Advances in Remote Sensing, 2024, 13, 18-40
https://www.scirp.org/journal/ars
ISSN Online: 2169-2688
ISSN Print: 2169-267X

Migration and Spatiotemporal Land Cover Change: A Case of Bosomtwe Lake Basin, Ghana

Richard Kwabena Adams[1], Lingling Zhang[1*], Zongzhi Wang[2]

[1]School of Public Administration, Hohai University, Nanjing, China
[2]National Key Laboratory of Water Disaster Prevention, Nanjing Institute of Hydraulic Research, Nanjing, China
Email: *llzhang007@163.com

How to cite this paper: Adams, R.K., Zhang, L.L. and Wang, Z.Z. (2024) Migration and Spatiotemporal Land Cover Change: A Case of Bosomtwe Lake Basin, Ghana. *Advances in Remoting Sensing*, **13**, 18-40.
https://doi.org/10.4236/ars.2024.131002

Received: February 3, 2024
Accepted: March 26, 2024
Published: March 29, 2024

Abstract

Internal migration is highly valued due to its increasingly acknowledged potential for social and economic development. However, despite its significant contribution to the development of towns and cities, it has led to the deterioration of many ecosystems globally. Lake Bosomtwe, a natural Lake in Ghana and one of the six major meteoritic lakes in the world is affected by land cover changes caused by the rising effects of migration, population expansion, and urbanization, owing to the development of tourist facilities on the lakeshore. This study investigated land cover change trajectories using a post-classification comparison approach and identified the factors influencing alteration in the Lake Bosomtwe Basin. Using Landsat imagery, an integrated approach of remote sensing, geographical information systems (GIS), and statistical analysis was successfully employed to analyze the land cover change of the basin. The findings show that over the 17 years, the basin's forest cover decreased significantly by 16.02%, indicating that population expansion significantly affects changes in land cover. Ultimately, this study will raise the awareness of stakeholders, decision-makers, policy-makers, government, and non-governmental agencies to evaluate land use development patterns, optimize land use structures, and provide a reference for the formulation of sustainable development policies to promote the sustainable development of the ecological environment.

Keywords

Land Cover Change, Supervised Classification, Migration, Landsat Imagery, Environmental Sustainability

1. Introduction

Natural resources are essential for the livelihoods of 1.8 billion people worldwide who rely on forest resources [1]. Human activities daily and the growing human population both impact how the natural environment is used and structured [2]. The vigorous expansion of the human population, changing climate, increasing consumption, urbanization, and economic expansion have further heightened tensions on natural resources and intensified their depletion, particularly among the vulnerable poor who depend on natural resources for their livelihood [3] [4] [5]. One significant natural resource that supplies ecosystem services to sustain livelihoods is forests [6]. The rise in population and changes in forest cover are negatively correlated, according to a study conducted in Kenya by [7]. This inverse link is more prevalent in economies where agriculture is the main income generator, like those in Asia and Africa [8]. Similarly, for survival and income, a large number of people depend on forests, either directly or through indirect means [9] [10]. A typical instance is how people use forest resources to build homes, make household items, and cook meals [8]. However, human reliance on forests for subsistence and revenue leads to the physical modification of the natural forest.

The increase in human population and their movement also alters the natural environment and adversely affects land use and cover. [11] noted that an upsurge in the size of migrants resulted in changes to land usage in the coastal areas of Kenya's Watamu Mida Creek. According to a 28-year land use/land cover (LULC) review conducted by [12] in Egypt's Damietta Estuary, there was a notable increase in urban settlements to the detriment of forest regions. [13] also pointed out a noteworthy increase in the built area of Morocco's Sebou Estuary between 1985 and 2017 indicating a large influx of people from the rural areas. [14] A 17-year study on the changing patterns of land cover also found a 16.02% fall in forest cover caused by a rise in human population and their movement, indicating that migration and expansion in the human population significantly impact LULC changes.

The natural environment undergoes modification by human interference in terms of land cover and uses [15] [16]. Human migration poses a detrimental effect on biodiversity through the removal of vegetation for settlements, fragmenting habitats, and other usages of land [17]. As shown by other studies [11] [18] [19] migration and human activities are the primary causes of environmental degradation globally. [20] indicated that the actions of people account for the world's estuary degradation in his study, which centered on the Dong Ho Estuary in Vietnam. Trends in land use and cover, as well as the diversity of plant and animal life on Earth, are believed to be heavily impacted by human migration from one rural area to another [17]. [21] indicated that the migration of low-wage farmers to other rural areas stimulates farming there and causes LULC shifts and the conversion of different land covers into agricultural uses. In the history of Ghana, there was a large movement between 1984 and 1992, with people leaving different parts of the country to reside in the Volta Basin [22] [23] [24]. Due to this relocation, the number of towns in the basin increased, which had a destructive impact on the forest areas that were cleared to create room for new settlements [24]. [25] also contends that human migration is one of the main causes of LULC changes. Internal migration was cited by [26] for Nepal's exacerbated human settlements as well as changes to the country's land usage and cover. Similarly, [27] reported a 0.73% decline in Mexico's forest cover as a result of the country's growing migratory rate and the ensuing need for land for agricultural purposes.

LULC change is an old concept that has gained a lot of attention because of human activity that modifies the physical characteristics of the natural world [28]. Africa's land cover change is mostly due to the conversion of forests to farms, which worsens the state of the continent's forests and poses a serious environmental threat to developing nations where agriculture is the primary economic activity [8] [29]. According to [30] and [31] human interactions with the environment have a range of effects, including modifications to land cover patterns. In this sense, precise and up-to-date data on land cover change should be provided to inform environmental planning and society development, given the rate at which population growth and the resulting demand for land are driving land cover change [32] [33].

Ghana's vegetation changes and land usage patterns have become the subject of numerous studies. For instance, [28] examined how vegetation in the Tano River Basin has changed and how it affected the objectives of sustainable development. [34] study outlined the primary determinants of changes in land cover and emphasized the impact growth in population and increased human habitation have on these changes. Similarly, [35] scrutinized how the transition in land use and climate affects the flow pattern of water in the Owabi basin. Comparatively, the Achimota Forest Reserve in Accra has experienced changes in land cover arising from the growing urbanization [10]. These studies mentioned above provide significant information about changes in Ghana's land cover and land use, confirming that population growth and urbanization are the main driving factors.

Ghana's sole natural lake, Lake Bosomtwe, also happens to be the largest in West Africa [36]. Recognized as a UNESCO World Biosphere Reserve, the lake's watershed sustains an extensive range of wildlife and vegetation types and is a popular tourist attraction in Ghana [3] [37]. Within the catchment, a total of 24 communities with about 50,000residents reside [38]. The principal sources of income for the people living around Lake Bosomtwe are subsistence farming and fishing [36] [37] [39]. Despite being one of the world's most exquisite natural lakes, Lake Bosomtwe has deteriorated over time; due to population increase and accompanying human activities, such as the demand for land for farming, housing, and other household necessities, resulting in a significant drop in vegetation cover [39].

With varying degrees of efficiency, multiple studies on integrating both Remote Sensing (RS) and Geographic Information System (GIS) technology to categorize and monitor land cover change information have been done [19] [40] [41] [42] [43]. Research has shown that the use of RS and GIS technology can provide reliable and precise methods for the detection, classification, and analysis of changes in vegetative cover [44]. [45] classified land cover classes and changes using Landsat images and identified vegetation, urban areas, sandy areas, rocky regions and water bodies producing an accuracy of 86.67% in Jizan Dam, Saudi Arabia. [44] [46] [47] classified and analyzed land cover change patterns in the Sulaimani region of Iraq using a new image processing technique as well as the maximum likelihood classification method. [48] assessed and identified variations in vegetation cover in Al-Jabal Al-Akhdar, Libya, applying time-series Landsat imagery from 1985 to 2017. RS and GIS have been extensively utilized to analyze deforestation on a local and national scale [49]. [3] utilized RS and GIS to visually represent the patterns of change from 1986 to 2014 while undertaking their research and examination of land use and vegetation changes in peri-urban Ghana. Thus, RS and GIS technologies are increasingly used due to their ability to provide timely, efficient and accurate ways to detect, classify and map LULC.

Nevertheless, despite the use of RS and GIS technologies in forest surveys in numerous studies and locations of Ghana [10] [28] [34] [50] [51] [52], the use of them in Ghana's forest management is still in its early stages of development. Also, a multi-temporal examination of the dynamics of forest cover has not been taken into account in the majority of previous studies, which concentrated on specific forest ecosystems. This has resulted in limited availability of data and knowledge on forest cover dynamics, the causes of these changes, and the ramifications for ecological sustainability around the Bosomtwe Lake region. This study integrates RS, GIS technologies, Landsat imagery, and socioeconomic data analysis to analyze the spatial and temporal trends of forest cover changes in terms of gains and losses from 2001 to 2018; as well as the causes and implications of these changes in the Lake Bosomtwe watershed. Setting itself above earlier studies, this study assesses the efficacy and implications of the environmental conservation policies and practices implemented in 2015 for basin region management. The results of this research will furnish decision-makers with significant insights to oversee the region's natural resources, facilitate socio-economic advancement, and strategize the suitable utilization of land for alternative uses such as urban growth, construction, and agriculture. The knowledge gained will be significant not only for the research location but also for other tropical areas that are comparable.

2. Materials and Methods

2.1. Study Area

The Bosomtwe Lake Basin stands in the Bosomtwe District of Ghana's Ashanti Region, which is home to Kutunase as its capital (**Figure 1**). The district, which is situated at latitude 6˚ 30 Nand longitude 1˚ 25 W, was put to birth by dividing two separate districts, Atwima Kwanwoma and Bosomtwe Atwima Kwanwoma and covers an area of about 178 square km [36]. Residents in and around the basin, as

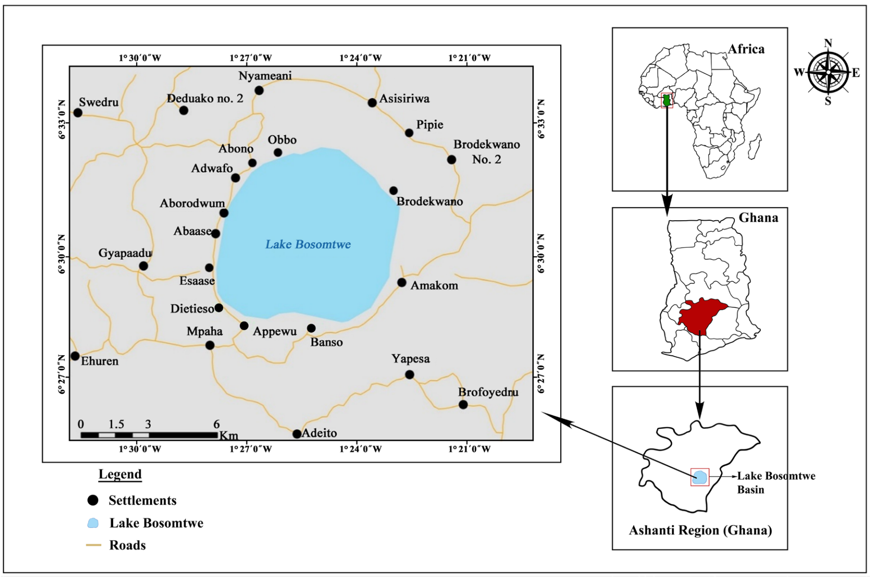

Figure 1. Map of Bosomtwe District Showing the Bosomtwe Basin.

well as others in the surrounding region, earn a living from the lake resort, which is a well-known tourist destination [36]. Sand, clay, and gold that are extracted from the lake's basin also add to the region's economic growth. This basin, which lies in the equatorial zone, receives rainfall that is typical of the moist semi-deciduous forest zone, which is home to a variety of highly valuable tropical hardwood species [36].

There are several tree species in the district, including Onyina (Ceiba pentandra), Mahogany (Khaya ivorensis), and Wawa (Triplochiton scleroxylon) [53]. The native forest cover in the district is being replaced by secondary forests and grasslands due to human activities such as unlawful small-scale gold mining, careless tree felling, illegal timber harvesting, and inappropriate farming practices [54]. The district's expansion in settlements is evidenced by its closeness to Kumasi Metropolis. The district is also one of the most active in the Ashanti Region because of its favourable infrastructure, economic activity, and booming tourism sector [54] [55].

2.2. Materials

We analyzed Landsat images from the following years: 2001, 2005, 2010, 2015, and 2018. To meet the need for a post-classification comparison, change detection technique, which involves grouping images obtained at different times, images of different dates were picked using the Landsat Enhanced Thematic Mapper (ETM+) satellite with a spatial resolution of 30 m × 30 m (Mas, 1999). The United States Geological Survey (USGS) website is where the above images were retrieved. The study's foundation was provided by the data sources listed in **Table 1**. Image pre-processing was done to fix the geometric and radiometric distortions of the images due to changes in the earth's rotation, atmospheric conditions, and sensor effects. An embedded haze correction module in the Erdas.

Table 1. Landsat images used and acquisition dates.

Landsat Image ID	Date Captured	Cloud Cover	Sensor
LE07_ LT1P_194055_20010402_2017(B1-B8)	4/2/2001	Lessthan 10%	Landsat ETM+
LE07_ LT1P_194055_20050107_2017(B1-B8)	1/7/2005	Lessthan 10%	Landsat ETM+
LE07_ LT1P_194055_2010020_2016(B1-B8)	6/2/2010	Lessthan 10%	Landsat ETM+
LE07_ LT1P_194055_20151205_2016(B1-B8)	05/12/2015	Lessthan 10%	Landsat ETM+
LE07_ LT1P_194055_20181229_2019(B1-B8)	29/12/2018	Lessthan 10%	Landsat ETM+

Imagine software was used to address haze in the 2001 and 2005 images, which is frequently caused by small floating particles in the atmosphere. The images from 2010 to 2018 were left unchanged because their reduced cloud distortions were not detrimental to the classification. To classify all types of land cover in the image, training samples from Google Earth were used, and to acquire a true representation of the various land cover classes, these samples were selected and looked at again.

2.3. Methods

The major software employed in this study included ERDAS Imagine 13.1, Environmental System Research Institute (ESRI) ArcGIS 10.6, and QGIS software version 3.4.2. The gathering of primary and secondary data is an essential part of all research endeavours [43]. The original data was acquired from ground-based coordinates and field observations; the secondary data was collected from the website of a private organization and Google Earth. Using the Landsat satellite, enhanced and geometrically adjusted images were gathered from the United States Geological Survey website for the years 2001, 2005, 2010, 2015, and 2018 [56]. The appropriate images were then downloaded and made available for further enhancement [43].

Preparing images for classification is an essential step in land cover categorization as it affects the precision of the classification outcomes [43] [44]. The image preprocessing phase increases the accuracy of the classification findings by correcting the image's geometric and radiometric distortions and establishing a clear connection between the secondary data and the primary data collected in the area under study [43] [44] [57]. Radiometric and geometric corrections were carried out to prevent obtaining false results, as photographs that bypass the rectification stage can result in unreliable data, due to the failure of some satellite scanlines and circumstances such as cloud cover [57]. Layer staking, picture improvement, radiometric correction, pan sharpening, study area extraction, data stacking, and edge masking were among the preliminary processing techniques employed in this study. The methods shown in **Figure 2** were followed to process the satellite imagery.

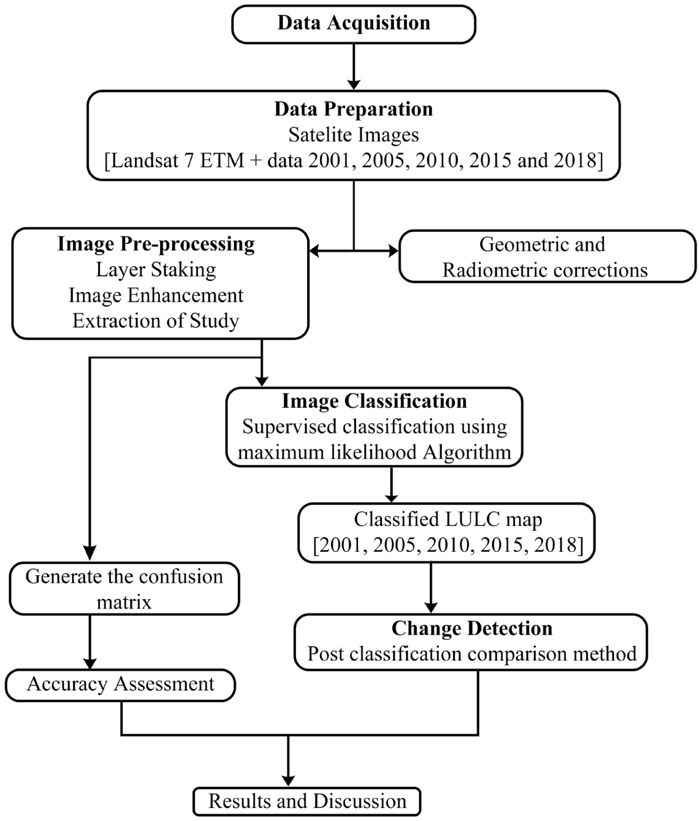

Figure 2. Flow chart that shows the various methods for land cover change analysis.

The data acquired (Landsat 7) were susceptible to information gaps due to the failure of the scanline's corrector linked with the ETM+ instrument. Hence, a process of data masking (gap filling) was carried out to improve each band using QGIS software. The data went through a stacking process after its masking. Since composite colour bands work best for grouping vegetation and highlighting the unique characteristics of different land cover classes, NIR, red, and green bands were combined to create a fake colour composite [43] [56]. The ERDAS Imagine computer application was used to complete the data stacking process.

The resolution of the launched photos was enhanced through a pan-sharpening process using the same ERDAS IMAGINE computer software, enabling small objects to be seen and seem finer than they were before [43] [58]. The study area was acquired by superimposing the Bosomtwe district shapefile over the acquired satellite picture. Subsequently, the research region was extracted making use of ERDAS IMAGINE computer software from the pan-sharpened image. Using the services of the Google Earth program, distinct locations with vegetation, bare terrain, water, and settlement were identified for every class. Fifty points were chosen for each of the four land cover classes, with the pre-cause that the points should be distributed equally and not geared to one point. This yielded a total of 200 training data points for all the different classified photos. Each class was assigned a value: water had a value of 1, settlement had a value of 2, bare ground had a value of 3, and vegetation had a value of 4.

Table 2. Description of land cover classification scheme used.

Land Cover Class	Description
Vegetation	Areas with a tree-crown areal density of 10% or more, and are populated with trees that can produce timber or other wood products
Water	These include Sea, rivers, lakes, streams, and reservoirs
Bare land	land with limited capacity to sustain life, and less than one-third of the area has vegetation or any other form of cover
Settlement	Areas of high utilization, with a large portion of the land covered by structures, included both cities and towns

Image Classification: Grouping all of the pixels in a photo into classifications related to land cover is the core objective of image classification. The satellite images were categorized into different classes with a pixel-based technique called the maximum likelihood classification algorithm. Experts in remote sensing assert that the maximum likelihood classification algorithm is a widely used technique because of its strong theoretical basis and adaptability to different kinds of land use and cover, satellite imagery, and data [50]. Supervised categorization groups pixels into classes based on a comparison between each pixel's spectral characteristics and a set of typical pixels from the user's training data [50]. Training datasets, classification, and accuracy evaluation were the three processes of supervised classification performed [43]. After a reconnaissance was conducted to identify land cover classes in the area under examination, four uniqueland cover classes were grouped: water body, vegetation, bare ground, and settlement (**Table 2**).

With the use of a common Microsoft Excel computing program, the surface areas of the various land cover classes were used in a trend analysis to determine the amount occupied by each class and create a graph using lines that illustrate the variations throughout the research years between the classes. This means that following classification, the ERDAS Imagine software provided us with the characteristics of the different land cover classes, from which their corresponding surface areas were derived. We then plugged those attributes into a written Excel program to create a chart that visually represented the trend of changes in land use and cover from the years 2001 to 2018. To calculate the producer accuracy, user accuracy, overall accuracy, and kappa coefficient, respectively, the following equations were used: Equation (1), Equation (2), Equation (3), and Equation (4) [43].

$$Producer's\ accuracy(\%) = \left(\frac{x_{kk}}{x_{+k}}\right) \times 100 \quad (1)$$

$$User's\ accuracy(\%) = \left(\frac{x_{kk}}{x_{k+}}\right) \times 100 \quad (2)$$

$$Overall\ accuracy(OA) = \frac{1}{N}\sum_{K=1}^{r} n_i \quad (3)$$

$$Kappa\ coefficient\,(k)=\frac{N\sum_{K=1}^{r}x_{kk}-\sum_{K=1}^{r}\left(x_{k+}\cdot x_{+k}\right)}{N^{2}-\sum_{K=1}^{r}\left(x_{k+}x_{+k}\right)} \tag{4}$$

Where x_{kk} represents the total of the pixels in rows "*K*" and columns "*k*," N denotes the total number of pixels, and r is the number of classes. Subscription x + *k* represents the total samples in column "*K*" of the error matrix, while x_k + represents the total samples in row "*K*" [43]. *K* > 80% denotes excellent accuracy and high agreement, 40% – 80% denotes moderate agreement, and < 40% denotes poor agreement [36] [59].

3. Results

3.1. Image Classification and Accuracy Assessment

After classifying images, determining accuracy is fundamental [43]. It is essential to adopt an evaluation procedure to guarantee the accuracy of the classification using dependable and effective means as LULC classification has the tendency to carry errors [60] [61]. We obtained the confusion matrix data from the ground truth data collected during the fieldwork, and we used this data with the kappa coefficient to assess accuracy. One well-liked instrument for assessing the precision of LULC classification methods is the confusion matrix [62] [63] [64]. The total accuracy (Equation 3), producer's accuracy (Equation 1), user's accuracy (Equation 2), and kappa coefficient (Equation 4) were computed from the generated error matrix. **Table 3** and **Table 4** present the accuracy level for the classified images.

Starting with the categorization of the 2001 satellite images, the researcher produced the following accuracy results (**Table 3**). The overall accuracy of the classification was 98.80% (**Table 3**). The producer accuracy for the classes of water and settlement was 100%, meaning that there was a perfect chance that the water and settlements on the ground would be classified and depicted as water and settlement on the classified map. The percentage of bare land was 60%, indicating that it was not categorized precisely when compared to water and settlement. In contrast, vegetation achieved 100% accuracy, indicating a good approximation of the actual ground feature. The percentage of sites that were absent (omitted) from the appropriate class on the classified map referred to as the error of omission was 6.4% for water, 0% for settlement, 0% for bear land, and

Table 3. Percentage level of accuracy for 2001, 2005 and 2010 classified images.

	2001		2005		2010	
Land Use Classes	**Producer**	**User**	**Producer**	**User**	**Producer**	**User**
Water	100	94.60	100	100	100	100
Settlement	100	100	100	96.67	94.34	99.01
Bare Land	60	90.20	63	87.50	96.20	93.83
Vegetation	100	95.83	76	90.48	95.45	95.45
Overall Accuracy	98.80		88.96		96.86	
Kappa Coefficient	0.9659		0.8568		0.9588	

4.35% for vegetation. The user accuracy for each class on the map, which shows the likelihood of the class appearing on the ground, was 94.6% for water, 100% for settlement, 90.2% for bare land, and 95.83 for vegetation (**Table 3**). This means that, in the majority of cases, a user using the classified map has a chance to recognize the classified classes on the ground where they are located. In terms of water, bare land, settlement, and vegetation, the error of commission was 6%, 0%, 0%, and 4.17%, respectively.

A satisfactory total accuracy of 88.96% was achieved in the 2005 classification (**Table 3**), indicating that the outcomes were precise and, therefore, reliable. Water and settlement had a producer accuracy of 100% (**Table 3**), which means that what was collected on the ground precisely matched the data on the categorization map. Vegetation had a better depiction of the actual ground feature with 76% accuracy, while bare land with an accuracy of 63% was not properly identified. The locations that were absent (omitted) from the appropriate class, were 0.03% for settlement, 9.09% for bear land, 8% for vegetation, and 0% for water. User accuracy, which measures the likelihood that a class on the map will exist on the ground was 100% for water, 96.67% for settlement, 87.50% for bare land, and 90.48 for vegetation (**Table 3**). This means that a user using the classified map is almost certain to see the classified classes on the ground. For water, the error of commission was 0%, for habitation, it was 3.33%, for bare ground, it was 12.5%, and for vegetation, it was 9.52%.

2010 recorded a 96.86% total precision rate (**Table 3**). On the classification map, water on the ground was precisely categorized as water because the producer accuracy for the water class was 100% (**Table 3**). The percentages of settlement, barren land, and vegetation were 94.34%, 96.20%, and 95.45%, respectively (**Table 3**), implying that all three had a good depiction of the actual ground feature. The percentage of the classified map that was not included in the correct class was 0% for water, 0.94% for settlement, 6.33% for bear land, and 4.55% for vegetation. 99.01% for settlement, 93.83% for barren terrain, 95.45% for vegetation, and 100% for water were the user accuracy rates on the field (**Table 3**). Generally speaking, those who utilize the classified map are likely to see the actual classified classes in reality. Concerning the classes of water, settlement, barren ground, and vegetation, the errors of commission were 0%, 0.99%, 6.17%, and 4.55%, respectively.

In 2015, the overall accuracy rate was 95.24% (**Table 4**). The producer achieved 100% accuracy for both water and bare land classes (**Table 4**). This implies that naked land and water on the ground were precisely categorized as water and bare land on the classification map. Both the vegetation and the settlement exhibited a good depiction of the actual ground features, with respective percentages of 90.48% and 94.44% (**Table 4**). The percentage of omitted class was 0% for water, 9.52% for settlement, and 14.28% and 5.55% for vegetation and bare land, respectively. The user accuracy was 87.50% for bare terrain and 100% for water, settlement, and vegetation, suggesting that the classified classes are most certain to be observed as they are in reality (**Table 4**). The percentage of error for water, settlement, bare land, and vegetation were respectively 0%, 0%, 12.50%, and 0%.

Table 4. Percentage level of accuracy for 2015 and 2018 classified images.

	2015		2018	
Land Use Classes	**Producer**	**User**	**Producer**	**User**
Water	100	100	100	100
Settlement	90.48	100	99.32	99.32
Bare Land	100	87.50	96.0	95.92
Vegetation	94.44	100	100	100
Overall Accuracy	95.24		98.95	
Kappa Coefficient	0.9359		0.9842	

A total of 98.95% accuracy was achieved in 2018 (Table 4), with a producer accuracy of 100% for water and vegetation (Table 4), these ground features were precisely categorized as water and vegetation on the classification map. The accuracy of bare land was 96.0%, whereas that of settlement was 99.32% (Table 4). Water had an error of 0%, settlement had 0.68%, while bare ground and vegetation had 4.08% and 0% error, respectively. It is evident from the user accuracy of 100% for water and vegetation, 99.32% for settlement, and 95.92% for bare land that users using the classified map are likely to see the categorized classes on the ground. For bare land, the error of commission was 4.0%, 0.68% for settlement, and 0% for water and vegetation, respectively.

3.2. Kappa Statistics Analysis from 2001 – 2018

A statistical test was used to determine the kappa coefficient, which indicated how accurate the classification was. In essence, Kappa assesses how successfully the classification was carried out in relation to values that were assigned at random. Thus, did the categorization do better than values that were chosen at random? The range of the kappa coefficient was −1 to 1. Whereas a kappa of 1 indicates that the classification is significantly better than randomly assigning values, a value of 0 indicates that the classification is no better than randomly assigning values. A negative kappa coefficient also indicates that the classification is significantly worse than randomly assigning values. Equation 4 gives the formula for the kappa coefficient. As stated in Table 3, the 2001 total kappa value was 0.9659. For both bare ground and vegetation, the conditional kappa was 1, indicating a considerable improvement over values that were chosen at random. The scores obtained for settlement and water were 0.9492 and 0.9265 respectively. This means that all of the coefficients are near 1, meaning that classification is much stronger than choosing values at random. The total kappa value for 2005 was 0.8568 (Table 3). The conditional kappa for water was 1, while the conditional kappa for bare ground, vegetation, and settlement were 0.8654, 0.8590, and 0.9589, respectively. These values were all near 1, suggesting that the classification of these variables was superior to assigning values at random. In 2010, the overall kappa value was 0.9588 (Table 3).The conditional kappa values were as follows: for water, it was 1; for bare land, it was 0.9851; for vegetation, it was 0.9512; and for settlement, it was 0.9179.This further demonstrates that all of their coefficients are near 1, which considerably increases their classification over value allocation at random. The overall kappa value for 2015 was 0.9359 (**Table 4**). Whereas the conditional kappa for bare land was 0.859, it was 1 for water, vegetation, and settlements. It is evident that all the coefficients are equal to or nearly equal to 1, showing that the classification is noticeably superior to choosing values at random. The 2018 total Kappa value was 0.9842 (**Table 4**). As opposed to 0.9518 and 0.981 for bare ground and settlement, the conditional kappa for water and vegetation was 1. Since all of these values were relatively near to 1, it was clear that their classification was more excellent than choosing values at random.

3.3. Land Cover Change

A map showing classified land cover in the Bosomtwe Lake Basin from 2001 to 2018 is presented in **Figure 3**. The figure shows that, despite some areas having already experienced depletion, there was still a sizable amount of natural vegetation cover in 2001.After water, which makes up the majority of the basin, the histogram in **Figure 4** shows that natural vegetation is the next land cover with a significant surface area, indicating that in 2001, the basin had a good proportion of natural vegetation. The histogram also indicates that the percentage of settlement was 11.92% of the Lake Bosomtwe Basin's total surface area. This indicates that the basin did not experience significant development during the reporting year, which helps to explain why the Bosomtwe Basin had a high percentage of natural vegetation in 2001.

Figure 3 reveals that in 2005, water made up the majority of the basin's cover, followed by vegetation, settlements, and bare ground. The various land cover classes' percentages are shown in **Figure 4**'s histogram. The majority of the basin (49.32%) is made up of water, with the remaining portions being made up of barren land (8.05%), vegetation (32.19%), and settlement (14.44%). The histogram shows that while vegetation declined in the Bosomtwe Basin area in 2005, the number of areas without vegetation and settlements increased.

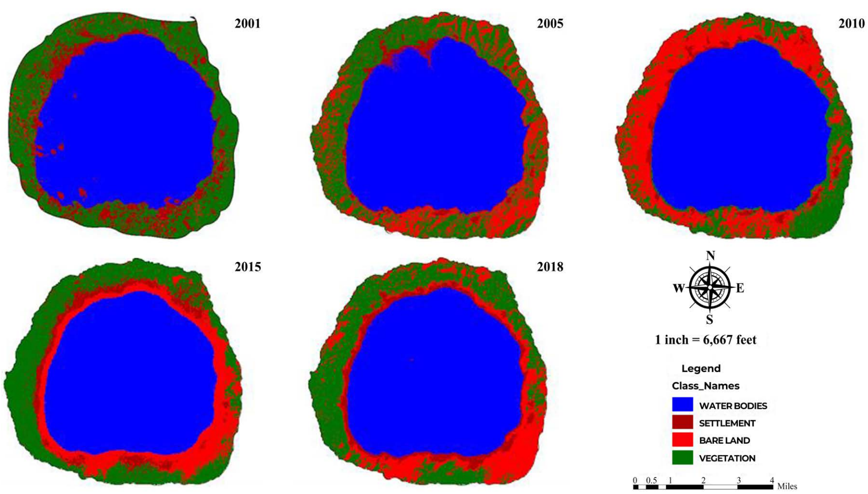

Figure 3. Land cover map of Lake Bosomtwe Basin in 2001, 2005, 2010, 2015 and 2018.

Figure 3 illustrates how, in 2010, water remained the predominant type of cover in the basin, with vegetation accounting for the second-highest percentage, behind bare ground and settlement, respectively. The various land cover classes' percentages are also displayed on the histogram. The basin's major component is made up of water (49.76%), which is followed by vegetation (22.40%), settlement (18.83%), and bare land (10.01%). Judging from the histogram, the Bosomtwe Basin area saw an increase in bare land, a decrease in vegetation, and an increase in settlements in 2010. The basin's cover was still largely made up of water in 2015, as seen in Figure 3. Vegetation, habitation, and bare ground were the next categories of cover. In line with the histogram, water makes up the majority of the basin (47.09%), with vegetation (24.97%), settlement (17.49%), and bare land (8.75%) coming in second, third and fourth respectively. Vegetation, habitation, and bare ground were the next categories of cover. In line with the histogram, water makes up the majority of the basin (47.09%), with vegetation (24.97%), settlement (17.49%), and bare land (8.75%) coming in second, third and fourth respectively. From the findings, it can be deduced that in the Bosomtwe Lake area in 2015, there were fewer settlements, more vegetation, and fewer bare areas. Figure 3 shows that in 2018, water accounted for the largest portion of the basin's cover, followed by vegetation, habitation, and bare ground. The histogram reveals that the majority of the basin (47.99%) consisted of water, with the other portions being made up of vegetation (20.78%), bare land (12.45%), and settlement (18.46%). During the reporting year 2018, the histogram explains why there was a rise in habitation, a corresponding increase in bare land, and a loss in vegetation in the Bosomtwe Lake area.

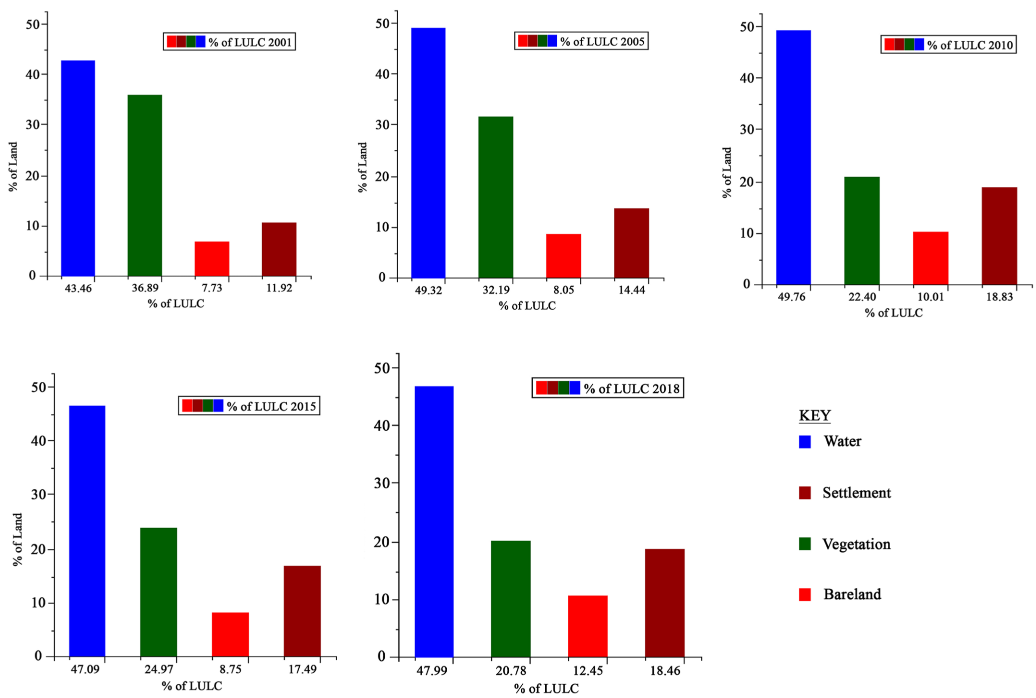

Figure 4. Histogram of percentages of land cover classes from 2001 to 2018.

4. Discussions

4.1. Land Cover Change Analysis from 2001 – 2018

The land cover patterns and transformations in the Bosomtwe Lake Basin from 2001 to 2018 are presented in the chart in **Figure 5**. With relatively little development taking place in the basin at the time, the land cover map in 2001 indicated a high proportion of vegetation cover. Even though the basin had already been drained, there was still a sizable amount of vegetative cover because the settlement made up about 11% of the basin's overall proportion of land cover classes.

The findings indicate that the low depletion can be linked to the area's low population growth or development. Proceeding to 2005, it was observed that there had been a decline in vegetative cover as compared to 2001, as well as an increase in settlements in the area. When comparing 2005 to 2001, the percentage of bare land increased. According to [32], one important element that causes degradation and deforestation is the increase in population and settlement of an area, which could have contributed to the decline in vegetation during the time. As said by [65] this could also imply that formerly forested areas have changed into or are already being transformed into barren ground or farming land. As the population of the Bosomtwe area increased due to immigration, there may have been widespread tree-cutting for residential, agricultural, or commercial purposes, which contributed to the reduction in vegetation. The loss of vegetation may also be due to the absence of environmental policies and practices aimed at protecting the forest. The Bosomtwe Lake Basin may have lost vegetation cover in 2005 as a result of all of these aforementioned activities.

The vegetative cover of the basin was found to have significantly decreased in 2010, as **Figure 5** shows. The area's population growth can be attributed to the significant amount of development that occurred in the basin in 2010 as a result of various human activities. Given that the basin's previous forest may now have been replaced by farms, settlements, or even barren ground, the decline can also

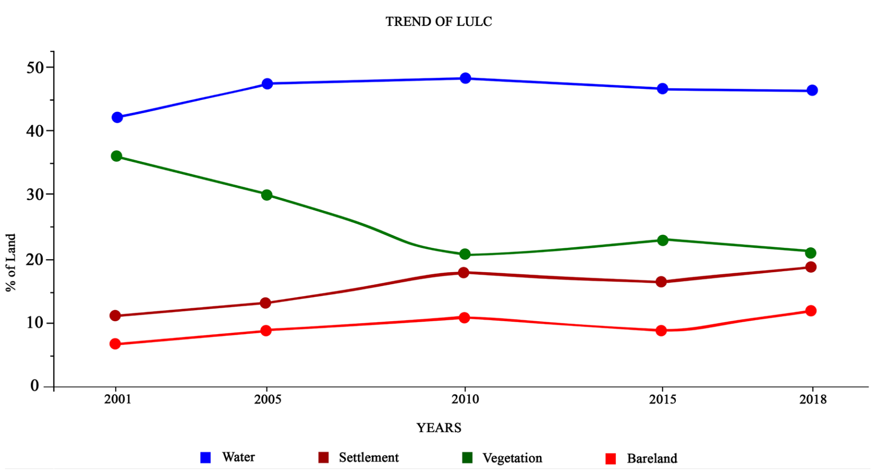

Figure 5. Chart of land cover trend from 2001 – 2018.

be linked to the region's growing population, the pace of migration, and urbanisation [8], [65]. Environmental laws and regulations that safeguard forests were absent in the basin, which could also be another explanation for the decline in vegetation.

2015 saw a rise in the amount of vegetative cover in the Bosomtwe Lake basin, defying the overall trend of declining cover. As the total area of barren ground and settlements reduced, the percentage of natural vegetation increased. Subsequent investigation showed that practices and efforts for environmental conservation that the basin's residents and non-residents observed contributed to the increase in vegetative cover in 2015. It became known that, as part of the World Environmental Day celebration, students from the Kumasi Institute of Tropical Agriculture (KITA) had planted trees in the Bosomtwe basin. This action had been acknowledged by the district chief executive of the Bosomtwe Atwima Kwanwoma district in 2015.250 trees or more were planted by them according to (business Ghana news.com). Additionally, farming was prohibited within 60 meters of the Bosomtwe basin, with penalties for those found farming there (graphic online.com). It is reasonable to conclude that the policies and practices implemented in 2015 to safeguard the environment contributed to the rise in vegetative cover in the basin.

Nevertheless, in 2018 everything had returned to normal and the general trend of declining vegetative cover persisted. The pace of urbanization in the region accelerated, leading to an increase in the number of settlements. There was more bare ground than there was in 2015. The abandonment of the environmental protection policies and practices that were implemented and carried out in 2015 may be the cause of this. As **Figure 5** illustrates, immigration, population expansion, and human activity can be cited for the Lake Bosomtwe Basin's decline in vegetation and rise in settlements and barren areas between 2001 and 2018.

4.2. Factors Causing Land Cover Changes in the Lake Bosomtwe Basin

Growing populations both locally and globally have put excess pressure on the environment's scarce resources, modifying land cover and use in the process [66]. The growing number of individuals relocating to towns surrounding the Bosomtwe Lake Basin subsequently led to the growth in settlements, barren land, and a decline in vegetation. This may be linked to the emergence of resorts and other tourism-related amenities around the basin. The built-up region surrounding Chaohu Lake expanded due to an upward trend in the province of Anhui's immigrant population [67]. [44] also acknowledged that urbanization and its subsequent disturbances to the natural environment were primarily caused by population growth and economic development.

The inactive or absence of environmental protection policies and management practices contributed significantly to land cover change in the lake basin. The majority of available laws and initiatives prioritised supplying wood for the country's wood industry over protecting or conserving the natural vegetation, which encouraged excessive use of the forest and led to the degradation of forest reserves. Reforestation and other restoration initiatives intended to protect forest reserves and promote sustainable forestry also failed because of financial limitations and a focus on the economic value of forests rather than their sustainability, highlighting the differences between the policies' intended and actual execution [68].

The rising need for resources is a further issue to speculate. This finding agrees with the outcome of [69] who noted in their study that rapid population increase and the demand for forest products deplete forest cover. The demand for goods and services, fuel, housing, household appliances, and land for agricultural operations rises as more people relocate to the Bosomtwe Lake region. Pressure from rising human populations and increased demand for environmental resources deplete the environmental resources that are already accessible [32] [37]. Thus, every environmental management strategy should consider how population growth is affecting the physical makeup of forest cover [8].

Changes in the environment also occur as a result of human interference. Land used for agricultural purposes, which is an economic activity carried out by humans, has replaced majority of the original natural vegetation [29]. Human activities such as population growth, poverty levels, food insecurity, livestock husbandry, and infrastructure relocation are the key drivers of environmental change [70]. Likewise, [71] noted decreasing output, rising incomes, and increasing pressure from populations. In addition to the modifications induced by human activity, other factors that have been linked to land cover change include population pressure, poverty, farming operations, habitat development, infrastructure growth, lack of alternative livelihood, unemployment, and drought [37]. Our results support that of other scholars who discovered that forest lands are being converted to farmlands to meet the current demand for land for agriculture [72]. In addition to agriculture, the Bosomtwe Basin's territory is exploited for human settlements, feeder roads, local track construction, and small-scale illicit mining [37]. The basin's natural cover changed as a result of all these human activities.

The incorrect management of both liquid and solid waste in the basin is not overlooked. People dispose of their waste in the lake or the forest since some communities lack waste bins, the available ones are also inaccessible owing to the rising numbers of people in the area. Some communities do not have access to public restrooms, thus those who live in areas without toilets or with limited access often use the lake or the forest as their lavatory [37].

4.3. Policy Failures and Recommendations

Ghana began administering its natural environment around 1906. However, following the United Nations Environment Conference in 1972, which resulted in the establishment of the Environmental Protection Council (EPC) and the implementation of national, regional, and local environmental protection policies in 1974, concerns about environmental degradation started to receive attention [68]. Significant forest management initiatives, including the creation of permanent forest estates, forest reserves, and legislation protecting forests, were implemented to guarantee the sustainability of forest resources, which slowed down the nation's forest resource depletion [73]. Surprisingly, the majority of the initiatives focused on providing wood for the nation's wood industry, which promoted overuse of the forest and caused forest reserves to deteriorate. Due to funding constraints and an emphasis on the financial worth of forests over their sustainability, afforestation and other restoration projects meant to preserve forest reserves and advance sustainable forestry failed. There was a clear difference between the intended and actual implementation of the forest policy [68].

To guarantee sustainable development and safeguard the environment, natural resource management, biodiversity management, protected forest management, land management, and forest restoration all require statutory legislation [28]. This study will assist the appropriate regulatory bodies in putting rules in place that will ensure that the sustainable use of natural resources is monitored. The implementation of community-based forestry, a shift from conservation for timber supply to conservation for sustainable development, and the enforcement of other forest policies are further recommendations made by this paper. For sustainable forest management to be achieved while safeguarding resources for future generations, local people and communities must be engaged and empowered [68].

5. Conclusions

This study's primary goals were to evaluate the changes in land cover in the Bosomtwe Lake Basin from 2001 to 2018 and to ascertain the pattern and rate of change between forest cover and related land cover classes. The factors behind the change in land cover as well as the effectiveness and ramifications of the environmental conservation laws and practices adopted in 2015 were examined. The study evaluated changes in land cover within the study area over 17 years using GIS, remote sensing, post-classification image analyses, and change analysis. These goals were met, patterns in land cover were examined, and several maps showing land cover were created. It was established by the analysis that during the 17-year study period, there were considerable changes in the composition and pattern of land cover within the basin. Land cover conversions for residential, agricultural, infrastructure, and economic purposes are the justification given for the observed pattern of declining forest cover within the basin. Urbanization, population growth, agricultural expansion, and overexploitation of forest products all contribute to the loss of vegetation, which has detrimental consequences on environmental sustainability. It was also discovered that the increase in vegetative cover in the basin in 2015 was primarily attributable to the conservation policies and measures implemented to protect the environment. Thus, one of the most important strategies for preserving and repairing the environment is through the implantation and enforcement of environmental policies.

Decision-makers, legislators, the government, and non-governmental organizations are among the many stakeholders who must pay particular attention to the issue of forest deterioration. Enforcing environmental protection laws, penalties, and initiatives to preserve and rehabilitate forests is necessary to boost the sustainability of the environment. This article is significant because environmental degradation is a global issue of which Ghana is not exempt, therefore participatory forest management practices and integrated forest conservation methods are necessary to preserve environmental sustainability.

The paper links land cover change in the basin to an increase in population, urbanization, agricultural expansion and other human activities in the basin. The tourism industry's growth has also led to the development of supportive infrastructure such as car parks, housing, lodgings, and shops. It is recommended that multidisciplinary research on the impacts of land use/land cover change on the lake's water quality be conducted in future. In addition, this study only looked at the historical changes in land use and land cover without factoring the future changes, which need to be considered in future research.

Acknowledgements

This study was supported by the National Science Foundation of China (No.72074068, U2240223). We would also like to express our gratitude to the anonymous reviewers for their insightful suggestions that improved the original version of the manuscript, and the USGS for making the Landsat data publicly available.

Conflicts of Interest

The authors declare that they have no competing interests regarding the publication of this paper.

References

[1] Mayers, J. and Vermeulen, S. (2018) Power from the Trees: How Good Forest Governance Can Help Reduce Poverty. International Institute for Environment and Development, London.

[2] Omar Sarif, M. and Gupta Dev, R. (2022) Spatiotemporal Mapping of Land Use/Land Cover Dynamics Using Remote Sensing and GIS Approach: A Case Study of Prayagraj City, India (1988-2018). *Environment*, *Development and Sustainability*, **24**, 888-920. https://doi.org/10.1007/s10668-021-01475-0

[3] Appiah, D.O., Forkuo, E.K., Bugri, J.T. and Apreku, T.O. (2017) Geospatial Analysis of Land Use and Land Cover Transitions from 1986-2014 in a Peri-Urban Ghana. *Geosciences*, **7**, Article 125. https://doi.org/10.3390/geosciences7040125

[4] Cobbinah, B.P., Erdiaw-Kwasie, M.O. and Amoateng, P. (2015) Africa's Urbanisation: Implications for Sustainable Development. *Cities*, **47**, 62-72. https://doi.org/10.1016/j.cities.2015.03.013

[5] Cobbinah, B.P., Erdiaw-Kwasie, M.O. and Amoateng, P. (2015) Rethinking Sustainable Development within the Framework of Poverty and Urbanisation in De-

veloping Countries. *Environmental Development*, **13**, 18-32. https://doi.org/10.1016/j.envdev.2014.11.001

[6] Zhang, W. and Li, H. (2016) Characterizing and Assessing the Agricultural Land Use Intensity of the Beijing Mountainous Region. *Sustainability*, **8**, Article 1180. https://doi.org/10.3390/su8111180

[7] Odawa, S. and Seo, Y. (2019) Water Tower Ecosystems under the Influence of Land Cover Change and Population Growth: Focus on Mau Water Tower in Kenya. *Sustainability*, **11**, Article 3524. https://doi.org/10.3390/su11133524

[8] Tsegaye, N.T., Dibaba, W.T. and Gemeda, D.O. (2023) Spatiotemporal Forest Cover Change and Its Implication for Environmental Sustainability in Dedo District of Jimma Zone, Southwest Ethiopia. Environ. *Environmental and Sustainability Indicators*, **19**, Article 100262. https://doi.org/10.1016/j.indic.2023.100262

[9] Appiah, M., Akoto Asare, D., Mahama Wumbeidow, H., Pentsil, S. and Ofori, D.A. (2017) Forestry Research Institute of Ghana Annual Report 2017. Council of Scientific & Industrial Research (CSIR), Fumesua.

[10] Tuffour-Mills, D., Antwi-Agyei, P. and Addo-Fordjour, P. (2020) Trends and Drivers of Land Cover Changes in a Tropical Urban Forest in Ghana. *Trees, Forests and People*, **2**, Article 100040. https://doi.org/10.1016/j.tfp.2020.100040

[11] Alemayehu, F. (2016) Land Use and Land Cover Change in the Coastal Area of Watamu Mida Creek, Kenya. *Open Journal of Forestry*, **6**, 230-242. https://doi.org/10.4236/ojf.2016.64019

[12] Esmail, M., Masria, A. and Negm, A. (2016) Monitoring Land Use/Land Cover Changes Around Damietta Promontory, Egypt, Using RS/GIS. *Procedia Engineering*, **154**, 936-942. https://doi.org/10.1016/j.proeng.2016.07.515

[13] El Adnani, A., Habib, A., El Khalidi, K. and Zourarah, B. (2019) Spatio-Temporal Dynamics and Evolution of Land Use Land Cover Using Remote Sensing and GIS in Sebou Estuary, Morocco. *Journal of Geographic Information System*, **11**, 551-566. https://doi.org/10.4236/jgis.2019.115034

[14] Molini, V. and Paci, P. (2015) Poverty Reduction in Ghana Progress and Challenges. The World Bank, Accra.

[15] López, E., Bocco, G., Mendoza, M. and Duhau, E. (2001) Predicting Land-Cover and Land-Use Change in the Urban Fringe a Case in Morelia City, Mexico. *Landscape and Urban Planning*, **55**, 271-285. https://doi.org/10.1016/S0169-2046(01)00160-8

[16] Misra, A., *et al*. (2015) Assessment of the Land Use/Land Cover (LU/LC) and Mangrove Changes along the Mandovi-Zuari Estuarine Complex of Goa, India. *Arabian Journal of Geosciences*, **8**, 267-279. https://doi.org/10.1007/s12517-013-1220-y

[17] Kutir, C., Agblorti, S.K.M. and Campion, B.B. (2022) Migration and Estuarine Land Use/Land Cover (LULC) Change along Ghana's Coast. *Regional Studies in Marine Science*, **54**, Article 102488. https://doi.org/10.1016/j.rsma.2022.102488

[18] Tian, B., Wu, W., Yang, Z. and Zhou, Y. (2016) Drivers, Trends, and Potential Impacts of Long-Term Coastal Reclamation in China from 1985 to 2010. *Estuarine, Coastal and Shelf Science*, **170**, 83-90. https://doi.org/10.1016/j.ecss.2016.01.006

[19] Ghayour, L., *et al*. (2021) Performance Evaluation of Sentinel-2 and Landsat 8 OLI Data for Land Cover/Use Classification Using a Comparison between Machine Learning Algorithms. *Remote Sensing*, **13**, Article 1349. https://doi.org/10.3390/rs13071349

[20] Vu, H.L., (2018) Anthropogenic Influences on Ecosystem Processes in a Tropical Estuary: Feedback Connections and Environmental Management Targets a Case Study of Dong Ho Estuary, Kien Giang, Vietnam. Ph.D. Thesis, School of Earth and Environmental Sciences, the University of Queensland, Brisbane.

[21] Nébié, E.K.I. and West, C.T. (2019) Migration and Land-Use and Land-Cover Change in Burkina Faso: A Comparative Case Study. *Journal of Political Ecology*, **26**, 614-632.

[22] Ackah, C., *et al*. (2010) Internal Migration in Ghana: Determinants and Welfare Impacts. The World Bank, Accra. https://doi.org/10.1596/1813-9450-5273

[23] Azumah, S.B. and Ahmed, A. (2023) Climate-Induced Migration among Maize Farmers in Ghana: A Reality or an Illusion? *Environmental Development*, **45**, Article 100808. https://doi.org/10.1016/j.envdev.2023.100808

[24] Braimoh, A.K. (2004) Seasonal Migration and Land-Use Change in Ghana. *Land Degradation & Development*, **15**, 37-47. https://doi.org/10.1002/ldr.588

[25] Maimaitijiang, M., Ghulama, A., Onésimo Sandoval, J.S. and Maimaitiyiming, M. (2015) Drivers of Land Cover and Land Use Changes in St. Louis Metropolitan Area over the Past 40 Years Characterized by Remote Sensing and Census Population Data. *International Journal of Applied Earth Observation and Geoinformation*, **35**, 161-174. https://doi.org/10.1016/j.jag.2014.08.020

[26] Bhawana, K.C. (2015) Land Use and Land Cover in Relation to Internal Migration and Human Settlement in the Middle Mountains of Nepal. Master's Thesis, University of Twente, Enschede.

[27] Angelsen, A., Aguilar-Støen, M., Ainembabazi, J.H., Castellanos, E. and Taylor, M. (2020) Migration, Remittances, and Forest Cover Change In Rural Guatemala and Chiapas, Mexico. *Land*, **9**, Article 88. https://doi.org/10.3390/land9030088

[28] Larbi, I. (2023) Heliyon Land Use-Land Cover Change in the Tano Basin, Ghana and the Implications on Sustainable Development Goals. *Heliyon*, **9**, E14859. https://doi.org/10.1016/j.heliyon.2023.e14859

[29] Hagos, H., Sewnet, A. and Birhane, E. (2023) Land Use / Land Cover Change Detection and Its Driving Factors in Suluh River Basin, Northern Highland Part of Ethiopia. *International Journal of Environmental Protection and Policy*, **11**, 10-20. https://doi.org/10.11648/j.ijepp.20231101.12

[30] Sharma, S., Mehta, B.K., Mehta, D., Nagar, H. and Mishra, A. (2012) HPTLC Method of Quantitation of Bioactive Marker Constituent Pinitol in Extracts of Pisonia Grandis (R.BR). *International Research Journal of Pharmacy*, **3**, 54-58.

[31] Ometto, J.P., Postigo, J.C., Castellanos, E.J. and Cuvi, N. (2022) Chapter 12: Central and South America. In: Pörtner, H.-O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. and Rama B., Eds., *Climate Change* 2022: *Impacts*, *Adaptation and Vulnerability*, Cambridge University Press, Cambridge, 1689-1816.

[32] Basin, A., *et al*. (2023) Analysis of Land Use/Land Cover Change Trends over Birr River Watershed. *Environmental and Sustainability Indicators*, **17**, Article 100222. https://doi.org/10.1016/j.indic.2022.100222

[33] Shalaby, A.A., Ali, R.R. and Gad, A. (2012) Urban Sprawl Impact Assessment on the Agricultural Land in Egypt Using Remote Sensing and GIS: A Case Study, Qalubiya Governorate. *Journal of Land Use Science*, **7**, 261-273. https://doi.org/10.1080/1747423X.2011.562928

[34] Antwi-Agyei, P., *et al*. (2019) Land Use and Land Cover Changes in the Owabi Re-

servoir Catchment, Ghana: Implications for Livelihoods and Management. *Geosciences*, **9**, Article 286. https://doi.org/10.3390/geosciences9070286

[35] Osei, M.A., Amekudzi, L.K., Wemegah, D.D., Preko, K., Gyawu, E.S. and Obiri-Danso, K. (2019) The Impact of Climate and Land-Use Changes on the Hydrological Processes of Owabi Catchment from SWAT Analysis. *Journal of Hydrology: Regional Studies*, **25**, Article 100620. https://doi.org/10.1016/j.ejrh.2019.100620

[36] Asare, A., Thodsen, H., Antwi, M., Opuni-Frimpong, E. and Sanful, P.O. (2021) Land Use and Land Cover Changes in Lake Bosumtwi Watershed, Ghana (West Africa). *Remote Sensing Applications: Society and Environment*, **23**, Article 100536. https://doi.org/10.1016/j.rsase.2021.100536

[37] Abreu, A., Hernandez Salinas, A. and Clusener-Godt, M. (2016) Sustainable Management of the Lake Bosomtwe in the Ashanti Region of Ghana. *International Journal of Sustainable Development & World Ecology*, **24**, 111-120.

[38] Adeline, M., Agyeman, S.P. and Dennis, T. (2019) Sustainable Ecosystem Services of Lake Bosomtwi, Ghana-Implications for Livelihood and Food Security. *Nature & Faune*, **32**, 58-61.

[39] Mohammed, A.K. (2018) An Assessment of Tourism's Environmental Impact on the Lake Bosomtwe Basin. *International Journal of Hospitality & Tourism Administration*, **19**, 259-288. https://doi.org/10.1080/15256480.2017.1324338

[40] Kumar, R., Nilanjana, B., Chatterjee, D. and Das, K. (2021) Land Use and Land Cover Change and Its Resultant Erosion Susceptible Level: An Appraisal Using RUSLE and Logistic Regression in a Tropical Plateau Basin of West Bengal, India. *Environment, Development and Sustainability*, **23**, 1411-1446. https://doi.org/10.1007/s10668-020-00628-x

[41] Saddique, N., Mahmood, T. and Bernhofer, C. (2020) Quantifying the Impacts of Land Use/Land Cover Change on the Water Balance in the Afforested River Basin, Pakistan. *Environmental Earth Sciences*, **79**, Article No. 448. https://doi.org/10.1007/s12665-020-09206-w

[42] Sang, X., Guo, Q., Wu, X., Xie, T., He, C. and Zang, J. (2021) The Effect of DEM on the Land Use/Cover Classification Accuracy of Landsat OLI Images. *Journal of the Indian Society of Remote Sensing*, **49**, 1507-1518. https://doi.org/10.1007/s12524-021-01318-5

[43] Seyam, M.M.H., Haque, M.R. and Rahman, M.M. (2023) Identifying the Land Use Land Cover (LULC) Changes Using Remote Sensing and GIS Approach: A Case Study at Bhaluka in Mymensingh, Bangladesh. *Case Studies in Chemical and Environmental Engineering*, **7**, Article 100293. https://doi.org/10.1016/j.cscee.2022.100293

[44] Darem, A.A., Alhashmi, A.A., Almadani, A.M., Alanazi, A.K. and Sutantra, G.A. (2023) Development of a Map for Land Use and Land Cover Classification of the Northern Border Region Using Remote Sensing and GIS. *The Egyptian Journal of Remote Sensing and Space Science*, **26**, 341-350. https://doi.org/10.1016/j.ejrs.2023.04.005

[45] Abdallah, S., Mostafa Abd, E., Hemdan, S. and Ibrahim, K. (2019) Assessment of Land Use/Land Cover Changes Induced by Jizan Dam , Saudi Arabia , and Their Effect on Soil Organic Carbon. *Arabian Journal of Geosciences*, **12**, Article No. 350. https://doi.org/10.1007/s12517-019-4474-1

[46] Khwarahm, N.R. (2021) Spatial Modeling of Land Use and Land Cover Change in Sulaimani , Iraq , Using Multitemporal Satellite Data. *Environmental Monitoring and Assessment*, **193**, Article 148. https://doi.org/10.1007/s10661-021-08959-6

[47] Salih, A. (2018) Classification and Mapping of Land Cover Types and Attributes in Al-Ahsaa Oasis, Eastern Region, Saudi Arabia Using Landsat-7 Data. *Journal of Remote Sensing & GIS*, **7**, Article 1000228. https://doi.org/10.4172/2469-4134.1000228

[48] Alawamy, J.S., Balasundram, S.K., Husni, A. and Hanif, M. (2020) Detecting and Analyzing Land Use and Land Cover Changes in the Region of Al-Jabal Al-Akhdar, Libya Using Time-Series Landsat Data from 1985 to 2017. *Sustainability*, **12**, Article 4490. https://doi.org/10.3390/su12114490

[49] Chatelain, C. and Gautier, L. (1996) Deforestation in Southern Cote D'Ivoire: A High-Resolution Remote Sensing Approach. In: Van Der Maesen, L.J.G., Van Der Burgt, X.M. and Van Medenbach De Rooy, J.M., Eds., *The Biodiversity of African Plants*, Springer, Dordrecht, 259-266. https://doi.org/10.1007/978-94-009-0285-5_34

[50] Addae, B. and Oppelt, N. (2019) Land-Use/Land-Cover Change Analysis and Urban Growth Modelling in the Greater Accra Metropolitan Area (GAMA), Ghana. *Urban Science*, **3**, Article 26. https://doi.org/10.3390/urbansci3010026

[51] Kumi-Boateng, B., Mireku-Gyimah, D. and Duker Kumi-Boateng, A.A. (2012) A Spatio-Temporal Based Estimation of Vegetation Changes in the Tarkwa Mining Area of Ghana. *Research Journal of Environmental and Earth Sciences*, **4**, 215-229.

[52] Obodai, J., Adjei, K.A., Odai, S.N. and Lumor, M. (2019) Land Use/Land Cover Dynamics Using Landsat Data in a Gold Mining Basin—The Ankobra, Ghana. *Remote Sensing Applications: Society and Environment*, **13**, 247-256. https://doi.org/10.1016/j.rsase.2018.10.007

[53] Sanful, P.O., Aikins, S., Frempong, E., Hall, R.I. and Hecky, R.E. (2017) Temporal Dynamics and Relationship between Climate, Limnological Variables and Zooplankton Composition in Climate-Sensitive Lake Bosumtwi, Ghana. *African Journal of Aquatic Science*, **42**, 21-33. https://doi.org/10.2989/16085914.2016.1268566

[54] Appiah, D.O., Schröder, D., Forkuo, E.K. and Bugri, J.T. (2015) Application of Geo-Information Techniques in Land Use and Land Cover Change Analysis in a Peri-Urban District of Ghana. *ISPRS International Journal of Geo-Information*, **4**, 1265-1289. https://doi.org/10.3390/ijgi4031265

[55] Appiah, D.O., Bugri, J.T., Forkuo, E.K. and Boateng, P.K. (2014) Determinants of Peri-Urbanization and Land Use Change Patterns in Peri-Urban Ghana. *Journal of Sustainable Development*, **7**, 95-109. https://doi.org/10.5539/jsd.v7n6p95

[56] Srivastava, P.K., Han, D., Rico-Ramirez, M.A., Bray, M. and Islam, T. (2012) Selection of Classification Techniques for Land Use/Land Cover Change Investigation. *Advances in Space Research*, **50**, 1250-1265. https://doi.org/10.1016/j.asr.2012.06.032

[57] Boakye, E., Anyemedu, F.O.K., Quaye-Ballard, J.A. and Donkor, E.A. (2019) Spatio-Temporal Analysis of Land Use/Cover Changes in the Pra River Basin, Ghana. *Applied Geomatics*, **12**, 83-93. https://doi.org/10.1007/s12518-019-00278-3

[58] Liu, X., Pedersen, M. and Wang, R. (2022) Survey of Natural Image Enhancement Techniques: Classification, Evaluation, Challenges, and Perspectives. *Digital Signal Processing*, **127**, Article 103547. https://doi.org/10.1016/j.dsp.2022.103547

[59] Mensah, I. and Mensah, R.D. (2018) Effects of Service Quality and Customer Satisfaction on Repurchase Intention in Restaurants on University of Cape Coast Campus. *Journal of Tourism, Heritage & Services Marketing*, **4**, 27-36.

[60] Alam, A. (2020) Using Landsat Satellite Data for Assessing the Land Use and Land Cover Change in Kashmir Valley. *GeoJournal*, **85**, 1529-1543.

https://doi.org/10.1007/s10708-019-10037-x

[61] Chebby, F., Mmbaga, N. and Ngongolo, K. (2023) Land Use Land Cover Change and Socio-Economic Activities in the Burunge Wildlife Management Area Ecosystem during COVID-19. *Heliyon*, **9**, E14064. https://doi.org/10.1016/j.heliyon.2023.e14064

[62] Alshari, E.A. and Gawali, B.W. (2022) Analysis of Machine Learning Techniques for Sentinel-2A Satellite Images. *Journal of Electrical and Computer Engineering*, **2022**, Article ID: 9092299. https://doi.org/10.1155/2022/9092299

[63] Syed, S. and Karthikeyan, R. (2022) Strength Prediction Models for Recycled Aggregate Concrete Using Random Forests, ANN and LASSO. *Journal of Building Pathology and Rehabilitation*, **7**, Article No. 5. https://doi.org/10.1007/s41024-021-00145-y

[64] Tan, J., Zuo, J., Xie, X., Ding, M., Xu, Z. and Zhou, F. (2021) MLAs Land Cover Mapping Performance across Varying Geomorphology with Landsat OLI-8 and Minimum Human Intervention. *Ecological Informatics*, **61**, Article 101227. https://doi.org/10.1016/j.ecoinf.2021.101227

[65] Gondo, R., Kolawole, O.D. and Mfundisi, K.B. (2023) Land Use and Land Cover Changes along the Boteti-Thamalakane River System in Ngamiland District, Botswana. **20**, Article e01595. https://doi.org/10.1016/j.sciaf.2023.e01595

[66] Islam, K., Jashimuddin, M., Nath, B. and Kumar, T. (2018) Land Use Classification and Change Detection by Using Multi-Temporal Remotely Sensed Imagery: The Case of Chunati Wildlife Sanctuary, Bangladesh. *The Egyptian Journal of Remote Sensing and Space Science*, **21**, 37-47. https://doi.org/10.1016/j.ejrs.2016.12.005

[67] Oyedotun, T.D.T. (2019) Land Use Change and Classification in Chaohu Lake Catchment from Multi-Temporal Remotely Sensed Images. *Geology, Ecology, and Landscapes*, **3**, 37-45. https://doi.org/10.1080/24749508.2018.1481657

[68] Adjei, P.O., Buor, D. and Addrah, P. (2014) Geo-Spatial Analysis of Land Use and Land Cover Changes in the Lake Bosomtwe Basin of Ghana. *Ghana Journal of Geography*, **6**, 1-23.

[69] Furtado, I.S. and Martins, M.B. (2018) The Impacts of Land Use Intensification on the Assembly of Drosophilidae (Diptera). *Global Ecology and Conservation*, **16**, Article e00432. https://doi.org/10.1016/j.gecco.2018.e00432

[70] Yalew, S.G., Van Griensven, A., Mul, M.L. and Van Der Zaag, P. (2016) Land Suitability Analysis for Agriculture in the Abbay Basin Using Remote Sensing, GIS and AHP Techniques. *Modeling Earth Systems and Environment*, **2**, Article No. 101. https://doi.org/10.1007/s40808-016-0167-x

[71] Gashaw, T., Tulu, T., Argaw, M. and Worqlul, A.W. (2017) Evaluation and Prediction of Land Use/Land Cover Changes in the Andassa Watershed, Blue Nile Basin, Ethiopia. *Environmental Systems Research*, **6**, Article No. 17. https://doi.org/10.1186/s40068-017-0094-5

[72] Zone, W., Negassa, M.D., Mallie, D.T. and Gemeda, D.O. (2020) Forest Cover Change Detection Using Geographic Information Systems and Remote Sensing Techniques: A Spatio-Temporal Study on Komto Protected Forest Priority Area, East Wollega Zone, Ethiopia. *Environmental Systems Research*, **9**, Article No. 1. https://doi.org/10.1186/s40068-020-0163-z

[73] Forestry Commion REDD+ (2014) Forestry Commission-Climate Change Unit Ministry of Lands and Natural Resources.