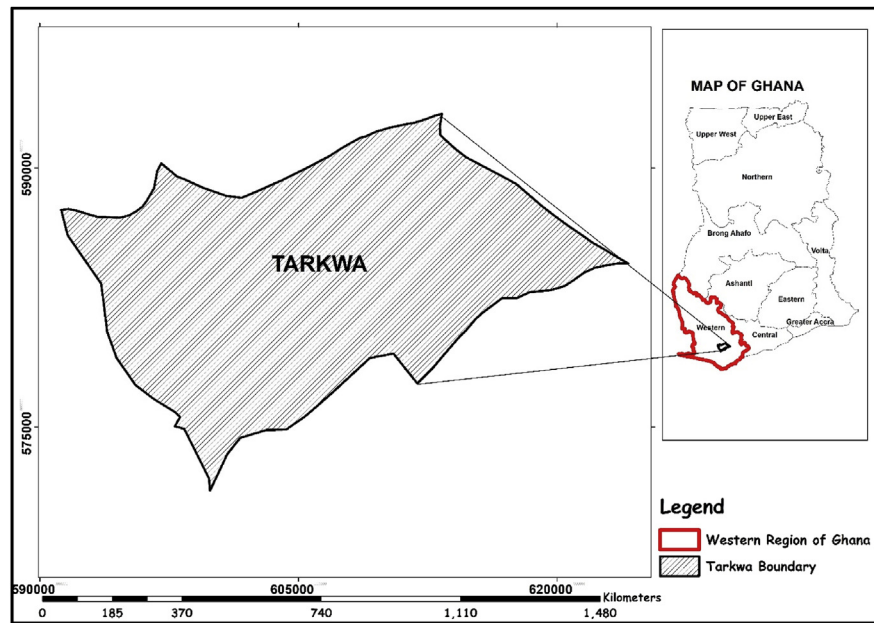**Fig. 1.** Small scale mining activities within the Tarkwa Township.

Fig. 2. Map of study area (Tarkwa, Western Region of Ghana).

used for the scan line removal. When the Landsat satellite images were obtained, radiometric corrections were performed on the images after which the area of interest was extracted. Below is a flowchart showing the workflow (Fig. 3).

Radiometric corrections consist of correcting the data for sensor irregularities and unwanted sensor or atmospheric noise and converting the data so that they accurately represent the reflected radiation measured by the sensor. The radiometric corrections done were the replacement of striping or missing lines of data and obtaining ground target reflectance values for assisting in data comparison. The scan line removal was done by the filling the scan lines with the gap masks of the various bands of the imagery. The gap masks were part of the imagery downloaded from the USGS website. The reflectance values were obtained by converting the digital numbers in the images to apparent radiance, and then from apparent radiance to reflectance. The reflectance imagery of the various years obtained was used for further analysis i.e. classification and image comparison. Geometric corrections take care of sensor-earth geometry variations and conversion of the data to real world coordinates (i.e. latitudes and longitudes) on the earth's surface. The Landsat Images downloaded were already in UTM zone 30 coordinates hence mosaicking them with each other and merging them with shapefiles of the area was quite straight forward.

The SOM model in IDRISI Taiga is based on Kohonen's Self-Organizing Map. The basic architecture includes a layer of input neurons connected by synaptic weights to neurons in an output layer arranged in a two-dimensional (usually square) array. The
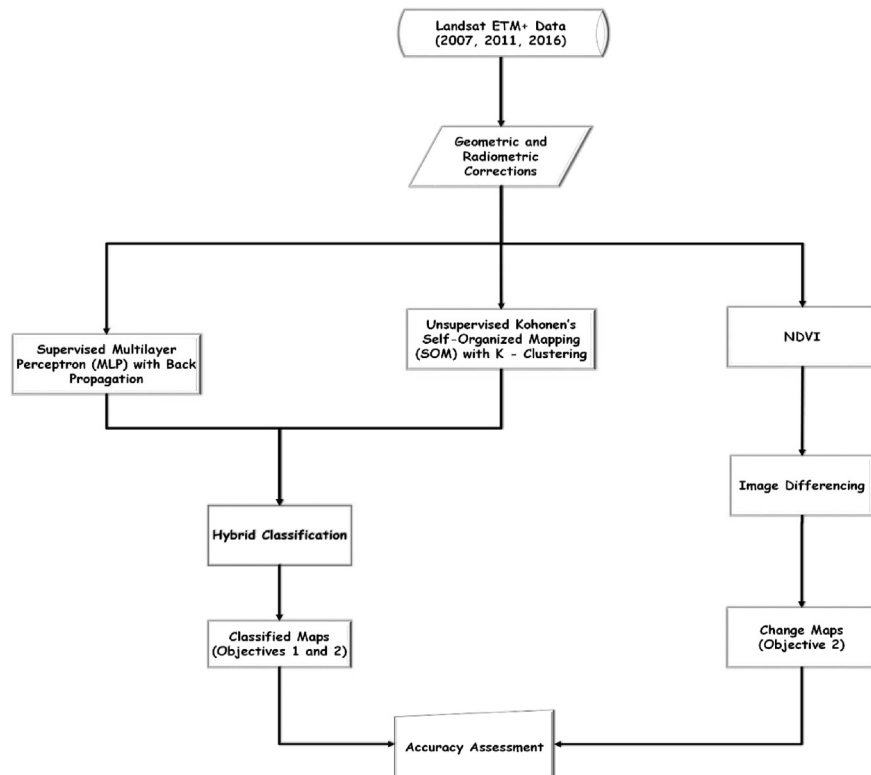
Fig. 3. Design of the workflow.

process began with a coarse tuning phase that was in effect the unsupervised classification. In a subsequent fine tuning stage, intra-class decision boundaries were refined using a Learning Vector Quantization (LVQ) procedure. The parameters of SOM used in the classification are presented in Table 4. The ground training data with the help of the unsupervised SOM classification maps served as a guide to segment and train the generated composite bands to generate the supervised MLP classification maps for the three years.

The MLP training set in this analysis used customized specifications (Table 5). The image segmentation procedure generated a representation of the border where each pixel belonged to a cluster, which was displayed using different colors. The training was done with the help of the ground training data and the unsupervised SOM map. The trained pixels were then used to generate the supervised MLP maps. An average of 200 pixels per class were used as training data as well as testing data for the year 2007, an average of 175 pixels per class for the year 2011 and 200 pixels per class for the year 2016. Four categories resulted from the classification (Table 6). The network parameters were progressively changed and the network performance monitored, namely: use of dynamic learning rate, and number of iterations (maximum of 100 000). Training ended when one of the stopping criteria was achieved: either a RMS ≤ 0.01, an accuracy of 100%,

Table 4. Parameters used for Unsupervised Classification (SOM).

Group	Parameter	Value used
Sampling in band images	Interval in Column	7
	Interval in Row	7
Network parameters	Output layer neuron	$4 \times 4 = 16$
	Initial neighborhood radius	6.66
	Min learning rate	0.5
	Max learning rate	1
Classification specification	Output hard classification map	Yes
	Display feature map	No
	Algorithm for unknown pixels	Minimum mean distance

Table 5. Parameters used for Supervised Classification (MLP).

Group	Parameter	Value used		
			2007	2011	2016
Input specifications	Average training and testing pixels per class				
		Training	200	175	200
		Testing	200	175	200
Network topology	Hidden layers				Varied
	Automatic training				No
	Dynamic learning rate				Yes
	End learning rate				0.001
	Momentum factor				0.5
	Sigmoid constant "a"				1
Stopping criteria	RMS				0.01
	Iterations				100000
	Accuracy				100%

Table 6. Class names and definitions.

Class name	Class definition
Vegetation	Vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes, sparse vegetation
Water bodies	All areas of open water
Settlement/built-up areas	Residential/commercial/industrial/transportation
Barelands/mined areas	Mine areas, bare construction sites, rock, sand, or fallow agricultural land

or the defined maximum number of iterations. the neural network included 4 input layer nodes, and varied hidden layers (see Table 5).

Statistical analysis was then performed on the classified images to gain quantitative information on changes which had occurred over the time series. NDVI was also used to track the success of reclamation in the area and was important for delineating areas where reclamation may be failing or where vegetation may be disturbed.

3. Results and Discussions

3.1. Land use/land cover analysis

The land use/land cover maps for 2007, 2011 and 2016 are shown in Figs. 4, 5, and 6. In 2007, mining activities were less intense than in 2011 (Fig. 4). Between the two dates, the Barelands/Mine area class increased in size by 26 km² of land which indicates damage by mining activities. The year 2011 was identified as that in which mining activities were most intense (Fig. 5). Some of the areas changed from active small-scale mining sites to reclaimed areas, or to some form of vegetation. Reclaimed areas have reverted to vegetation since mining activities in the area have become less intensive.

Between 2011 and 2016, the area covered by the Barelands/Mined Area category decreased (Fig. 6). This was due to decreased min0ing in the area and increase in vegetation regeneration which proves that, reclamation activities were in progress (Fig. 7). It was deduced that the small-scale mining activities occurred mainly at the expense of vegetation and settlements. Also, inhabitants of the areas which were being mined moved out and settled at other places due to an increase in the settlement class by 87.3% from 2011 to 2016.

In as much as using ANN for this classification produced accurate results, research conducted by Mostafa Sabzekar, Mohammad Ghasemigol and Mahmoud Naghibzadeh, H. S. Yazdi using Direct Acrylic Graph support vector machines (DAG-SVM) showed that it performs better classification in compression of another
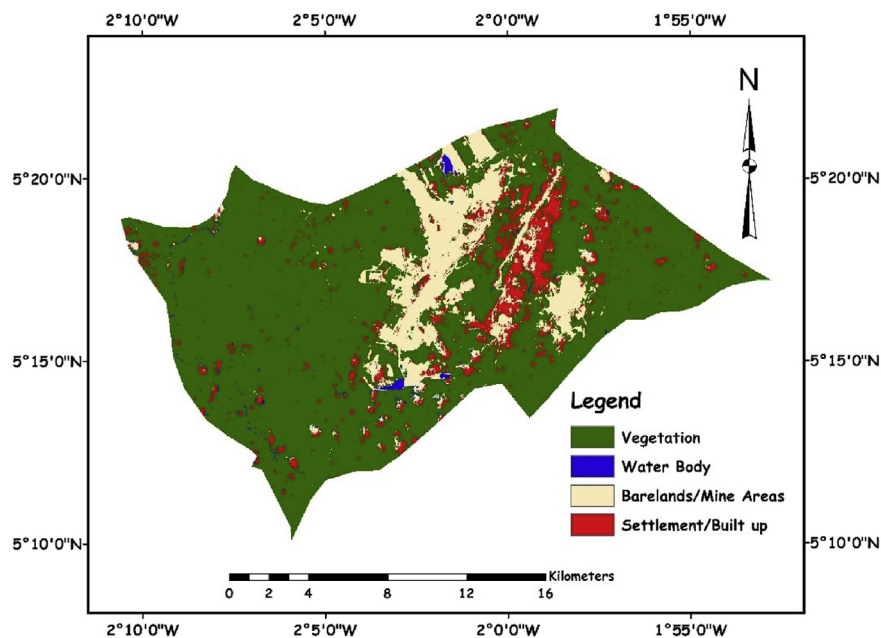

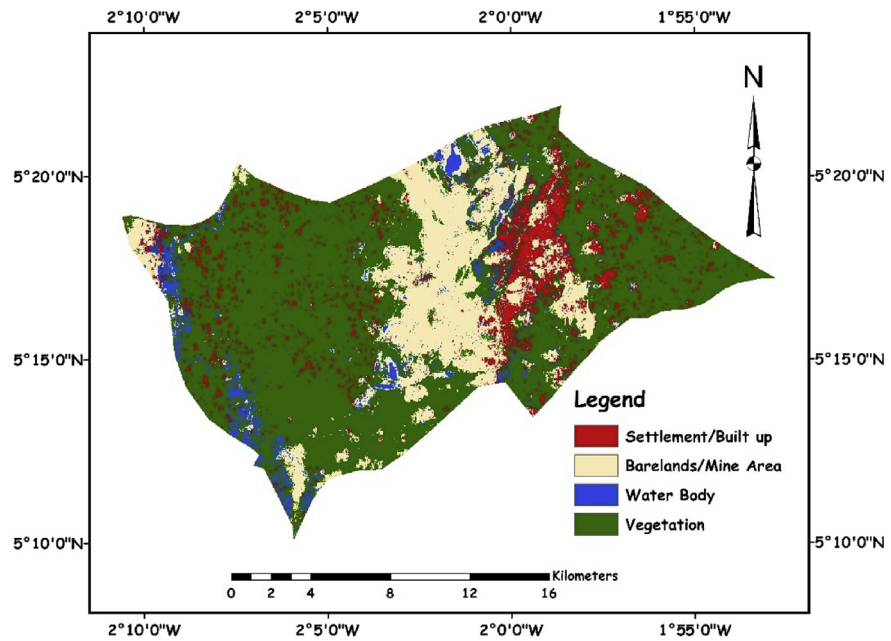**Fig. 4.** Land use land classification map 2007.

Fig. 5. Land use land classification map 2011.

binary multi-class classification. Feature data is mapping by the graph portion technique applied by DAG.

Also, the research conducted by Seetha et al. (2008) concluded that the neural network approach of classification improves the accuracy and the finer

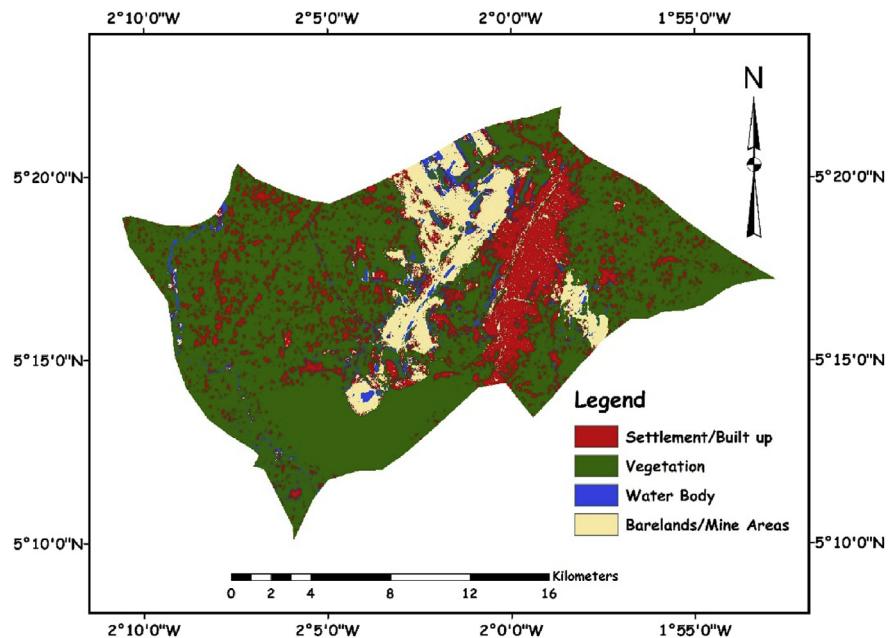**Fig. 6.** Land use land classification map 2016.

	2007	%	2011	%	2016	%
■ Vegetation	257.99	78.27	209.73	63.63	219.76	66.67
■ Water Bodies	2.9	0.88	18.04	5.47	14.04	4.26
■ Barelands/Mine Areas	42.59	12.92	68.31	19.21	32.99	10.01
■ Settlement/Built-up Areas	26.14	7.93	33.55	10.78	62.83	19.06

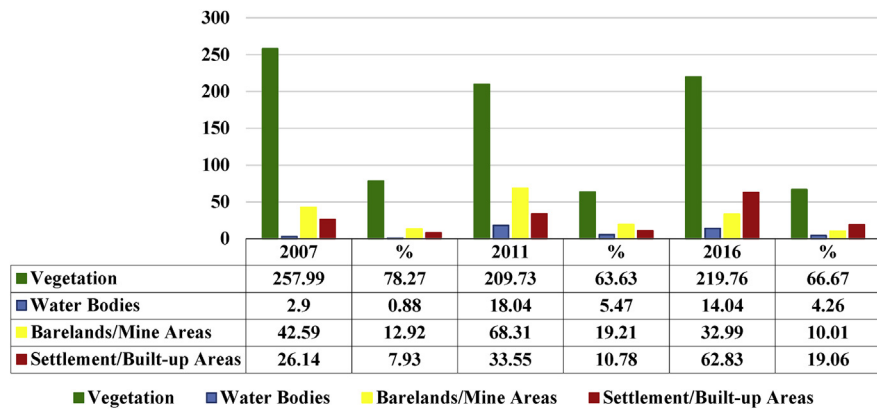■ Vegetation   ■ Water Bodies   ■ Barelands/Mine Areas   ■ Settlement/Built-up Areas

Fig. 7. Bar chart showing areas (Sq Km) of LULC classes for 2007, 2011 and 2016.

information from the individual class is obtained by using textures. He also concluded that Fuzzy support vector machines resolve unclassifiable regions caused by conventional support vector machines and its generalization ability is superior. The combined genetic algorithm plus conventional classifier system achieves higher performance than either the conventional classifier or the Genetic Algorithm method.

3.2. NDVI analysis

Mining areas were strongly associated with low NDVI values compared to the rest of the landscape i.e. -0.204 to 0.089 (2007), -0.593 to 0.337 (2011) and -0.203 to 0.181 (2016) (Figs. 10, 11, and 12). A striking pattern of change can be seen across the area from 2007 through to 2016.

Low NDVI values correspond to the purple colour and indicate areas where vegetation has been disturbed or removed. Reclaimed or revegetated areas, and areas near rivers and streams had the highest NDVI values (Figs. 8, 10, 11, and 12). Areas undergoing active reclamation had higher values because more plants are grown in these places to compensate for plant species that have potentially low survival rate. Areas near water bodies had high NDVI values ($0.400-0.661$ in 2016) because trees grew more densely in these areas.

Change maps obtained by subtracting the NDVI image of one year from that of another year were very useful in the identification of disturbed, undisturbed and reclaimed areas (Fig. 9). In the change map created, disturbed areas had the lowest values (-0.033 to 0.508) while reclaimed areas had the highest ($0.682-0.836$) (Figs. 13 and 14). NDVI analysis was used to monitor the progress of reclamation activities in small-scale mining areas. NDVI values on a regular basis relative to the surrounding area gave an idea of the success of reclamation activities.
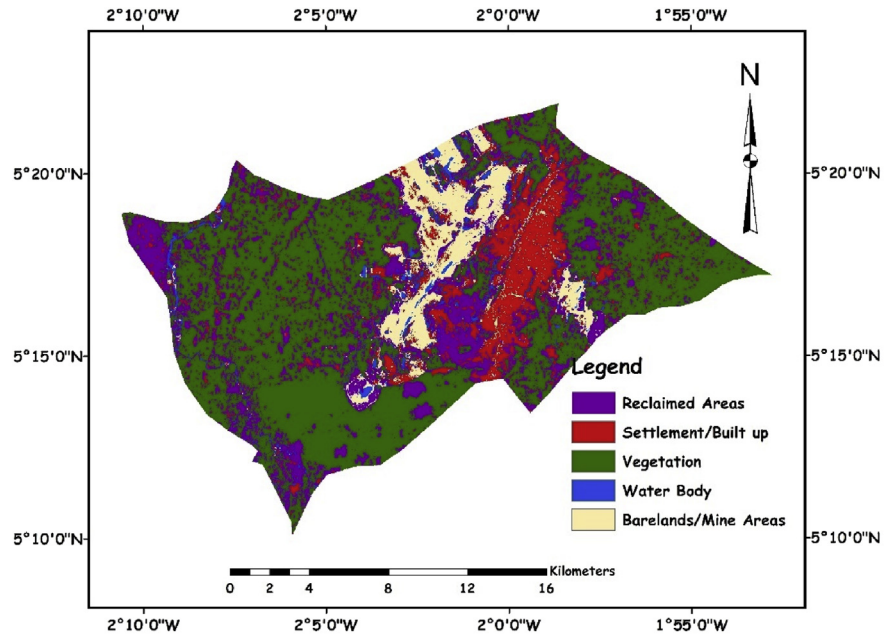
Fig. 8. Reclaimed areas as of 2016.

3.3. Discussions

The maps for the years 2007, 2011 and 2016 (Figs. 4, 5, and 6) as well as statistical information shown in Fig. 7 indicates evidence of land degradation as a result of mining activities in the area. Land Use/Land cover classification produced straight forward results. A visual comparison of the three images shows
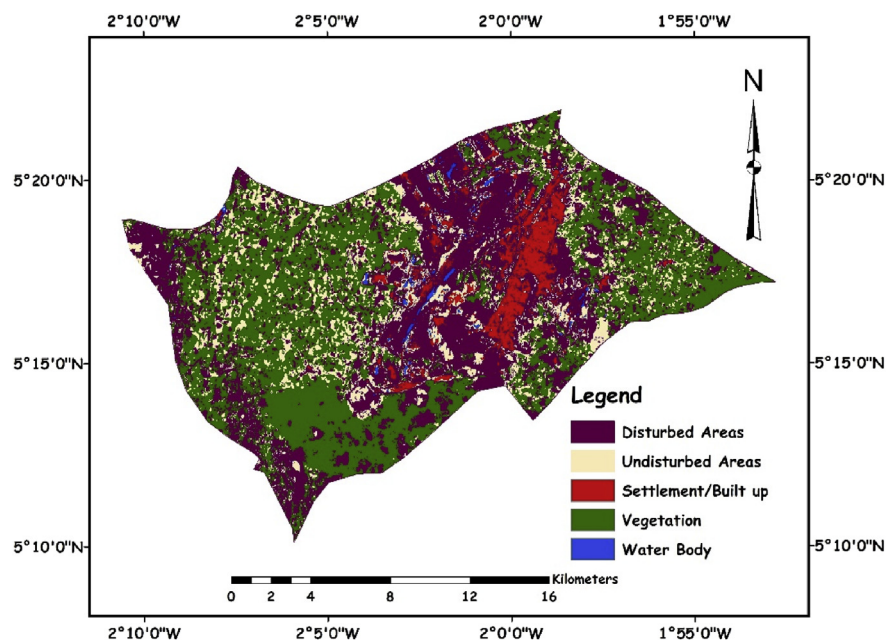

Fig. 9. Disturbed and undisturbed areas as at 2016.

a sharp increase in mining activity from 2007 to 2011 and the evidence of recla-mation from 2011 to 2016.

This analysis led to the identification of a number of changes. These include areas that have been disturbed by mining, areas previously disturbed by mining that were now revegetated, areas previously disturbed where vegetation had not recovered, and areas of no change (undisturbed areas). Maps showing the changes mentioned (Figs. 8 and 9), NDVI maps (Figs. 10, 11, and 12), NDVI change maps (Figs. 13 and 14) as well as statistical information displayed in the bar chart (Fig. 15) show the extent to which the reclamation activities have gone.

Existing research on small-scale mining, reclamation and artificial neural networks have placed emphasis on environmental and livelihood effects of small — scale mining (Ontoyin and Agyemang, 2014), the effect of small-scale mining on soil physical properties (Mensah et al., 2014), using tasseled cap transformation, at-brightness temperature and K-means algorithm to monitor coal surface mining and reclamation (Alden, 2009), artificial neural networks for soil analysis (Amato et al., 2015) and wildfire detection using artificial neural networks (Miller et al., 2003). However, not much research has been done using artificial neural networks to monitor reclamation activities in small-scale mining areas which is why this research focused on it.

Also, previous studies on multispectral image classification have confirmed a better classification accuracy performance from ANNs than traditional classification methods (Yuan et al., 2009). There is difficulty providing a comprehensible
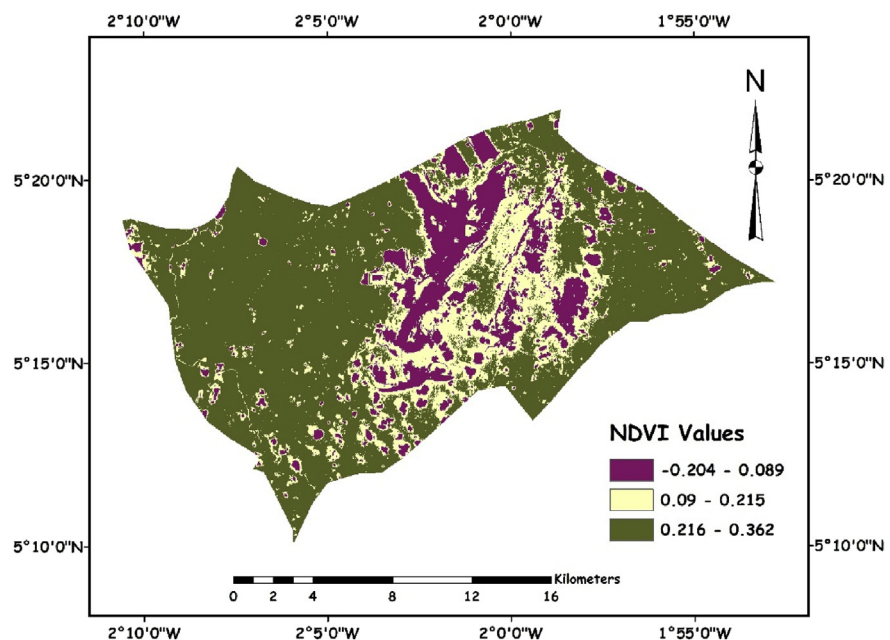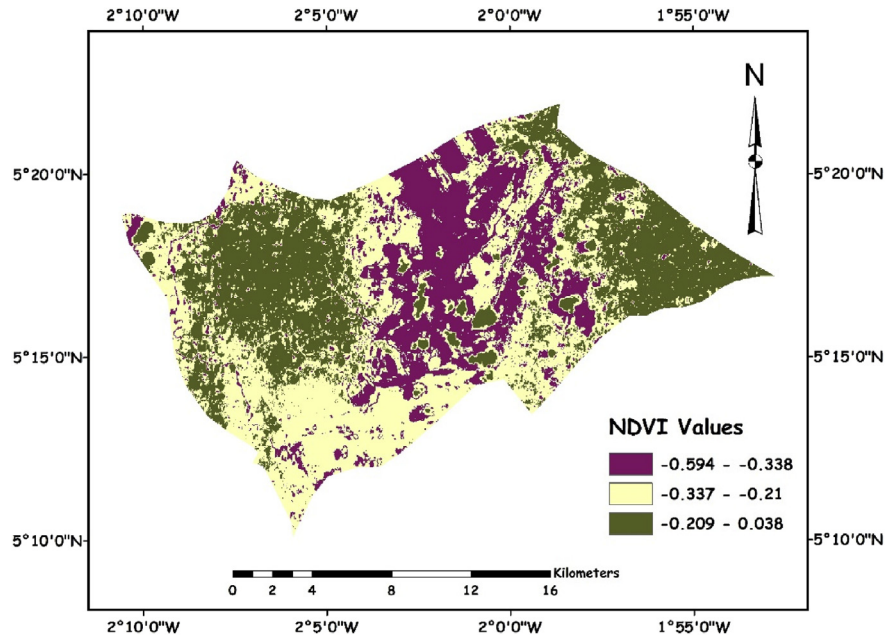
Fig. 10. NDVI 2007.

Fig. 11. NDVI 2011.

explanation of the process through which a given output has been obtained from a neural network even though ANN's provide very good results in image classification. This is because, neural networks hide the relation between inputs and outputs in the weights of the neurons of its hidden layers and hence, the characteristics of the data set cannot be understood further (Qiu and Jenson, 2004). The reasons
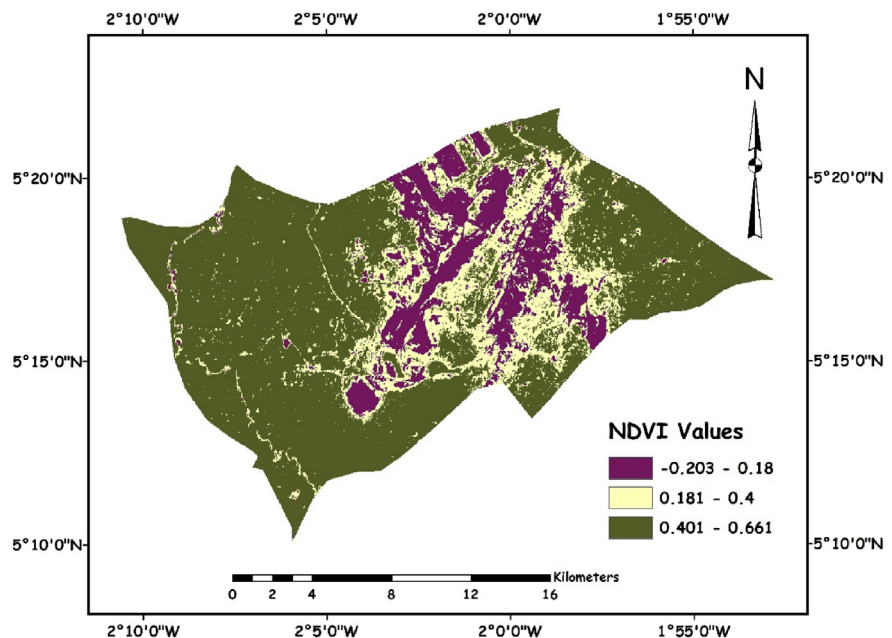

Fig. 12. NDVI 2016.

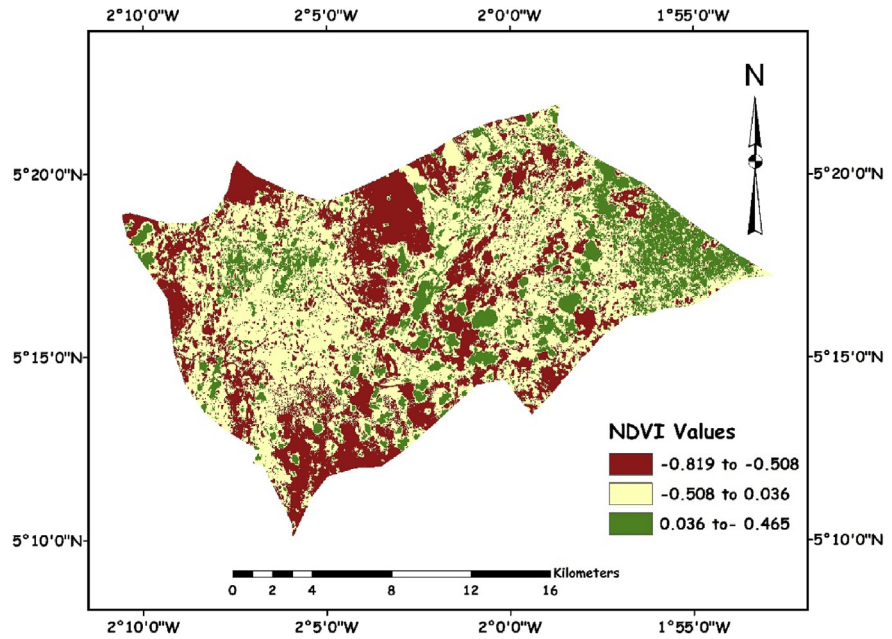**Fig. 13.** NDVI change map (2007−2011).

mentioned above informed the decision to research in this area and proves how relevant it is to apply ANN research in this part of the world. More so, the multi − temporal nature of the research has helped to appreciate the difference in accuracy in using ANN for analysis as against other traditional methods.
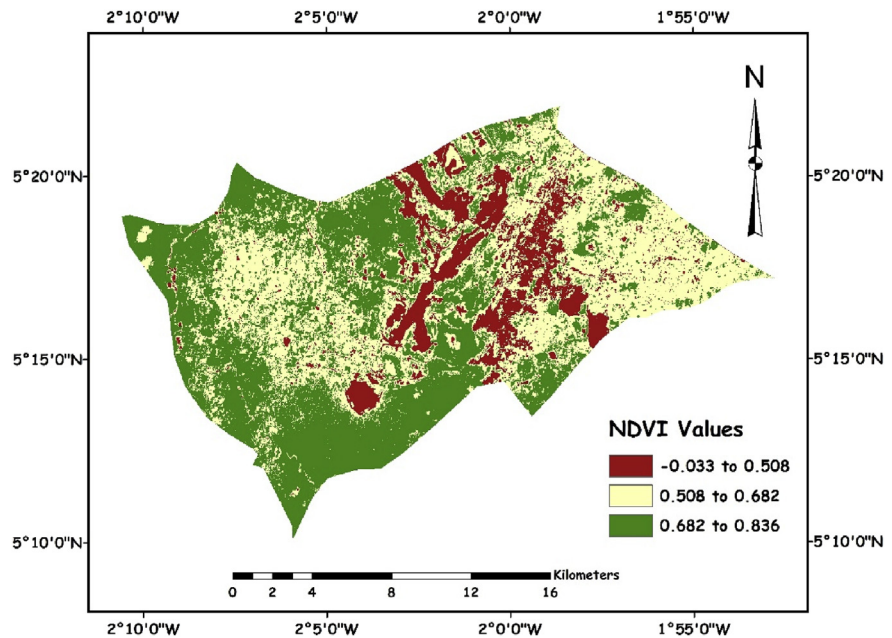

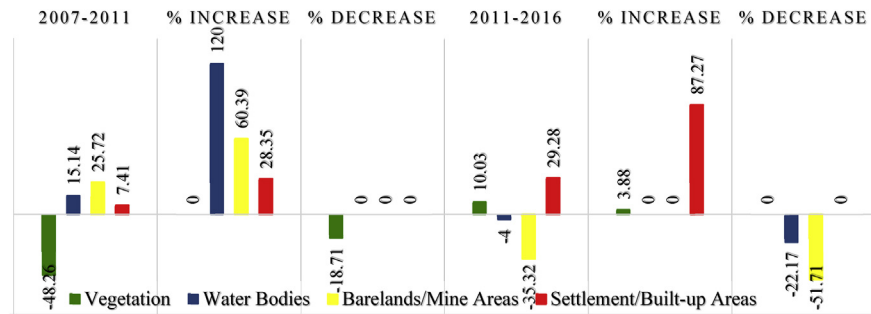**Fig. 14.** NDVI change map (2011−2016).

Fig. 15. Land use/land cover change from 2007 to 2016.

Table 7. Overall accuracy and kappa statistics of MLP classifications.

Year	Overall accuracy	Kappa
2007	84.2 %	0.7070
2011	82.4 %	0.7004
2016	87.9 %	0.7898

The Kappa was calculated from the software IDRISI. It computed the kappa using the formula:
KAPPA Index of Agreement = KIA = $(p_0 - p_c)/(1 - p_c)$, where,
p_0 = Observed accuracy = proportion of agreeing units = accuracy of satellite imagery.
p_c = chance agreement = proportion of units for expected chance agreement = accuracy of ground truth data.

Table 8. Error matrix for 2007 from MLP classification.

		Reference data					
		1	**2**	**3**	**4**	**Classified totals**	**Users accuracy**
MLP 2007	1	**54780**	7267	963	1736	64746	**84.6 %**
	2	60	**1263**	40	48	1411	**89.5 %**
	3	113	746	**14382**	1585	16826	**85.5 %**
	4	367	140	1731	**8141**	10379	**78.4%**
	Reference totals	55320	9416	17116	11510	**93362**	
	Producers accuracy	**99.0 %**	**13.4 %**	**84.0%**	**70.7 %**		

Overall accuracy: 78566/93362 = 84.2 %

3.4. Accuracy assessment

The images for the three years were assessed based on the random sampling scheme, in order to derive their best overall accuracies and kappas. The accuracies and kappas were assessed in IDRISI Taiga using the MLP maps for the various years as reference information. For each year, the overall accuracy was computed from the contingency table (error matrix), as the percentage of agreement. Table 7 shows the kappa and the overall accuracies for the years 2007, 2011 and 2016 as well as their error matrices in Tables 8, 9, and 10.

Table 9. Error matrix for 2011 from MLP classification.

		Reference data				Classified totals	Users accuracy
		1	**2**	**3**	**4**		
MLP 2011	1	9928	922	281	1179	12310	**80.6** %
	2	2600	**19411**	1647	1475	24133	**80.4** %
	3	433	1067	**4493**	1512	7505	**59.9** %
	4	3818	2211	3186	**61004**	**70**219	**86.9** %
	Reference totals	16779	23611	9607	65170	**115117**	
	Producers accuracy	**59.2** %	**82.2** %	**46.8** %	**93.6** %		
		Overall accuracy: 94936/115167 = 82.4 %					

Table 10. Error matrix for 2016 from MLP classification.

		Reference data				Classified totals	Users accuracy
		1	**2**	**3**	**4**		
MLP 2016	1	**11310**	644	359	2289	14602	**77.5** %
	2	691	**47170**	3323	856	52040	**90.6** %
	3	40	262	**3094**	484	3880	**79.7** %
	4	605	41	483	**11287**	12416	**90.9** %
	Reference totals	12646	48117	7259	14916	**82938**	
	Producers accuracy	**89.4** %	**98.0** %	**41.1** %	**75.7** %		
		Overall accuracy: 72861/82938 = 87.9 %					

The Error Matrix for 2007 (Table 8) contained a total of 93362 classified pixels out of which 78566 were classified accurately, representing 84.2%. The Error Matrix for 2011 (Table 9) contained a total of 115117 classified pixels out of which 94936 were classified accurately, representing 82.4%. The Error Matrix for 2016 (Table 10) contained a total of 82938 classified pixels out of which 72861 were classified accurately, representing 87.9%.

4. Conclusions

The research was able to assess the extent of damage caused in the study area over time by analyzing maps obtained from the use of ANN, backed with statistical information. Visual observation of the three images indicated a sharp increase in mining activities from 2007 to 2011. The Barelands/mined areas class increased by 60.4% while the vegetation decreased by 18.7% during the same time period. The overall kappa and other accuracies obtained from the ANN classifications in this research have proven it to be a more accurate classification method compared to other traditional classification methods due to factors such as the size and quality of training data, network architecture, and training parameters.

The extent of reclamation in the study area was confirmed by identifying a number of changes in the study area such as areas disturbed by mining, reclaimed areas, areas disturbed by mining which had not yet been reclaimed and undisturbed areas. These changes were depicted by maps obtained through ANN classification with the help of statistical information, NDVI and class mask analysis. Low NDVI values corresponded to areas where vegetation had been disturbed or removed whereas high NDVI values corresponded to areas where there was vegetation or reclamation.

The NDVI analysis also showed that areas undergoing reclamation had higher values because they are often heavily seeded to make up for plant species that have low survival rate. There was evidence of revegetation from 2011 to 2016 with the Barelands/Mined Area class decreasing by 51.7%, the vegetation class increasing by 3.9% and an increase in the settlement class by 87.3% hence concluding that:

- Small-scale mining activities were done mainly at the expense of land under vegetation cover and settlements.
- Inhabitants of the areas which were being mined left and resettled at other places.

Artificial Neural Networks should be encouraged and be used more for image classification in general and reclamation monitoring in particular due to the size and quality of training data, network architecture, and training parameters as well as the ability to improve the accuracy and fine tune information obtained from individual classes as compared to other classification methods. Though successful, the research encountered a significant drawback being the difficulty in gaining access to some of the small scale mining sites to gather ground truth data. This was due to the concession lessees being uncomfortable with my presence. On some occasions, they threatened with physical assault although there were attempts to convince them that the purpose of the visit was for research purposes only.

Declarations

Author contribution statement

Christian Abaidoo: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Edward Matthew Osei Jnr: Performed the experiments.

Anthony Arko-Adjei: Contributed reagents, materials, analysis tools or data.

Benjamin Eric Kwesi Prah: Conceived and designed the experiments; Performed the experiments.

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The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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