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Land-Cover Change Monitoring in Obuasi, Ghana: An Integration of Earth Observation, Geoinformation Systems and Stochastic Modelling

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Abstract: For over twenty years, Obuasi Municipality, Ghana, has experienced land-cover change arising from gold mining and urbanisation. This project quantified the land-cover changes that have taken place and projected likely future land-cover. An integration of EO (earth observation), GIS (geographical information science) and Stochastic Modelling was examined. Post-classification Change Detection employed Landsat TM or ETM+ images in 1986, 2002 and 2008. Subsequently, Markov Chain Analysis projected the land-cover distribution for 2020. Seven broad land-use and land-cover classes were identified and mapped, namely: built-up areas, mine sites tailing ponds barren land forestland farmland and rangeland. The results obtained for the 2008 to 2020 projection revealed a continuous expansion of built-up areas (1.63%), mine sites (0.89%) and farmland (3.4%), and a reduction of forestland (4.17%) and rangeland (2.59%). Despite the advent of very high resolution satellite imagery, this use of EO and GIS technology focussed on low-cost and lower resolution satellite imagery, coupled with Markov Modelling and was found to be beneficial in describing and analysing land-cover change processes in the study area, and was hence potentially useful for strategic planning purposes.

Key words: Ghana, TM, ETM+, GIS, change detection, tailing ponds, gold mining.

1. Introduction

LULCC (land-use/land-cover change) is an essential input to global environmental change monitoring [1]; LULCC studies have led to a greater understanding of the forces driving environmental change, as evidenced on the 1992 United Nations Conference on Environment and Development [2]. The human population has been recognized as the dominant force behind LULCC change, although similar changes do arise naturally and gradually [3, 4] in trying to maximize benefits from the land, human beings put pressure on the land, modifying its land-cover.

Lambin et al. [5] categorized the human influences on land-cover to be: socio-economic, technological, institutional, demographic, cultural or related to globalisation. The environmental effects of LULCC can be positive or negative, permanent or reversible, short or long term, and can be grouped into: biodiversity change, climate change, pollution, and other impacts [6]. For example: converting forest to other uses can lead to climate change, deforestation to biodiversity loss, and overgrazing to pollution. Environmental changes affect society [2], so information on LULCC can support decision makers.

It has been shown that the application of EO, with GIS, can produce accurate, timely information on the spatial distribution of land-cover change [7]. Because of repetitive data acquisition, synoptic views and their digital format, data such as Landsat, Aster, Spot and Avhrr have been the primary data source for change detection. As well as the combined use of EO and GIS, modelling land-cover change dynamics can also be

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enhanced by Stochastic Modelling.

Lu et al. [8] stated that change detection provides information on: area of change and change rate, spatial distribution of change types, change trajectories of land-cover types, and accuracy assessment of change detection results. Change detection techniques have been broadly categorized into: pre-classification and post-classification [9, 10]. This study focuses on post-classification-widely used when multi-image comparison is involved [11].

To be useful for planning, change detection should analyse the dynamics of past LULCC, and also model future LULCC. Consequently, in this study, two geo-simulation tools, namely Markov Chain Analysis and Cellular Automata, as reported in Benenson and Torrens [12], were used to model and predict future LULCC. Markov Chain Analyses incorporate several assumptions [13]: one basic assumption regards LULCC as a stochastic process; other assumptions are based on the states of a chain. Cellular Automata can be implemented in GIS [14], and many geographers have adopted it for modelling spatial dynamics.

The aims of this study are: (1) to quantify LULCC in the Obuasi area of Ghana (Fig. 1), based on Earth Observation data for recent decades (1986-2008); (2) to model and predict LULCC by 2020; and (3) to identify the drivers of these changes.

2. Study Area and Data

The study area is in Obuasi Municipality—an administration district in the Ashanti Region, Ghana, centred at $6^{o}10$'N and $01^{o}40$'W, within a semi-deciduous forest zone undergoing degradation consequent on anthropogenic action; the forest provides hard wood lumber [15]. This study covers a rectangular area of approximately 689.82 km^2 and can be located on the 0602C2 and 0602C4 1:50,000 scale Topographic map sheets of Ghana.

The topography of the Obuasi area is undulating

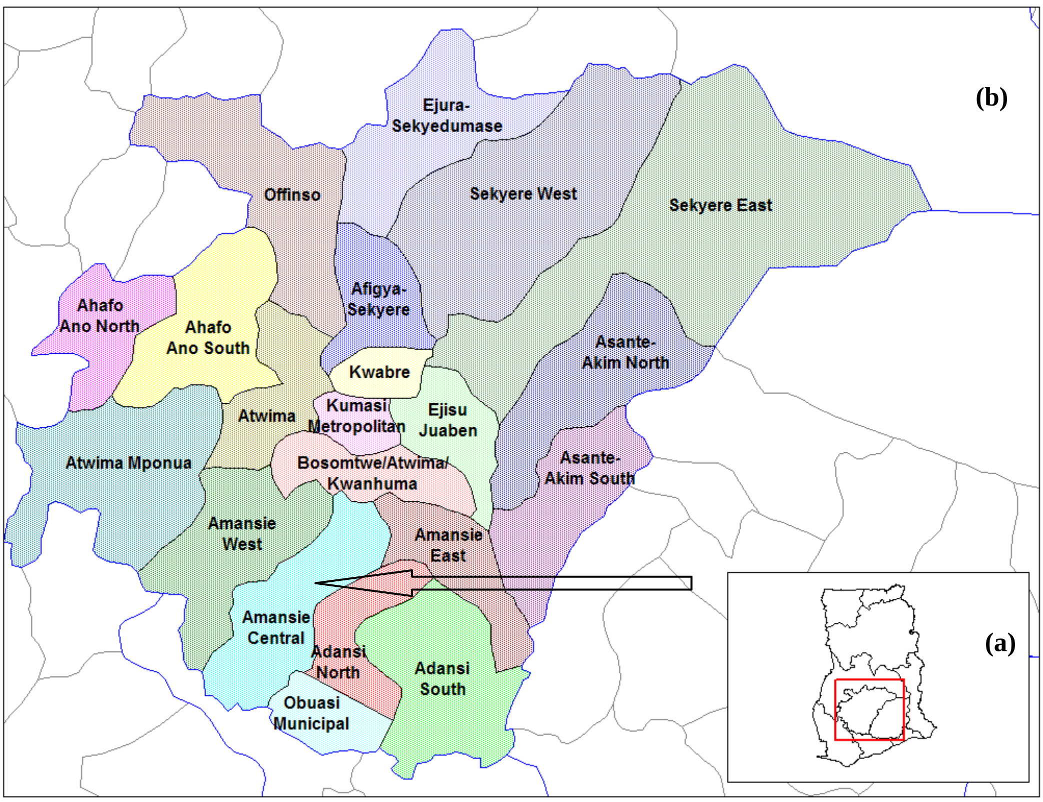

Fig. 1 Map of study area (Source: Wikipedia).

Map a: Ghana and Map b: administrative districts of Ashanti Region.

with a number of rivers; its gold deposits are part of the Proterozoic (*Birimian*) volcano-sedimentary and igneous formations that extend for a distance of approximately 300 kilometres trending north-east/south-west in south-western Ghana. Obuasi mineralisation is comprised of quartz veins containing free gold and the main sulphide ore in which narrow veins contain gold trapped within arsenopyrite [16].

This study is based on the data sources listed in the Table 1, grouped into EO (earth observation) and reference data, and uses a time series of Landsat, TM (thematic mapper) and ETM+(enhanced thematic mapper plus) images of scene 194/56 acquired in the years 1986, 2002 and 2008. These data were downloaded from the USGS (U.S. Geological Survey) database using its Glovis facility, selected on the basis of availability, season and cloud. Unfortunately all the available 1990s images have unacceptable cloud cover. The reference data include topographical maps and aerial photographs of the study area.

3. Methodology

The steps undertaken in this project include image pre-processing, image classification, change detection and modelling, predicting change and validation.

3.1 Pre-processing

Pre-processing corrected errors that arose from imaging sensors, atmospheric effects and curvature of the Earth, all of which can lead to false results. The individual bands (excluding the 120 m pixel resolution thermal IR band 6) of each of the three images (1986 TM, 2002 ETM+ and 2008 ETM+) were combined into three single images. A subset of the resulting images, containing only the study area, was extracted. The 1986 image was corrected for haze. Upon careful examination, band combination 5, 3, 2 was found to clearly identify road intersections and the intended land-cover categories were distinguishable. The images were subsequently enhanced using Histogram Equalization.

The three resultant images were originally on the UTM/WGS84 projection but were re-projected, still using the Transverse Mercator Projection but on the Ghana (Accra) datum (using the 'War Office' spheroid). Fifteen GCPs (ground control points) were extracted at road intersections from the digital topographic maps of the study area and used to geo-reference the 2008 ETM+ image; a highly satisfactory 0.375 pixel Root Mean Square Error was obtained. A Nearest Neighbour re-sampling technique was employed during geo-referencing—chosen as it honours the original pixel values. This 2008 geo-referenced image was later use to co-register the two other images, 1986 TM and 2002 ETM+. All the images were re-sampled to a 30 by 30 meters pixel resolution.

3.2 Image Classification

A supervised classification was employed to classify seven land-cover categories: (1) built-up areas; (2) mine sites; (3) tailing ponds; (4) barren (i.e. bare) land; (5) forestland; (6) farmland; and, (7) rangeland, based on the Anderson classification scheme [17]. To ensure

Table 1 Data used in this study.

EO data	Acquisition date	Resolution	Sources
Landsat TM	January, 1986	30 m	USGS EROS Centre
Landsat ETM+	January, 2002	30 m	USGS EROS Centre
Landsat ETM+	February, 2008	30 m	USGS EROS Centre
Reference data	Acquisition Date	Scale	Sources
Topographical Map	2008	1:50,000	Govt. Survey Dept., Ghana
Aerial Photograph	2004	1:10,000	Govt. Survey Dept., Ghana
Digitized Topographical Map	2002	1:50,000	Geomatic Engineering Dept., Kwame Nkrumah Univ. Science & Technology, Ghana

the quality of change-detection results [18], a total of sixty check sites were extracted, from a random selection, from the 2004 aerial photography to perform the accuracy assessment of the 2002 and 2008 images. One might challenge the use of 2004 "ground truth" to check 2002 and 2008 scenes, but the sixty check sites were selected, from the random selection, using "local knowledge", being locations believed to have undergone no change in the period 2002-2008. The accuracy of the 1986 classified image could not be assessed since suitable check data was not available.

3.3 Change Detection with Land-Cover Modeler (Idrisi Andes®)

A Post-Classification approach to Change Detection was used to assess LULCC over the twenty-two (1986-2008) years. This was achieved using the LCM (land-cover modeler) module of Idrisi Andes®, which cross-tabulates two thematic maps of the same dimensions, at a time. With the 1986, 2002 and 2008 thematic maps as input to LCM, the following outputs were obtained for the three time periods (1986-2002, 2002-2008 and 1986-2008): (1) net gains or losses in hectares (ha) and percentages (%) for each land-cover category; (2) contributors to the net change by each land-cover type; (3) change maps; (4) change matrices; and, (5) matrices of transition probabilities to provide information on the probability associated with a land-cover class either remaining unchanged or changing to one of the other classes.

3.4 Modelling and Predicting Change

3.4.1 Markov Chain Modelling

This study adopted Markov Chain analysis and Cellular Automata (CA-Markov) to predict land-cover change. Markov Chain analysis determines the probability of land-cover change from one period to another by developing a transition matrix between time t_1 and time t_2. Markov Chain analysis does not consider spatial distribution so, to overcome this, CA (Cellular Automata) is integrated with Markov Chain analysis. The CA component of the CA-Markov model allows the transition probabilities of one pixel to be a function of its neighbouring pixels. CA-Markov models the change of several classes of cells by using: a Markov transition matrix, a "suitability" map, and a neighbourhood filter [19].

Markov Chain analysis was implemented using the Idrisi Andes® Markov module. The 1986-2002 land-cover maps were first used as input to generate a transition matrix and a set of conditional probability images between the two dates of the thematic maps. These outputs from the Markov module were later loaded in the CA-Markov module in the software and a 5 × 5 (five by five) filter were applied to generate the 2008 predicted map. Afterwards, the predicted 2008 land-cover map was compared with actual land-cover map of 2008 for validation. Following validation the 1986-2008 land-cover maps were used to predict the 2020 land-cover map.

3.4.2 Validation

Observed land-cover changes between sequences can be represented as hectares in a contingency matrix. The validity of predicted land-cover changes, between sequences, based on Markov Chain analysis can be examined by considering three requirements: (1) their statistical independence; (2) their Markovian compatibility; and (3) their stationarity [20].

Considering the first of these, a way of testing for statistical independence is to use the chi-squared (χ^2) test and compare the observed and the expected events. This (χ^2) can be given by:

$$\chi^2 = \sum_{ij}^{N} \left\{ \frac{\left(n_{ij} - e_{ij}\right)^2}{e_{ij}} \right\} \tag{1}$$

where n_{ij} is from the observed values in the contingency matrix and e_{ij} is from the expected values assuming:

$$e_{ij} = \frac{\left(n_i \times n_j\right)}{N} \tag{2}$$

where n_i and n_j represent the row and column totals of the contingency matrix respectively, and N is the grand total of observations in that matrix. The chi-squared (χ^2) statistic can be computed and the variable, ρ, obtained from a chi-squared distribution table assuming $(C\text{-}1)^2$ degrees of freedom, where C is the number of classes in the contingency matrix. Any computed value of ρ less than the selected critical value (e.g. 5%) will lead to the conclusion that the null hypothesis can be rejected and that the data do exhibit statistical independence.

If a Markov Chain process is performed next, the resulting (i.e. expected) values can be compared with the observed ones to test for Markovian compatability, using the Chapman-Kolmogorov equation [21], thus:

$$\chi^2 = \sum_{ijk}^{N} \left\{ \frac{\left(n_{ijk} - e_{ijk}\right)^2}{e_{ijk}} \right\} \tag{3}$$

with

$$e_{ijk} = \frac{\left(n_{ij\bullet} \times n_{\bullet jk}\right)}{n_{\bullet j\bullet}} \tag{4}$$

and

$n_{ij\cdot}$ number of transitions from category i to j during the period 1986-2002;

$n_{\cdot jk}$ number of transitions from category j to k during the period 2002-2008; and,

$n_{\cdot j\cdot}$ number of units in category j in the year 2002.

Based on the above mentioned equations and using the three matrices of transition probabilities (1986-2002, 2002-2008 and 1986-2008), the presence of the three statistical requirements was determined, as will be described in Section 4.4.

4. Results

Results will be considered on the basis of Image Classification, the extent of the land-cover classes, quantification of change, causes of change, hypothesis testing, Markov chain analysis and the predicted 2020 land-cover map.

4.1 Image Classification

Excluding the unclassified class, seven land-use/land-cover classes were produced using supervised classification, in the study area. Three land-cover maps (1986, 2002 and 2008) were generated as shown in Fig. 2.

Accuracy assessment is essential, and particularly when using post-classification change detection methods [18, 22]. As mentioned, the overall accuracy of two land-cover maps, 2002 and 2008, was determined using aerial photography, and found to be 88.3% and 80.0% correct. (As mentioned, there was no reference material considered suitable to check the 1986 map). The 2002 data met the minimum standard of 85% as recommended by the USGS classification scheme [17]. The 2008 data fell below the standard but this could be attributed to the age of the 2004 photography (unfortunately the best available) used in assessing the accuracy of the 2008 land-cover map. Ashanti [16, 23] reported successive flooding and spilling from tailing ponds (a small land-cover class) and "local knowledge" [24] reported frequent spills from ore trucks both of which led to rapid change in nearby land-cover; thus check data from a 2004 aerial photograph might not, despite our best intentions, have yielded reliable accuracy results in all areas of the 2008 land-cover map. Of course the quality of the check data is important in determining the accuracy of the image classification [25].

4.2 Extent of Land-Cover Categories

Table 2 reveals that the most extensive land-cover category in Obuasi in the years 1986, 2002 and 2008 was rangeland which covers about 54% of the area, followed by farmland (20%), forestland (14%), built-up areas (4.5%), barren land (4.3%), mine sites (1%) and tailing ponds (0.6%). This is not unexpected as Ghana's land-cover is dominated by vegetation and it also confirms the World Bank's 1992 report that rangeland covered about 66% of Ghana's land area [26].

Table 2 reveals that the built-up areas and mine sites categories showed an increase over the past two

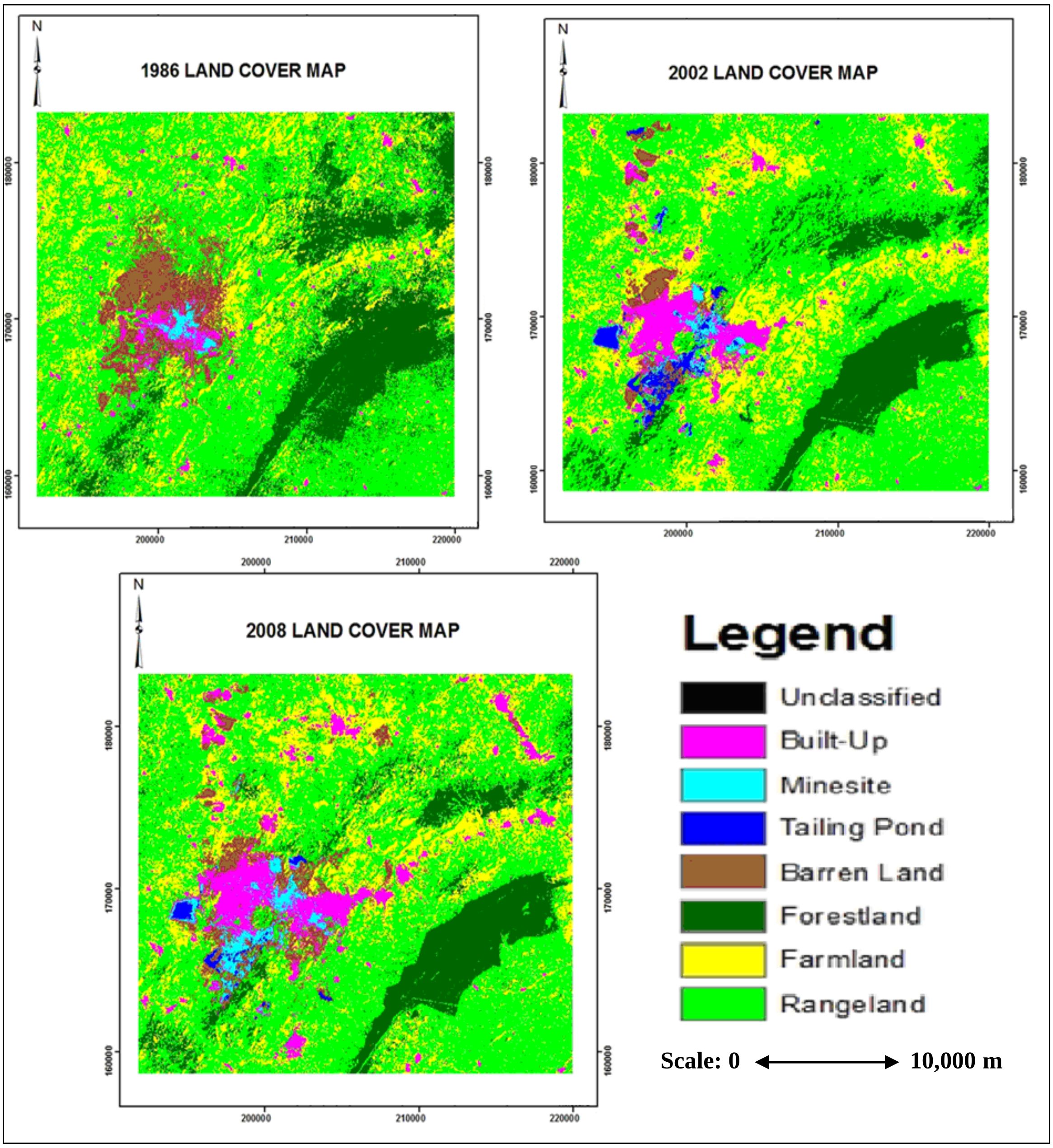

Fig. 2 The three land-cover maps of the years 1986, 2002 and 2008.

Table 2 Extent of land-cover categories expressed in hectares (ha) and percentages (%).

Land cover class	1986 area (ha)	1986 area (%)	2002 area (ha)	2002 area (%)	2008 area (ha)	2008 area (%)
Built-up areas	1,428.93	2.07	3,241.17	4.70	4,357.71	6.32
Mine sites	333.9	0.48	620.01	0.90	1,045.98	1.52
Tailing ponds	0	0.00	980.82	1.42	359.82	0.52
Barren land	4,527.27	6.56	1,479.42	2.14	2,960.73	4.29
Forestland	12,972.6	18.81	8,128.35	11.78	8,038.53	11.65
Farmland	13,287.78	19.26	15,047.73	21.81	14,749.11	21.38
Rangeland	36,431.46	52.81	39,484.44	57.24	37,470.46	54.32
Totals	68,981.94	100.00	68,981.94	100.00	68,981.94	100.00

decades while other categories (rangeland, farmland and tailing ponds) showed an increase in the period 1986-2002 and a slight decrease in the period 2002-2008. Barren land decreased in the period 1986-2002 by 4.42% and increased slightly in the period 2002-2008. Forestland showed a continuous decrease over the review period.

4.3 Quantification of Land-Use Land-Cover Changes

In order to understand the trends in LULCC in the study area, over the twenty-two year periods, two change matrices (1986-2002 and 2002-2008) were developed from the three (1986, 2002 and 2008) land-cover maps (Tables 3 and 4).

Values in the tables' diagonals represent unchanged land-cover classes and those in the off-diagonal represent changed land-cover classes, in the period of concern. The tables show that, in 1986-2002, 56.41% (38,914.02 ha) of the total land-cover of the area remain unchanged, with an 2.7% annual rate of land-cover change, whereas 67.58% (46,616.67 ha) of the land-cover remain unchanged within the next six years (2002-2008) with an annual rate of land-cover change of 5.4%. Thus, more abrupt changes occurred in the period 2002-2008.

As an example, Table 3 values in bold italics summarize the changes (Gains + and Losses -) in hectares (ha) and percentages (%) resulting from the various land-cover conversions for the period of 1986-2002. It can be seen from the table that rangeland, farmland, tailing ponds, mine sites and built-up areas land-cover categories experienced some expansion with the rangeland land-cover category gaining most (4.43%) within the sixteen year period. Forestland and barren land are seen to have experienced losses at the expense of other land-cover classes with forestland experiencing a net loss of 7.02%.

Further analysis (Fig. 3) of the contributions to the

Table 3 1986-2002 land-use/land-cover change matrix (units are hectares).

Class	1986 built-up areas	1986 mine-sites	1986 tailing ponds	1986 barren land	1986 forest-land	1986 farmland	1986 range-land	2002 totals
2002 built-up areas	895.23	73.53	0	1,091.07	7.74	494.46	679.14	3,241.17
2002 mine sites	120.42	145.53	0	157.95	4.14	46.71	145.26	620.01
2002 tailing ponds	66.42	66.42	0	212.85	41.49	109.8	483.84	980.82
2002 barren land	50.67	26.46	0	664.02	23.49	232.56	482.22	1,479.42
2002 forestland	3.87	0.18	0	57.6	6,607.35	123.75	1,335.6	8,128.35
2002 farmland	182.25	4.14	0	1,066.86	724.05	5,183.46	7,886.97	15,047.73
2002 rangeland	110.07	17.64	0	1,276.92	5,564.34	7,097.04	25,418.43	39,484.44
1986 totals	1,428.93	333.9	0	4,527.27	12,972.6	13,287.78	36,431.46	68,981.94
Net change (ha)	***+1,812.24***	***+286.11***	***+980.82***	***-3,047.85***	***-4,844.25***	***+1,759.95***	***+3,052.98***	
Net change (%)	***+2.63***	***+0.41***	***+1.42***	***-4.42***	***-7.02***	***+2.55***	***+4.43***	

Table 4 2002-2008 land-use/land-cover change matrix (units are hectares).

Class	2002 built-up areas	2002 mine-sites	2002 tailing ponds	2002 barren land	2002 forest-land	2002 farmland	2002 range-land	2008 TOTALS
2008 built-up areas	2,580.93	143.91	76.95	293.49	1.62	1,063.8	197.01	4,357.71
2008 mine sites	169.11	320.58	414.45	98.28	0.554	14.58	28.44	1,045.98
2008 tailing ponds	1.08	6.84	305.37	17.64	23.58	0.45	4.86	359.82
2008 barren land	290.88	106.29	147.33	850.05	37.26	949.86	579.06	2,960.73
2008 forestland	0.18	2.88	2.61	3.6	6,335.1	65.34	1,628.82	8,038.53
2008 farmland	136.98	2.07	6.57	150.93	82.17	6,774.39	7,596	14,749.11
2008 rangeland	62.01	37.44	27.54	65.43	1,648.08	6,179.31	29,450.25	37,470.06
2002 totals	3,241.17	620.01	980.82	1,479.42	8,128.35	15,047.73	39,484.44	68,981.94
Net change (%)	***+1,116.54***	***+425.97***	***-621.00***	***+1,481.31***	***-89.82***	***-298.62***	***-2,014.38***	

Net change (%)	***+1.62***	***+0.62***	***-0.90***	***+2.15***	***-0.13***	***-0.43***	***-2.92***

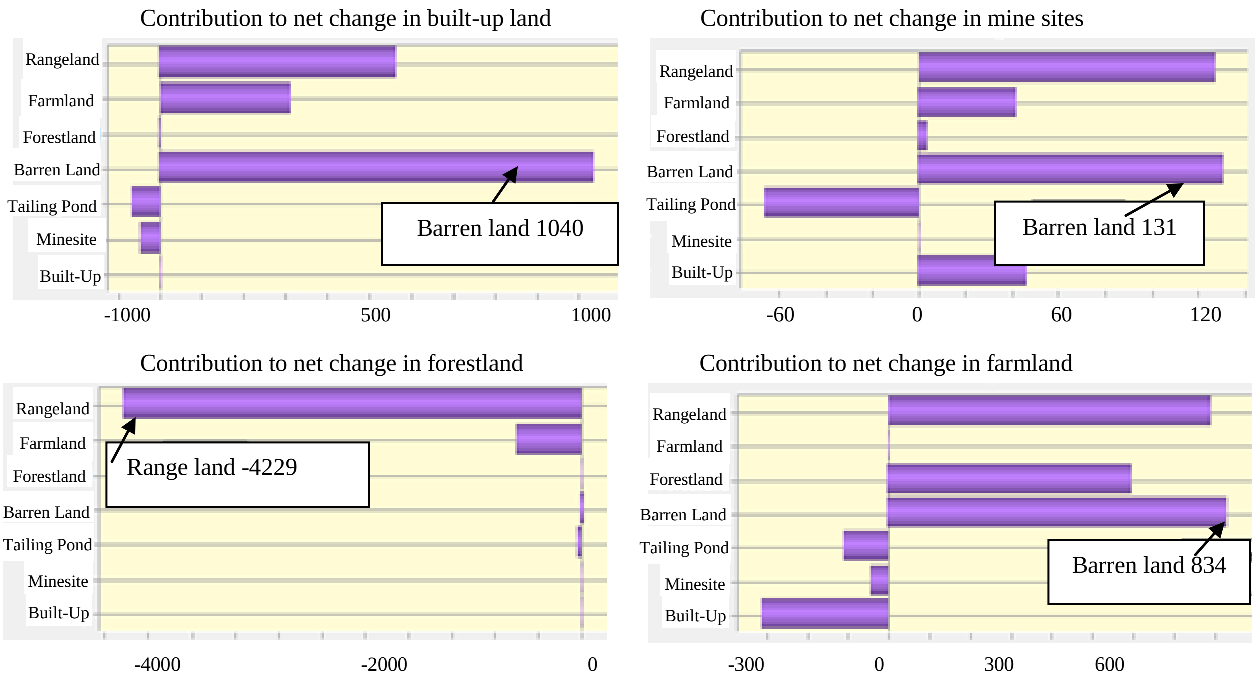

Fig. 3 Contribution to net change of the selected land-cover classes between 1986 and 2002 (units are in hectares).

land-cover change shows the contributions in four selected land-cover classes (built-up areas, mine sites, forestland and farmland). Within the period under review, forestland, rangeland and barren land have experienced huge losses as a result of farmland, built-up areas and mine sites expansion. Subsidies and incentives given to cocoa farmers by the government since the year 2000 and the establishment of fruit processing companies are considered reasons for the increase in farmland in the area.

For the six-year period (2002-2008), Table 4 reveals that only barren land, mine sites and built-up areas gained. Barren land is the land-cover class that has gained most (2.15%). The four classes rangeland, farmland, forestland and tailing ponds decreased, with rangeland decreasing by the most (2,014.38 ha).

Fig. 4 shows the net contribution to four selected land-cover classes over the whole period under review (1986-2008) and that forestland, rangeland, barren land had experienced losses as a result of farmland, built-up areas and mine sites expansion. Built-up areas and mine sites are seen to have expanded more at the expense of rangeland, barren land and farmland. Forestland is seen, noticeably, to have given way to rangeland.

4.4 Causes of LULCC (Land-Use/Land-Cover Changes)

Mining operations going on in the study area have been identified as one of the major driving forces causing rapid land-cover changes (the other is urbanisation). Mine sites in the area have increased from 333.9 ha (0.48% of the study area) in 1986 to 1,045.98 ha (1.52% of the study area) in 2008. The Tables 3, 4 and Figs. 3 and 4 reveal that mine sites increased at the expense of rangeland, farmland and barren land. This confirms a report that the upsurge of gold mining between 1986 and 1996 led to the increase in gold production from an annual total of 400,000 troy ounces in 1987 to 1.2million troy ounces by 1996, which established Ghana as Africa's second largest gold producer, after South Africa [27, 28]. Moreover, the Anglo-Gold Ashanti Company also confirms that mining in the area has grown over the time and is encroaching into farmland [23]. The company has also complained about the presence of large numbers of

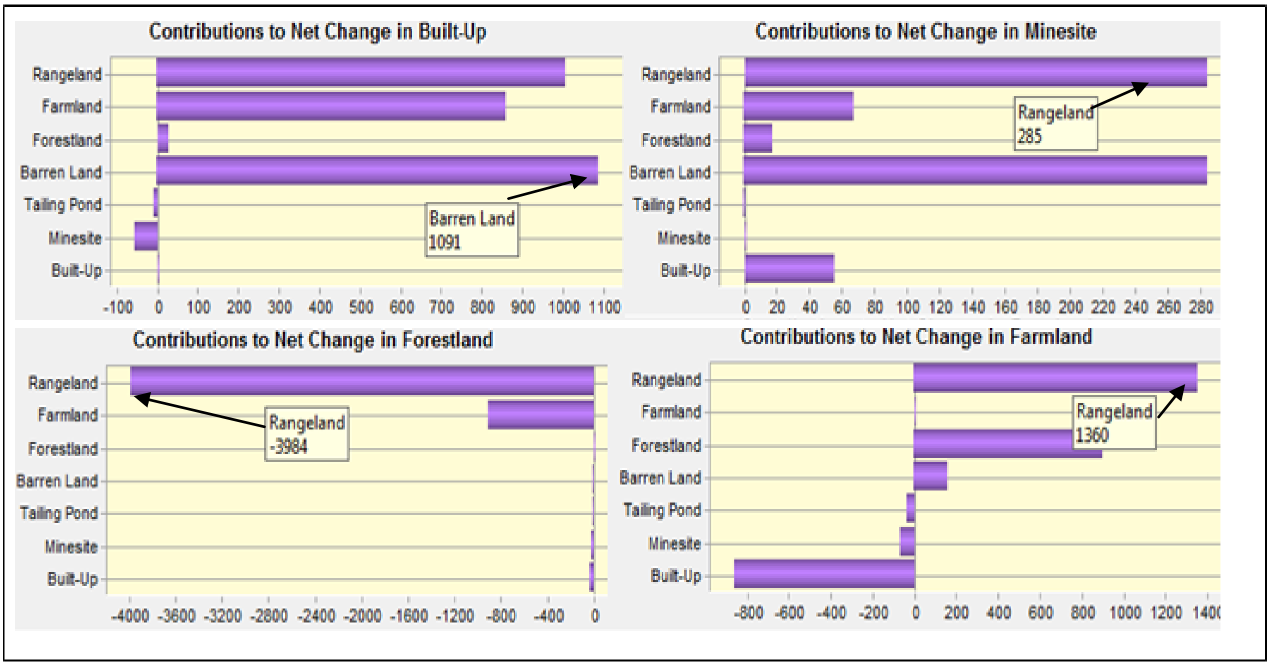

Fig. 4 Contribution to net change of the selected land-cover between 1986 and 2008 (units are in hectares).

artisanal and small-scale miners who encroach illegally onto the company-owned land in their search for minerals. Thus the barren land is seen to have increased from 1,479.42 ha (2.14%) in 2002 to 2,960.73 ha (4.29%) in 2008, while farmland in this period is found to have lost 799 ha to barren land, because illegal miners, in their search for gold, leave the land surface bare after exploiting it.

Considering urbanisation, the population of Obuasi in 1986 was 60,617 and rose to 115,564 in 2000, an annual growth rate of 4% (Ghana Statistical Service, 2002 [29]) and an increase of about 90%. The high population growth can be attributed to the booming mining activities as many people came to live in Obuasi, seeking employment. The effect of this is clearly seen in the sharp increase in built-up areas between the period of 1986 and 2008. In Figures 3, 4 and Tables 3, 4, a 2,929 ha increase in built-up areas (4.25%) was revealed, at the expense of rangeland, farmland and barren land. Forestland has declined by 7.15% within the study area giving way to rangeland and farmland. These land-cover conversions are an indication of the influx of people who claim farmland and rangeland close to built-up areas for development purposes. The dislocated farmers, searching for new space to farm, turn to the available forestland and rangeland. Deforestation caused by timber and mining companies, illegal chainsaw operators and bushfires further contribute to the conversion of forestland to rangeland. The rate at which the forestland decrease slowed within the period between 2002 and 2008 indicates institutional intervention to salvage this situation.

4.5 Hypothesis Testing

To help interpret the conversion of each land-cover class, a chi-squared test of independence was carried out using the Eqs. (1) and (2) (see Section 3.4) and yielding the results shown in Table 5 (with 36 degrees of freedom).

From the Table 5, it can be seen that for the computed χ^2 values of each of the three matrices of transition probabilities the critical ρ-value of 0.05 is exceeded. These results therefore reveal that the land-cover classes are statistically dependent and hence the null hypothesis of independence can be rejected. Practically,

Table 5 Chi-square χ^2 values computed from the three transition matrices.

Period	χ^2-value	ρ-value
1986-2002	55,980.78	$0.975 < \rho < 0.99$
2002-2008	51,161.81	$0.95 < \rho < 0.975$
1986-2008	13,251.00	$\rho < 0.995$

this means that the probability of conversion to other classes depends on the current land-cover [30].

The next consideration is whether the conversions between the land-cover classes are Markovian. Using Eqs. (3) and (4) from section 3.4, this was tested. The χ^2 value of 34,302.24 ($0.05 < \rho < 0.95$) was obtained by comparing the observed transition matrix of 1986-2008 and the estimated transition matrix of 1986-2008 computed from the two matrices of transition probabilities of 1986-2002 and 2002-2008. This value was found to be greater than the critical ρ-value of 0.05 with 36 degrees of freedom, thus the null hypothesis can be rejected and it can be, initially, concluded that land-cover changes in the study area are not Markovian.

In order to predict future land-cover change, a Markov chain process requires stationarity (the statistical evidence of no changed) to model the transition mechanisms [20, 31]. To seek evidence of stationarity, the magnitude of unchanged land in each of the land-cover classes (diagonal elements) in the three different change matrices was extracted and compared, as seen in Fig. 5.

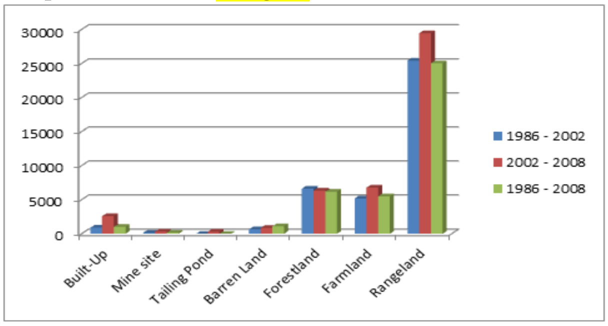

Fig. 5 Investigating stationarity (i.e. unchanged classes) using the three transition matrices 1986-2002, 2002-2008 and 1986-2008 (Units are hectares).

The figure 5 above reveals that stationarity can be discounted since it shows divergent distributions of land-cover change over the three different periods. Hence, it can be deduced that the transition mechanisms (driving forces) implementing land-cover changes are different.

4.6 Modelling Using Markov Chain Analysis

Despite the initial conclusion that land-cover changes in the study area are not Markovian and the lack of stationarity, both alluded to in the previous section, Markov Chain Analysis was used to predict the future land-cover map of 2008, using the land-cover maps of the years 1986-2002. This predicted map was subsequently compared with the reference land-cover map of 2008 for validation (Fig. 6).

The predicted land-cover map of 2008 was evaluated using the kappa statistics: Kstandard (46%), Kno (61%), Klocation (51%) and Klocationstrata (51%)

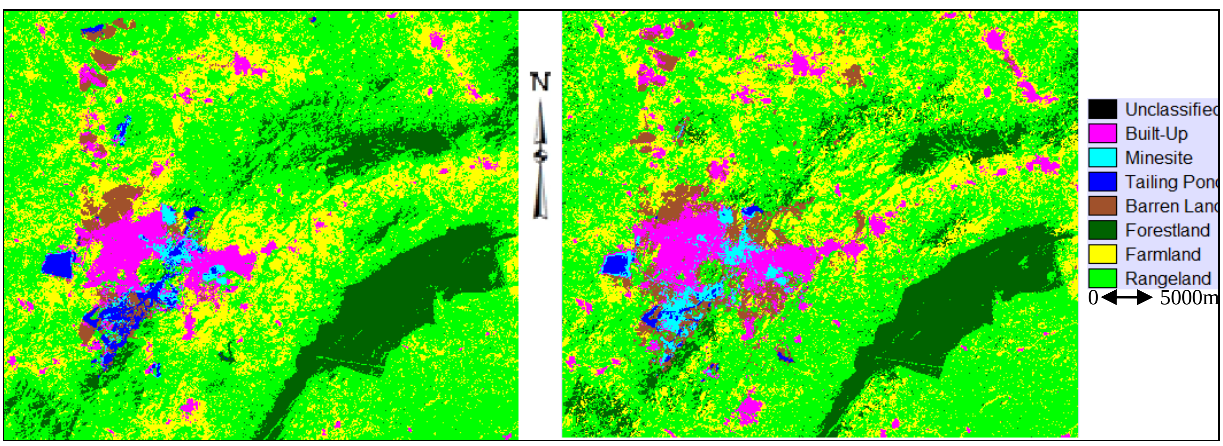

Fig. 6 Predicted (left) and reference (right) land-cover maps of 2008.

generated from the Validate module in Idrisi Andes®. These values are found to fall within the standard values suggested by Monserud and Leamans [32] in that kappa statistics of 75% or greater show a very good to excellent classifier performance (including prediction), while a values less than 40% are poor (40% to 75% being standard).

Based on the above suggestions of Monserud and Leamans [32], the model can be said to be an acceptable (although not excellent) prediction; it has already been explained that the land-cover changes do not exhibit stationarity. Reasons for the failure to achieve an excellent prediction can also be attributed to inadequate sources used for classification during the modelling process and also the contiguity filter applied. The maps and the contiguity filter have a great influence on the results of the model. Markov chain analysis predicts the future land-cover patterns only on the basis of known land-cover patterns of the past [19, 33]. Logically Markov chain analysis used to predict the 2008 land-cover map based on 1986-2002 land-cover maps could not incorporate new factors, such as the unexpected flooding of and spilling from tailing ponds in 2006 and 2007 which influenced land cover change between 2002 and 2008. Thus the discrepancies between the predicted and reference land-cover maps of 2008 revealed a less than excellent outcome.

4.7 Predicted Land-cover Map

The land-cover map for 2020 was predicted using the 1986 and 2008 land-cover maps in the same way and assumed that the transmission mechanisms stayed the same. The transition probability matrix generated is shown in Table 6 and the resulting 2020 predicted land-cover map is shown in Fig. 7. The diagonal values in *bold* represent the probability each of the land-cover classes has of remaining unchanged for the twelve years (2008-2020).

Table 6 reveals that in the twelve years (2008-2020), built-up areas will increase at the expense of farmland by 6.7% and farmland in turn, will increase at the expense of rangeland and forestland by 45.0% and 2.1%, respectively. In addition, mine sites and barren land are expected to increase at the expense of both each other and other classes. Mine sites are expected to gain by 22.7% from barren land, and barren land to gain by 7.2% from mine sites over the twelve year period.

Land-cover change that is expected in the next twelve years (2008-2020) is shown in Table 7. It is evident from the table that all the land-cover classes except rangeland and forestland are expected to be expanding, with farmland and built-up areas experiencing a gain of about 3.4% and 1.6%, respectively.

5. Conclusions

This study used the integration of earth observation, GIS and Stochastic Modelling to analyse and quantify land-cover changes (in terms of the amount, rate, trend and location) that have occurred between 1986 and 2008, in Obuasi. The area has witnessed extensive land-cover change, with a 2% annual rate of change.

Table 6 Transition probability matrix between 2008 and predicted 2020.

Class	2008 built-up areas	2008 mine-sites	2008 tailing ponds	2008 barren land	2008 forest-land	2008 farmland	2008 range-land
2020 built-up areas	0.6746	0.1434	0.0077	0.0813	0.0023	0.0668	0.024
2020 mine sites	0.2625	0.5105	0	0.227	0	0	0
2020 tailing ponds	0.1667	0.1667	0	0.1667	0.1667	0.1667	0.1667
2020 barren land	0.2515	0.0724	0.0267	0.2909	0.0216	0.13	0.207
2020 forestland	0	0	0	0	0.5302	0.0637	0.406
2020 farmland	0.0606	0	0.0016	0.033	0.0207	0.4345	0.4496

2020 rangeland	0.0152	0.006	0.0093	0.0379	0.0414	0.2519	0.6383

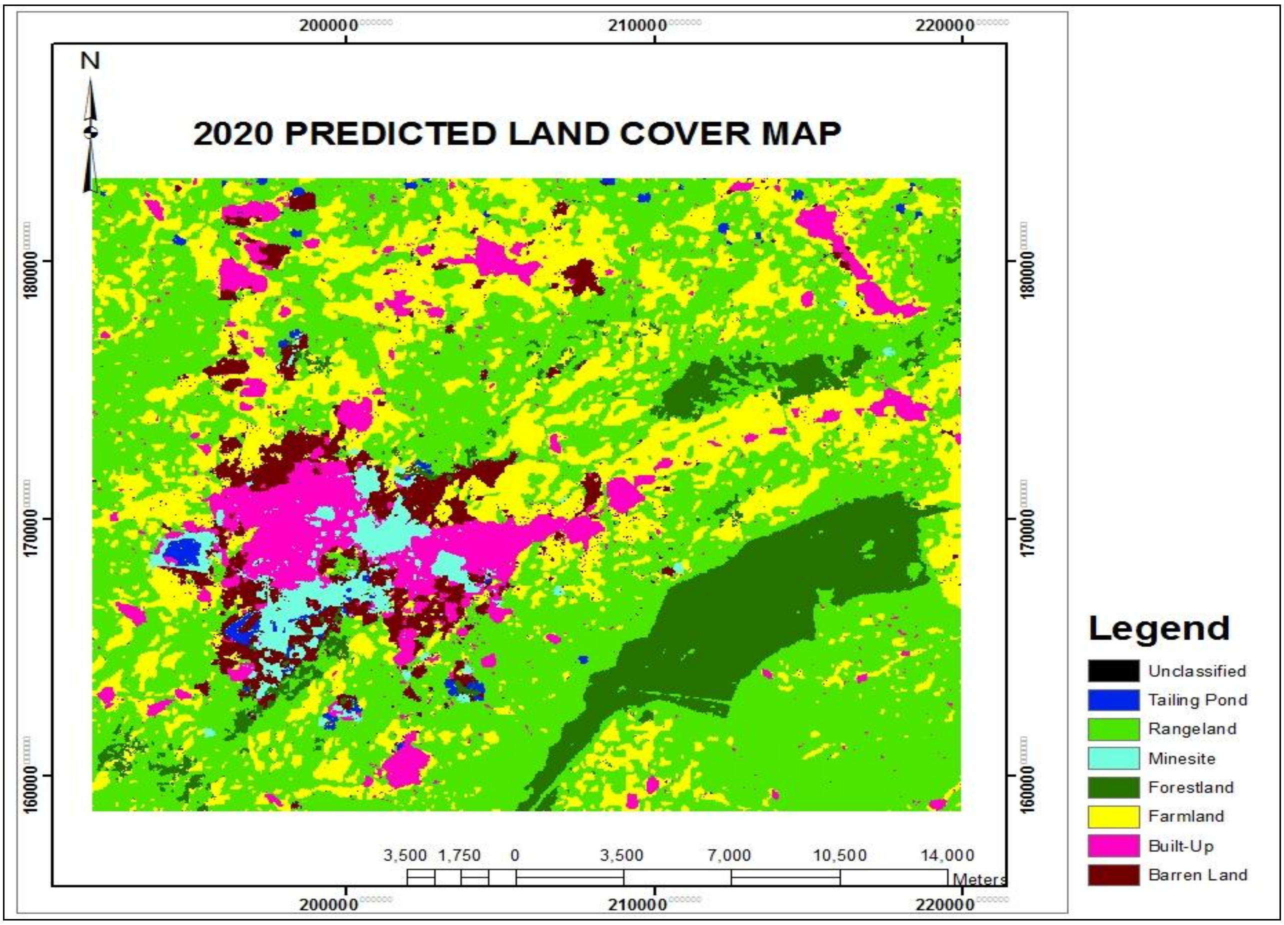

Fig. 7 2020 predicted land-cover map.

Table 7 Table showing the predicted change between 2008 and 2020.

	2008 Area (ha)	2008 Area (%)	2020 Area (ha)	2008 Area (%)	Net change (%)	Annual rate of change
Built-up areas	4,357.71	6.32	5,483.88	7.95	1.63	0.14
Mine sites	1,045.98	1.52	1,659.42	2.41	0.89	0.07
Tailing ponds	359.82	0.52	481.86	0.70	0.18	0.01
Barren land	2,960.73	4.29	3,420.81	4.96	0.67	0.06
Forestland	8,038.53	11.65	6,252.21	9.06	-2.59	-0.22
Farmland	14,749.11	21.38	17,093.43	24.78	3.40	0.28
Rangeland	37,470.06	54.32	34,590.33	50.14	-4.17	-0.35
Total	68,981.94	100.00	68,981.94	100.00		

The period 2002-2008 supported most rapid change, with an annual rate of change of 5.4%. The extent of the built-up areas and mine sites has increased, indicating increasing human pressure on the land. Forestland has decreased considerably (7%) within the twenty-two year period, but, the rate at which it decreased, stabilized within the period of 2002-2008.

The application of Landsat multi-temporal images to identify land-cover types in the study area was executed successfully and provided an inexpensive means to detect land-cover changes, though the accuracy assessment for the 2008 image indicated slightly sub-standard results-attributed to the use of 2004 aerial photographs for ground truth.

The Markov Chain analysis used in this study predicted a likely land-cover map for 2020. The prediction revealed a continuous increase of built-up areas, mine sites and farmland at the expense of forestland and rangeland. Our next task is expected to involve a 2012 check on the predictions, and if this validates our Markov Chain analysis, the predicted map produced in this study, for 2020, can be used, with greater confidence, by decision-makers protecting fragile areas (forest land) and strategic planners managing access to such areas.

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