American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-7, Issue-7, pp-77-88
www.ajer.org
Research Paper Open Access

Monitoring Food Security In The Akuapem South Of Ghana Using Normalize Difference Vegetation Index

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ABSTRACT: *High population growth rate and infrastructural development in the developing countries have led to food insecurity in recent years. This is coupled with decrease in natural conditions that support plant growth like rainfall, good weather conditions and others. In this research the food security of the Akuapem South District of Ghana was assessed by using Landsat images of 1991, 2003, and 2017. The lowest and the highest NDVI values of the years of study were determined. A priori defined four land cover classes in the classification scheme were built-up areas, farm lands, thin forest and thick forests. It was observed that the farmlands increased from 9% in 1991 to 23% in 2003 and to 28% in 2017. This gave the idea that, there has been an improvement in food production. However, it was observed that, there was a decrease in the forest reserves and also the conditions that supported plant growth such as rainfall and favourable weather conditions decreased by 4% and 14% in 2003 and 2017 respectively compared to 1991. Although the security of food is quite stable currently, it was concluded that, if nothing is done about the rate at which the forest is destroyed, there would be food unavailability in the future. It was recommended that measures should be put in place to reduce the rate at which the various forests cover are being destroyed and an afforestation plans should be embarked upon.*

KEYWORDS – *Food Insecurity, Normalize, Vegetation, Index, Forest*

Date of Submission: 28-06-2018 Date of acceptance: 13-07-2018

I. INTRODUCTION

Food is basic necessity for human survival. Until recent times there had been abundant land resource to produce enough food to sustain the relatively small population. However, with the explosion in the population coupled with the remarkable growth rate, developmental activities such as building road construction, deforestation and many other anthropogenic activities, there has been a significant reduction in the available agricultural land (Zubair, 2006). Moreover, due to the continuous use of the limited available farmlands year-in year-out, there has been a significant reduction in their potency as to how they support plant growth.

Vegetation cover around the world has undergone various changes due to the direct effects of natural sources such as fires global warming and dryness; and these changes have become increasingly visible in the last decades (Elmendorf et al., 2012) Land use and land cover change have become a central component in current strategies for monitoring natural resources and also environmental changes. The advancement in the concept of vegetation mapping has greatly increased research on land use and land cover change thus providing an accurate evaluation of the extent and health of the world's forest, grassland and agricultural resources which have become an important priority (Zubair, 2006). With respect to these reasons there is the need to systematically and scientifically monitor the limited agricultural land to allow the land managers to know how their lands are doing with regards to supporting plant growth and to develop more appropriate land management practices (Pradhan, 2003).

To study the rate at which the various land covers are changing as a means to ensuring food security, the following study is designed for the Akuapem South District which is largely known for its agricultural activities. To monitor the vegetation changes, time series of Normalize Difference Vegetation Index (NDVI) images are used for the study as NDVI images have been proven to be a powerful tool to monitor biomass growth (Gross, 2005).

II. MATERIALS AND METHODS USED

2.1 Study Area

The Akuapem South District is located at the south eastern part of the Eastern Region of Ghana between latitudes 05 48' 00" N and longitude 00 21' 00" W. It covers a land area of about 440 km2. See Fig. 1.

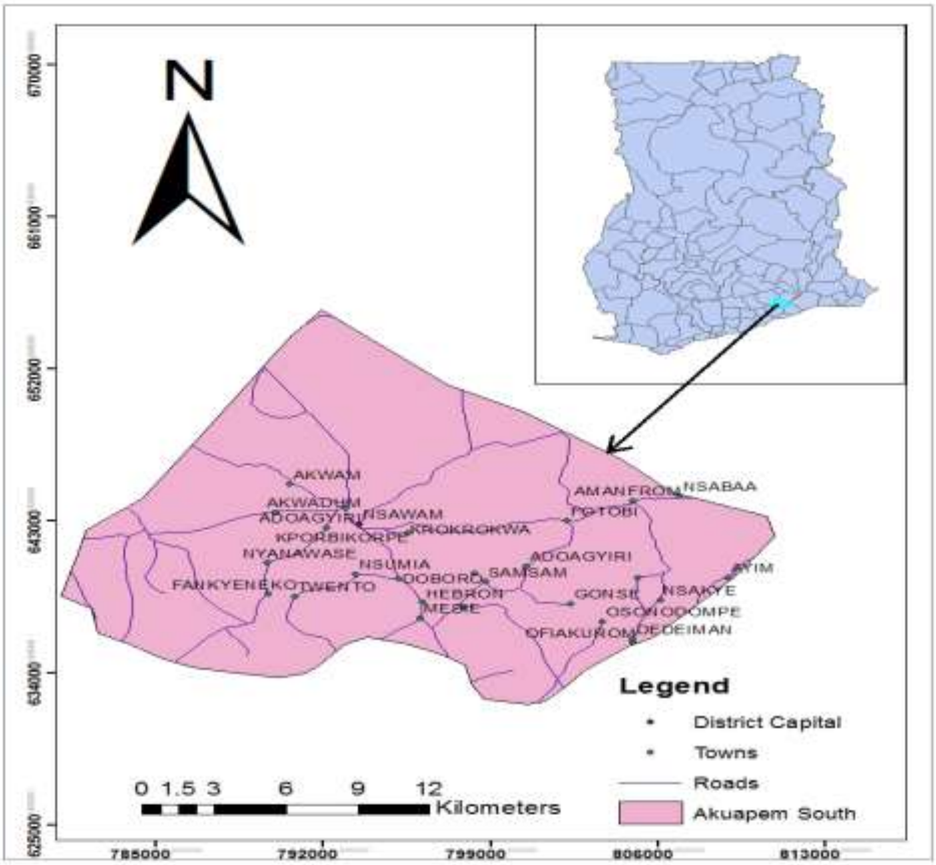

Fig. 1 Map of Akuapem South District

It is bordered to the west by the Nsawam-Adoagyiri Municipality, to the south-east by the Kpone Katamanso district, to the south by Ga East district and to the North-East by the Akuapem North Municipality (Anon., 2010).

The weather condition in the district is generally cold with annual average temperature of 24 C recorded between March and April, with the lowest temperature of 20 C in August. The district lies within the semi-equatorial climatic region, and experiences two rainfall seasons in a year, with an average rainfall between 125 cm and 200 cm (Anon., 2010).

The forest covers about 90% of the district (Anon., 2010). Soil types are generally sandy loam with clays found in the valley bottoms. The Akuapem South district is characteristically agricultural based with 60% of its population engaged in subsistence and commercial farming (Anon., 2012).

2.2 Land Cover Change

Land use and land cover dynamics are widespread, accelerating, and significant processes driven by human actions but also producing changes that impact humans. These dynamics alter the availability of different biophysical resources including soil, vegetation, water, animal feed and others. Consequently, land use and cover changes could lead to a decreased availability of different products and services for human, livestock, agricultural production and damage to the environment as well (Oumer, 2009).

It is estimated that undisturbed (or wilderness) areas represent 46% of the earth's land surface. Forests covered about 50% of the earth's land area 8 000 years ago, as opposed to 30% today. Agriculture has expanded into forests, savannas, and there have been measures in all parts of the world to meet the demand for food and fiber (Lambin *et al*., 2003). Based on data from diverse sources, the Global Forest Resources Assessment 2000 estimated that the world's natural forests decreased by 16.1 million hectares per year on average during the 1990s, which is a loss of 4.2% of the natural forest that existed in 1990 (Lambin *et al*., 2003). Land use in West Africa has changed swiftly over the last half-century: expansion of mixed crop-livestock systems into former grazing land and other natural areas and intensification of agriculture are the two largest changes that have been detected (Oumer, 2009).

Land change studies attempt to explain the areas where change is occurring, what land cover types are changing, the types of transformation occurring, the rate at which the land is changing and the driving forces and the proximate course of change. The ultimate reasons for studying these change characteristics are to understand land change trends, evaluate and manage the consequences of these changes and define future scenarios of change (Loveland and Acevedo, 2016). The impacts of change in land cover may be positive or negative spatially or temporally but mostly negative in the tropical forest areas. In the long term, these negative changes reduce the ability of the earth to produce goods and services on which human survive (Dale *et al*., 2000).

The ability to forecast land cover change and to predict the consequences of the change will depend on the ability to understand the past, current and the future drivers of land cover change (Anon., 2017). The patterns of land cover change are shaped by the interaction of the economic, social, environmental and technological forces. The drivers of the change are mostly as a result of human activities other than naturally occurring. Some natural courses include landslides, storm, and fire (Asubonteng, 2007). Rapid urban development, agricultural activities, mining as well as quarrying are the notable human activities which influence the land cover change (Asubonteng, 2007). Increase in population which has resulted in the various developmental projects is also a major factor.

An important aspect of change detection is to determine what is actually changing to what i.e. which land use class is changing to the other. This information will reveal the desirable and undesirable changes and classes that are “relatively” stable over time. This information will also serve as a vital tool in management decisions. This process involves a pixel to pixel comparison of the study year images through overlay (Zubair, 2006).

2.3 Food

Food is any substance consumed to provide nutritional support for the body. It is usually of plant or animal origin, and contains essential nutrients such as carbohydrates, fats, proteins, vitamins, or minerals. Most food has its origin in plants. Some food is directly obtained from plants. Some foods not from animal or plant sources includes various edible fungi, especially mushrooms (Anon., 2017).

Food security is considered differently depending on whether the focus is at the macro or the micro level. At the macro level, food security means that enough food has to be available to cover the whole population’s nutritional requirements. At the micro level, for households and individuals, three conditions need to be considered: sufficient food at the macro level, stability in supply, and a regular access to food for all households and their members (Wangthamrong, 201

The World Food Summit of 1996 defined food security as existing “when all people at all times have access to sufficient, safe, nutritious food to maintain a healthy and active life”. Commonly, the concept of food security is defined as including both physical and economic access to food that meets people’s dietary needs as well as their food preferences. In many countries, health problems related to dietary excess are an ever increasing threat. In fact, malnutrition and foodborne diarrhea have become double burden.

Food security is built on two pillars:

i. Food availability: sufficient quantities of food available on a consistent basis; and
ii. Food use: appropriate use based on knowledge of basic nutrition and care, as well as adequate water and sanitation.

Food security is a complex sustainable development issue, linked to health through malnutrition, but also to sustainable economic development, environment, and trade (Anon., 2017).

2.4 Normalize Difference Vegetation Index

The Normalize difference Vegetation Index (NDVI) is the ratio of NIR (near-infrared radiation) and red bands (see equation 1).

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

The NDVI was employed in numerous studies to estimate vegetation biomass, greenness, primary production and dominant species, leaf area index (LAI), fraction of absorbed photosynthetically active radiation (Senay and Elliot, 2000). NDVI is calculated from the visible and the near-infrared light reflected by vegetation. Healthy vegetation absorbs most of the visible light that incidents on it and reflects a substantial amount of the near-infrared radiations. Unhealthy or spares vegetation reflect more visible light and less near-infrared light. Bare soil on the other hand reflects moderately in both the visible and the infrared portion of the electromagnetic spectrum (Holme *et al*., 1987). Being aware of how plants behave across the electromagnetic spectrum, we can derive NDVI information by laying emphasis on the satellite bands that is the most sensitive to the vegetation information. Calculation for NDVI for a given pixel always result in a number that ranges from (-1) to $(+1)$;

however no green leave gives a value close to zero. A zero means no vegetation and close to (+1) (0.8-0.9) indicate the highest possible density of green leaves (Anon., 2017). There are different vegetation indices; however those that rely on NIR and red reflectance as their principal input will typically yield the same information as the NDVI. One of the reasons for the popularity of the NDVI is that many sensors (from handheld to satellite) provide measurements in the NIR and red portion of the spectrum. NIR is also used in the color infrared photographs. Most, if not all, of the new commercial satellites will have red and NIR bands, so the availability of these data will increase (Anon., 2010).

The NDVI is well-known satellites derive measure, which is directly related to total green biomass and the photosynthetic activity of the vegetation. The NDVI is based on the reflective properties of vegetation. The NDVI is generally an indicative of the amount of vegetation on the earth's surface. By using temporal NDVI measures from multi-dated satellite imageries, we can compare spatial and temporal variabilities of the amount of vegetation in a specific area. Since NDVI indicates the amount of vegetation it has direct association with rainfall and other factors affecting plant growth and vegetation (Pradhan, 2003

2.5 Materials

The data used for the project include:

i. Boundary Shapefile of the study area; and
ii. Landsat images.

Table 1 Data Used

Type of Data	Path and Row	Acquisition Year	Spatial Resolution
Landsat 4-5 TM	193/056	1991	30 m
Landsat 7 ETM+	193/056	2003	30 m
Landsat 7 ETM+	193/056	2011	30 m

2.6 Methods Used

The methods used were:

i. Field data collection for ground truthing;
ii. Data Processing;
iii. NDVI Calculation;
iv. Supervised Classification; and
v. Accuracy assessment.

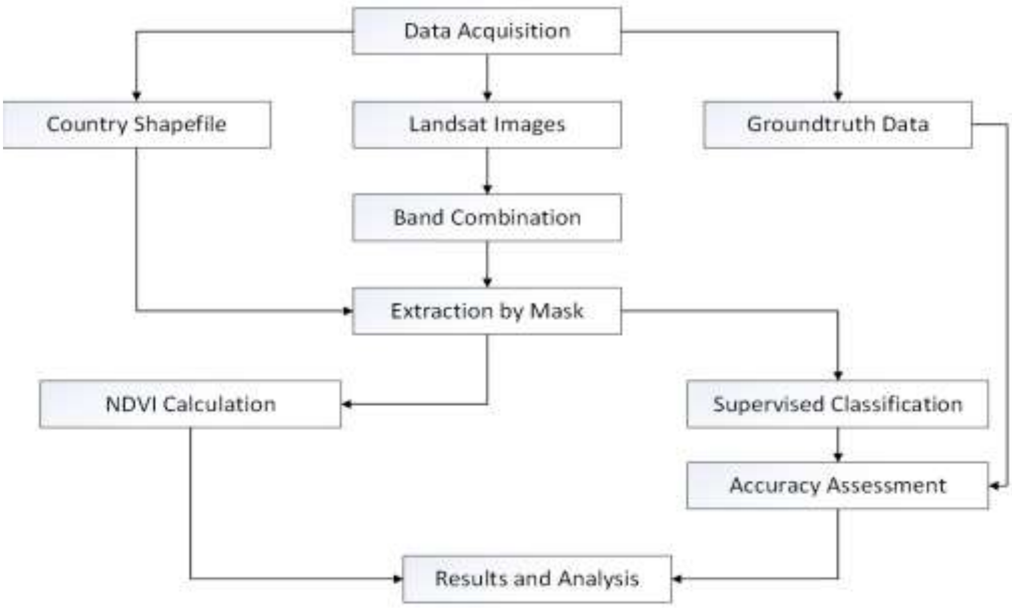

Fig. 2 Flow Chart of the Methods Used

2.6.1 Field Data Collection and Ground Truthing

The purpose of the field survey was to observe how the different image characteristics look like in reality. On the field, points were picked with GPS receiver on the different vegetation cover that exist in the area of study, to be able to understand the satellite images better for interpretation. The classes of interest such as thick forest, thin forest, farmlands and built-up areas were recorded.

2.6.2 Image Processing

The satellite images were processed using ArcGIS software. The satellite image processes include layer stacking and radiometric correction (haze). The application of atmospheric correction is very essential for the current study for two reasons. Firstly, the study compares the relationship between field-based data and spectral information. Secondly, the images that are being used were acquired on dates with varying atmospheric conditions and also collected by different types of sensors via different platforms.

Removing atmospheric effects involve calibration and atmospheric correction. Calibration adjusts the image by converting raw radiance values of each pixel to atmospheric absolute (radiance) or relative (reflectance) values. An atmospheric correction then adjusts these values to ground radiance or reflectance at each pixel based on sun-ground-sensor geometry and atmospheric composition.

2.6.3 Image Enhancement

This is the process of rendering the image more visually interpretable for a particular application. Enhancement makes important features of raw remotely-sensed image more interpretable to the human eye. The graphical model algorithms in ArcGIS were employed to perform the enhancement of the images. Radiometric enhancement for haze was done to correct for any irregular brightness in the picture due to the sensor irregularities and unwanted sensor. This correction was done so as to accurately represent the true reflectance of the image.

2.6.4 Interpretation of Satellite Images

After the printing of satellite images, they are inspected to aid in the preparation of the legend. The legend was established in terms of the image characteristics after which the interpretation was done. Homogenous areas were identified and defined in terms of the image characteristics. These are the colour, pattern, texture, shape, size and location (Bakker *et al*., 2004). A number was assigned to each homogenous area.

2.6.5 NDVI Calculation

The NDVI of the images of the different years of study was calculated. The different bands of the landsat images were separated. The NDVI was calculated from the reflectance measurements in the red and near infrared portions (NIR) portions of the spectrum.

$$NDVI = (NIR - Red) / (NIR + Red) \quad (2)$$

2.6.6 Classification

Image classification is based on the different spectral characteristics of the different materials on the earth's surface (Bakker *et al*., 2004). It is a process that operates in feature space. The process of the image classification involved these four steps:

i. Selection and preparation of the image data;
ii. Definition of the clusters in the feature space;
iii. Selection of the classification algorithm; and
iv. Running the actual classification.

Various land cover types from the image were determined and classified. This was done using the field knowledge, the positions of the GPS points taken from the field and their positions on the image (Lillesand and Kiefer, 1994).

The various land cover groupings and their descriptions used for the classification are shown in Table 2

Table 2 Data Used and their Sources

Land Cover type	Description
Built-Up Areas	This include residential and commercial facilities
Farmlands	A land suitable or reserved for the cultivation of crops
Thin Forest	Consist of trees with no overhead canopy
Thick Forest	Consists of trees with canopy that can block sunlight from reaching the floor

2.6.7 Accuracy Assessment

Accuracy assessment is an important part of any classification project. It compares the classified to another data source that is considered to be accurate or ground truth data. Ground truth can be collected on the field. The most common way to assess the accuracy of a classified map is to create a set of random points from the ground truth data and compare that to the classified data.

III. RESULTS AND DISCUSSION

3.1 Results

3.1.1 NDVI Maps

Normalize Difference Vegetation Index maps were produced to assess the density of the greenness of the area of study. It also provided us with tools to make analysis concerning the state of the various vegetation classes as to whether the vegetation is healthy. These are shown in Fig. 3, Fig. 4, and Fig. 5.

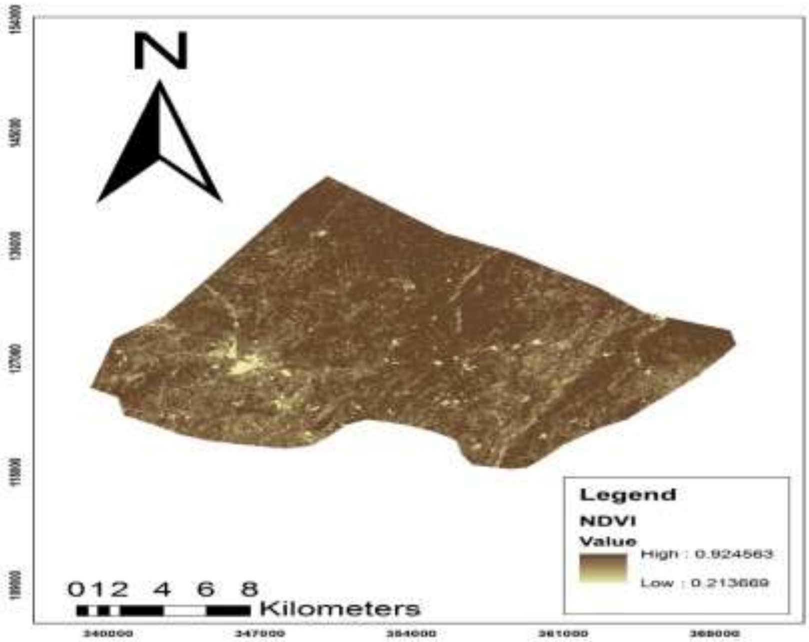

Fig. 3 A 1991 NDVI Map of the District

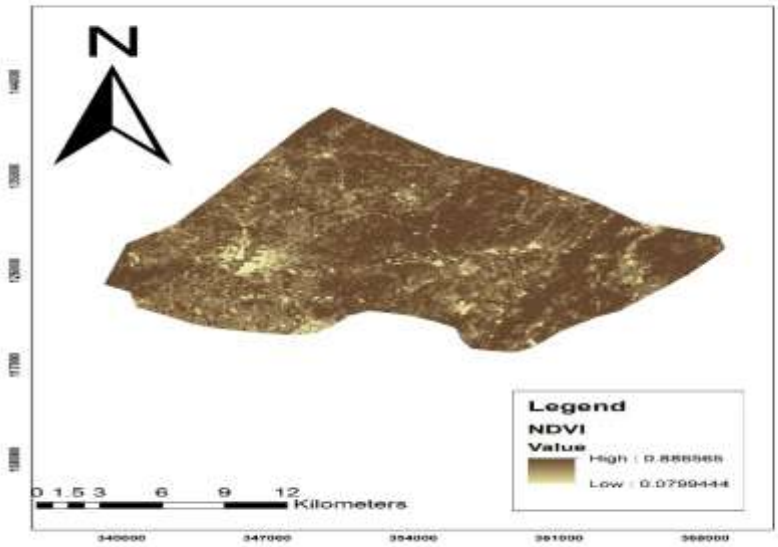

Fig. 4 A 2003 NDVI Map of the District

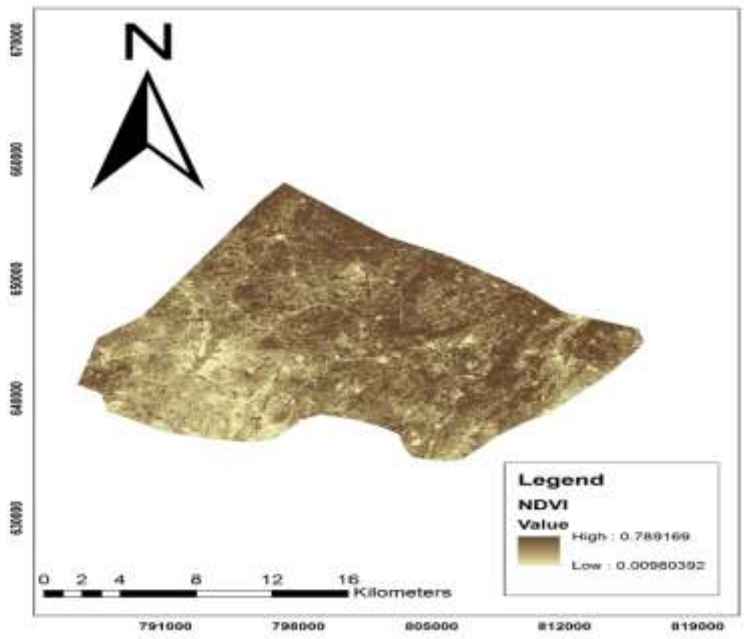

Fig. 5 A 2017 NDVI Map of the District

3.1.2 Classification Maps

From the supervised classification, three land cover maps for 1991, 2003, and 2017 were produced. Four land cover classes were delineated. The classes are built-up areas, farmlands, thin forests and thick forests. Fig. 6, Fig. 7, and Fig. 8 shows the classified maps of the study area for the years 1991, 2003, and 2017.

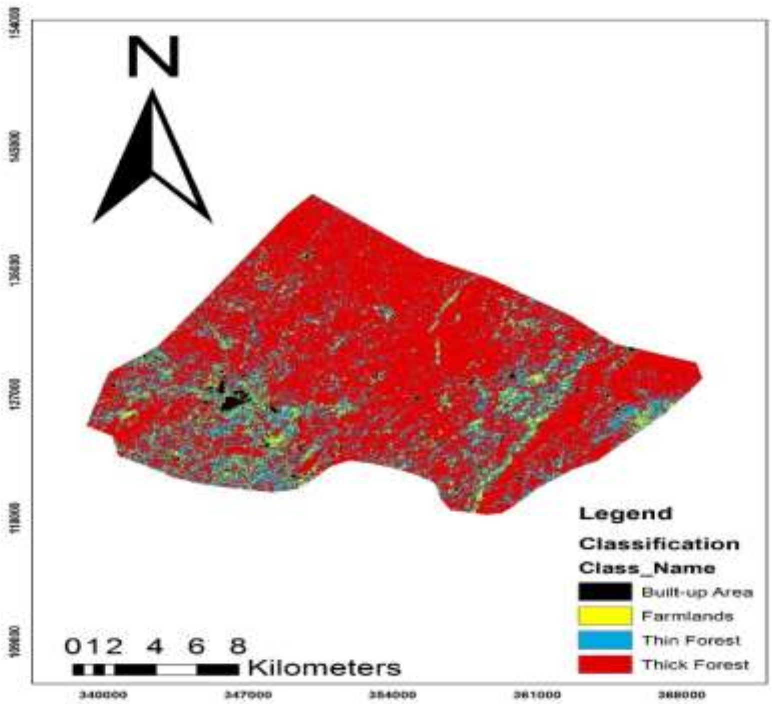

Fig. 6 A 1991 Classified Map of the District

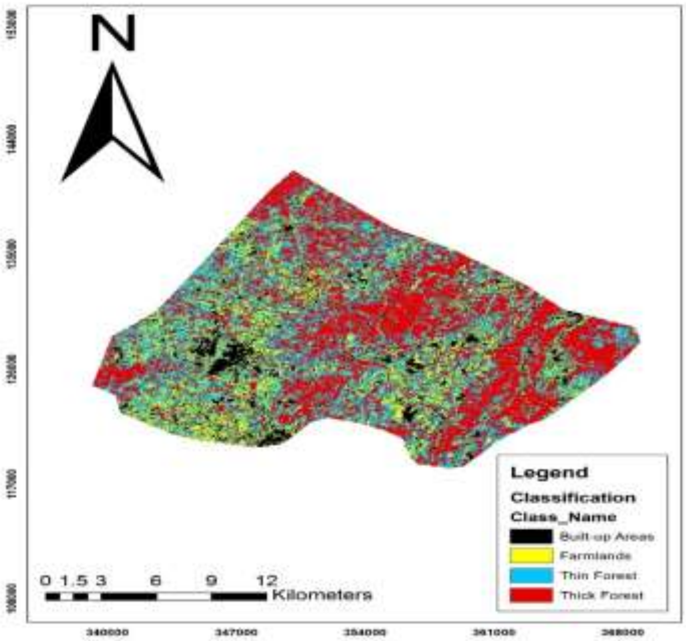

Fig. 7 A 2003 Classified Map of the District

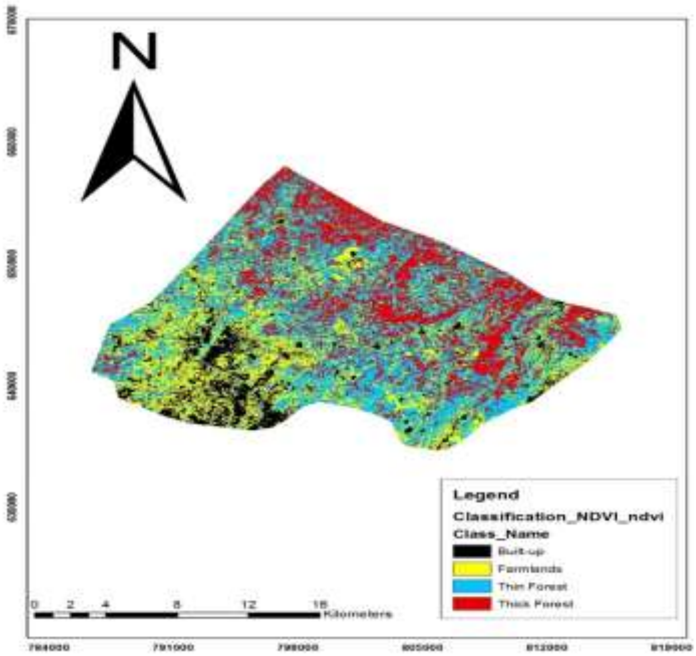

Fig. 8 A 2017 Classified Map of the District

Figures of pie charts of land use cover distribution maps for 1991, 2003, and 2017 are presented in Fig. 9, Fig. 10, and to Fig. 11.

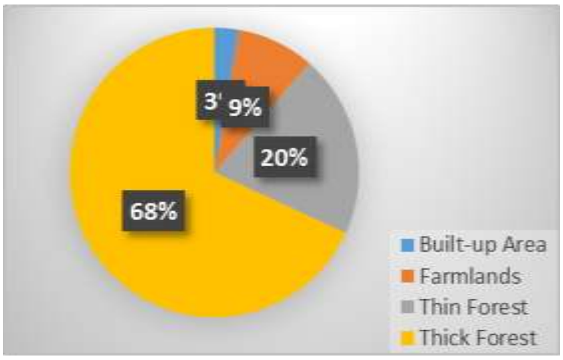

Fig. 9 Pie Chart of 1991 Land Cover Map

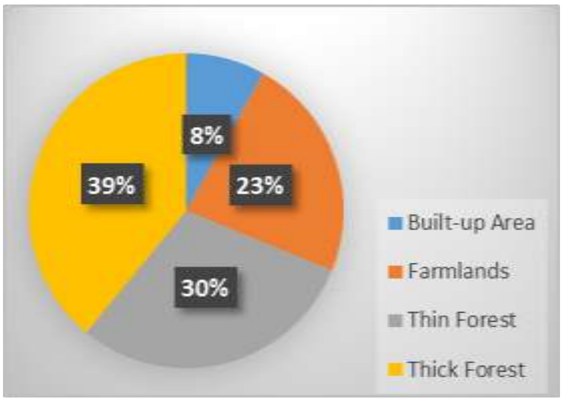

Fig. 10 Pie Chart of 2003 Land Cover Map

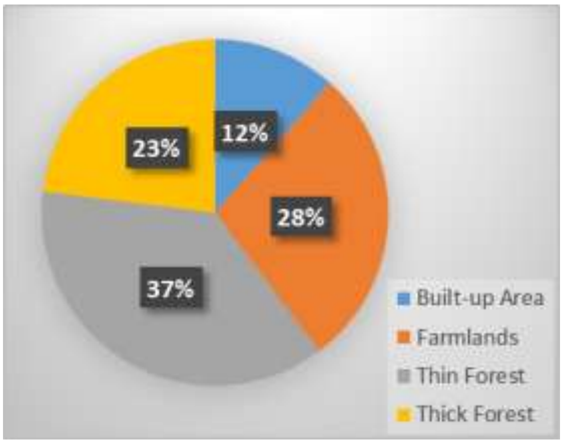

Fig. 11 Pie Chart of 2017 Land Cover Map

The land cover changes of the study area were assessed and the results are presented in the Table 3.

Table 3 Land Cover changes of 1991, 2003 and 2017

Land Cover Classes	**1991**	**%**	**2003**	**%**	**2017**	**%**
Built-up Area	18.008	4.093	35.811	8.139	50.797	11.545
Farmlands	38.173	8.676	101.482	23.064	122.095	27.749
Thin Forest	90.022	20.460	130.862	29.741	159.748	36.306
Thick Forest	293.797	66.772	171.845	39.056	107.360	24.400
Total	440	100	440	100	440	100

The data was converted and the bar chart of the land cover classes of the years 1991, 2003, and 2017 is presented in Fig. 12 and the actual extent of the changes in land cover are presented in Table 4.

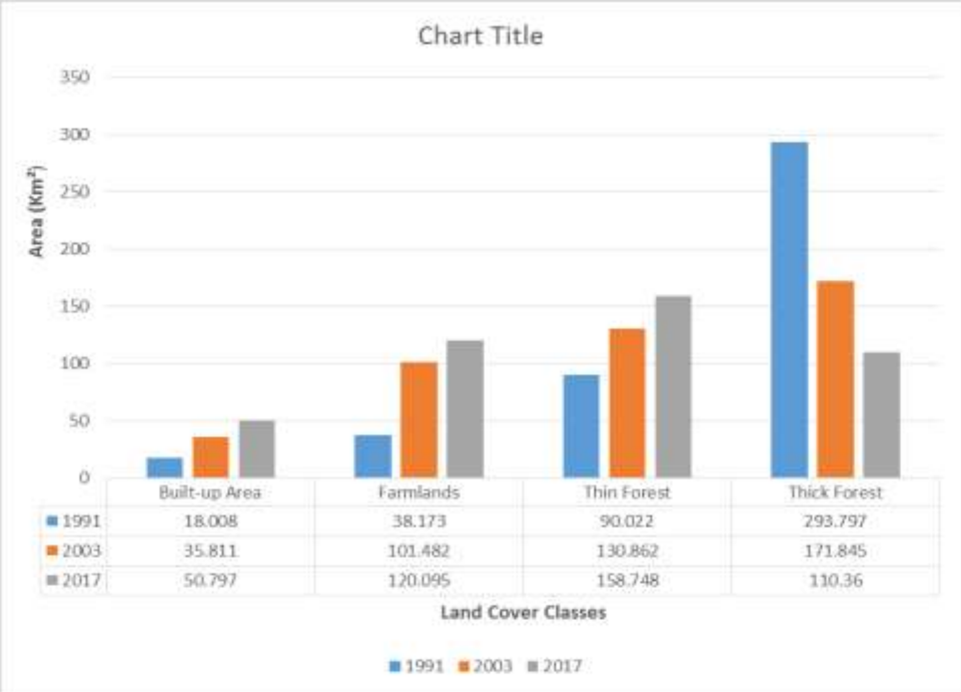

Fig. 12 Bar Chart of Land Cover Classes of 1991, 2003, and 2017

Table 4 Actual Extent and Rates of Changes (Km²)

Class	1991-2003		2003-2017		1991-2017		Annual Change	
	Change	Rate (%)	Change	Rate (%)	Change	Rate (%)	change	Rate (%)
Built-up	23.803	4.046	14.986	3.406	38.789	7.452	1.492	0.287
Farmlands	63.309	14.388	22.613	5.139	85.922	19.528	3.305	0.751
Thin Forest	40.84	9.282	32.886	7.474	73.726	16.756	2.836	0.644
Thick Forest	-127.952	-29.08	-70.485	-16.019	-198.437	-45.099	-7.632	-1.735

3.1.3 Accuracy Assessment

To assess the accuracy of the three classified images, the ground truth points were overlaid on the 1991, 2003 and 2017 classified images. 48 transformed ground control points were used and the accuracies obtained are 77%, 81.3% and 87.5% for the years 1991, 2003 and 2017 respectively. The accuracies increased from 1991 to 2003 through to 2017. This is because the more current the image, the more accurately it represent modern state of the area. The accuracy assessment for 1991, 2003, and 2017 are presented in Table 5, Table 6, and Table 7 respectively.

Table 5 Accuracy Assessment for 1991

Land Cover Class	Reference Totals	Number Correct	Individual Accuracy (%)
Built-Up Area	16	13	81.25
Farmlands	14	11	78.6
Thin Forest	10	7	70
Thick Forest	8	6	75
Total	48	37	
Overall Accuracy	77%		

Table 6 Accuracy Assessment for 2003

Land Cover Class	**Reference Totals**	**Number Correct**	**Individual Accuracy (%)**
Built-Up Area	16	14	87.5
Farmlands	14	12	85.7
Thin Forest	10	7	70
Thick Forest	8	6	75
Total	48	39	
Overall Accuracy	81.3%		

Table 7 Accuracy Assessment for 2003

Land Cover Class	Reference Totals	Number Correct	Individual Accuracy (%)
Built-Up Area	16	14	87.5
Farmlands	14	12	85.7
Thin Forest	10	8	80
Thick Forest	8	8	100
Total	48	42	

3.2 Discussions

The NDVI is a well-known satellite derives measure which is directly related to total green biomass and the photosynthetic activity of the vegetation. The temporal NDVI measures from the images help us to analyse the variability in the amount and conditions of vegetation in the study area. Since NDVI indicates the amount of vegetation, it has direct association with rainfall and other factors affecting plant growth and vegetation (Pradhan, 2003).

Figure 5.1 shows the NDVI image of 1991. A study of the NDVI image of 1991 indicates the highest NDVI value of 0.924563 and the lowest value of 0.213669. The image shows that the areas that gave the high NDVI is widely spread. It shows thick vegetation covers and also the fact that the conditions that support plant growth such as rainfall is very common. Figure 5.4 shows the land cover classes. It was revealed that 68% of the total land Cover was thick forest, 20% was covered with thin forest, 9% were farmlands and 3% was areas that were Buit-Up.

Figure 5.2 shows the NDVI image of 2003. A study of the image shows the highest NDVI value as 0.886565 and the lowest value as 0.079944. The areas with the high NDVI values were moderately spread. The conditions that supported plant growth was reduced by 4% when compared with the 1991 image. Figure 5.5 shows the land cover classes. The total area had 39% of the area as thick forest, 30% as thin forest, 23% as farmlands and 8% as Built-Up areas.

Figure 5.3 shows the NDVI image of 2017. A study of the image shows the highest NDVI value as 0.789169 and the lowest value as 0.009880. The areas with the high NDVI values were considerably small with most of the total areas with average to very small NDVI values. The conditions that supported plant growth was reduced by 14% when compared with the 1991 image. Figure 5.6 shows that 23% of the total area is covered with thick forest, 37% is covered with thin forest, 28% is covered with farmlands and 12% of the total Built-Up.

Although a very small portion of the total area was farmlands (9%), there was a very high food security because one could depend on the large forest lands and the conditions that supported plant growth to produce more food crop. The situation changed considerably in 2003 because of the increase in population and the decrease in plant cover which contributed significant decrease in the other factors that encourage plant growth. More land (23%) was to be cleared for agricultural purposes to meet the increasing demand for food. The situation became critical in 2017 with a sharp decrease in forest cover coupled with the increase in population and its attendant decrease in the factors that support crop growth. Therefore more lands (37%) were to be used for crop production to support the ever-increasing demand for food.

IV. CONCLUSION

The project has helped determined the state of food security in the Akuapem South District within the intended time period (1991-2017). This was done by creating NDVI maps for 1991, 2003 and 2017. Furthermore, classified maps of the same period were also created to further clarify the extent of the changes. A pie and bar charts were developed to quantify the classification of the land cover change dynamics. For example, in 1991the built-up area covered 3%, farmland covered 9%, thin forest covered 20% and thick forest covered 68%. By 2017 the land cover dynamics of the area had change tremendously. In 2017the built-up area covered 12%, farmland covered 28%, thin forest covered 37% and thick forest covered 23%. Furthermore, the annual rate at which the various land covers are changing has been determined. Remote sensing observations have revealed that there is a direct interdependency between high vegetation cover and the various factors such as rainfall and other factors that support rainfall. From the study it was concluded that as population increases and the factors which aid plant growth decreases, more farmlands would be required to grow more food crops to sustain the population. This will also bring an increase in rate at which the forest covers will be cleared to produce more food crops to sustain the population. It is recommended that measures should be put in place to reduce the rate at which the various forests cover are being destroyed and a reforestation plans should be embarked upon. There should also be a critical look at the underlying factors causing the various land cover changes and further studies should be carried out to find out why these changes have such an impact on food production.

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